Speaker Verification using I-vector Features

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Abstract

Speaker recognition is a non-invasive and convenient technology that has the potential to be applied to several applications, including access control, transaction authentication over a telephone connection and forensic suspect identification by voice. Compared to many other biometrics, speaker recognition is a non-obtrusive technology and does not require special purpose acquisition hardware other than a microphone.

Even though speaker recognition research has been ongoing for more than four decades, the state-of-the-art speaker recognition systems still have several limitations. This thesis has investigated three major challenges, which need to be addressed for the wide spread deployment of speaker recognition technology: (1) combating the train/ test (or enrolment/verification) mismatch, which is invariably present due to differences in acoustic conditions, (2) reducing the large amount of development data that is required to collected to enable the design the state-of-the-art speaker recognition systems, and (3) reducing the duration of speech required to train and verify speaker models.

In order to address the enrolment and verification mismatch issue, several novel advanced channel compensation approaches, including weighted linear discriminant analysis (WLDA) and source-normalized LDA (SN-WLDA), were proposed to improve the performance of state-of-the-art cosine-similarity scoring (CSS) and probabilistic linear discriminant analysis (PLDA) i-vector speaker recognition systems.

To address the significant amount of speech required for development of robust speaker recognition systems, especially in the presence of large intersession variability, the effect of limited development data on PLDA speaker recognition design was investigated. As a result, a weighed median Fisher discriminator (WMFD) projection prior to PLDA modelling and linear-weighted PLDA parameters estimation approach were proposed and found to improve speaker verification performance in conditions where limited development data was available.

To address the shortcomings of reduction in training and/or testing data, the effect of using short utterances for CSS and PLDA i-vector speaker recognition systems were studied. It was found that while long utterance i-vectors vary predominantly with speaker and session variations, short utterance i-vectors also had another significant source of variation based largely on the linguistic content of the utterances. Based upon this observation, novel short utterance variance normalisation (SUVN) and short utterance variance (SUV) modelling approaches were respectively proposed to improve performance of CSS i-vector and PLDA speaker verification systems in short utterance evaluation conditions.

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List of Abbreviations

Cosine similarity scoring	CSS
Cepstral mean subtraction	CMS
Cepstral mean and variance normalization	CMVN
Discrete cosine transform	DCT
Decision cost function	DCF
Expectation maximization	EM
Expected log-likelihood ratio	ELLR
Fast fourier transform	FFT
Factor analysis	FA
Gaussian mixture model	GMM
Gaussian PLDA	GPLDA
Group delay function	GDF
Heavy-tailed PLDA	HTPLDA
Instantaneous frequency deviation	IFD
Joint factor analysis	JFA
Kernel eigenspace-based MLLR	KEMLLR
Linear discriminant analysis	LDA
Linear frequency cepstral coefficients	LFCC
Linear prediction cepstral coefficients	LPCC

Maximum margin criterion	MMC
Mel frequency cepstral coefficients	MFCC
Maximum-a-posteriori	MAP
Maximum likelihood	ML
Maximum likelihood linear regression	MLLR
Multiple frame size	MFS
Multiple frame rate	MFR
Nuisance attribute projection	NAP
Probabilistic linear discriminant analysis	PLDA
Perceptual linear prediction cepstral coefficients	PLPCC
Reference speaker weighting	RSW
Support vector machine	SVM
Source-normalized LDA	SN-LDA
Source-normalized MMC	SN-MMC
Source-normalized WMMC	SN-WMMC
Source-normalized WLDA	SN-WLDA
Source- and utterance-normalized LDA	SUN-LDA
Short utterance variance normalization	SUVN
Short utterance variance	SUV
Signal to noise ratio	SNR
Symmetric normalization	s-norm
Single frame size and rate	SFSR
Scatter difference NAP	SD-NAP
Speaker recognition evaluation	SRE
Test normalization	t-norm
Universal background model	UBM
Voice activity detection	VAD
Weighted LDA	WLDA
Weighted MMC	WMMC
Within-class covariance normalization	WCCN
Weighted median fisher discriminator	WMFD
Zero normalization	z-norm
Zero test normalization	zt-norm

Certification of Thesis

The work contained in this thesis has not been previously submitted for a degree or diploma at any other higher educational institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

Signed: QUT Verified Signature

Date: 01/10/2014

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Chapter 1

Introduction

1.1 Motivation and overview

Speaker biometrics is the science and technology of analysing speaker characteristics of speech, which is used to uniquely identify individuals. Speaker biometrics is often split into two distinct applications, referred to as speaker identification and verification. Speaker identification is the task of determining an unknown speaker's identity, whereas speaker verification is the process of authenticating the identity of a person by analysing their speech signal.

Among these, speaker verification is the most popular due to its importance in security and access control applications. It is a non-invasive and convenient technology and has the potential to be applied to a number of person authentication applications, including credit card verification, over-the-phone (wireless, landline and internet telephony) secure access in call centres, suspect identification by voice, national security measures for combating terrorism by using voice to locate and track terrorists, detection of a speaker's presence at a remote location, annotation and indexing of speakers in audio data, voice-based signatures and secure building access. With security of personal details becoming more and more of an issue for people in today's society, people want companies to make sure that the best possible preventative measures are in place to prevent the possibility of identity fraud occurring.

Speaker verification is by no means a new research field. The earliest attempts to build speaker verification systems were made in the early 1950s [27, 79, 92]. Continuous research in this field has been ongoing for the last twenty years with notable progress being made [1, 9, 14, 22, 25, 27, 64, 65, 75, 101]. Recent studies have found that training (enrolment) and testing (verification) mismatch significantly affect the speaker verification performance [14, 50, 62, 78, 103]. In addition, in the current state-of-the-art speaker verification systems, a significant amount of speech is required for speaker model training (enrolment), as well as for testing (verification) [46, 49, 66, 73, 104, 106].

In order to ensure the wide spread deployment of speaker verification technology in many practical situations where speaker verification is desirable, three major challenges must be faced:

1. Effective methods must be developed to combat the training and testing mismatch which is invariably present due to the adverse (harsh and non-stationary) acoustic conditions which reduce the speaker verification accuracy.

2. The amount of development data required to design state-of-the-art speaker verification systems must be reduced as it hard to collect and annotate large amount of speech data.

3. The duration of speech required to train speaker models as well the duration of testing utterances that are needed to be spoken by users must be reduced

significantly for effective use of the technology.

1.2 Scope of PhD

The broad scope of this PhD research is to address the above-mentioned three major challenges, which could pave the way to successful implementation of efficient and accurate speaker verification. The outcome of the research is of benefit to many applications of speaker verification technology.

In recent times, cosine similarity scoring (CSS) i-vector and probabilistic linear discriminant analysis (PLDA) speaker verification systems have become state-of-the-art systems. In CSS i-vector speaker verification, channel compensation approaches are applied to target and test i-vectors to compensate the channel variation and CSS is used to estimate the score. On other hand, in PLDA speaker verification, speaker and channel variations are separately modelled using the PLDA approach. These two state-of-the-art systems are used to address the above-mentioned three challenges.

1.3 Thesis structure

The remaining chapters of the thesis are organized as follows:

- **Chapter** 2 provides an overview of speaker verification technologies. The significant focus is given to Gaussian mixture model (GMM) based generative and support vector machine (SVM) based discriminative approaches, and finally joint factor analysis (JFA) based session compensation techniques are also detailed.

- **Chapter** 3 describes the recent state-of-the-art CSS i-vector speaker verification system, which covers the i-vector feature extraction and standard channel compensation techniques. PLDA modelling approaches are detailed in the second part.

- **Chapter** 4 details the CSS i-vector and PLDA speaker verification system framework and experimental protocol as the comprehensive framework is required for experimental work in this thesis.

- **Chapter** 5 introduces several novel advanced channel compensation techniques, including weighted linear discriminant analysis (WLDA), weighted maximum margin criterion (WMMC), source-normalized WLDA (SN-WLDA), and source-normalized WMMC (SN-WMMC), to CSS i-vector speaker verification system. It also investigates whether more speaker discriminant information would be extracted if different types of channel compensation approaches were fused together.

- **Chapter** 6 investigates how PLDA speaker verification compensates the channel variation. Subsequently, a novel approach is proposed where the PLDA approach is combined with channel compensation approaches to compensate the additional channel variation. Further, several new approaches are introduced to improve the performance of PLDA speaker verification in limited session data and limited microphone data.

- **Chapter** 7 analyses the CSS i-vector speaker verification with short utterance evaluation and development data. Based upon this analysis, a novel source- and utterance-normalised LDA (SUN-LDA) approach is introduced to improve the CSS i-vector system in short utterance evaluation conditions. Finally, PLDA speaker verification is also analysed with short utterance evaluation and development data.

- **Chapter 8** investigates the shortcomings of short utterance i-vectors, and introduces a novel short utterance variance normalization (SUVN) technique to CSS i-vector speaker verification to compensate the session and utterance variations. Subsequently, a novel short utterance variance (SUV) approach is combined with Gaussian PLDA (GPLDA) speaker verification to also improve the performance in short utterance evaluation conditions.

- **Chapter 9** concludes the dissertation with a summary of the contributions of this research, and suggests further directions for continuing research in CSS i-vector and PLDA speaker verification systems.

1.4 Original contributions

This research programme has contributed to the field of speaker verification, by addressing the challenges identified above. The recent state-of-the-art speaker verification systems, including CSS i-vector and PLDA approaches, were built to investigate the aforementioned three major challenges. The framework of CSS i-vector and PLDA speaker verification system are detailed in Chapter 4.

1. As i-vector features are based on one variability space, effective channel compensation techniques are required to compensate the channel variation, and that has become an active area of research. Several novel advanced

channel compensation approaches, including weighted linear discriminant analysis, weighted maximum margin criterion, source-normalized WLDA, and source-normalized WMMC, were introduced to the CSS i-vector speaker verification system in Chapter 5, and these approaches have shown that they provide improvement over standard channel compensation approaches, LDA and within-class covariance normalization (WCCN). In addition, it was also found that if different types of channel compensation approaches are fused together in score level, that system provides an improvement over individual channel compensation-based CSS i-vector speaker verification. These research outcomes were published at the ICASSP conference in 2012 [47] and in Computer Speech & Language [45].

2. It was initially analysed as to how the PLDA approach compensates the channel variations, by modelling the speaker and channel space separately. Subsequently, a novel approach was introduced in Chapter 6 where the best channel compensation approach was used to compensate the additional channel variation prior to PLDA modelling. This approach has shown an improvement over the standard PLDA approach, and reduced the computational complexity as PLDA modelling and scoring were estimated on a reduced subspace. An source-normalised WLDA approach was used to compensate the additional channel variations, as it was found as the best channel compensation approach in Chapter 5. These research outcomes were published at the Speaker Odyssey conference in 2012 [48] and in Computer Speech & Language [45].

3. In mismatched conditions, a larger number of sessions-per-speaker data is required to adequately compensate the intra-speaker variance. However, it is hard to collect a larger amount of session data. Initially, the PLDA approach was studied with limited session data in Chapter 6 and it was found that when a number of sessions-per-speaker reduces, it significantly

affects the speaker verification performance. However, it is hypothesised that when limited session data is available, a median-based LDA approach would be better than a mean-based LDA approach. A novel median Fisher discriminator based dimensionality reduction technique was introduced to the GPLDA speaker verification system, and it has shown improvement over the LDA-based GPDA system in limited session data conditions. These research outcomes were published at the ICASSP conference in 2014 [43].

4. It is impossible to evenly collect different types of data, including telephone and microphone speech data in practice. It is also known that microphone speech data has more channel variations than telephone speech data, which means that a larger amount of microphone speech is required to adequately model the PLDA approach. However, it is feasible to collect a substantial amount of telephone speech data from the NIST data set, but there is much less microphone speech data available. Several novel approaches were introduced in the i-vector feature and PLDA model domain in Chapter 6 to improve the PLDA speaker verification performance in limited microphone conditions. In the i-vector feature domain, pooled and concatenated total-variability approaches were investigated to improve the speaker verification performance in scarce microphone condition. In the PLDA model domain, a new approach was introduced to GPLDA to estimate reliable model parameters as a linearly weighted model, taking more input from the large volume of available telephone data and smaller proportional input from limited microphone data. These research outcomes were published at the Interspeech conference in 2013 [42].

5. The CSS i-vector speaker verification system was extensively studied with short utterance evaluation data in Chapter 7, and it was found that when the evaluation data utterance length reduces, it affects the speaker verification performance. Subsequently, it was also analysed with short utterance

development data, and found that when short utterances are included for intra-speaker variance, it affects the speaker verification performance; however short utterance-based inter-speaker variance does not affect the performance. Based upon this study, a novel source- and utterance-normalised LDA approach was introduced to improve the CSS i-vector speaker verification performance in short utterance evaluation conditions. The PLDA speaker verification system was then investigated with short utterance evaluation and development data conditions. It was found that when the PLDA approach is trained using short-length utterances, it shows an improvement over when the PLDA is trained on full-length utterances. These research outcomes were published at the Interspeech conference in 2011 [49] and the Speaker Odyssey conference in 2012 [48].

6. Although a number of novel approaches were used to improve the CSS i-vector and PLDA speaker verification performance short utterance conditions, the problem has not been solved yet. Finally, in Chapter 8 the shortcomings of short utterance i-vectors were studied using scatter plot analysis, and it was found that long-length utterance i-vectors may vary with speaker and channel variations, whereas short-length utterance i-vectors may vary with speaker, channel and phonetic content or, in general, utterance variation. A novel short utterance variance normalization approach was introduced to the CSS i-vector system to compensate the channel and utterance variations, and this approach has shown an improvement over baseline approach, a LDA followed by WCCN CSS i-vector system. Subsequently, it was also found that instead of compensating the short utterance variation, the PLDA approach could alternatively be used to directly model the short utterance variance. The LDA and SN-LDA followed by short utterance variance modelling using the PLDA approach has also been shown to provide improvement over a standard GPLDA approach, which suggests

that the short utterance variance added full-length utterances are required for PLDA modelling. These research outcomes were published in Speech Communication [44].

1.5 Publications

Listed below are the peer-reviewed publications and under-review submissions resulting from this research programme.

Peer-reviewed international journals

1. **A. Kanagasundaram**, D. Dean, S. Sridharan, M. McLaren and R. Vogt, 'I-vector based speaker recognition using advanced channel compensation techniques,' Computer Speech & Language, January 2014.
2. **A. Kanagasundaram**, D. Dean, S. Sridharan, J. Gonzalez-Dominguez, J. Gonzalez-Rodriguez and D. Ramos, 'Improving short utterance i-vector speaker recognition using utterance variance modelling and compensation techniques,' Speech Communication, April 2014.

Peer-reviewed international conferences

1. **A. Kanagasundaram**, R. Vogt, D. Dean, S. Sridharan and M. Mason, 'I-vector based speaker recognition on short utterances,' Proceed. of INTERSPEECH, International Speech Communication Association (ISCA), pp. 2341-2344, August 2011.

2. **A. Kanagasundaram**, D. Dean, R. Vogt, M. McLaren, S. Sridharan and M. Mason, 'Weighted LDA techniques for i-vector based speaker verification,' IEEE Int. Conf. on Acoustics, Speech and Signal Processing, pp.4781-4784, March 2012.

3. **A. Kanagasundaram**, D. Dean, S. Sridharan and R. Vogt, 'PLDA based speaker recognition with weighted LDA techniques,' The Speaker and Language Recognition Workshop (Odyssey), June 2012.

4. **A. Kanagasundaram**, R. Vogt, D. Dean, and S. Sridharan, 'PLDA based speaker recognition on short utterances,' The Speaker and Language Recognition Workshop (Odyssey), June 2012.

5. **A. Kanagasundaram**, D. Dean and S. Sridharan, 'JFA based speaker recognition using delta-phase and MFCC features,' Proceedings of the 14th Australian International Conference on Speech Science and Technology, December 2012.

6. J. Gonzalez-Dominguez, J. Franco-Pedroso, D. Ramos, D. Toledano, J. Gonzalez-Rodriguez, **A. Kanagasundaram**, D. Dean and S. Sridharan, 'ATVS-QUT NIST SRE 2012 system,' Proceedings of NIST Speaker Recognition Evaluation, December 2012.

7. **A. Kanagasundaram**, D. Dean, J. Gonzalez-Dominguez, S. Sridharan, D. Ramos and J. Gonzalez-Rodriguez, 'Improving the PLDA based speaker verification in limited microphone data conditions,' Proceed. of INTERSPEECH, International Speech Communication Association (ISCA), August 2013.

8. **A. Kanagasundaram**, D. Dean, J. Gonzalez-Dominguez, S. Sridharan, D. Ramos and J. Gonzalez-Rodriguez, 'Improving short utterance based i-vector speaker recognition using source- and utterance-duration normaliza-

tion techniques,' Proceed. of INTERSPEECH, International Speech Communication Association (ISCA), June 2013.

9. **A. Kanagasundaram**, D. Dean and S. Sridharan, 'Improving PLDA speaker verification with limited development data,' IEEE Int. Conf. on Acoustics, Speech and Signal Processing, May 2014.

10. **A. Kanagasundaram**, D. Dean and S. Sridharan, 'Weighted median Fisher discriminator and linear-weighted approaches to limited development data GPLDA speaker verification,' in Proceed. of INTERSPEECH, International Speech Communication Association (ISCA), 2014 (Submitted).

Chapter 2

An Overview of Speaker Verification Technology

2.1 Introduction

Acoustic speech signals transmit large volumes of information to listeners. Primarily, the information conveyed is related to the message of the speech itself, but speech also conveys information about the language being spoken, and information relating to the emotion, gender and identity of the speaker [9, 84]. The goal of a speaker verification system is to take all the information contained in a speaker's voice to recognize their identity. Speaker verification has a unique advantage over other biometrics approaches, in that it can be used to remotely verify the person's identity using landline or mobile network. Speaker verification is also becoming an increasingly important area of research in recent times with public security becoming more of a concern.

The task of speaker verification is usually differentiated from the task of speaker identification [5, 9]. While speaker identification attempts to identify an unknown speaker from a group of speaker models, speaker verification requires that the unknown speaker claims an identity and only requires that the identity be accepted or rejected [25, 26]. Speaker verification is more popular compared to speaker identification as it can be used in the security and access control applications. Speaker verification is also computationally easier to perform (only one or two model comparisons required vs N comparisons) and a case can be made that improvements in speaker verification can generally be carried over to identification [84].

Speaker verification systems can also be classified into two types based on the speech used for recognition: (1) text-dependent, (2) text-independent. In the text-dependent case, the speaker is directed to speak a known word or phrase [25, 91]. On the other hand, for the text-independent case, users are not restricted to say any specific words or phrases. These characteristics are not directly measured [26, 101]. One of the main advantages of text-dependent speaker recognition is that the short utterance enrolment and verification data is enough to achieve a good performance. However, in order to achieve a good recognition performance with text-independent speaker verification, longer utterances are required for enrolment and verification. An adverse noise environment also affects the text-independent speaker verification system performance. Text-independent speaker verification allows for more flexible deployment and use in situations where the speaker recognition is not cooperative. Currently, text-independent verification is the basis for most speaker verification applications and is the main commercially viable task.

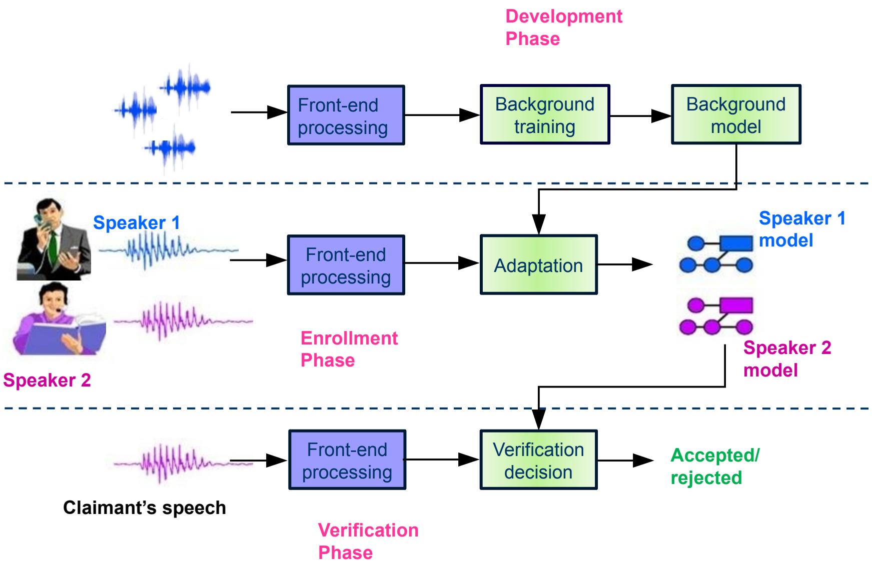


Figure 2.1: A block diagram of a text independent speaker verification system

2.2 Overview of speaker verification

The general process of speaker verification involves three stages: development, enrolment and verification, as is clearly shown in Figure 2.1. Development is the process of learning speaker independent parameters using the large amount of data that is to be used to learn about speech characteristics. Enrolment is the process of learning the distinct characteristics of a speaker's voice and is used to create a claimed model to represent the enrolled speaker during verification. In verification, the distinct characteristics of a claimant's voice are compared with the previously enrolled claimed speaker model to determine if the claimed identity is correct.

Recent work in the field of speaker verification is mainly focused on the problem of the channel/ session variability between enrolment and verification segments, as it considerably affects the speaker verification performance. The channel/ session variability depends on the following factors,

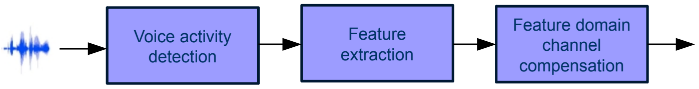


Figure 2.2: A block diagram of a front-end processing

- The microphones - carbon-button, electret, hands-free, array, etc
- The acoustic environment - office, car, airport, etc.
- The transmission channel - landline, cellular, VoIP, etc.
- The differences in speaker voice - aging, mood, spoken language, etc.

Channel compensation is an approach which is used to reduce the mismatch between training and testing. Channel compensation occurs at the different levels, such as feature domain, model domain and score domain. In the feature domain, adaptive noise suppression, cepstral mean subtraction (CMS), RASTA filtering and feature warping are used to compensate the channel variability. JFA, JFA-SVM and i-vector approaches are used to compensate the mismatch between enrolment and verification in the model domain. In the score domain, score normalization approaches, such as test normalization (T-norm), symmetric normalization (S-norm) and zero test normalization (ZT-norm) are used to compensate the session variability. These approaches are briefly detailed in the following sections.

2.3 Speech acquisition and front-end processing

The front-end processing is used to process the audio and produce the features that are useful for speaker verification. The front-end processing generally consists of three sub-processes as shown in Figure 2.2: VAD, feature extraction and feature-level channel compensation [5, 9, 83].

Firstly, the acquired speech is processed by a voice activity detection (VAD) system to ensure that the verification is only performed when speech is occurring. Gaussian-based VAD has been commonly used in recent times in which the distribution of both high energy and low energy frames are modelled. Frames belonging to the higher energy Gaussian are retained, and the remainder are removed from the feature set [81]. In this approach, VAD can operate successfully on audio with a relatively low signal-to-noise ratio (SNR) compared to other alternative approaches [63]. VAD is already in common use in telephony applications through standards, such as G729 Annex B [1, 4] or the ETSI Advanced Front-End [23].

The feature extraction approach is used to convert the raw speech signal into a sequence of acoustic feature vectors, carrying characteristic information about the signal, which can identify the speaker [93]. There are a number of feature extraction techniques available, including mel frequency cepstral coefficients (MFCC), linear prediction cepstral coefficients (LPCC) and perceptual linear prediction cepstral coefficients (PLPC) [28, 82]. All these features are based on the spectral information derived from a short time windowed segment of speech, and they mainly differ by the detail in the power spectrum representation. The MFCC and linear frequency cepstral coefficient (LFCC) features are derived directly from the fast fourier transform (FFT) power spectrum, whereas the LPCC and PLPC use an all-pole model to represent the smooth spectrum. Researchers have also found that phase spectrum-based features, such as modified group delay function (GDF) and instantaneous frequency deviation (IFD) can be also used to extract complementary speaker information [76, 76, 111].

The most commonly chosen feature extraction technique for the state-of-the-art speaker verification system is MFCC as this feature representation has been

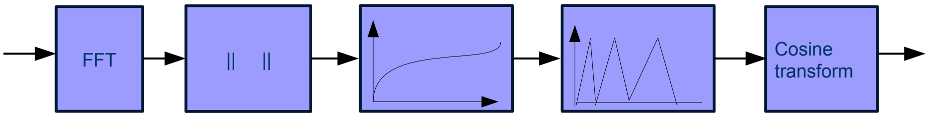


Figure 2.3: A block diagram of extracting the MFCC features

shown to provide better performance than other approaches [28, 82]. A basic block diagram for extracting MFCC is given in Figure 2.3. The MFCC features are calculated through pre-emphasis filtering, framing and windowing, triangular filtering and discrete cosine transform (DCT). Time derivatives of the MFCC coefficients are used as additional features, and are generally appended to each feature to capture the dynamic properties of the speech signal [82].

The final stage of the front-end processing is the feature-domain channel compensation approach which will be discussed in Section 2.7.1.

2.4 GMM-based speaker verification

2.4.1 Brief overview of Gaussian mixture modelling

Gaussian mixture models (GMMs) were proposed by Reynolds *et al.* [83, 86, 87] to model the speaker, and they perform very effectively in speaker verification systems.

A GMM is a weighted sum of M component Gaussian densities as given by the equation,

$$P(\mathbf{x} \mid \lambda) = \sum_{k=1}^{M} \mathbf{w}_k \times g(\boldsymbol{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \tag{2.1}$$

where $\mathbf{x}$ is a $\mathbf{D}$-dimensional feature vector, $\mathbf{w}_k$, $\boldsymbol{\mu}_k$, $\boldsymbol{\Sigma}_k$, $k = 1, 2, ...M$, are the mixture weights, mean and covariance. $g(\mathbf{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$, $k = 1, 2, 3.........M$, are the component Gaussian densities.

Each component density is a $\mathbf{D}$-variate Gaussian function of the form,

$$g(\boldsymbol{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) = \frac{1}{(2\pi)^{\frac{D}{2}} \left|\boldsymbol{\Sigma}_k\right|^{\frac{1}{2}}} \exp\left\{-\frac{1}{2}\left(\boldsymbol{x} - \boldsymbol{\mu}_k\right)^{\mathrm{T}} \boldsymbol{\Sigma}_k^{-1}\left(\boldsymbol{x} - \boldsymbol{\mu}_k\right)\right\} \tag{2.2}$$

where mean vector $\boldsymbol{\mu}_k$ and covariance matrix $\boldsymbol{\Sigma}_k$, the mixture weights satisfy the constraint $\sum_{k=1}^{M} \mathbf{w}_i = 1$. The complete GMM is parameterized by the mean vectors, covariance matrices and mixture weights from all component densities, and these parameters are collectively represented by $\lambda = \{\mathbf{w}_k, \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k\}$, $k = 1, 2, 3.........M$.

An expectation-maximization (EM) algorithm is an iterative method for finding maximum likelihood or *maximum a posteriori* estimates of parameters in statistical models. The EM algorithm is used to learn the GMM parameters, based on maximizing the expected log-likelihood of the training data. The motivation of the EM algorithm is to estimate a new and improved model λ from the current model λ^{old} using the training utterance features x_n such that the probability $\prod_{n=1}^{N} P(\mathbf{x}_n \mid \lambda) \geq \prod_{n=1}^{N} P(\mathbf{x}_n \mid \lambda^{old})$. This is an iterative technique where the new model becomes the current model for the following iteration.

The initial GMM parameters are typically defined using the k-means algorithm often used in the vector quantisation approach [33]. The k-means algorithm is also based on an iterative approach in which the mixture of training feature vectors is performed through the estimation of mixture means.

The EM algorithm attempts to maximise the auxiliary function $Q(\lambda; \lambda^{old})$. This is generally implemented using Jensen's inequality ensuring $\prod_{n=1}^{N} P(\mathbf{x}_n \mid \lambda) \geq$

$\prod_{n=1}^{N} P(\mathbf{x}_n \mid \lambda^{old})$. The auxiliary function can be formulated as

$$Q(\lambda; \lambda^{old}) = \sum_{n=1}^{N} \sum_{k=1}^{M} P(k \mid \mathbf{x}_n) \; log\mathbf{w}_k g(\boldsymbol{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \tag{2.3}$$

where $P(k \mid \mathbf{x})$ forms the E step for producing observation $\mathbf{x}$ using

$$P(k \mid \mathbf{x}) = \frac{\mathbf{w}_k g(\boldsymbol{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{P(\mathbf{x} \mid \lambda^{old})} \tag{2.4}$$

The M step then sees the auxiliary function $Q(\lambda; \lambda^{old})$ maximised using Equation 2.3. This maximisation results in the GMM parameters being estimated as

$$\mathbf{w}_k = \frac{n_k}{T} \sum_{n=1}^{N} P(k \mid \mathbf{x}_n, \lambda^{old}) \tag{2.5}$$

$$\boldsymbol{\mu}_k = \frac{1}{n_k} \sum_{n=1}^{N} P(k \mid \mathbf{x}_n, \lambda^{old}) \mathbf{x}_n \tag{2.6}$$

$$\boldsymbol{\Sigma}_k = \frac{1}{n_k} \sum_{n=1}^{N} P(k \mid \mathbf{x}_n, \lambda^{old}) \mathbf{x}_n \mathbf{x}_n^T - \boldsymbol{\mu}_k \boldsymbol{\mu}_k^T \tag{2.7}$$

where n_k is the component occupancy count from all the observations of the utterance x.

2.4.2 Universal background model (UBM) training

In typical speaker verification tasks, as there is a limited amount of data available to train the speaker models, the speaker models can't be directly estimated reliably with the expectation maximization (EM) algorithm. For this reason, *maximum a posteriori* (MAP) adaptation [86] is often used to train the speaker models for speaker verification systems. This approach estimates the speaker model from the universal background model (UBM) [86]. A UBM is a high-order GMM, trained on a large quantity of speech obtained from a wide sample of the speaker population of interest, and is designed to capture the general form of a speaker model and represents the speaker-independent distribution of features. The UBM parameters are estimated using the EM algorithm described in the previous section.

2.4.3 Speaker enrolment through MAP adaptation

In MAP adaptation, the speaker model is derived from the UBM by considering specific speaker vectors. As a variant of the EM algorithm, first initializing the speaker models with the parameters of UBM iteratively updates the parameters of the GMM $\lambda = \{\mathbf{w}_k, \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k\}$ such that total likelihood for an enrolment utterance $\mathbf{x}_1, \mathbf{x}_2....\mathbf{x}_N$ is maximized:

$$\prod_{n=1}^{N} P(\mathbf{x}_n \mid \lambda) \geq \prod_{n=1}^{N} P(\mathbf{x}_n \mid \lambda^{old}) \tag{2.8}$$

The updated model is then used as the initial model for the next iteration. The process is repeated until some convergence threshold is reached. For each iteration of the EM algorithm, the expressions of the maximum likelihood (ML) estimates of the GMM parameters, which guarantee a monotonic increase of the model's likelihood, are as described in the previous section.

During the adaptation of the speaker models, common practice is to adapt only the means of the mixture components of the UBM to match the speaker characteristics, as it has been found that adapting the covariances do not show an improvement [86].

The MAP adapted means $\boldsymbol{\mu}_k^{MAP}$ for Gaussian component k are updated from the prior distribution means $\boldsymbol{\mu}_k$ using

$$\boldsymbol{\mu}_k^{MAP} = \alpha_k \boldsymbol{\mu}_k + (1 - \alpha_k)\boldsymbol{\mu}_k^{ML} \tag{2.9}$$

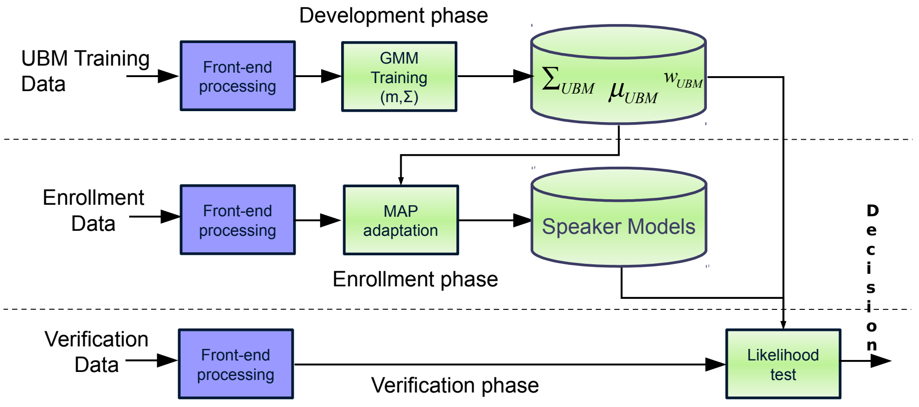


Figure 2.4: A block diagram of GMM-based speaker verification system

where $\boldsymbol{\mu}_k^{ML}$ is estimated using maximum likelihood estimation as detailed in previous section and α_k is the mean adaptation coefficient defined as $\alpha_k = \frac{n_k}{n_k+\tau_k}$ where n_k is the component occupancy count for the adaptation data and τ_k is the relevance factor, typically set between 8 and 32.

2.4.4 GMM-UBM speaker verification

The GMM-UBM-based speaker verification was the standard approach to text-independent speaker verification a decade ago [86]. Even though the data requirements with the MAP adaptation of UBM to obtain the speaker models in this approach are significantly less than the data requirements for estimating the speaker model directly, the technique sill requires a considerable amount of training data in order to take full advantage of the technique [86]. This is due to the large number of parameters that need to be estimated in the relevance MAP adaptation process of this technique. When limited training data is available, the model is unable to saturate, and the ability of the speaker model produced by the process to accurately represent the speaker is limited.

A block diagram of a GMM-based speaker verification system is shown in Figure 2.4. In the development phase, the UBM parameters are estimated on a larger amount of data, which represents the speaker independent parameters. The MAP adaptation is used to estimate the speaker dependent parameters in the enrolment phase. In the verification phase, the scoring is calculated using the likelihood ratio.

The task in speaker verification is to ascertain whether or not a test set of speech frames $X = x_1, x_2, ..., x_N$ belongs to the claimed speaker s. With generative models, the aim is to test the following hypotheses:

- H_{tar}: X is uttered by speaker s
- H_{impo} : X is not uttered by speaker s

The decision score is based on a likelihood ratio. It is evaluated by the following formula:

$$S(X) = \frac{P(X \mid H_{tar})}{P(X \mid H_{impo})} \geq \Theta \Rightarrow target \tag{2.10}$$

where $P(X \mid H_{tar})$ and $P(X \mid H_{impo})$ are respectively the likelihood of X under the assumption that X is uttered or not by speaker s, and Θ represents a decision threshold. If the computed score $S(X)$ is greater than the decision threshold Θ, we conclude that test segment X is indeed uttered by speaker s. Otherwise, speaker s is deemed to be an impostor.

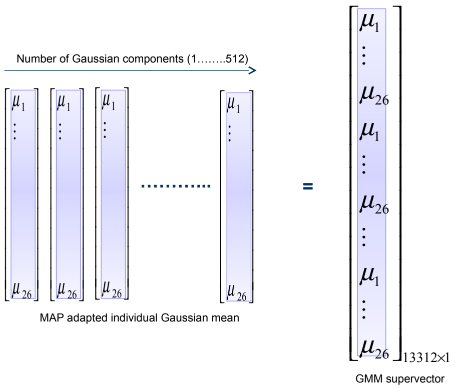

Number of Gaussian components (1........512)
μ_1
μ_{26}
=
MAP adapted individual Gaussian mean
13312×1
GMM supervector

Figure 2.5: A block diagram of extracting GMM super-vectors

2.5 GMM super-vectors

In the GMM-UBM speaker verification system, MFCC acoustic features are used as input features. On the other hand, in SVM and JFA speaker verification systems, high-dimensional GMM super-vectors are used as input features. A block diagram of extracting GMM super-vectors is shown in Figure 2.5. The GMM mean super-vector is the concatenation of GMM mean vectors. It is defined by a column vector of dimension CF containing the means of each mixture component in the speaker GMM where F represents the dimensionality of the feature vectors used in the model and C denotes the total number of mixture components used to represent the GMM.

2.6 SVM-based speaker verification

SVMs have proven to be a new effective method for speaker verification [11, 13, 17, 74, 110]. SVM-based classifiers can be used to find a separator between two classes. SVM is a linear classification technique, and for the speaker verification task, a non-linear kernel mapping is generally required to project the non-linearly

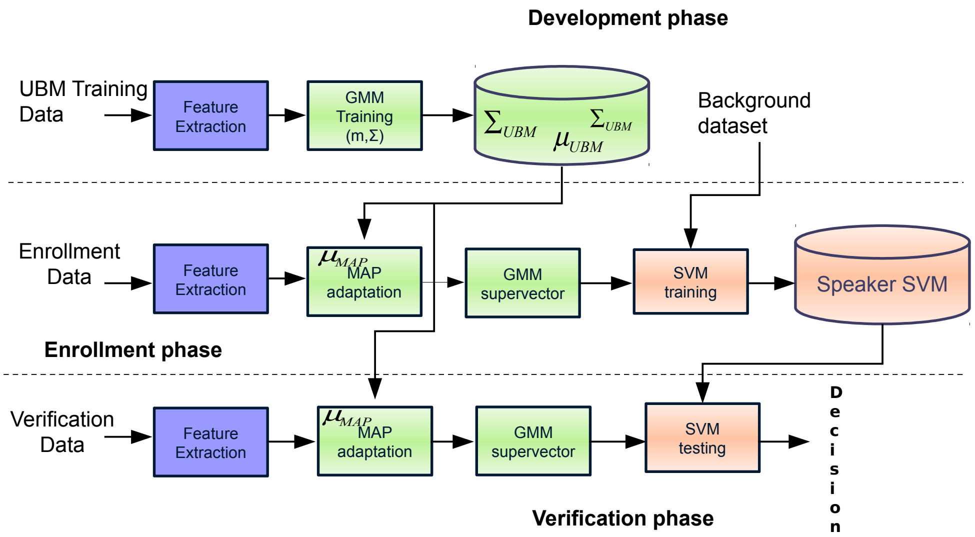


Figure 2.6: SVM-based speaker verification system

separable data into a high dimensional linearly separable space. A block diagram of an SVM-based speaker verification system is shown in Figure 2.6.

2.6.1 SVM classification

In speaker verification, one class consists of the target speaker training vectors (labelled as +1), and the other class consists of the training vectors from an impostor (background) population (labelled as -1). Using the labelled training vectors, SVM training finds a separating hyper plane that maximizes the margin of separation between these two classes.

Formally, the discriminate function of SVM is given by,

$$f(\mathbf{x}) = \sum_{i=1}^{N} \alpha_i t_i K(\mathbf{x}, \mathbf{x}_i) + d \tag{2.11}$$

where $t_i \in \{-1+1\}$ are ideal output values, $\sum_{i=1}^{N} \alpha_i t_i = 0$ and $\alpha_i \geq 0$

The support vectors $\mathbf{x}_i$, their corresponding weights α_i and the bias term d, are

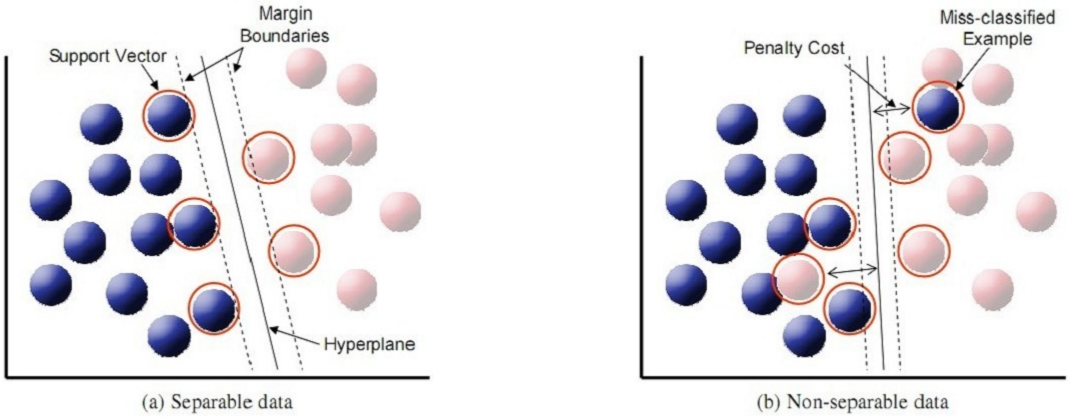


Figure 2.7: An example of a two-dimensional SVM trained using (a) linearly-separable data and (b) non-linearly-separable data (From [70])

determined from a training set using an optimization process.

2.6.2 Linearly separable training

Consider the problem of separating the set of N training vectors $[(\mathbf{x}_1, \mathbf{y}_2), ..., (\mathbf{x}_n, \mathbf{y}_n)]$ belonging to two different classes $\mathbf{y}_i \in (-1, 1)$. The goal is to find the linear decision function $D(\mathbf{x})$ and the separation plane H. An example of a two-dimensional SVM trained using linearly-separable data is given in Figure 2.7 (a).

$$H :< w, \mathbf{x} > +b = 0 \tag{2.12}$$

$$D(\mathbf{x}) = sign(w * \mathbf{x} + b) \tag{2.13}$$

where b is the distance of the hyperplane from the origin and w is the normal to the decision region.

Let the "margin" of the SVM be defined as the distance from the separating hyperplane to the closest two classes. The SVM training paradigm finds the separating hyperplane, which gives the maximum margin. The margin is equal to $\frac{2}{\|w\|}$. Once the hyperplane is obtained, all the training examples satisfy the following inequalities,

$$\mathbf{x}_i * w + b \geq +1 \quad \text{for } y_i = +1 \tag{2.14}$$

$$\mathbf{x}_i * w + b \geq -1 \quad \text{for } y_i = -1 \tag{2.15}$$

We can summarize the above procedure to the following:

Minimize

$$L(w) = \frac{1}{2}\|w\|^2 \tag{2.16}$$

subject to

$$\mathbf{y}_i(\mathbf{x}_i * w + b) \geq +1, i = 1, 2, 3, 4, ...N \tag{2.17}$$

2.6.3 Non-linearly separable training

In the case of performing SVM training on non-linearly separable data, such as the 2-D example shown in Figure 2.7 (b), the miss-classification of training examples will cause the Lagrangian multipliers to grow exceedingly large and prevent a feasible solution. To account for such issues, a slack variable with an associated cost C must be introduced to penalize the miss-classification of training examples.

This approach translates into a further constraint being placed on the Lagrangian multipliers, which is a strategy for finding the local maxima and minima of a function, such that

$$0 \leq \alpha_i \leq C \tag{2.18}$$

This approach can be viewed as introducing an additional soft margin extending from the hyperplane margin that only comes into effect when mis-classified training examples are encountered. The larger the value of C, the more impact mis-classified training examples have on the location of the hyperplane.

Non-linear kernels: The application of kernel function to classical SVM classifiers allows more complex problems to be solved [16]. An SVM kernel is used to transform training and testing data into a higher dimensional space, which provides better linear separation. In non-linear classification, a kernel approach is done by defining the kernel function as,

$$K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i) * \phi(\mathbf{x}_j) \tag{2.19}$$

where $\phi(\mathbf{x})$ is a mapping function used to convert input vectors $\mathbf{x}$ to a desired space. The mapping function is selected on an application-specific basis as it defines the discriminative space in which linear classification is to be performed.

There are a number of kernels that have been shown to work well for speaker classification. Those are GLDS kernel [10], the GMM mean super-vector kernel [13], MLLR kernel [96], frame-based kernel [109], sequence kernel [39], fisher-kernel [109] and cosine kernel [20].

2.7 Combating training and testing mismatch

Feature-domain channel compensation approaches, model-domain channel compensation approaches, such as JFA and JFA-SVM, and score-domain approaches, including zero normalization (z-norm), test normalization (t-norm), symmetric normalization (s-norm) and zero test normalization (zt-norm), are discussed in this section.

2.7.1 Feature-domain approaches

Under the train-and-test mismatch condition, speech can be corrupted by channel, noise and transducer effects. In the feature-domain, channel compensation techniques, such as adaptive noise filtering, cepstral mean subtraction (CMS), RASTA filtering and feature warping, are used to compensate the effect of channel and slowly varying additive noise [24, 36, 77, 112].

In the signal domain, adaptive noise filtering is used to remove the wide band noise from speech signals [38, 112]. The basic idea of an adaptive noise cancellation algorithm is to pass the corrupted signal through a filter that tends to suppress the noise, while leaving the signal unchanged. This is an adaptive process which means it does not require *a priori* knowledge of signal or noise characteristics.

A common method of improving the robustness of a feature set is CMS [24, 84]. This process reduces the effects of channel distortion by removing the mean from cepstral coefficients. It was also found that it removes the speaker-specific information with channel information, and subsequently, the cepstral mean and variance normalization (CMVN) was proposed as an extensive approach to CMS [102].

An alternate method to CMS and CMVN, the RASTA was proposed by Hermansky and Morgan [36] with the purpose of suppressing very slowly or very quickly varying components in the filter banks during the feature extraction. The RASTA filtering is essentially a band-pass filter used on the time trajectories of feature vectors extracted from speech. It has also been found that the RASTA also removes the speaker specific information in the low frequency bands.

A few years ago, Pelecanos *et al.* [77] introduced the feature warping approach to speaker verification to compensate the effect of channel and slowly varying additive noise in the feature domain. The authors found that the feature warping is a much more effective method to significantly compensate the non-linear distortions. The feature warping algorithm maps the distribution of cepstral feature vectors to a target distribution. As the target distribution is unknown, an assumption is made that the target distribution is a standard normal distribution. Feature warping provides a robustness to additive noise and linear channel mismatch while retaining the speaker specific information that can be lost when using CMS, CMVN and RASTA processing.

2.7.2 Model-domain approach (JFA)

A significant contributor to the performance degradation of traditional GMM-UBM speaker verification is the presence of session variability between the training and testing conditions. The JFA approach has been introduced to combat the mismatch between training and testing [50, 53, 55, 56, 57, 58, 103]. The technique outlined below is based on the decomposition of the GMM mean super-vectors into speaker-dependent and session-dependent parts. Figure 2.8 illustrates that the JFA approach considers the variability of the GMM as a linear combination of the variability of the speaker and channel unobservable components:

$$\mathbf{M} = \mathbf{s} + \mathbf{c} \tag{2.20}$$

where $\mathbf{s}$ is the speaker super-vector and $\mathbf{c}$ is the channel (session) super-vector. The GMM super-vector $\mathbf{M}$ of a given utterance is therefore expressed as the sum of a speaker-dependent contribution $\mathbf{s}$ and a speaker independent session contribution $\mathbf{c}$.

The motivation behind the factor analysis is to explicitly model each of these contributions in a low-dimensional subspace of the GMM mean super-vector space in order to form a more accurate speaker GMM for speaker verification purposes.

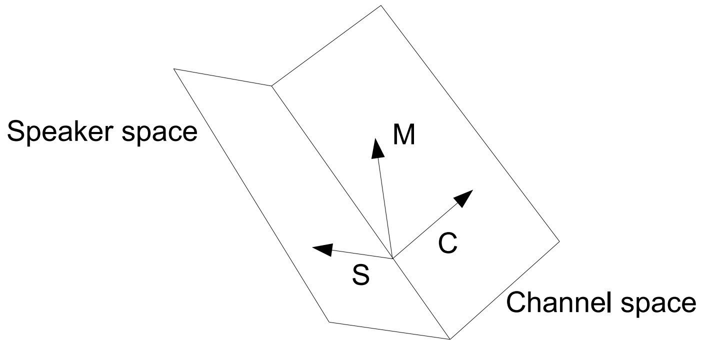


Figure 2.8: $\mathbf{M}$ can be written as sum of speaker factors ($\mathbf{s}$) and channel factors($\mathbf{c}$)

We define $\mathbf{s}$ and $\mathbf{c}$ as

$$\mathbf{s} = \mathbf{m} + \mathbf{V}\mathbf{y} + \mathbf{D}\mathbf{z} \tag{2.21}$$

$$\mathbf{c}_h = \mathbf{U}\mathbf{x}_h \tag{2.22}$$

where speaker dependant variable, $\mathbf{y}$, and residual variable, $\mathbf{z}$, are assumed to be independent and to have standard normal distributions; $\mathbf{s}$ is assumed to be normally distributed with mean $\mathbf{m}$ and covariance matrix $\mathbf{v}\mathbf{v}^* + \mathbf{d}^2$.

In the above equations, the variable can be divided into the system hyper parameters ($\mathbf{m}$, $\mathbf{V}$, $\mathbf{D}$, $\mathbf{U}$) and the hidden speaker and session variables ($\mathbf{x}$, $\mathbf{y}$, $\mathbf{z}$). These parameters are estimated using maximum likelihood and minimum divergence algorithms [50],

where $\mathbf{m}$ - Speaker and session independent mean super vector- $(CF \times 1)$

$\mathbf{U}$ - Eigenchannel matrix (low dimension rectangular matrix - $CF \times Rc$)

$\mathbf{V}$ - Eigenvoice matrix (low dimensional rectangular matrix- $CF \times Rs$)

$\mathbf{D}$ - Residual scaling matrix(diagonal matrix - $CF \times CF$)

$\mathbf{x}_h$ - Session dependent variable

$\mathbf{y}$ - Speaker dependent variable

$\mathbf{z}$ - Residual variable

There have been several approaches to the problem of estimating the hyper parameters which define the inter-speaker variability and inter-session variability model of the joint factor analysis [58]. Those are the classical MAP approach, eigenvoice MAP approach, eigenchannel MAP approach, joint estimation and decoupled estimation. The eigenvoice MAP and classical MAP are used to model the inter speaker variability. The eigenchannel MAP is used to model the intersession variability. The intersession variability in the spectral speech features is generally caused by channel transmission effects. It has also been found that the decoupled estimation gave the best performance compared with other estimation methods [56].

Classical MAP adaptation: Kenny *et al.* [56] proposed ML-based estimation of the *a priori* variance of the speaker population within a training corpus. In this new modelling, the super-vector $\mathbf{s}$ of a randomly chosen speaker can be written in the form of hidden variables as follows,

$$\mathbf{s} = \mathbf{m} + \mathbf{D}\mathbf{z} \tag{2.23}$$

where $\mathbf{s}$ is assumed to be normally distributed with mean $\mathbf{m}$ and covariance matrix $\mathbf{d}^2$.

MAP adaptation using *a priori* distribution is equivalent to ML training of the speakers when sufficient speaker data are available for adaptation. $\mathbf{D}$ is constraint to satisfy $\mathbf{I} = \tau \mathbf{D}^T \mathbf{\Sigma}^{-1} \mathbf{D}$. Here τ is relevance factor and $\mathbf{\Sigma}$ is diagonal matrix. If the number of mixture components C is large, classical MAP tends to saturate slowly in the sense that large amounts of enrolment data are needed to use it to full advantage.

Eigenvoice MAP adaptation: Eigenvoice adaptation operates on the assumption of a low rank rectangular matrix $\mathbf{V}$ of dimension $CF \times Rs$, with $Rs \ll CF$, that defines a representation of the speaker space [52]. The super-vector s of a randomly chosen speaker is obtained by:

$$\mathbf{s} = \mathbf{m} + \mathbf{V}\mathbf{y} \tag{2.24}$$

where $\mathbf{s}$ is assumed to be normally distributed with mean $\mathbf{m}$ and covariance matrix $\mathbf{V}\mathbf{V}^{'}$.

When few observations are available, eigenvoice adaptation is more powerful than MAP adaptation for estimating speaker GMMs. Since we only need to estimate low dimensional hidden variable $\mathbf{y}$. Eigenvoice adaptation is based on the assumption that the rank Rs of estimated matrix $\mathbf{V}$ is less than or equal to the number of speakers in the training corpus.

Combining relevance MAP and eigenvoice MAP: The strengths and weaknesses of classical MAP and eigenvoice MAP complement each other. If small amounts of data are available, eigenvoice MAP is preferable for speaker adaptation and if large amounts are available, classical MAP is preferable. Therefore, it is useful to assume that the speaker model takes a form which combines both relevance MAP and speaker subspace adaptation. The super-vector $\mathbf{s}$ of a randomly chosen speaker is obtained by,

$$\mathbf{s} = \mathbf{m} + \mathbf{V}\mathbf{y} + \mathbf{D}\mathbf{z} \tag{2.25}$$

The two hidden vectors $\mathbf{y}$ and $\mathbf{z}$ are mutually independent and each vector has a standard normal prior distribution. The super-vector $\mathbf{s}$ follows a prior normal distribution characterized by mean $\mathbf{m}$ and covariance matrix $\mathbf{d}^2 + \mathbf{V}\mathbf{V}^{'}$. We refer to the components of $\mathbf{y}$ as speaker factors and to the components of $\mathbf{z}$ as common factors.

Channel variability modelling: It is assumed in this formulation of the speaker model that the most significant session variability effects may also be described in a low-dimensional subspace of the full mean super-vector space. This allows for a channel compensation super-vector to be introduced into the speaker model, in order to minimize the effect of this inter-session variability. To achieve this, a speaker GMM may be considered as the combination of a session-independent speaker model with an additional offset of the model means representing the recording conditions of the session h. This can be expressed as

$$\mathbf{c}_h = \mathbf{U}\mathbf{x}_h \tag{2.26}$$

where

$\mathbf{U}$ - Eigenchannel matrix (low dimension rectangular matrix - $CF \times Rc$)

$\mathbf{x}_h$ - session dependent variable

This technique is referred to as eigenchannel adaptation, which has the same form as the eigenvoice adaptation procedure outlined in above section.

Mathematical representation of JFA modelling: First, a UBM is trained using the EM algorithm. The UBM is composed of C Gaussian components trained on F dimensional feature frames, and it can be characterized by weights $\mathbf{w}$, a mean vector $\mathbf{m}$ $(CF \times 1)$ and covariance matrix $\mathbf{\Sigma}$ $(CF \times CF\ )$.

The UBM is then used to extract the zero order, $\mathbf{N}_c(s)$, first order, $\tilde{\mathbf{F}}_c(s)$ and second order, $\tilde{\mathbf{S}}_c(s)$, Baum-Welch statistics. Baum-Welch statistics are sufficient statistics, which can be calculated using the following equations,

$$\mathbf{N}_c(s) = \sum_t \boldsymbol{\gamma}_t(c), \tag{2.27}$$

$$\tilde{\mathbf{F}}_c(s) = \sum_t \boldsymbol{\gamma}_t(c)(\mathbf{Y}_t - \mathbf{m}_c), \tag{2.28}$$

$$\tilde{\mathbf{S}}_c(s) = diag[\sum_t \boldsymbol{\gamma}_t(c)(\mathbf{Y}_t - \mathbf{m}_c)(\mathbf{Y}_t - \mathbf{m}_c)^{'}]. \tag{2.29}$$

where c is the Gaussian index, $\boldsymbol{\gamma}_t(c)$ is the posterior probability. $\mathbf{Y}_t$ are MFCC feature frames and $\mathbf{m}_c$ is UBM mean.

The hyperparameter is calculated using the EM algorithm. The EM algorithm is performed in two steps. In the E step, we evaluate the posterior distribution of the hidden variable, $\mathbf{y}(s)$, given the speaker sufficient statistics and current hyperparameter, $\mathbf{v}$ estimation. Posterior distribution is calculated using Baum-Welch statistics. Hidden variable, $\mathbf{y}(s)$ is calculated using following equations,

$$\mathbf{l}(s) = \boldsymbol{I} + \mathbf{v}^T\boldsymbol{\Sigma}^{-1}\mathbf{N}(s)\mathbf{v}, \tag{2.30}$$

$$E[\mathbf{y}(s)] = \boldsymbol{l}^{-1}(s)\mathbf{v}\boldsymbol{\Sigma}^{-1}\tilde{\mathbf{F}}(s), \tag{2.31}$$

$$E[\mathbf{y}(s)\mathbf{y}(s)^T] = \boldsymbol{l}^{-1}. \tag{2.32}$$

In the EM algorithm, the M step consists in updating the JFA hyperparameter, $\mathbf{v}$, based on the expectations, $E[\mathbf{y}(s)]$ and covariance matrices, $E[\mathbf{y}(s)\mathbf{y}(s)^T]$ of the hidden variable obtained in the previous step. We evaluate the hyperparameter, $\mathbf{v}$ using the following equations, Maximum likelihood re-estimation,

$$\mathbf{N}_c = \sum_s \mathbf{N}_c(s), \tag{2.33}$$

$$\boldsymbol{\Im}_c = \sum_s \mathbf{N}_c(s) E[\mathbf{y}(s)\mathbf{y}(s)^T], \tag{2.34}$$

$$\boldsymbol{\partial} = \sum_s \tilde{\mathbf{F}}(s) E[\mathbf{y}(s)^T], \tag{2.35}$$

$$\mathbf{N} = \sum_s \mathbf{N}(s). \tag{2.36}$$

$\mathbf{v}$, $\boldsymbol{\Sigma}$ is updated by solving the following equations,

$$\mathbf{v}_i \boldsymbol{\Im}_c = \boldsymbol{\partial}_i, \tag{2.37}$$

$$\boldsymbol{\Sigma} = \mathbf{N}^{-1}[\mathbf{S}(s) - diag(\boldsymbol{\partial}\mathbf{v}^T)]. \tag{2.38}$$

In the above calculations, pooling the Baum-Welch statistics is motivated by the fact that averaging the statistics over all utterances of each speaker removes the channel effects. All the JFA hyper-parameters are estimated iteratively in order to maximize the likelihood of the training corpus. The training database is composed of many speakers, and every speaker has several recordings under different channel conditions.

The eigenchannel MAP model parameters can be calculated using a similar method of the above-mentioned eigenvoice MAP modelling.

JFA scoring: In the JFA approach, the calculated mean super-vector $\mathbf{M}$ is used to represent the speaker specific GMM in comparison to the background UBM, in order to provide more robustness to the session and intra-speaker variability than the traditional MAP approach.

However, due to the unknown channel factor vector $\mathbf{x}$, the JFA-calculated mean super-vector cannot be used directly as the speaker specific GMM super-vector in

ELLR score calculation. A number of approaches have been proposed to account for the channel factor:

- Integration over prior distribution
- Channel point estimation
- Linear approximation of channel point estimate

Glembek *et al.* [30] investigated different scoring techniques. While, in most cases, the performance of session variability does not change dramatically, the speed of evaluation is the major difference. The fastest scoring method is linear scoring. It can be implemented by a simple dot product, allowing for much faster scoring with little-to-no degradation in performance [30].

A block diagram of JFA-based speaker verification system is shown in Figure 2.9. In the development phase, the UBM parameters are learnt using the large amount of data to represent the speaker independent parameters, and the JFA hypo-parameters (**V**, **D**, **U**) are estimated using maximum likelihood and minimum divergence algorithms. In the enrolment phase, the speaker variability hidden variables (**y** and **z**) are estimated for each target speakers. The channel variability hidden variable (**x**) for test speakers and scoring are calculated in the verification phase.

2.7.3 Model-domain approach (JFA-SVM)

Dehak *et al.* [21] investigated several techniques to combine the SVM and JFA model for speaker verification. In this combination, the SVMs are applied to different sources of information, such as GMM super-vectors, speakers and common factors which are produced by the JFA. It has been found that when the

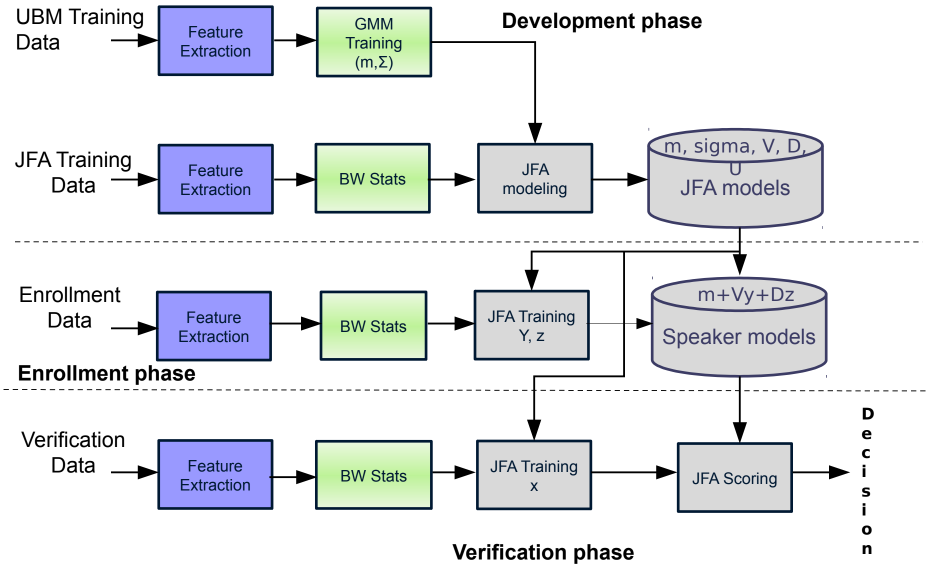


Figure 2.9: A block diagram of JFA-based speaker verification system

linear or cosine kernels are defined in speaker and common factors, the JFA-SVM achieves better performance than using the linear Kullback Leibler kernel [11, 21]. It has also been found that if the within-class covariance normalization (WCCN) approach, which is commonly used to attenuate the intra-speaker variance, is applied to speaker space to compensate the channel variation, JFA-SVM shows further improvement [21, 35]. In addition, the results of the JFA-SVM using the speaker factors are comparable to the classical JFA scoring [21].

2.8 Score normalization approaches

The decision-making process in speaker verification based on GMM-UBM is to compare the likelihood ratio obtained from the claimed speaker model and the UBM model with a decision threshold as previously shown in Section 2.4.4 [5]. Due to the score variability between the verification trials, the tuning of decision thresholds is an important and troublesome problem. Score variability mainly consists of two different sources. The first one is the different quality of speaker modelling caused by enrolment data varying. The second one is the possible mismatches and environment changes among test utterances when compared to the enrolment utterances.

Score normalization means normalizing the distribution of the scores. There are four types of normalization methods [2]. Those are,

- Zero normalization (Z-norm)
- Test normalization (T-norm)
- Symmetric normalization (S-norm)
- Combined normalization (ZT-Norm)

Z-norm: The z-norm addresses the problem of speaker score variability. It allows finding a decision threshold that is independent of the target speaker. For the z-norm, we consider J impostor segments $\mathbf{X}_1, \mathbf{X}_2, ..., \mathbf{X}_j$. For each proclaimed identity L, we compute a speaker-dependent $\boldsymbol{\mu}_L$ and $\boldsymbol{\sigma}_L$ as follows:

$$\boldsymbol{\mu}_L = \frac{1}{J}\sum_{j=1}^{J} S(\mathbf{X}_j, \boldsymbol{\lambda}_L), \tag{2.39}$$

$$\boldsymbol{\sigma}_L = \sqrt{[\frac{1}{J}\sum_{j=1}^{J}(S(\mathbf{X}_j, \boldsymbol{\lambda}_L) - \boldsymbol{\mu}_L)^2]}. \tag{2.40}$$

where $S(\mathbf{X}_j, \boldsymbol{\lambda}_L)$ is raw score of $\mathbf{X}_j$ impostor segment and L proclaimed identity.

Z-norm can be calculated as follows,

$$S(\mathbf{X}, \boldsymbol{\lambda}_L)_{norm} = \frac{S(\mathbf{X}, \boldsymbol{\lambda}_L) - \boldsymbol{\mu}_L}{\boldsymbol{\sigma}_L} \tag{2.41}$$

T-norm: The t-norm addresses the problem of session variability. It compensates the differences between the training and testing conditions. For the t-norm, we consider a set of impostor models $\boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2, ...\boldsymbol{\lambda}_N$. For each test segment $\mathbf{X}$, we compute a test-dependent $\boldsymbol{\mu}_X$ and $\boldsymbol{\sigma}_X$ as follows:

$$\boldsymbol{\mu}_X = \frac{1}{N}\sum_{n=1}^{N} S(\mathbf{X}, \boldsymbol{\lambda}_n) \tag{2.42}$$

$$\boldsymbol{\sigma}_X = \sqrt{[\frac{1}{N}\sum_{n=1}^{N}(S(\mathbf{X}, \boldsymbol{\lambda}_n) - \boldsymbol{\mu}_X)^2]} \tag{2.43}$$

T-norm can be calculated as follows,

$$S(\mathbf{X}, \boldsymbol{\lambda}_L)_{norm} = \frac{S(\mathbf{X}, \boldsymbol{\lambda}_L) - \boldsymbol{\mu}_X}{\boldsymbol{\sigma}_X} \tag{2.44}$$

S-norm: Symmetric normalization can be calculated using t-norm and z-norm scores as follows,

$$S(\mathbf{X}, \boldsymbol{\lambda}_L)_{norm} = \frac{S(\mathbf{X}, \boldsymbol{\lambda}_L) - \boldsymbol{\mu}_L}{\boldsymbol{\sigma}_L} + \frac{S(\mathbf{X}, \boldsymbol{\lambda}_L) - \boldsymbol{\mu}_X}{\boldsymbol{\sigma}_X} \tag{2.45}$$

Combined normalization (ZT-norm): State-of-the-art systems often combine several score normalization techniques in order to boost performance. The application of Z-Norm followed by T-Norm (commonly called ZT-Norm) has been found to provide a dramatic improvement in speaker verification performance [7, 103]. By combining both normalization methods, both the speaker-centric and test-centric advantages of the two individual techniques are combined.

2.9 Review of short utterance speaker verification

For the wide deployment of speaker verification technology in practical applications, training and testing utterance length must be reduced below that required in current systems for user's convenience. Li *et al.* [66] proposed an approach for the short utterances-based speaker verification system, which uses a statistical model of the speaker's vector quantized speech. This technique retains text-independent properties while allowing considerably shorter test utterances than comparable speaker recognition systems. The speaker recognition performance depends on the statistical distribution of the distances between the speech frames from the unknown speaker and the closest points in the model, models were generated with 100 seconds of conversational training speech for each of 11 male speakers. The system was able to identify 11 speakers with 96%, 87%, and 79% accuracy from sections of unknown speech of durations of 10, 6, and 3 seconds, respectively.

Jayanna *et al.* [40] investigated the multiple frame size and rate analysis for speaker recognition under limited data condition. In typical state-of-the-art speaker verification systems, fixed frame size and rate is used for feature extraction, which may be termed as single frame size and rate (SFSR) analysis. In a limited data condition, if the SFSR analysis is used, then it may not provide sufficient feature vector to train and test the speaker. In addition, an insufficient feature vector could lead to poor speaker modelling during training and may not yield a reliable decision during testing. The multiple frame size and rate techniques are specifically useful to mitigate the sparseness of limited feature vectors during training and testing. These techniques could produce relatively more numbers of feature vectors, and lead to better modelling and testing under limited data conditions.

Thilo *et al.* [95] investigated a dimension-decoupled GMM-based speaker verification system with short utterances. A great challenge is to use these techniques in a situation where only small sets of training and evaluation data are available, which typically results in poor statistical estimates. Based on the observation of marginal MFCC probability densities, he has suggested to greatly reduce the number of free parameters in the GMM by modelling the single dimensions separately after proper pre-processing. Saving about 90% of the free parameters as compared to an already optimized GMM and thus making the estimates more stable, this approach considerably improves recognition accuracy over the baseline as the utterances get shorter and save a huge amount of computing time both in training and evaluation, enabling real-time performance.

Vogt *et al.* [104, 106] investigated and compared the several alternative procedures for the factor analysis subspace estimation for speaker verification with short utterances, specifically focused on training and testing with short utterances. It was found that better performance can be obtained when independent rather than simultaneous optimization of the two core variability subspaces is used. Disjoint and coupled estimation of **U** and **V** have led to best performance. It was found that for verification trials on short utterances, it is important for the session subspace to be trained with matched length utterances [104]. It was also found that the factor analysis modelling approach to GMM speaker verification is an ideal solution for combining the benefits of speaker subspace MAP adaptation for short utterances and standard relevance MAP adaptation for longer utterances to provide a speaker modelling approach that is optimal over a wide range of utterance lengths [106].

McLaren *et al.* [73] investigated the effects of limited speech data in the context of speaker verification using the GMM mean super-vector SVM classifier.

Verification performance was analysed with regards to the duration of impostor utterances used for background, score normalization and session compensation training cohorts. It was found that the duration of utterances used to train the background dataset have a considerable effect on classification performance. Matching these impostor utterances to test utterance length expected in trials was found to significantly improve SVM-based performance, and the NAP approach was seen to session compensation often degrade performance [73].

Vogt *et al.* [107, 108] proposed an approach to minimize the utterance length through the confidence-based early verification decisions. The early verification decision method, based on these confidence interval estimates, achieves a drastic reduction in the typical data requirements for producing confident decisions in an automatic speaker verification system. An average of 5-10 seconds of speech is sufficient to produce verification rates approaching those achieved previously, using an average in excess of 100 seconds of speech. A speech sample is gathered from a speaker over a period of time, and a verification score is then produced for said sample over period. Once the verification score is determined a confidence measure is produced based on frame score observations from said sample over the period and a confidence measure is calculated based on the standard Gaussian distribution.

2.10 Chapter summary

This chapter has detailed the overview of speaker verification technology, and has also explained the GMM- and SVM-based speaker verification systems. As mismatch between training and testing utterances considerably affects the speaker verification, several channel compensation approaches were introduced in difference levels to compensate the channel variations; these have been thoroughly explained in this chapter. In a typical speaker verification system, a significant amount of speech is required for model training and testing; however, it is hard to collect this amount of data in practical environments. A number of research studies have been conducted to solve this issue; they have been also detailed in this chapter.

Chapter 3

Speaker Verification using I-vector Features

3.1 Introduction

The previous chapter focused on GMM-based generative approaches and SVM-based discriminative approaches. Subsequently, GMM-UBM generative model approaches were also extended to the JFA approach to compensate the session variability, by modelling the speaker and channel variability separately [50]. Recent research in speaker verification has focused on the i-vector front-end factor analysis technique. This technique was firstly proposed by Dehak *et al.* [19, 20] to provide an intermediate speaker representation between the high dimensional GMM super-vector and traditional low dimensional MFCC feature representations. The extraction of these intermediate-sized vectors, or i-vectors, were motivated by the existing super-vector based JFA approach. The JFA approach models the speaker and channel variability space separately, whereas the i-vectors are formed by modelling a single low-dimensional total-variability space that covers both speaker and channel variability [19, 20]. It is also believed that some of the speaker discriminant information may be lost in channel space in the JFA approach [20].

As the i-vectors are based on one variability space that contains speaker and channel variability information, compensation techniques are required to limit the effects of channel variability in the i-vector speaker representations. The channel compensation approaches play a major role in the i-vector speaker verification systems. When the i-vector approach was introduced, the several channel compensation approaches, including WCCN, linear discriminant analysis (LDA), nuisance attribute projection (NAP) and scatter difference NAP (SD-NAP) were used to compensate the channel variation in the i-vector speaker verification system [20]. Subsequently, Kenny noticed that each utterance can be represented by low-dimensional i-vector features, and introduced the PLDA to model the channel variability within the i-vector space [51].

This chapter is divided into several sub-parts. The i-vector feature extraction approach is detailed in Section 3.2. The cosine similarity scoring (CSS), or SVM i-vector speaker verification system and standard channel compensation approaches are described in Section 3.3.1. The PLDA speaker verification system is described in Section 3.4.

3.2 I-vector feature extraction

In contrast to the separate speaker and channel dependent subspaces of the JFA, i-vectors represent the GMM super-vector using a single total-variability subspace. This single-subspace approach was motivated by the fact that the channel space of the JFA contains information that may be used to distinguish between speakers [19, 20]. A speaker and channel dependent GMM super-vector, **s**, can be represented as follows;

$$\mathbf{s} \;=\; \mathbf{m} + \mathbf{T}\mathbf{w}, \tag{3.1}$$

where: **m** is the speaker and channel independent background UBM super-vector, **T** is the total-variability subspace which is a low rank matrix representing the primary directions' variation across a large collection of development data. **w** is normally distributed with parameters $N\left(0,1\right)$, and is the *i-vector* representation used for speaker verification. The extraction of i-vectors is based on the Baum-Welch zero-order, **N**, and centralized first-order, **F**, statistics. The statistics are calculated for a given utterance with respect to C UBM components and F dimension MFCC features. The i-vector for a given utterance can be extracted as follows [20],

$$\mathbf{w} \;=\; (\mathbf{I} + \mathbf{T}^{T}\mathbf{\Sigma}^{-1}\mathbf{N}\mathbf{T})^{-1}\mathbf{T}^{T}\mathbf{\Sigma}^{-1}\mathbf{F}, \tag{3.2}$$

where **I** is a $CF \times CF$ identity matrix, **N** is a diagonal matrix with $F \times F$ blocks $N_c\mathbf{I}$ $(c = 1, 2, ...C)$, and the super-vector, **F**, is formed through the concatenation of the centralized first-order statistics. The covariance matrix, $\mathbf{\Sigma}$, represents the residual variability not captured by **T**. An efficient procedure of estimating the total-variability subspace, **T**, is described in [20, 58]. The process of training the total-variability space (**T**) is equivalent to JFA eigenvoice training except for one difference. In JFA eigenvoice training, all the sessions of given speaker are considered to be the same person but in total variability space training, all the sessions of given speaker are considered to be the different persons in order to capture the channel variation, as total-variability is used to capture both speaker and channel variations [20].

3.3 SVM/ CSS based i-vector speaker verification system

Inspired by the earlier use of JFA speaker factors directly as features for SVM classification, Dehak *et al.* [19] originally proposed an SVM/CSS i-vector speaker verification approach where i-vector features are directly used as features for SVM/CSS classifier. As i-vector features are based on one variability space, containing speaker and channel variability information, they have to combine with channel compensation approaches to remove the channel variability information.

In SVM/CSS i-vector speaker verification system, channel compensation also occurs at several levels, such as feature domain, model domain and score domain. Feature warping techniques are commonly used in the feature domain, to provide a robustness to additive noise and linear channel mismatch while retaining the speaker specific information [77]. In the model domain, LDA followed by WCCN channel compensation approach is commonly used to compensate the channel variation [20]. In the score domain, t-normalization addresses the problem of session variability which compensates the mismatch between the enrolment and verification conditions [2]. As most channel variations occur at the model domain, the model domain channel compensation approaches are an active area of research, and several advanced channel compensation techniques will be introduced in the next chapter.

3.3.1 SVM and CSS classification techniques

Classification techniques, such as SVMs and CSS, are used with i-vector speaker verification systems [19, 20]. CSS is a computationally more efficient approach than SVMs, and it was also found that it provides better performance than SVM approaches [20].

SVMs: SVM is used as a classifier to find the separation between two classes. SVMs' kernel functions are used to project the input vectors into high dimensional feature space to obtain linear separability. These kernel functions allow us to compute the scalar product directly in the feature space, without defining the mapping function. Dehak *et al.* [19, 20] have found that the appropriate kernel function between test i-vector, $\hat{\mathbf{w}}_{\text{test}}$, and target i-vector, $\hat{\mathbf{w}}_{\text{target}}$, is the cosine kernel, calculated as,

$$\mathrm{K}(\hat{\mathbf{w}}_{\text{target}}, \hat{\mathbf{w}}_{\text{test}}) = \frac{\langle \hat{\mathbf{w}}_{\text{target}}, \hat{\mathbf{w}}_{\text{test}} \rangle}{\|\hat{\mathbf{w}}_{\text{target}}\| \, \|\hat{\mathbf{w}}_{\text{test}}\|}. \tag{3.3}$$

CSS: I-vectors were originally considered as a feature for SVM classification; however, fast scoring approaches using a cosine kernel directly as a classifier were found to provide better performance than SVMs with a considerable increase in efficiency [19]. The CSS operates by comparing the angles between a test i-vector, $\hat{\mathbf{w}}_{\text{test}}$, and a target i-vector $\hat{\mathbf{w}}_{\text{target}}$:

$$\mathrm{S}(\hat{\mathbf{w}}_{\text{target}}, \hat{\mathbf{w}}_{\text{test}}) = \frac{\langle \hat{\mathbf{w}}_{\text{target}}, \hat{\mathbf{w}}_{\text{test}} \rangle}{\|\hat{\mathbf{w}}_{\text{target}}\| \, \|\hat{\mathbf{w}}_{\text{test}}\|}. \tag{3.4}$$

3.3.2 Standard channel compensation approaches

As i-vectors are defined by a single variability space, containing both speaker and channel information, there is a requirement that an additional channel compensation approach be taken before verification. Channel compensation approaches are estimated based on the within- and between-class scatter variances. Within-class scatter (within-speaker variability) depends on microphones, acoustic environments, transmission channel and differences in speaker voice. On the other hand, between-class scatter (between-speaker variability) depends on speaker' characteristics. These channel compensation techniques are typically designed to maximize the effect of between-class variability and minimize the effects of within-class variability.

WCCN: Hatch *et al.* [35] introduced the WCCN approach to SVM-based speaker verification systems. Later, Dehak *et al.* [20] used WCCN as a channel compensation technique to scale a subspace in order to attenuate dimensions of high within-class variance. For use in i-vector-based speaker verification, a within-class covariance matrix, $\mathbf{W}$, is calculated using

$$\mathbf{W} = \frac{1}{S}\sum_{s=1}^{S}\sum_{i=1}^{n_s}(\mathbf{w}_i^s - \bar{\mathbf{w}}_s)(\mathbf{w}_i^s - \bar{\mathbf{w}}_s)^T, \tag{3.5}$$

where the mean i-vector for each speaker, $\bar{\mathbf{w}}_s$, is defined by,

$$\bar{\mathbf{w}}_s \;=\; \frac{1}{n_s}\sum_{i=1}^{n_s}\mathbf{w}_i^s \tag{3.6}$$

where S is the total number of speakers and n_s is number of utterances of speaker s. In evaluation, the inverse of $\mathbf{W}$ is used to normalize the direction of the projected i-vector components, which is equivalent to scaling the subspace by the matrix $\mathbf{B}_1$, where $\mathbf{B}_1{\mathbf{B}_1}^T = \mathbf{W}^{-1}$. The WCCN channel compensated i-vector ($\hat{\mathbf{w}}_{WCCN}$) can be calculated as follows,

$$\hat{\mathbf{w}}_{WCCN} = {\mathbf{B}_1}^T\mathbf{w} \tag{3.7}$$

LDA: Dehak *et al.* [20] had also used an LDA approach as a channel compensation technique. LDA seeks to reduce dimensionality while preserving as much of the speaker discriminatory information as possible. This attempts to find a reduced set of axes $\mathbf{A}$ that minimizes the within-class variability while maximizing the between-class variability through the eigenvalue decomposition of

$$\mathbf{S}_b\mathbf{v} = \lambda\mathbf{S}_w\mathbf{v}. \tag{3.8}$$

where the between-class, $\mathbf{S}_b$, and within-class scatter, $\mathbf{S}_w$, can be calculated as follows,

$$\mathbf{S}_b = \sum_{s=1}^{S} n_s(\bar{\mathbf{w}}_s - \bar{\mathbf{w}})(\bar{\mathbf{w}}_s - \bar{\mathbf{w}})^T, \tag{3.9}$$

$$\mathbf{S}_w = \sum_{s=1}^{S} \sum_{i=1}^{n_s} (\mathbf{w}_i^s - \bar{\mathbf{w}}_s)(\mathbf{w}_i^s - \bar{\mathbf{w}}_s)^T. \tag{3.10}$$

where the mean i-vector for across-all-speakers, $\bar{\mathbf{w}}$, is defined by

$$\bar{\mathbf{w}} = \frac{1}{N} \sum_{s=1}^{S} \sum_{i=1}^{n_s} \mathbf{w}_i^s \tag{3.11}$$

where N is the total number of sessions.

The LDA channel compensated i-vector ($\hat{\mathbf{w}}_{LDA}$) can be calculated as follows,

$$\hat{\mathbf{w}}_{LDA} = \mathbf{A}^T \mathbf{w} \tag{3.12}$$

NAP: NAP is also used to combat the session variations [94]. NAP attempts to remove the unwanted within-class variations from the feature vector. NAP matrix can be calculated as follows,

$$\mathbf{P} = \boldsymbol{I} - \mathbf{V}\mathbf{V}' \tag{3.13}$$

$$\mathbf{J}(v) = \mathbf{v}^T \mathbf{S}_w \mathbf{v} \tag{3.14}$$

$$\mathbf{S}_w = \frac{1}{S} \sum_{s=1}^{S} \frac{1}{n_s} \sum_{1=1}^{ns} (\mathbf{w}_i^s - \bar{\mathbf{w}}_s)(\mathbf{w}_i^s - \bar{\mathbf{w}}_s)' \tag{3.15}$$

where $\boldsymbol{I}$ is the identity matrix and $\boldsymbol{V}$ can be obtained by applying an eigen decomposition to the matrix($\boldsymbol{S}_w$). The NAP-only channel compensated i-vector is calculated as follows,

$$\hat{\mathbf{w}}_{NAP} = \mathbf{P}^T \mathbf{w} \tag{3.16}$$

SD-NAP: The NAP is, in current form, removing between-class scatter information from the feature space; this information can be used to discriminate between speakers. Vogt *et al.* [105] proposed that the SD-NAP minimizes this information loss. The SD-NAP extends on the NAP approach by incorporating the between-class scatter matrix in the eigenvalue problem. The SD-NAP can be calculated as follows,

$$\begin{aligned} \mathbf{J}(v) &= \mathbf{v}^T(\mathbf{S}_w - m\mathbf{S}_b)\mathbf{v} && (3.17) \\ \mathbf{S}_b &= \sum_{s=1}^{S}(\mathbf{w}_s - \bar{\mathbf{w}})(\mathbf{w}_s - \bar{\mathbf{w}})' && (3.18) \end{aligned}$$

where $\mathbf{S}_b$ is the between-class scatter variance and m controls the influence of the between-class scatter variance. The SD-NAP-only channel compensated i-vector is calculated as follows,

$$\hat{\mathbf{w}}_{SD\text{-}NAP} = \mathbf{P}^T\mathbf{w} \tag{3.19}$$

SN-LDA: McLaren *et al.* found that the between-class scatter calculated using the standard LDA approach can be influenced by source variation under mismatched conditions where sources were defined as microphone and telephone recorded speech [71, 72]. This influence can be reduced by estimating the between-class scatter using source-normalized i-vectors and fixing the within-class scatter as the residual variations in the i-vector space [71]. The source-normalized between-class scatter, $\mathbf{S}_b^{src}$, can be composed of the source-dependent between-class scatter matrices for telephone and microphone-recorded speech, which can be calculated as follows,

$$\mathbf{S}_b^{src} = \mathbf{S}_b^{tel} + \mathbf{S}_b^{mic} \tag{3.20}$$

where

$$\mathbf{S}_b^{tel} = \sum_{s=1}^{S_{tel}} n_s(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_{tel})(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_{tel})^T, \tag{3.21}$$

$$\mathbf{S}_b^{mic} = \sum_{s=1}^{S_{mic}} n_s(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_{mic})(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_{mic})^T, \tag{3.22}$$

where the mean i-vector for telephone source ($\bar{\mathbf{w}}_{tel}$) is equal to $\frac{1}{n_{tel}} \sum_{i=1}^{n_{tel}} \mathbf{w}_i^{tel}$, mean i-vector for microphone source ($\bar{\mathbf{w}}_{mic}$) is equal to $\frac{1}{n_{mic}} \sum_{i=1}^{n_{mic}} \mathbf{w}_i^{mic}$. Rather than estimating the within-class scatter separately as in Equation 3.10, McLaren *et al.* [71, 72] calculated the within-class scatter matrix as the difference between a total variance matrix, $\mathbf{S}_t$, and the source-normalized between-class scatter:

$$\mathbf{S}_w = \mathbf{S}_t - \mathbf{S}_b^{src}, \tag{3.23}$$

where

$$\mathbf{S}_t = \sum_{n=1}^{N} (\mathbf{w}_n - \bar{\mathbf{w}})(\mathbf{w}_n - \bar{\mathbf{w}})^T. \tag{3.24}$$

This approach allows $\mathbf{S}_w$ to be more accurately estimated when a development dataset does not provide examples of each speech source from every speaker. Similarly to the LDA approach outlined previously, the SN-LDA channel compensated i-vector is calculated using Equation 3.12.

Sequential channel compensation: Previously, several individual channel compensation techniques were detailed. Individual LDA techniques are generally used to increase the inter-speaker variability while minimizing the intra-speaker variability, and the WCCN approach is used to reduce the channel effect by minimizing the intra-speaker variability. Dehak *et al.* [20] found that the sequential approach of first transforming the subspace using LDA, and then further transforming the new subspace with WCCN (or, alternatively WCCN of LDA, represented as WCCN[LDA]) extracts more speaker discriminant features than individual LDA and WCCN approaches, but continued research has found that any type of LDA followed by WCCN is generally the best approach [47, 71]. In the first stage of the WCCN[LDA] approach, LDA attempts to find a reduced set of axes $\mathbf{A}$ that minimizes the within-class variability while maximizing the between-class variability. The estimation of LDA ($\mathbf{A}$) was briefly described in Section 3.3.2.

In the second stage, WCCN is used as a channel compensation technique to scale a subspace in order to attenuate dimensions of high within-class variance. The WCCN transformation matrix ($\mathbf{B}_2$) is trained using the LDA-projected i-vectors from the first stage. The WCCN matrix ($\mathbf{B}_2$) is calculated using Cholesky decomposition of $\mathbf{B}_2{\mathbf{B}_2}^T = \mathbf{W}^{-1}$, where the within-class covariance matrix $\mathbf{W}$ is calculated using

$$\mathbf{W} = \frac{1}{S}\sum_{s=1}^{S}\sum_{i=1}^{n_s}(\mathbf{A}^T(\mathbf{w}_i^s - \bar{\mathbf{w}}_s))(\mathbf{A}^T(\mathbf{w}_i^s - \bar{\mathbf{w}}_s))^T \tag{3.25}$$

where $\mathbf{w}_i^s$ is the i-vector representation of i session of speaker s, the mean i-vector for each speaker ($\bar{\mathbf{w}}_s$) is equals to $\frac{1}{n_s}\sum_{i=1}^{n_s}\mathbf{w}_i^s$, S is the total number of speakers and n_s is number of utterances of speaker s.

The WCCN[LDA]-channel-compensated i-vector can be calculated as follows,

$$\hat{\mathbf{w}}_{WCCN[LDA]} = \mathbf{B}_2^T\mathbf{A}^T\mathbf{w} \tag{3.26}$$

3.3.3 I-vector score normalization

In the score domain, score normalization approaches, t-, z- and zt-norm, are commonly used with i-vector speaker verification, and previous studies also found that zt-norm performs better than t- and z-norm approaches [20]. Dehak *et al.* [18] also introduced a modification to the CSS that does not require explicit score normalization, relying on simple mean and covariance statistics from a collection of impostor speaker i-vectors. This new scoring simulates zt-norm, and can be calculated as follows,

$$\mathrm{S}(\hat{\mathbf{w}}_{\text{target}}, \hat{\mathbf{w}}_{\text{test}}) \quad = \quad \frac{(\hat{\mathbf{w}}_{\text{target}} - \hat{\mathbf{w}}_{\text{imp}})(\hat{\mathbf{w}}_{\text{test}} - \hat{\mathbf{w}}_{\text{imp}})}{\|C_{imp}.\hat{\mathbf{w}}_{\text{target}}\| \, \|C_{imp}.\hat{\mathbf{w}}_{\text{test}}\|}. \tag{3.27}$$

where $\hat{\mathbf{w}}_{\text{imp}}$ is the mean of imposter i-vectors. C_{imp} is a diagonal matrix, which contains the square root of the diagonal covariance matrix of the impostor i-vectors. In our experiments, zt-norm was used as there is no difference performance-wise, between this new scoring and the zt-norm.

3.4 PLDA speaker verification

The standard channel compensation approaches CSS/SVM i-vector speaker verification system was detailed in the previous section. Rather than attempting to compensate the channel variability in the i-vector space, recently, Kenny [51] has introduced the PLDA approach where the channel variability can be modelled within the i-vector space. As i-vector features are smaller in size, this allowed him to investigate the PLDA-based generative approach with speaker verification systems. The PLDA technique was originally proposed by Price *et al.* [80] for face recognition, and later it was adapted for modelling the i-vector distributions for speaker verification [8, 51, 88]. Two PLDA approaches, GPLDA and HTPLDA were introduced [51]. It was also found that the HTPLDA approach achieved a significant improvement over the GPLDA approach on the standard NIST SRE conditions as more closely modelled the true heavy-tailed distribution of i-vector features [51]. Recently, Garcia-Romero *et al.* [29] found that the heavy-tailed behaviour of i-vector features can be converted into Gaussian behaviour by using the length-normalized approach, and the length-normalized GPLDA has shown similar performance as the HTPLDA.

Previously Dehak *et al.* [20] proposed that FA be used as a feature extractor to extract low dimensional i-vectors (total variability factors). Subsequently, Kenny proposed that the i-vectors, $\mathbf{w}_r$, can be decomposed into speaker part, $\bar{\mathbf{s}}$, and channel part, $\bar{\mathbf{c}}_r$.

$$\mathbf{w}_r = \bar{\mathbf{s}} + \bar{\mathbf{c}}_r \tag{3.28}$$

$$\mathbf{w}_r = \mathbf{m} + \mathbf{U}_1\mathbf{x}_1 + \mathbf{U}_2\mathbf{x}_{2r} + \boldsymbol{\varepsilon}_r \tag{3.29}$$

where for given speaker recordings $r = 1, ...R$; $\mathbf{U}_1$ is the eigenvoice matrix and $\mathbf{U}_2$ is the eigenchannel matrix, $\mathbf{x}_1$ and $\mathbf{x}_{2r}$ are the speaker and channel factors respectively and $\boldsymbol{\varepsilon}_r$ is the residuals. In PLDA modelling, the speaker specific part is represented as $\mathbf{U}_1\mathbf{x}_1$. The covariance matrix of the speaker part is $\mathbf{U}_1{\mathbf{U}_1}^T$, which represents the between-speaker variability. The channel specific part is represented as $\mathbf{U}_2\mathbf{x}_{2r} + \boldsymbol{\varepsilon}_r$. The covariance matrix of the channel part is $\boldsymbol{\Lambda}^{-1} + \mathbf{U}_2{\mathbf{U}_2}^T$, which describes the within-speaker variability, where $\boldsymbol{\Lambda}$ is the precision matrix of residual factors. It is assumed that speaker part ($\mathbf{s}$) and channel part ($\mathbf{c}$) are statistically independent [51].

Extra notation is introduced as follows,

$$\mathbf{w}_r = \mathbf{U}_1^+\mathbf{x}_1^+ + \mathbf{U}_2^+\mathbf{x}_{2r}^+ + \boldsymbol{\varepsilon}_r \tag{3.30}$$

where $\mathbf{x}_1^+$ is the vector of dimension $(N_1 + 1) \times 1$ obtained by appending 1 to $\mathbf{x}_1$ and similarly for $\mathbf{x}_{2r}^+$. $\mathbf{U}_1^+$ is the matrix of dimension $F \times (N_1 + 1)$ obtained by appending a column vector $\mathbf{m}_1$ to $\mathbf{U}_1$ and similarly for $\mathbf{U}_{2r}^+$, and $\mathbf{m}_1 + \mathbf{m}_2 = \mathbf{m}$. The mathematical derivations in Sections 3.4.1 and 3.4.2 are based on work of Kenny [51].

3.4.1 GPLDA

For the Gaussian case, the speaker factor ($\mathbf{x}_1$) is assumed to be a vector having a standard normal distribution of dimension N_1, the channel factor ($\mathbf{x}_{2r}$) is assumed to be a vector having a standard normal distribution of dimension N_2, and the residual ($\boldsymbol{\varepsilon}_r$) is an F-dimensional vector having a normal distribution with mean 0 and precision matrix ($\boldsymbol{\Lambda}$). The graphical representation of GPLDA is shown in Figure 3.1 where the boxes denote plates. The R plate represents the R recordings of given speakers. The shaded circular node represents the observed variables, and the unshaded circular node indicates hidden variables [51].

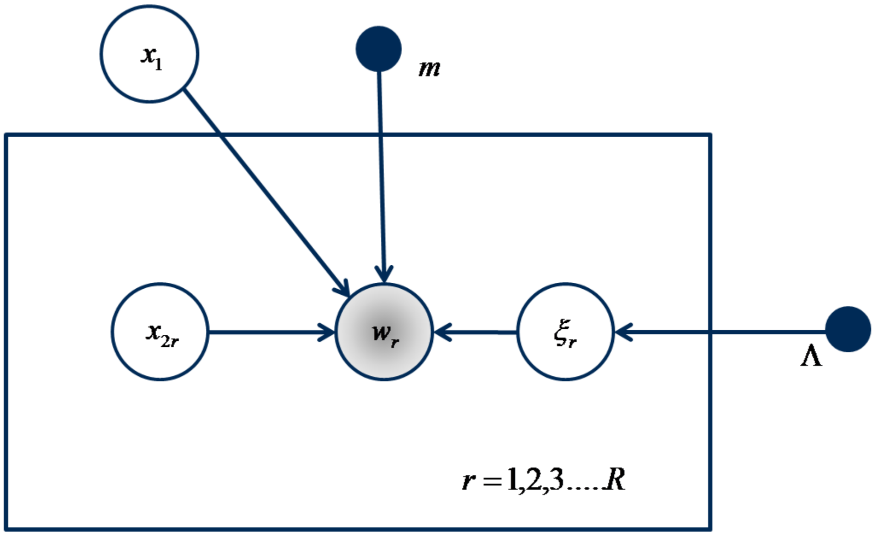


Figure 3.1: Graphical representation of GPLDA model. From [51]

Mathematical representation of the GPLDA modelling: R recordings of single speaker are used to calculate the posterior distribution of the hidden variables. The posterior distribution $\ln P(\mathbf{x}_1, \mathbf{x}_{2r} \mid \mathbf{w}_r)$ is calculated using variational approximation form,

$$\ln P(\mathbf{x}_1, \mathbf{x}_{2r} \mid \mathbf{w}_r) \simeq \ln Q(\mathbf{x}_1) + \sum_{r=1}^{R} \ln Q(\mathbf{x}_{2r}) \tag{3.31}$$

where $Q(\mathbf{x}_1)$ and $Q(\mathbf{x}_{2r})$ are Gaussian distribution.

Updating the Gaussian distribution parameters: The mean and covariance of $Q(\mathbf{x}_1)$ and $Q(\mathbf{x}_{2r})$ are estimated by,

$$Cov(\mathbf{x}_1, \mathbf{x}_1) = (\boldsymbol{I} + R\mathbf{U}_1^T\mathbf{\Lambda}\mathbf{U}_1)^{-1}, \tag{3.32}$$

$$\langle\mathbf{x}_1\rangle = (\boldsymbol{I} + R\mathbf{U}_1^T\mathbf{\Lambda}\mathbf{U}_1)^{-1} \times \sum_{r=1}^{R} \mathbf{U}_1^T\mathbf{\Lambda}(\mathbf{w}_r - \mathbf{m}_1 - \mathbf{U}_2^+\langle\mathbf{x}_{2r}^+\rangle), \tag{3.33}$$

$$Cov(\mathbf{x}_{2r}, \mathbf{x}_{2r}) = (\boldsymbol{I} + \mathbf{U}_{2r}^T\mathbf{\Lambda}\mathbf{U}_{2r})^{-1}, \tag{3.34}$$

$$\langle\mathbf{x}_{2r}\rangle = (\boldsymbol{I} + \mathbf{U}_{2r}^T\mathbf{\Lambda}\mathbf{U}_{2r})^{-1} \times \mathbf{U}_{2r}^T\mathbf{\Lambda}(\mathbf{w}_r - \mathbf{m}_2 - \mathbf{U}_1^+\langle\mathbf{x}_1^+\rangle). \tag{3.35}$$

Likelihood calculations: The likelihood of $P(\mathbf{w} \mid \mathbf{x})$ is estimated as follows,

$$\begin{aligned}\ln P(\mathbf{w} \mid \mathbf{x}) = K &- 0.5(\ln\det(\mathbf{\Lambda}) \\ &+ (\mathbf{w}_r - \mathbf{U}_1^*\mathbf{x}_1^+ - \mathbf{U}_{2r}^*\mathbf{x}_{2r}^+)^T\mathbf{\Lambda}(\mathbf{w}_r - \mathbf{U}_1^*\mathbf{x}_1^+ - \mathbf{U}_{2r}^*\mathbf{x}_{2r}^+))\end{aligned} \tag{3.36}$$

where K is a constant, and $L_1 = \ln P(\mathbf{w} \mid \mathbf{x})$

Maximum likelihood estimation: Model parameters $\mathbf{U}_1$, $\mathbf{U}_2$ and $\mathbf{\Lambda}$ are estimated using maximum likelihood estimation by maximizing L_1. It is equivalent to minimizing the following equation,

$$\sum_s \sum_{r=1}^{R} \langle(\mathbf{w}_r(s) - \mathbf{W}\mathbf{z}_r(s))^T\mathbf{\Lambda}(\mathbf{w}_r(s) - \mathbf{W}\mathbf{z}_r(s))\rangle$$

where $\mathbf{W} = (\mathbf{U}_1^+\mathbf{U}_2^+)$.

W is calculated by estimating the derivative of the above equation, and that leads to the below formula,

$$\mathbf{W}\sum_s \sum_{r=1}^{R} \langle\mathbf{z}_r(s)\mathbf{z}_r^T(s)\rangle = \sum_s \sum_{r=1}^{R} \mathbf{w}_r(s)\langle\mathbf{z}_r^T(s)\rangle \tag{3.37}$$

where

$$\langle \mathbf{z}_r \rangle = \begin{pmatrix} \langle \mathbf{x}_1^+ \rangle \\ \langle \mathbf{x}_{2r}^+ \rangle \end{pmatrix} \tag{3.38}$$

$$\langle \mathbf{z}_r \mathbf{z}_r^T \rangle = \begin{pmatrix} \langle \mathbf{x}_1^+ (\mathbf{x}_1^+)^T \rangle & \langle \mathbf{x}_1^+ (\mathbf{x}_{2r}^+)^T \rangle \\ \langle \mathbf{x}_{2r}^+ (\mathbf{x}_1^+)^T \rangle & \langle \mathbf{x}_{2r}^+ (\mathbf{x}_{2r}^+)^T \rangle \end{pmatrix} \tag{3.39}$$

where

$$\langle \mathbf{x}_1^+ (\mathbf{x}_1^+)^T \rangle = \begin{pmatrix} Cov(\mathbf{x}_1, \mathbf{x}_1) + \langle \mathbf{x}_1 \rangle \langle \mathbf{x}_1^+ \rangle & \langle \mathbf{x}_1^+ \rangle \\ \langle \mathbf{x}_1 \rangle & 1 \end{pmatrix} \tag{3.40}$$

$\langle \mathbf{x}_{2r}^+ (\mathbf{x}_{2r}^+)^T \rangle$ is evaluated similarly.

$\mathbf{\Lambda}$ is estimated by,

$$\mathbf{\Lambda} \quad = (\tfrac{1}{R} \textstyle\sum_s \sum_{r=1}^{R} \langle (\mathbf{w}_r(s) - \mathbf{W}\mathbf{z}_r(s))(\mathbf{w}_r(s) - \mathbf{W}\mathbf{z}_r(s))^T \rangle)^{-1} \tag{3.41}$$

Minimum divergence estimation: The minimum divergence algorithm is applied to modal parameters and hidden variables to speed up convergence. A minimum divergence estimate of eigenvoice parameters, $(\mathbf{x}_1(s), \mathbf{U}_1, \mathbf{m}_1)$, are given by,

$$\mathbf{x}_1(s)^{'} = \mathbf{A}(\mathbf{x}_1(s) - \mathbf{a}), \tag{3.42}$$

$$\mathbf{U}_1^{'} = \mathbf{U}_1 \mathbf{A}^{-1}, \tag{3.43}$$

$$\mathbf{m}_1^{'} = \mathbf{m}_1 + \mathbf{U}_1 \mathbf{a}. \tag{3.44}$$

where

$$\mathbf{a} = \frac{1}{S} \sum_s \langle x_1(s) \rangle, \tag{3.45}$$

$$\mathbf{A}^{-1} = \mathbf{L}. \tag{3.46}$$

and $\mathbf{L}$ is calculated from Cholesky decomposition of

$$\frac{1}{S}\sum_{s}\langle\mathbf{x}_1(s)\mathbf{x}_1(s)^T\rangle - \mathbf{a}\mathbf{a}^T$$

The minimum divergence estimate of the eigenchannel parameters, $(\mathbf{x}_{2r}(s), \mathbf{U}_{2r}, \mathbf{m}_2)$, are given by,

$$\mathbf{x}_{2r}(s)^{'} = \mathbf{A}(\mathbf{x}_{2r}(s) - \mathbf{a}), \tag{3.47}$$

$$\mathbf{U}_2^{'} = \mathbf{U}_2\mathbf{A}^{-1}, \tag{3.48}$$

$$\mathbf{m}_2^{'} = \mathbf{m}_2 + \mathbf{U}_2\mathbf{a}. \tag{3.49}$$

where,

$$\mathbf{a} = \frac{1}{R}\sum_{s}\sum_{r=1}^{R}\langle\mathbf{x}_{2r}(s)\rangle, \tag{3.50}$$

$$\mathbf{A}^{-1} = \mathbf{L}. \tag{3.51}$$

and $\mathbf{L}$ is calculated from Cholesky decomposition of

$$\frac{1}{R}\sum_{s}\sum_{r=1}^{R}\langle\mathbf{x}_{2r}(s)\mathbf{x}_{2r}(s)^T\rangle - \mathbf{a}\mathbf{a}^T$$

A major drawback of GPLDA approach is the lack of robustness to outliers in the speaker and channel subspaces [51]. In order to account with these outliers, Kenny [51] proposed that Student's t-distribution can be used as an alternative to the Gaussian for modelling the subspaces.

3.4.2 HTPLDA

As Student's t-distribution has heavy-tail behaviour compared to the exponentially-decaying tails of a Gaussian behaviour, this approach provides a better representation of outliers encountered in the i-vector space [61]. For the

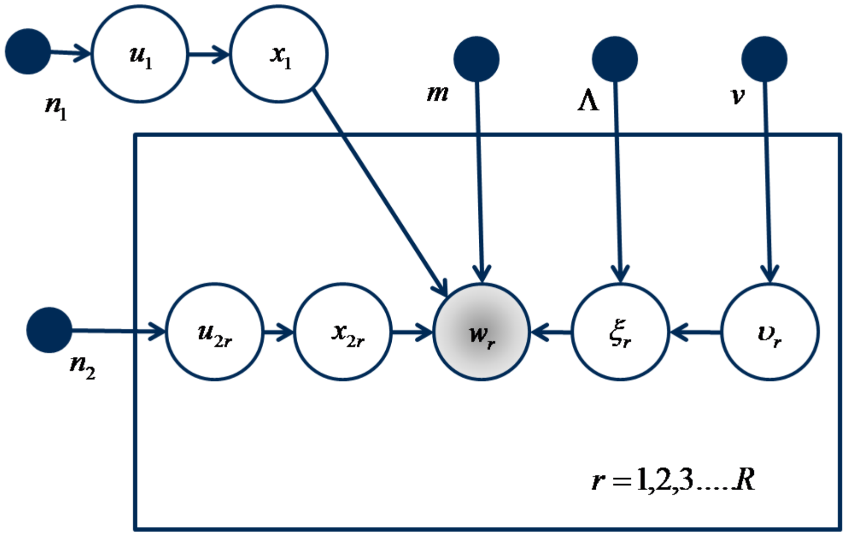


Figure 3.2: Graphical representation of HPLDA model. From [51]

heavy-tailed case, speaker factor($\mathbf{x}_1$), channel factor($\mathbf{x}_{2r}$) and residual($\boldsymbol{\varepsilon}_r$) have student's t distribution. It is assumed that,

$$\mathbf{x}_1 \sim N(0, {u_1}^{-1}\mathbf{I}) \text{ where } u_1 \sim G(n_1/2, n_1/2) \tag{3.52}$$

$$\mathbf{x}_{2r} \sim N(0, {u_{2r}}^{-1}\mathbf{I}) \text{ where } u_{2r} \sim G(n_2/2, n_2/2) \tag{3.53}$$

$$\boldsymbol{\varepsilon}_r \sim N(0, {v_r}^{-1}\boldsymbol{\Lambda}^{-1}) \text{ where } v_r \sim G(v/2, v/2) \tag{3.54}$$

where n_1, n_2 and v are the number of degree of freedom and u_1, u_{2r} and v_r are scalar-value hidden variables. The graphical representation of HPLDA is shown in Figure 3.2. The shaded small circles represent the model parameters.

Mathematical representation of HTPLDA modelling: R recordings of single speaker are used to calculate the posterior distribution of the hidden variables. The posterior distribution $\ln P(\mathbf{x}, u, v \mid \mathbf{w})$ is estimated using the variational approximation form,

$$\ln P(\mathbf{x}, u, v \mid \mathbf{w}) \simeq \ln Q(\mathbf{x}_1) + \sum_{r=1}^{R} \ln Q(\mathbf{x}_{2r}) + \ln Q(u_1) + \sum_{r=1}^{R} \ln Q(u_{2r}) + \sum_{r=1}^{R} \ln Q(v_r) \tag{3.55}$$

where $Q(u_1)$, $Q(u_{2r})$ and $Q(v_r)$ are Gamma distribution, $Q(\mathbf{x}_1)$ and $Q(\mathbf{x}_{2r})$ are Gaussian distribution.

Updating Gaussian distribution parameters: The mean and covariance of $Q(\mathbf{x}_1)$ and $Q(\mathbf{x}_{2r})$ are estimated by,

$$Cov(\mathbf{x}_1, \mathbf{x}_1) = (\langle u_1 \rangle \boldsymbol{I} + \sum_{r=1}^{R} \langle v_r \rangle \mathbf{U}_1^T \boldsymbol{\Lambda} \mathbf{U}_1)^{-1} \tag{3.56}$$

$$\langle \mathbf{x}_1 \rangle = (\langle u_1 \rangle \boldsymbol{I} + \sum_{r=1}^{R} \langle v_r \rangle \mathbf{U}_1^T \boldsymbol{\Lambda} \mathbf{U}_1)^{-1} \times \sum_{r=1}^{R} \langle v_r \rangle \mathbf{U}_1^T \boldsymbol{\Lambda} (\mathbf{w}_r - \mathbf{m} - \mathbf{U}_2^{+} \langle \mathbf{x}_{2r} \rangle) \tag{3.57}$$

$$Cov(\mathbf{x}_{2r}, \mathbf{x}_{2r}) = (\langle u_{2r} \rangle \boldsymbol{I} + \langle v_r \rangle \mathbf{U}_{2r}^T \boldsymbol{\Lambda} \mathbf{U}_{2r})^{-1} \tag{3.58}$$

$$\langle \mathbf{x}_{2r} \rangle = (\langle u_{2r} \rangle \boldsymbol{I} + \langle v_r \rangle \mathbf{U}_{2r}^T \boldsymbol{\Lambda} \mathbf{U}_{2r})^{-1} \times \langle v_r \rangle \mathbf{U}_{2r}^T \boldsymbol{\Lambda} (\mathbf{w}_r - \mathbf{m} - \mathbf{U}_1^{+} \langle \mathbf{x}_r \rangle) \tag{3.59}$$

where the expectation, $\langle u_1 \rangle$, $\langle u_{2r} \rangle$ and $\langle v_r \rangle$, are calculated from posteriors $Q(u_1)$, $Q(u_{2r})$ and $Q(v_r)$.

Updating Gamma distribution parameters: The parameters of $Q(u_1)$ are given by,

$$a_1 = \frac{n_1 + N_1}{2} \tag{3.60}$$

$$b_1 = \frac{n_1 + \langle \mathbf{x}_1^T \mathbf{x}_1 \rangle}{2} \tag{3.61}$$

$$\langle u_1 \rangle = \frac{a_1}{b_1} \tag{3.62}$$

$$\langle \ln u_1 \rangle = \psi(a_1) - \ln(b_1) \tag{3.63}$$

The parameters of $Q(u_{2r})$ are given by,

$$a_{2r} = \frac{n_2 + N_2}{2} \tag{3.64}$$

$$b_{2r} = \frac{n_2 + \langle \mathbf{x}_{2r}^T \mathbf{x}_{2r} \rangle}{2} \tag{3.65}$$

$$\langle u_{2r} \rangle = \frac{a_{2r}}{b_{2r}} \tag{3.66}$$

$$\langle \ln u_{2r} \rangle = \psi(a_{2r}) - \ln(b_{2r}) \tag{3.67}$$

The parameters of $Q(v_r)$ are given by,

$$\alpha_r = \frac{\nu + F}{2} \tag{3.68}$$

$$\beta_r = \frac{\nu + \langle \boldsymbol{\epsilon}_r^T \boldsymbol{\Lambda} \boldsymbol{\epsilon}_r \rangle}{2} \tag{3.69}$$

$$\langle v_r \rangle = \frac{\alpha_r}{\beta_r} \tag{3.70}$$

$$\langle \ln v_r \rangle = \psi(\alpha_r) - \ln(\beta_r) \tag{3.71}$$

where

$$\langle \boldsymbol{\epsilon}_r^T \boldsymbol{\Lambda} \boldsymbol{\epsilon}_r \rangle = tr(\mathbf{U}_1^T \boldsymbol{\Lambda} \mathbf{U}_1 Cov(\mathbf{x}_1, \mathbf{x}_1) + \mathbf{U}_2^T \boldsymbol{\Lambda} \mathbf{U}_2 Cov(\mathbf{x}_{2r}, \mathbf{x}_{2r})) + \langle \boldsymbol{\epsilon}_r^T \rangle \boldsymbol{\Lambda} \langle \boldsymbol{\epsilon}_r \rangle \tag{3.72}$$

$$\langle \boldsymbol{\epsilon}_r \rangle = \mathbf{w}_r - \mathbf{U}_1^+ \mathbf{x}_1 - \mathbf{U}_2^+ \mathbf{x}_{2r} \tag{3.73}$$

Likelihood Calculations: The likelihood of $P(\mathbf{w})$ is calculated by marginalizing $P(\mathbf{w}, \mathbf{h})$ with respect to hidden variables $\mathbf{h}$ $(\mathbf{x}, u, v)$. Lower bound L as a proxy for $\ln P(\mathbf{w})$, and it is estimated as follows,

$$P(\mathbf{w}) = \int P(\mathbf{w}, \mathbf{h}) dh \tag{3.74}$$

$$L = E[\ln \frac{P(\mathbf{w}, \mathbf{h})}{Q(\mathbf{h})}] \tag{3.75}$$

$$L = L_1 + L_2 \tag{3.76}$$

$$L_1 = E[\ln P(\mathbf{w} \mid \mathbf{h})] \tag{3.77}$$

$$L_2 = -D(Q(\mathbf{h}) \parallel P(\mathbf{h})) \tag{3.78}$$

$$L_1 = \sum_{r=1}^{R} (\frac{F}{2} \langle \ln v_r \rangle + \ln \frac{1}{(2\pi)^{\frac{F}{2}} (\det(\mathbf{\Lambda}^{-1}))^{\frac{1}{2}}} - \frac{1}{2} \langle v_r \rangle \langle \boldsymbol{\epsilon}_r^T \mathbf{\Lambda} \boldsymbol{\epsilon}_r \rangle) \tag{3.79}$$

$$\begin{aligned} L_2 = {} & D(Q(\mathbf{x}_1, u_1) \parallel P(\mathbf{x}_1, u_1)) + \sum_{r=1}^{R} D(Q(\mathbf{x}_{2r}, u_{2r}) \parallel P(\mathbf{x}_{2r}, u_{2r})) \\ & + \sum_{r=1}^{R} D(Q(v_r) \parallel P(v_r)) \end{aligned} \tag{3.80}$$

where $D(\ \parallel\ )$ denotes the Kullback-Leibler divergence.

$$\begin{aligned} D(Q(\mathbf{x}_1, u_1) \parallel P(\mathbf{x}_1, u_1)) = {} & -\frac{N_1}{2} - \frac{N_1}{2} \langle \ln u_1 \rangle - \frac{1}{2} \ln \det(Cov(\mathbf{x}_1, \mathbf{x}_1)) \\ & + \frac{1}{2} \langle u_1 \rangle \langle \mathbf{x}_1^T \mathbf{x}_1 \rangle + D(Q(u_1) \parallel P(u_1) \end{aligned} \tag{3.81}$$

Maximum likelihood estimation: Model parameters $\mathbf{U}_1$, $\mathbf{U}_2$ and $\mathbf{\Lambda}$ are estimated using maximum likelihood algorithm by maximizing L_1,

$$\mathbf{W} \sum_{s} \sum_{r=1}^{R} \langle v_r(s) \rangle \langle \mathbf{z}_r(s) \mathbf{z}_r^T(s) \rangle = \sum_{s} \sum_{r=1}^{R} \langle v_r(s) \mathbf{w}_r(s) \langle \mathbf{z}_r^T(s) \rangle \tag{3.82}$$

where

$$\langle \mathbf{z}_r \rangle = \begin{pmatrix} \langle \mathbf{x}_1^+ \rangle \\ \langle \mathbf{x}_{2r}^+ \rangle \end{pmatrix} \tag{3.83}$$

$$\langle \mathbf{z}_r \mathbf{z}_r^T \rangle = \begin{pmatrix} \langle \mathbf{x}_1^+ (\mathbf{x}_1^+)^T \rangle & \langle \mathbf{x}_1^+ (\mathbf{x}_{2r}^+)^T \rangle \\ \langle \mathbf{x}_{2r}^+ (\mathbf{x}_1^+)^T \rangle & \langle \mathbf{x}_{2r}^+ (\mathbf{x}_{2r}^+)^T \rangle \end{pmatrix} \tag{3.84}$$

where

$$\langle \mathbf{x}_1^+ (\mathbf{x}_1^+)^T \rangle = \begin{pmatrix} Cov(\mathbf{x}_1, \mathbf{x}_1) + \langle \mathbf{x}_1 \rangle \langle \mathbf{x}_1^+ \rangle & \langle \mathbf{x}_1^+ \rangle \\ \langle \mathbf{x}_1 \rangle & 1 \end{pmatrix} \tag{3.85}$$

and $\langle \mathbf{x}_{2r}^+ (\mathbf{x}_{2r}^+)^T \rangle$ is evaluated similarly.

$\mathbf{\Lambda}$ is estimated by,

$$\mathbf{\Lambda} \;\; = (\tfrac{1}{R} \textstyle\sum_s \sum_{r=1}^R \langle v_r(s) \rangle \langle (\mathbf{w}_r(s) - \mathbf{W}\mathbf{z}_r(s))(\mathbf{w}_r(s) - \mathbf{W}\mathbf{z}_r(s))^T \rangle)^{-1} \tag{3.86}$$

Minimum divergence estimation: Minimum divergence algorithm is applied to modal parameters $(\mathbf{U}_1, \mathbf{U}_2, \mathbf{m}, \mathbf{p})$ and hidden variables $(\mathbf{x}_1, \mathbf{x}_{2r}, u_1, u_{2r}, v_r)$, to speed up convergence. A minimum divergence estimate of eigenvoice $(\mathbf{x}_1(s), \mathbf{U}_1, u_1, \mathbf{m}_1,)$ parameters is estimated by,

$$\mathbf{x}_1(s)^{'} = \mathbf{A}(\mathbf{x}_1(s) - \mathbf{a}), \tag{3.87}$$

$$\mathbf{U}_1^{'} = \mathbf{U}_1 \mathbf{A}^{-1}, \tag{3.88}$$

$$\mathbf{m}_1^{'} = \mathbf{m}_1 + \mathbf{U}_1 \mathbf{a}, \tag{3.89}$$

$$u_1(s)^{'} = k u_1(s). \tag{3.90}$$

where

$$k = \frac{S}{\sum_s \langle u_1(s) \rangle}, \tag{3.91}$$

$$\mathbf{a} = \frac{1}{\sum_s \langle u_1(s) \rangle} \sum_s \langle u_1(s) \rangle \langle \mathbf{x}_1(s) \rangle, \tag{3.92}$$

$$\mathbf{A}^{-1} = \mathbf{L}. \tag{3.93}$$

$\mathbf{L}$ is calculated from Cholesky decomposition [60] of

$$\frac{1}{\sum_s \langle u_1(s) \rangle} \sum_s \langle u_1(s) \rangle \langle \mathbf{x}_1(s) \mathbf{x}_1(s)^T \rangle - \mathbf{a}\mathbf{a}^T$$

Minimum divergence estimate of eigenchannel $(\mathbf{x}_{2r}(s), \mathbf{U}_{2r}, u_{2r}, \mathbf{m}_2)$ parameters are given by,

$$\mathbf{x}_{2r}(s)^{'} = \mathbf{A}(\mathbf{x}_{2r}(s) - \mathbf{a}), \tag{3.94}$$

$$\mathbf{U}_2^{'} = \mathbf{U}_2\mathbf{A}^{-1}, \tag{3.95}$$

$$\mathbf{m}_2^{'} = \mathbf{m}_2 + \mathbf{U}_2\mathbf{a}, \tag{3.96}$$

$$u_{2r}(s)^{'} = ku_{2r}(s). \tag{3.97}$$

where,

$$k = \frac{R}{\sum_s \sum_{r=2}^{R} \langle u_{2r}(s) \rangle}, \tag{3.98}$$

$$\mathbf{a} = \frac{1}{\sum_s \sum_{r=1}^{R} \langle u_{2r}(s) \rangle} \sum_s \sum_{r=1}^{R} \langle u_{2r}(s) \rangle \langle \mathbf{x}_{2r}(s) \rangle, \tag{3.99}$$

$$\mathbf{A}^{-1} = \mathbf{L}. \tag{3.100}$$

L is calculated from Cholesky decomposition[60] of

$$\frac{1}{\sum_s \sum_{r=1}^{R} \langle u_{2r}(s) \rangle} \sum_s \sum_{r=1}^{R} \langle u_{2r}(s) \rangle \langle \mathbf{x}_{2r}(s)\mathbf{x}_{2r}(s)^T \rangle - \mathbf{a}\mathbf{a}^T$$

Minimum divergence estimate of precision $(v_r(s), \mathbf{\Lambda})$ parameters are given by,

$$\mathbf{\Lambda}^{'} = \frac{\mathbf{\Lambda}}{k}, \tag{3.101}$$

$$v_r(s)^{'} = kv_r(s). \tag{3.102}$$

where k is calculated as follows,

$$k = \frac{R}{\sum_s \sum_{r=1}^{R} \langle v_r(s) \rangle} \tag{3.103}$$

Degree of freedom (n_1, n_2, ν) are calculated using following equations,

$$\psi(\frac{n_1}{2}) - \ln\frac{n_1}{2} = 1 + \frac{1}{S}\sum_s (\langle \ln u_1(s) \rangle - \langle u_1(s) \rangle), \tag{3.104}$$

$$\psi(\frac{n_2}{2}) - \ln\frac{n_2}{2} = 1 + \frac{1}{R}\sum_s \sum_{r=1}^{R} (\langle \ln u_{2r}(s) \rangle - \langle u_{2r}(s) \rangle), \tag{3.105}$$

$$\psi(\frac{\nu}{2}) - \ln\frac{\nu}{2} = 1 + \frac{1}{R}\sum_s \sum_{r=1}^{R} (\langle \ln v_r(s) \rangle - \langle v_r(s) \rangle). \tag{3.106}$$

The above equations can be solved by newton raphson method.

3.4.3 Length-normalized GPLDA

Recently, Garcia-Romero *et al.* [29] have found the way to convert the i-vector feature behaviour from heavy-tailed to Gaussian. They have introduced the length-normalization approach, and it has shown a similar performance as HT-PLDA and a more computationally efficient approach than HTPLDA. The length-normalization approach is used to transform the non-Gaussian i-vector feature behaviour into Gaussian i-vector feature behaviour [68]. This technique follows two steps: (1) linear whitening and (2) length-normalization. A linear whitened i-vector, w_{wht}, can be estimated as follows,

$$\mathbf{w}_{wht} = \mathbf{d}^{-\frac{1}{2}}\mathbf{U}^{T}\mathbf{w} \tag{3.107}$$

where $\mathbf{\Sigma}$ is a covariance matrix, which is estimated using development i-vectors. $\mathbf{U}$ is an orthonormal matrix containing the eigenvectors of $\mathbf{\Sigma}$ and $\mathbf{d}$ is a diagonal matrix containing the corresponding eigenvalues.

Length-normalized i-vector feature, $\mathbf{w}^{norm}$, can be calculated as follows,

$$\mathbf{w}^{norm} = \frac{\mathbf{w}_{wht}}{\|\mathbf{w}_{wht}\|} \tag{3.108}$$

If the i-vector feature behaviour is standard Gaussian distribution, the length distribution of i-vector features should follow a Chi distribution with number of degrees of freedom (DOF) equal to the dimension of the i-vector. Garcia-Romero *et al.* [29] have found that the length distribution of development and evaluation data i-vectors fails to match the Chi distribution, and the mismatch led to a conclusion that i-vector feature is having heavy-tailed behaviour. The authors have also shown in [29] that length normalization approach can be used to transform the non-Gaussian i-vector feature behaviour into Gaussian i-vector feature behaviour.

We illustrate this finding by Garcia-Romero et al *et al.*, in Figure 3.3 by choosing

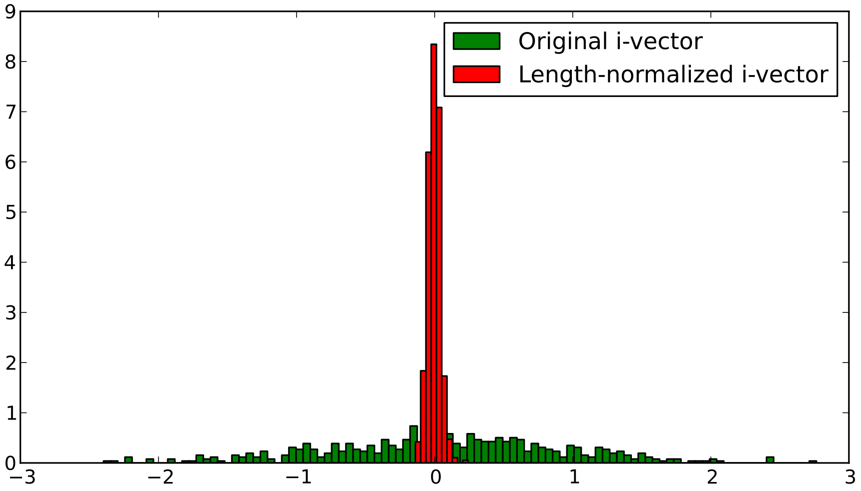


Figure 3.3: Histogram of original and length-normalized values of the nth i-vector feature, where n was randomly selected.

an arbitrary speaker. A speaker (1148-sre04) and dimension (n) were randomly selected for a histogram plot to illustrate the effect of length-normalisation of i-vectors. It can be seen, by comparing the histograms of standard i-vectors and length-normalized i-vectors in the Figure 3.3, that i-vector feature behaviour is moving from Heavy-tailed to Gaussian.

3.4.4 PLDA scoring

GPLDA, HTPLDA and length-normalized GPLDA based i-vector system's scoring is calculated using batch likelihood ratio [51]. Batch likelihood calculation is computationally more expensive than cosine distance scoring. Given two i-vectors $\mathbf{w}_{target}$ and $\mathbf{w}_{test}$, batch likelihood ratio can be calculated as follows,

$$\ln \frac{P(\mathbf{w}_{target}, \mathbf{w}_{test} \mid H_1)}{P(\mathbf{w}_{target} \mid H_0) P(\mathbf{w}_{test} \mid H_0)} \tag{3.109}$$

where H_1: the speakers are same, H_0: the speaker are different. Lower bound L as a proxy for the log likelihood and it is estimated using Equation 3.77.

$P(\mathbf{w}_{target}, \mathbf{w}_{test} \mid H_1)$ is estimated using w_{target} and w_{test} utterances by evaluating the L when R equals 2. $P(\mathbf{w}_{target} \mid H_0)$ and $P(\mathbf{w}_{test} \mid H_1)$ are respectively estimated using w_{target} and w_{test} utterances by evaluating the L when R equals 1.

3.5 Chapter summary

In recent times, CSS i-vector and PLDA speaker verification systems have become state-of-the-art approaches, and these two approaches deeply detailed in this chapter. Initially, this chapter detailed the i-vector feature extraction approach, standard channel compensation approaches, including LDA and WCCN, and cosine similarity scoring. Subsequently, GPLDA, HTPLDA, and length-normalized GPLDA approaches were also detailed. These two speaker verification systems will be used to evaluate the newly proposed techniques in next chapters.

Chapter 4

Speaker Verification Framework

4.1 Introduction

In recent times, CSS i-vector and PLDA speaker verification systems have become state-of-the-art techniques [20, 51]; these approaches were extensively detailed in the previous chapter. For the experimental work in this thesis, a comprehensive framework was required. The framework of CSS i-vector and PLDA speaker verification systems and experimental protocol, which is used to train the systems, are detailed in this chapter. It is also explained how short-length utterances are extracted from long-length utterances.

4.2 An overview of speaker verification databases

The switchboard series of corpora: The Switchboard series of corpora was collected by the Linguistic Data Consortium (LDC) [31]. Switchboard I consisted of landline-based telephony speech from both electret and carbon-button handset types. This corpus was collected from 543 U.S. participants with a total of 4800 conversation sides or speech segments. Switchboard II consisted of three separate phases differing in demographic region; Mid-Atlantic, Midwest, southern regions respectively. The majority of participants were sourced from local universities. Switchboard II Phase I consisted of 3638, 5-minute telephone conversations from 657 participants. Phase II consisted of 4,472 conversations involving 679 participants [31]. Phase III used 5,456 sides from 640 participants under varied environmental conditions. The Switchboard Cellular series of corpora was released in two parts in 2001 and 2004 respectively. Part 1 focussed primarily on GSM cellular phone technology with a total of 2618 sides (1,957 from GSM cell phones) from 254 participants roughly divided in gender. Part 2 focussed on cellular phone technology from a variety of service types, with CDMA technology being most dominant due to its popularity at the time of collection. A total of 4,040 sides (2,950 cellular) from 419 participants were recorded under a variety of environmental conditions [12].

NIST databases (years 2004 to 2006): In 2004, the NIST SRE presented a new evaluation protocol in which the previous core condition and extended evaluation tasks were combined [97]. In this way, evaluations could include training data from 10 seconds through to 16 training sides with test conditions using speech segments of 10 seconds to a full conversation side. All participating sites, however, were required to perform the compulsory one side train-one side test condition of the evaluation with all other conditions being optional.

The NIST 2006 SRE reused a proportion of the data from the 2005 SRE which, consequently, presented difficulties during the system development process due to the potential overlap in speakers between the development and unseen data. The difficulties associated with diverse and substantial data collection resulted in the following NIST SREs being held every two years [98].

NIST databases (years 2008 to 2010): The NIST 2008 SRE saw the introduction of several challenging tasks. Most dominant of these was the use of conversational speech data recorded using a microphone in an interview type scenario and taken from the Mixer 5 Interview speech corpus [99]. Additionally, conversational telephone speech was recorded over a microphone channel to introduce a new test condition. The use of interview style data allowed longer speech segments (approximately 15 minutes) to be used for training and testing. A proportion of target speakers from the NIST 2006 SRE were also present in the 2008 SRE, however, there was no overlap in speech segments between the corpora.

The 2010 evaluation is similar to that of 2008 but different from prior evaluations by including in the training and test conditions for the core (required) test, not only conversational telephone speech recorded over ordinary (wired or wireless) telephone channels, but also such speech recorded over a room microphone channel, and conversational speech from an interview scenario recorded over a room microphone channel [100]. But unlike in 2008 and in prior evaluations, some of the data involving conversational telephone style speech have been collected in a manner to produce particularly high, or particularly low, vocal effort on the part of the speaker of interest. Unlike 2008, the core test interview segments are of varying duration, ranging from three-to-fifteen minutes.

The 2010 evaluation primarily uses recently collected speech data from speakers not included in previous evaluations, but also included some old and new conversational telephone speech segments from speakers in various past evaluations. Some new speech has recently been collected from speakers appearing in earlier evaluations.

4.3 Performance measures

Speaker verification performance is typically measured using the equal error rate (EER) and minimum decision cost function (DCF) [85]. These measures represent different performance characteristics of a system, however, their accurate estimation relies on a sufficient number of trials to be evaluated in order to robustly calculate the relevant statistics. System performance can also be represented graphically to assist in the direct comparison of systems. For such a task, the detection error trade-off (DET) plots are utilised.

The performance of a speaker verification system can be represented by two specific types of errors; false alarms (false acceptance), and missed detections (false rejection). A false alarm occurs when a speech segment from an impostor speaker is incorrectly identified as originating from the target speaker. On the other hand, a missed detection (false rejection) refers to the rejection of the target speaker from the system. There exists a trade-off between these two types of error such that a system can be tuned to a specific application-dependent operating point.

With regard to performance metrics, the EER provides a measure of missed detections and false alarms when defining the decision threshold to cause an equal proportion of errors to occur. In contrast, the DCF assigns a cost to each of these errors and takes into account the prior probability of a target trial. The decision cost function is defined as,

$$C_{DET} = C_{Miss} P_{Miss|Target} P_{Target} + C_{False} P_{False|NonTarget} P_{NonTarget} \tag{4.1}$$

where the cost of a missed detection and false alarm are given by C_{Miss} and C_{False}, respectively, P_{Target} and $P_{NonTarget}$ represent the prior probabilities of encountering target and non-target trials, respectively, and $P_{Miss|Target}$ and $P_{FalseAlarm|NonTarget}$ are the system-dependent miss detection and false alarm rates, respectively. The decision threshold of a system can then be selected to minimise the cost function. The ability to adjust the parameters of the decision cost function makes the minimum DCF metric suitable for the evaluation of a variety of application-specific systems.

4.4 CSS i-vector speaker verification system

4.4.1 Experimental protocol

All CSS i-vector experiments in this thesis were evaluated using the NIST 2008 and NIST 2010 SRE corpora. For NIST 2008, the performance was evaluated using the EER and DCF and calculated using $C_{miss} = 10$, $C_{FA} = 1$, and $P_{target} = 0.01$ as defined in NIST 2008 speaker recognition evaluation plan [99]. NIST 2008 evaluation was performed using the *telephone-telephone*, *interview-interview*, *telephone-microphone* and *interview-telephone* enrolment-verification conditions [99]. For NIST 2010 speaker recognition evaluation, new set of parameter values ($C_{miss} = 1$, $C_{FA} = 1$, and $P_{target} = 0.001$) are used to compute the detection cost for 8conv/core test conditions. The old parameter values ($C_{miss} = 10$, $C_{FA} = 1$, and $P_{target} = 0.01$) which were used in previous evaluations are used to estimate the old minimum DCF (DCF_{old}). The performance for the NIST 2010

SRE was evaluated using the EER and DCF_{old} [100]. The evaluation was performed using the *telephone-telephone*, *interview-interview*, *interview-microphone* and *interview-telephone* condition [100].

For CSS i-vector experiments, 13-dimensioned feature-warped MFCCs with appended delta coefficients and two gender-dependent UBM containing 512 Gaussian mixtures were used. The MFCC features' dimension and the number of UBM components were kept in low values, in order to reduce the computational cost, and because it is easy to adapt to real world applications. The UBMs were trained on telephone and microphone speech from NIST 2004, 2005, and 2006 SRE corpora. These gender-dependent UBMs were used to calculate the Baum-Welch statistics before training a gender dependent total-variability subspace of dimension $R_w = 500$, which was then used to calculate the i-vector speaker representations. Total-variability representation and channel compensation matrices were trained using telephone and microphone speech data from NIST 2004, 2005 and 2006 SRE corpora as well as Switchboard II. Randomly selected telephone and microphone utterances from NIST 2004, 2005 and 2006 were pooled to form the ZT normalization dataset.

For the NIST 2008 evaluation, in most of the cases, the system achieved the best performance, when the channel compensation approach dimension was selected as 150. For NIST 2010 evaluation, channel compensation approach dimension was chosen as 150, in order to show that the best value for NIST 08 evaluation is robust to other dataset as well.

4.4.2 CSS i-vector speaker verification system framework

The mathematical representation of i-vector feature extraction and standard channel compensation techniques were detailed in Chapter 3. An overview of

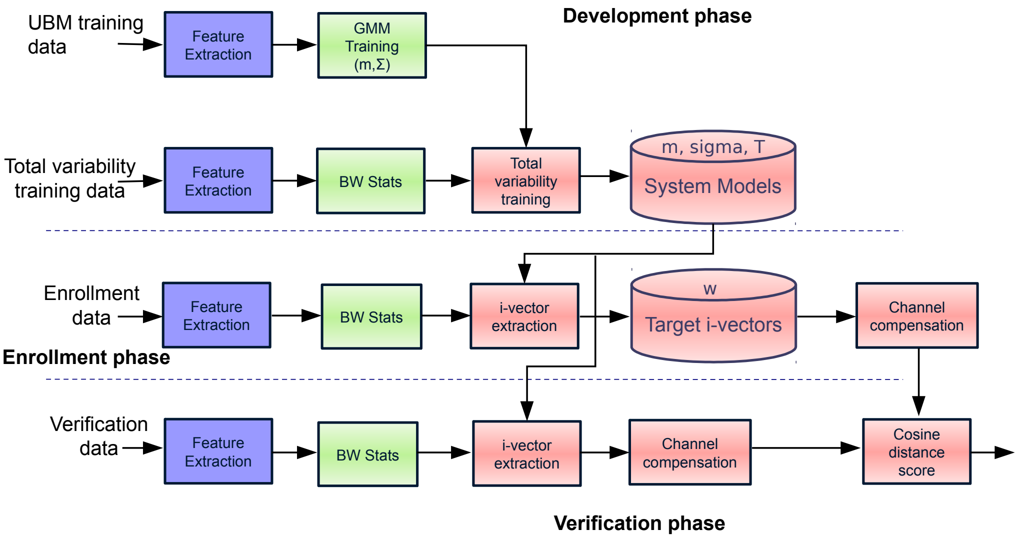


Figure 4.1: *A block diagram of an i-vector based speaker verification system.*

the CSS i-vector system framework is shown Figure 4.1. It consists of three phases: development, enrolment and verification.

The development is the process of learning speaker independent parameters. Firstly, 512 Gaussian component UBM parameters were trained on telephone and microphone speech from NIST 2004, 2005 and 2006 SRE corpora, and the total-variability space representation, $\boldsymbol{T}$, was trained using the eigenvoice MAP from telephone and microphone speech data from NIST 2004, 2005 and 2006 SRE corpora as well as Switchboard II. The total-variability space training is a similar process of JFA eigenvoice MAP, except one difference. All the recordings of given speakers are considered as different persons in order to capture the channel variations. The channel compensation approaches were also trained using the same development data, which were used to train total-variability space.

In the enrolment phase, the target i-vectors were extracted using the Baum-Welch statistics and the total-variability space matrix. In the verification phase, the test i-vectors were also extracted using a similar process to the target i-vectors extraction. The channel compensation approaches were applied to the target and test i-vectors in order to compensate the channel variations, and test i-vectors were then compared with target i-vectors using CSS.

4.5 PLDA speaker verification system

4.5.1 Experimental protocol

The PLDA speaker verification experiments were evaluated using the NIST 2008 and 2010 SRE corpora. NIST 2008 and 2010 speaker recognition evaluation plan is detailed in Section 4.4.1.

The 13-dimensioned feature-warped MFCCs with appended delta coefficients and two gender-dependent UBM containing 512 Gaussian mixtures were used throughout the experiments. The UBMs were trained on telephone and microphone speech from NIST 2004, 2005, and 2006 SRE corpora for telephone and microphone i-vector experiments. These gender-dependent UBMs were used to calculate the Baum-Welch statistics before training a gender dependent total-variability subspace of dimension $R_w = 500$ which was then used to calculate the i-vector speaker representations.

For the telephone and microphone speech PLDA experiments, the total-variability representation, channel compensation approaches and GPLDA model parameters were trained using telephone and microphone speech data from NIST 2004, 2005 and 2006 SRE corpora as well as Switchboard II. Based upon speaker verification performance, 120 eigen-voices (N_1) were empirically selected, and the precision matrix was defined as full rather than diagonal. The channel compensation approach dimension was chosen as 150, based upon speaker verification perfor-

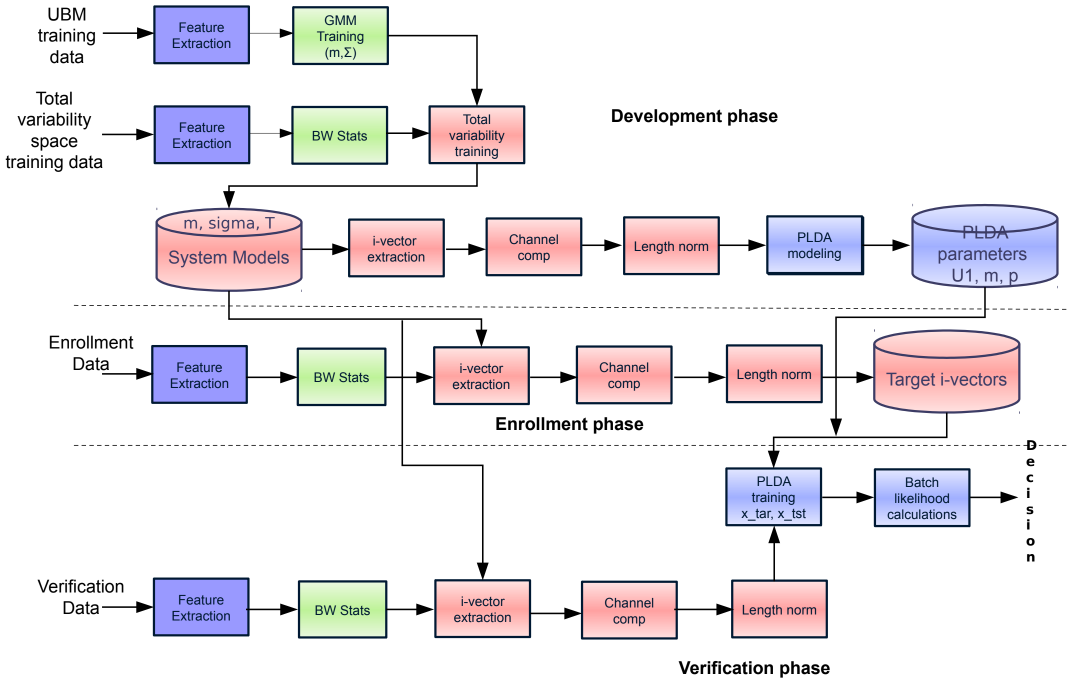


Figure 4.2: *A block diagram of length-normalized GPLDA-based speaker verification system.*

mance on NIST 2008 evaluation set. S normalization was applied to telephone and microphone speech-based length-normalized GPLDA system experiments. Randomly selected telephone and microphone utterances from NIST04, 05 and 06 were pooled to form the S normalization dataset.

4.5.2 PLDA speaker verification system framework

The i-vector feature extraction and PLDA model parameter estimation approaches were detailed in Chapter 3. Several types of PLDA approaches, such as HTPLDA, GPLDA and length-normalized GPLDA were introduced by researchers in recent times [29, 51]. Though HTPLDA is a better approach than GPLDA, as i-vector feature behaviour is heavy-tailed distribution, it is computationally a much more expensive approach. Recently, it was also found that by using the length-normalization approach, the heavy-tailed data behaviour can be converted into Gaussian behaviour, and length-normalized GPLDA could provide similar performance as HTPLDA. The length-normalized GPLDA approach was used in most of the following chapters as it is computationally a efficient approach.

An overview of PLDA speaker verification framework is shown in Figure 4.2. Similarly to the CSS i-vector speaker verification system, the GPLDA speaker verification system also involves three phases: development, enrolment and verification.

In the development phase, the UBM parameters were trained on telephone and microphone from NIST 2004, 2005 and 2006 SRE corpora to learn speaker independent parameters. Total-variability space representation, $\mathbf{T}$, was trained using telephone and microphone speech data from NIST 2004, 2005 and 2006 SRE corpora as well as Switchboard II. In the PLDA modelling stage, the GPLDA model parameters ($\mathbf{U}_1$, $\mathbf{m}$, $\mathbf{p}$) were estimated using the maximum likelihood and minimum divergence algorithms, which were detailed in Section 3.4.

In the enrolment and verification stage, the GPLDA hidden variables were estimated using variational posterior distribution and the scoring was calculated using the batch likelihood ratio, detailed in Chapter 3.

4.6 Score-level fusion

Score-level fusion combines the output scores of independently operating classifiers to produce a final or fused classification score. Score fusion is often accomplished using a set of weights which are typically determined from a training set with the objective of reducing logistic regression or the mean-squared error over the training set.

In this dissertation, score-level fusion is performed using linear weights calculated via logistic regression. Score-level fusion is implemented using the FoCal toolkit [6] to optimize linear regression parameters.

4.7 Extraction of short utterances

The NIST standard evaluation condition mostly has long utterances, and it is hard to find several short utterance evaluation conditions. In order to conduct research on short utterance speaker verification systems, the shortened evaluation utterances were obtained by truncating the NIST 2008 *short2-short3* and NIST 2010 *core-core* conditions to the specified length of active speech for both enrolment and verification. Prior to the evaluation and development utterance truncation, the first 20 seconds of active speech were removed from all utterances to avoid capturing similar introductory statements across multiple utterances.

4.8 Chapter summary

This chapter has provided the experimental set up of both CSS i-vector and PLDA speaker verification systems. In following chapters several techniques will be proposed to overcome the problems of training and testing mismatch and short utterance issues. The framework developed in this chapter can be used to test those techniques. As it is hard find short utterance evaluation conditions in NIST standard conditions, an approach was also introduced in this chapter to extract short utterances.

Chapter 5

I-vector Speaker Verification using Advanced Channel Compensation Techniques

5.1 Introduction

In this chapter, several novel advanced channel compensation techniques are introduced for the purpose of improving speaker verification performance in the presence of high session variability. In recent times, the CSS i-vector speaker verification system has become a state-of-the-art speaker verification system, as it has been shown to provide a considerably more efficient approach to speaker verification, primarily due to the much lower dimensionality than the super-vector classification approaches taken in more traditional GMM and SVM approaches. These i-vector features contain channel variability information, which need to be compensated using channel compensation techniques. Previously Dehak *et al.* [20] had introduced the standard channel compensation techniques, including

LDA, WCCN and NAP to attenuate channel variability in the i-vector space. These approaches have been clearly explained in Chapter 3. However, no single channel compensation approach has found yet to effectively compensate the channel variation.

In this chapter, firstly standard channel compensation techniques, such as WCCN, LDA and SN-LDA, are investigated in an individual and sequential manner to support the previous findings. Subsequently, novel advanced channel compensation techniques, including WMMC, SN-WMMC, WLDA and SN-WLDA are introduced in a sequential manner as an alternative to LDA and SN-LDA approaches. Score-level fusion techniques are also introduced to combine different types of channel compensation techniques, in order to capture complementary speaker information between them, and show improved performance over existing individual channel compensation techniques.

As most of the channel variations occur at the model domain, several novel channel compensation and combination techniques are extensively introduced in this chapter, and tested using CSS i-vector speaker verification. The mathematical representation of i-vector feature extraction and standard channel compensation approaches were detailed in Chapter 3. The framework of CSS i-vector speaker verification system was detailed in Chapter 4.

5.2 Channel compensation techniques

In a CSS based i-vector system, as i-vectors are defined by a single variability space, containing both speaker and channel information, there is a requirement that additional intersession or channel compensation approaches be taken before verification. The channel compensation techniques are typically designed to maximize the effect of between-class variability and minimize the effects of within-class variability. The main aim of this chapter is to identify the best channel compensation approach for a telephone and microphone-based i-vector speaker verification system.

5.2.1 WMMC

In this research, the WMMC approach, originally introduced for face recognition [15, 37], is introduced to CSS i-vector speaker verification system. In the LDA and SN-LDA approaches, the transformation matrix is calculated as the ratio of between-class scatter to within-class scatter, and the level of importance of within- and between-class scatters cannot be changed. The main advantage of WMMC for i-vector speaker verification is that the level of importance of within- and between-class scatters can be changed using weighing coefficients [3, 37]. In face recognition, WMMC also provided a solution to the inability of inverting the within-class scatter, or the 'singularity problem' [15, 37], but this problem is rarer in i-vector speaker verification due to the lower dimensionality.

The objective function of WMMC under projection matrix **A** is defined as,

$$J(\mathbf{A}) = tr\{\mathbf{A}^T W \times \mathbf{S}_w - \mathbf{S}_b)\mathbf{A}\}. \tag{5.1}$$

where an **A** that maximizes Equation 5.1 can be calculated through the following eigenvalue equation,

$$(W \times \mathbf{S}_w - \mathbf{S}_b)a = \lambda a, \tag{5.2}$$

where the between-class scatter ($\mathbf{S}_b$) and within-class scatter ($\mathbf{S}_w$) are estimated as described in Equations 3.9 and 3.10. W is a weighting coefficient defining the relative influence of the $\mathbf{S}_w$ and $\mathbf{S}_b$.

The manual weighting coefficients are investigated as the performance of WMMC is directly dependent on its weighted coefficient. The WMMC channel compensated i-vector will be calculated using Equation 3.12.

The SN-LDA approach was detailed in Section 3.3.2, which was previously proposed by McLaren *et al* [71, 72] as an extension to the i-vector system. From the basics of SN-LDA approach, the SN-WMMC approach is introduced to the i-vector system, and that can be used to improve the performance in both mismatched enrolment/verification conditions. In this case, the between-class scatter matrix ($\mathbf{S}_b$), and the within-class scatter matrix ($\mathbf{S}_w$) are estimated using Equation 3.20 and 3.10.

5.2.2 WLDA

In this thesis, WLDA approach is introduced to CSS i-vector speaker verification system, as traditional LDA approach has some limitations. Traditional LDA techniques attempt to project i-vectors into a more discriminative lower-dimensional subspace, calculated based on within- and between-class scatter matrix estimations. However, this approach cannot take advantage of the discriminative relationships between the class pairs, which are much closer due to channel similarities, and traditional estimation of between-class scatter matrix is not able to adequately compensate. WLDA technique can be used to overcome this problem [67], by weighting the classes that are closer to each other to reduce class confusion. Even though WLDA techniques have been introduced for face recognition [67], effective weighting functions that could help to extract more discriminative information haven't been found yet. In this chapter, the WLDA approach is introduced to i-vector speaker verification and explores the application of several alternative weighting functions to extract more speaker discriminative information. In a WLDA approach, the between-class scatter matrix is redefined by adding a weighting function, $w(d_{ij})$, according to the between-class distance of each pair of classes i and j. In [67], the equations, which are used to calculate the within- and between-class scatter estimations, are bit different from equations that are used in i-vector speaker verification [47, 71]. So, the modifications were done on weighted between-class scatter estimation. The weighted between-class scatter matrix, $\mathbf{S}_b^w$, is defined as

$$\mathbf{S}_b^w = \frac{1}{N}\sum_{i=1}^{S-1}\sum_{j=i+1}^{S} w(d_{ij})n_i n_j(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)^T, \tag{5.3}$$

where $\bar{\mathbf{w}}_x$, and n_x are the mean i-vector and session count respectively of speaker x.

In Equation 5.3, the weighting function $w(d_{ij})$ is defined such that the classes that are closer to each other will be more heavily weighted. As is shown below, when $w(d_{ij})$ is set to 1, the weighted between-class scatter estimations will converge to the standard non-weighted between-class scatter from Equation 3.9.

In this chapter, the Euclidean distance, Mahalanobis distance and Bayes error weighting functions are introduced for speaker verification for the purpose of increasing the discriminant ability.

The Euclidean distance weighting function, $w_{(d_{ij})_{Euc}}$, can be defined as follows,

$$w_{(d_{ij})_{Euc}} = ((\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)^T(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j))^{-n}, \tag{5.4}$$

where $\bar{\mathbf{w}}_i$ and $\bar{\mathbf{w}}_j$ are the mean i-vectors of speaker i and j respectively, and n is a factor introduced to increase the separation for the classes that are closer. Classification performance will be analysed with several arbitrary values of n. The Euclidean distance-based weighting function is a monotonically-decreasing function, so the classes that are closer together will be heavily weighted and classes that are away (outlier classes) will be lightly weighted to increase the discriminant ability.

The Mahalanobis distance, $\triangle_{ij}$, between the means of classes i and j can be defined as,

$$\triangle_{ij} = \sqrt{(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)^T(\mathbf{S}_w)^{-1}(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)}. \tag{5.5}$$

where the within-class scatter matrix, $\mathbf{S}_w$, is estimated from Equation 3.10. If the session i-vectors ($\mathbf{w}$) are uncorrelated in each speaker and are scaled to have unit variance, then $\mathbf{S}_w$ would be the identity matrix and the Mahalanobis distance will converge as the Euclidean distance between $\bar{\mathbf{w}}_i$ and $\bar{\mathbf{w}}_j$. It is believed that there is some correlation between session i-vectors in each speaker and the within-class scatter is not an identity matrix. It can be shown that the presence of within-class scatter ($\mathbf{S}_w$) of $\mathbf{w}$ in the quadratic form in Equation 5.5 allows for the different scales on which the variables are measured and for non-zero correlations between the variables.

The Mahalanobis distance weighting function is introduced to i-vector speaker verification. It is also a monotonically-decreasing function, so it will also heavily weight the speakers that are closer. In addition, it can be used to alleviate the dominant role of the outlier classes, so the Mahalanobis weighted between-class scatter has more discriminant ability than the Euclidean weighted between-class scatter.

The Mahalanobis distance weighting function, $w_{(d_{ij})_{Maha}}$, can be defined as follows,

$$w_{(d_{ij})_{Maha}} = (\triangle_{ij})^{-2n}. \tag{5.6}$$

where the Mahalanobis distance, $\triangle_{ij}$, is estimated from Equation 5.5.

The final weighting parameter is based upon the Bayes error approximations of the mean accuracy amongst class pairs. The Bayes error weighting function

$w_{(d_{ij})_{Bayes}}$, can be calculated as,

$$w_{(d_{ij})_{Bayes}} = \frac{1}{2(\triangle_{ij})^2}\mathrm{Erf}(\frac{\triangle_{ij}}{2\sqrt{2}}), \tag{5.7}$$

where the Mahalanobis distance, $\triangle_{ij}$, is estimated from Equation 5.5. The Bayes error weighting function is also used to heavily weight the classes that are very close.

Once the weighted between-class scatter, $\mathbf{S}_b^w$, is estimated for the chosen weighting function, the standard within-class scatter $\mathbf{S}_w$ and the corresponding WLDA matrix ($\mathbf{A}$) can be estimated and applied as in traditional LDA. Finally, the WLDA channel compensated i-vector will be calculated using Equation 3.12.

5.2.3 SN-WLDA

In this thesis, the SN-WLDA approach is also introduced to the i-vector system as an extension of the more basic SN-LDA approach, and several source-dependent and source-independent weighting functions for i-vector speaker verification are analysed, which should show an improvement in performance across both matched and mismatched enrolment/ verification conditions. Similarly to the SN-LDA between-class scatter calculated in Equation 3.20, the source normalized weighted between-class scatter matrix, $\mathbf{S}_b^{w_{src}}$, can be calculated as follows,

$$\mathbf{S}_b^{w_{src}} = \mathbf{S}_b^{w_{tel}} + \mathbf{S}_b^{w_{mic}}, \tag{5.8}$$

where the telephone-sourced, dependent-weighted, between-class scatter, $\mathbf{S}_b^{w_{tel}}$, and the microphone-sourced, dependent-weighted, between-class scatter, $\mathbf{S}_b^{w_{mic}}$, are individually calculated for telephone and microphone sources using Equations 3.21 and 3.22.

The source-independent Euclidean distance weighting function (Equation 5.4) will be investigated as it does not depend on any source variations. However, the source-dependent Mahalanobis distance and Bayes error weighting functions will be investigated instead of source-independent weighting function, calculated using source-dependent within-class scatter variance to capture the source variation. The telephone and microphone source-dependent Mahalanobis distance, ${\triangle_{ij}}^{tel}$ and ${\triangle_{ij}}^{mic}$, can be defined as follows,

$$
\begin{aligned}
{\triangle_{ij}}^{tel} &= \sqrt{(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)^T(\mathbf{S}_w^{tel})^{-1}(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)}, && (5.9)\\
{\triangle_{ij}}^{mic} &= \sqrt{(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)^T(\mathbf{S}_w^{mic})^{-1}(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)}. && (5.10)
\end{aligned}
$$

where $\mathbf{S}_w^{tel}$ and $\mathbf{S}_w^{mic}$ are telephone and microphone source-dependent, within-class scatter, matrices, individually calculated from telephone and microphone sources using Equation 3.10. Once the source-dependent Mahalanobis distances, ${\triangle_{ij}}^{tel}$ and ${\triangle_{ij}}^{mic}$, are estimated from Equation 5.10 and 5.10, the source-dependent Mahalanobis distance and Bayes error weighting functions will be individually estimated from telephone and microphone sources using Equations 5.6 and 5.7.

In the SN-LDA algorithm, the within-class scatter matrix was estimated as the difference between total variance and the source-normalized between-class variance, but this approach is not taken for SN-WLDA, as the weighting parameters destroy the relationship between the total variance and the between-class scatter variance. For this reason, the within-class variance is estimated independently using Equation 3.10 as in the LDA approach.

An example of weighted between-class scatter estimation: In order to show how the weighted between-class scatter extracts more discriminant information, Figure 5.1 depicts an example of vectors used to calculate the standard and weighted between-class scatter matrices from a typical training dataset. There are four classes (speakers); each of them have two dimension features. In this

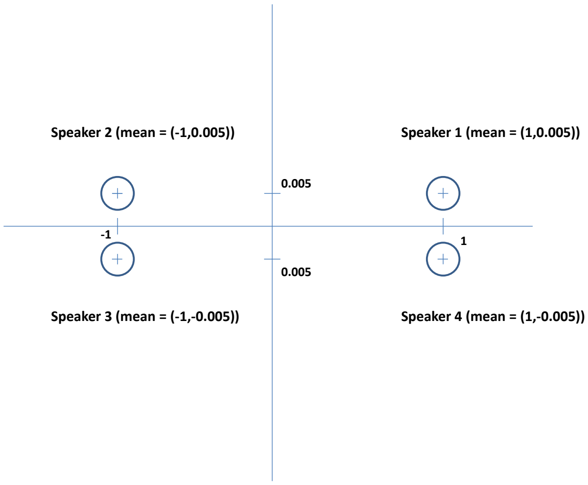

Speaker 2 (mean = (-1,0.005))
Speaker 1 (mean = (1,0.005))
0.005
-1
1
0.005
Speaker 3 (mean = (-1,-0.005))
Speaker 4 (mean = (1,-0.005))

Figure 5.1: *An example of vectors used to calculate standard and weighted between-class scatter matrices from a typical training dataset.*

case the standard between-class scatter matrix is

$$\begin{pmatrix} 1 & 0 \\ 0 & 1 \times 10^{-4} \end{pmatrix} \tag{5.11}$$

Discriminant information can be measured using the trace of matrix. From the above example, it could be seen that the standard between-class scatter matrix ignores some discriminant information due to (speaker 1, speaker 4) and (speaker 2, speaker 3) being closely situated. For the same typical data set, the Euclidean-weighted between-class scatter matrix is

$$\begin{pmatrix} 6.25 \times 10^{-2} & 0 \\ 0 & 5 \times 10^{7} \end{pmatrix} \tag{5.12}$$

Where n selected as 1 to estimate the Euclidean weighting function in Equation 5.4. It is also clear from the above example that when two classes are closely situated, the weighted between-class scatter estimation extracts more discriminant information than standard between-scatter estimation.

Weighted between-class scatter estimation with unity weighting function: It is necessary to show that when $w(d_{ij})$ is set to 1, the weighted between-class scatter estimations will converge to the standard between-class scatter estimation, as weighting functions are only used to increase the separation between classes that are closely situated. When weighting function $w(d_{ij})$ is equal to 1, the weighted between-class scatter equation can be written as follows,

$$\mathbf{S}_b^w = \frac{1}{N}\sum_{i=1}^{S-1}\sum_{j=i+1}^{S} n_i n_j (\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)^T, \tag{5.13}$$

$$\begin{aligned}\mathbf{S}_b^w = \frac{1}{2N}\Big(&2n_1n_2(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_2)(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_2)^T + 2n_1n_3(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_3)(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_3)^T\\ &+ .... + 2n_1n_s(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_s)(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_s)^T + 2n_2n_3(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_3)(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_3)^T\\ &+ 2n_2n_4(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_4)(\bar{\mathbf{w}}_2\bar{\mathbf{w}}_4)^T + ... + 2n_2n_s(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_s)(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_s)^T\\ &.......\\ &....... + 2n_{s-1}n_s(\bar{\mathbf{w}}_{s-1} - \bar{\mathbf{w}}_s)(\bar{\mathbf{w}}_{s-1} - \bar{\mathbf{w}}_s)^T\Big)\end{aligned} \tag{5.14}$$

$$\begin{aligned}\mathbf{S}_b^w = \frac{1}{2N}\Big(&n_1n_1(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_1)(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_1)^T + n_1n_2(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_2)(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_2)^T\\ &+ .... + n_1n_s(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_s)(\bar{\mathbf{w}}_1 - \bar{\mathbf{w}}_s)^T + n_2n_1(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_1)(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_1)^T\\ &+ n_2n_2(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_2)(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_2)^T .... + n_2n_s(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_s)(\bar{\mathbf{w}}_2 - \bar{\mathbf{w}}_s)^T\\ &.......\\ &....... + n_sn_1(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_1)(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_1)^T + n_sn_2(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_2)(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_2)^T\\ &....... + n_sn_s(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_s)(\bar{\mathbf{w}}_s - \bar{\mathbf{w}}_s)^T\Big)\end{aligned} \tag{5.15}$$

$$\mathbf{S}_b^w = \frac{1}{2N}\sum_{i=1}^{S}\sum_{j=i}^{S} n_i n_j (\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)(\bar{\mathbf{w}}_i - \bar{\mathbf{w}}_j)^T \tag{5.16}$$

$$\mathbf{S}_b^w = \frac{1}{2N}\sum_{i=1}^{S}\sum_{j=1}^{S} n_i n_j \Big((\bar{\mathbf{w}}_i - \bar{\mathbf{w}}) + (\bar{\mathbf{w}} - \bar{\mathbf{w}}_j)\Big) \times \Big((\bar{\mathbf{w}}_i - \bar{\mathbf{w}}) + (\bar{\mathbf{w}} - \bar{\mathbf{w}}_j)\Big)^T \tag{5.17}$$

$$\begin{aligned}\mathbf{S}_b^w = \frac{1}{2N}\sum_{i=1}^{S}\sum_{j=1}^{S} n_i n_j \Big(&(\bar{\mathbf{w}}_i - \bar{\mathbf{w}})(\bar{\mathbf{w}}_i - \bar{\mathbf{w}})^T + (\bar{\mathbf{w}}_i - \bar{\mathbf{w}})(\bar{\mathbf{w}} - \bar{\mathbf{w}}_j)^T\\ &+ (\bar{\mathbf{w}} - \bar{\mathbf{w}}_j)(\bar{\mathbf{w}}_i - \bar{\mathbf{w}})^T + (\bar{\mathbf{w}} - \bar{\mathbf{w}}_j)(\bar{\mathbf{w}} - \bar{\mathbf{w}}_j)^T\Big)\end{aligned} \tag{5.18}$$

Since $\sum_{i=1}^{S} \frac{n_i}{N} = 1$, the first and last outer product terms are combined above to get

$$\mathbf{S}_b^w = \sum_{i=1}^{S} n_i(\bar{\mathbf{w}}_i - \bar{\mathbf{w}})(\bar{\mathbf{w}}_i - \bar{\mathbf{w}})^T + \frac{1}{2N}\sum_{i=1}^{S}\sum_{j=1}^{S} n_i n_j(\bar{\mathbf{w}}_i - \bar{\mathbf{w}})(\bar{\mathbf{w}} - \bar{\mathbf{w}}_j)^T$$
$$+ \frac{1}{2N}\sum_{i=1}^{S}\sum_{j=1}^{S} n_i n_j(\bar{\mathbf{w}}_j - \bar{\mathbf{w}})(\bar{\mathbf{w}} - \bar{\mathbf{w}}_i)^T \tag{5.19}$$

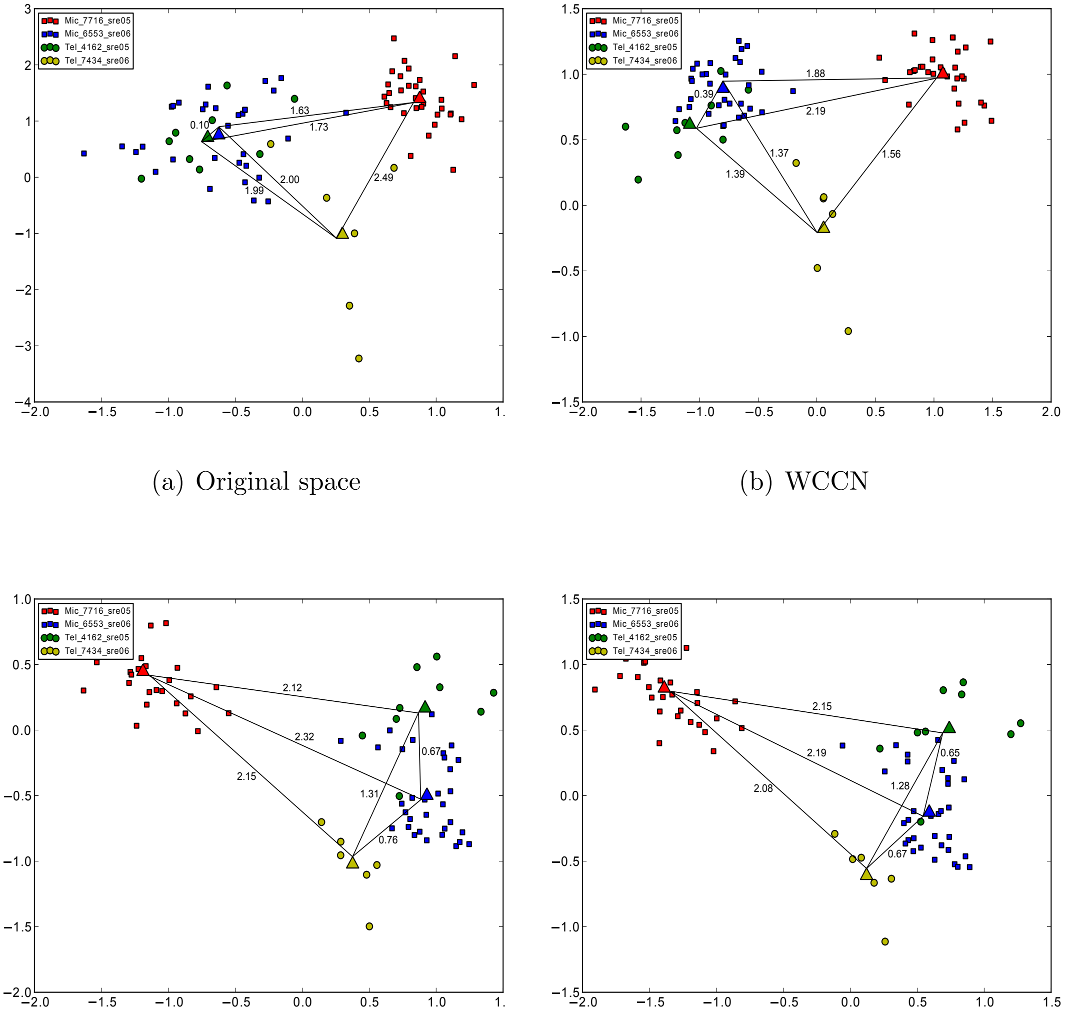
Examining the last two terms above, it is noted that $\sum_{i=1}^{S} \frac{n_i}{N}\bar{\mathbf{w}}_i = \bar{\mathbf{w}}$ and therefore $\sum_{i=1}^{S} \frac{n_i}{N}(\bar{\mathbf{w}} - \bar{\mathbf{w}}_i) = 0$. Weighted between-class scatter will converge as follows,

$$\mathbf{S}_b^w = \sum_{i=1}^{S} n_i(\bar{\mathbf{w}}_i - \bar{\mathbf{w}})(\bar{\mathbf{w}}_i - \bar{\mathbf{w}})^T \tag{5.20}$$

5.2.4 Real data scatter plot examination

In this section, how the original i-vector space and channel-compensated i-vector spaces separate the speakers will be graphically observed. An overview of all seven channel compensation techniques alongside the raw i-vectors is shown in Figures 5.2 and 5.3. All seven channel compensation techniques have been trained on the whole development dataset, and the details of the development set for channel compensation training is given in the experimental and framework in Chapter 4. Then, four representative speakers are randomly chosen to project the original i-vector space into the channel compensated reduced space using the channel compensation matrix. In the channel compensation matrix estimation, the eigen-vectors were sorted in descending order, according to corresponding eigen-values in order to illustrate the larger variation in Figures 5.2 and 5.3.

It can be observed with the aid of Figure 5.2 (b) that WCCN projections scale a subspace in order to attenuate the high within-class variance. When the WCCN and LDA projections are compared with the aid of Figures 5.2 (b) and 5.2 (c),



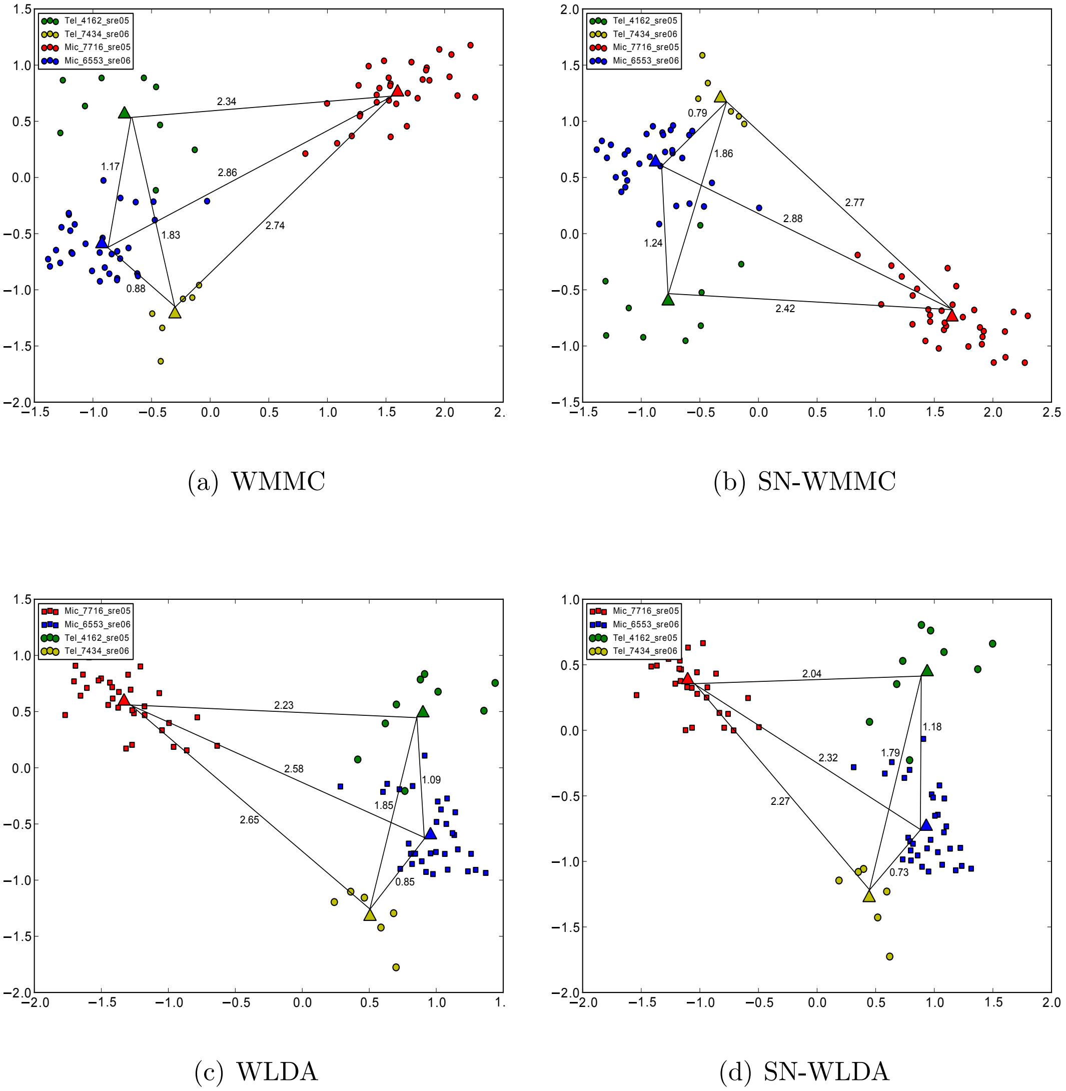
(a) Original space

(b) WCCN

(c) LDA

(d) SN-LDA

Figure 5.2: *Distribution of first two dimensions of female i-vectors features into* (a) *original space, or space projected using* (b) *WCCN,* (c) *LDA* *and* (d) *SN-LDA.*



(a) WMMC

(b) SN-WMMC

(c) WLDA

(d) SN-WLDA

Figure 5.3: *Distribution of first two dimensions of female i-vectors features into space projected using* (a) *WMMC (W=0.25),* (b) *SN-WMMC (W=0.25),* (c) *WLDA (Euc (n=3)) and* (d) *SN-WLDA (Euc (n=3)).*

it can be observed that the LDA projection maximizes the between-speaker variability while minimizing the within speaker variability. After that, when the LDA and WLDA projections are compared with the aid of Figures 5.2 (c) and-Figures 5.3 (c), it can be clearly seen that the WLDA projection increases the between speaker separability compared to the LDA projections. Similarly to the

LDA and WLDA comparison, when the SN-LDA and SN-WLDA projections are observed with the aid of Figures 5.2 (d) andFigures 5.3 (d), it can be clearly seen that the SN-WLDA projection increases the between speaker separability compared to the SN-LDA projections.

5.2.5 Sequential channel compensation

The WCCN[LDA], or LDA followed by WCCN, approach is commonly used to compensate the channel variability in i-vector-based speaker verification systems [20]. Similarly to the WCCN[LDA] approach outlined in Chapter 3, other channel compensation techniques, including SN-LDA, WMMC, SN-WMMC, WLDA and SN-WLDA followed by WCCN are investigated.

5.3 Advanced channel compensation speaker verification

The experimental protocol was detailed in Chapter 4. In this chapter, initially the channel compensation approaches, including WCCN, LDA and SN-LDA are defined as unweighted channel compensation approaches, as they don't depend on any weighting coefficients. However, the channel compensation approaches, including WLDA, SN-WLDA, WMMC, and SN-WMMC are defined as weighted channel compensation approaches as they depend on weighting coefficients. Initial experiments were conducted without channel compensation techniques (raw i-vectors) and with unweighted channel compensation techniques, including WCCN, LDA and SN-LDA. Unweighted channel compensation techniques were analysed both with and without WCCN. Following this, several

Table 5.1: *Comparison of i-vector approach performance with/ without standard channel compensation techniques on the common set of the 2008 NIST SRE short2-short3 conditions.*

System	***Interview-interview***		***Interview-telephone***		***Telephone-microphone***		***Telephone-telephone***	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Individual approach								
Raw i-vectors	11.09%	0.0522	14.10%	0.0505	9.44%	0.0362	5.68%	0.0255
WCCN	6.84%	0.0357	7.74%	0.0356	5.70%	0.0239	3.71%	0.0166
LDA	6.94%	0.0328	8.03%	0.0379	7.06%	0.0283	3.95%	0.0178
SN-LDA	7.20%	0.0330	7.83%	0.0382	6.93%	0.0286	3.87%	0.0170
Sequential approach								
WCCN[LDA]	**4.61%**	**0.0228**	5.99%	0.0293	5.10%	0.0222	**2.80%**	**0.0134**
WCCN[SN-LDA]	4.73%	0.0235	**5.90%**	**0.0278**	**4.83%**	**0.0208**	2.96%	0.0136

weighted channel compensation techniques will be analysed in combination with WCCN to identify the best overall channel compensation approach. After that, several channel compensation techniques were analysed to combine through score-level fusion to illustrate the complementary nature of the channel compensation techniques.

5.3.1 Unweighted channel compensation techniques

Speaker verification experiments were conducted with individual channel compensation techniques, and in combination with WCCN (as motivated by Dehak *et al.* [20]) to see how channel compensated i-vectors perform over raw uncompensated i-vectors. Table 5.1 presents the results from these experiments on the common set of the 2008 NIST SRE short2-short3 conditions. The results have found that channel compensation can achieve major improvement over the raw i-vector approach. If the individual channel compensation techniques are closely investigated, it can be clearly seen that WCCN performs better than LDA and SN-LDA as channel variations mainly depend on the within-speaker variation than between-speaker variation.

Further, if the channel compensation techniques are combined with the WCCN, it shows improved performance over individual channel compensation systems, which supports the findings of Dehak *et al.* [20]. Based upon the results shown here, and similar findings by McLaren *et al.* [71], it is clear that best performance can be obtained by accompanying more sophisticated channel compensation techniques with WCCN, and this is the approach that will be taken throughout the reminder of the experiments in this chapter.

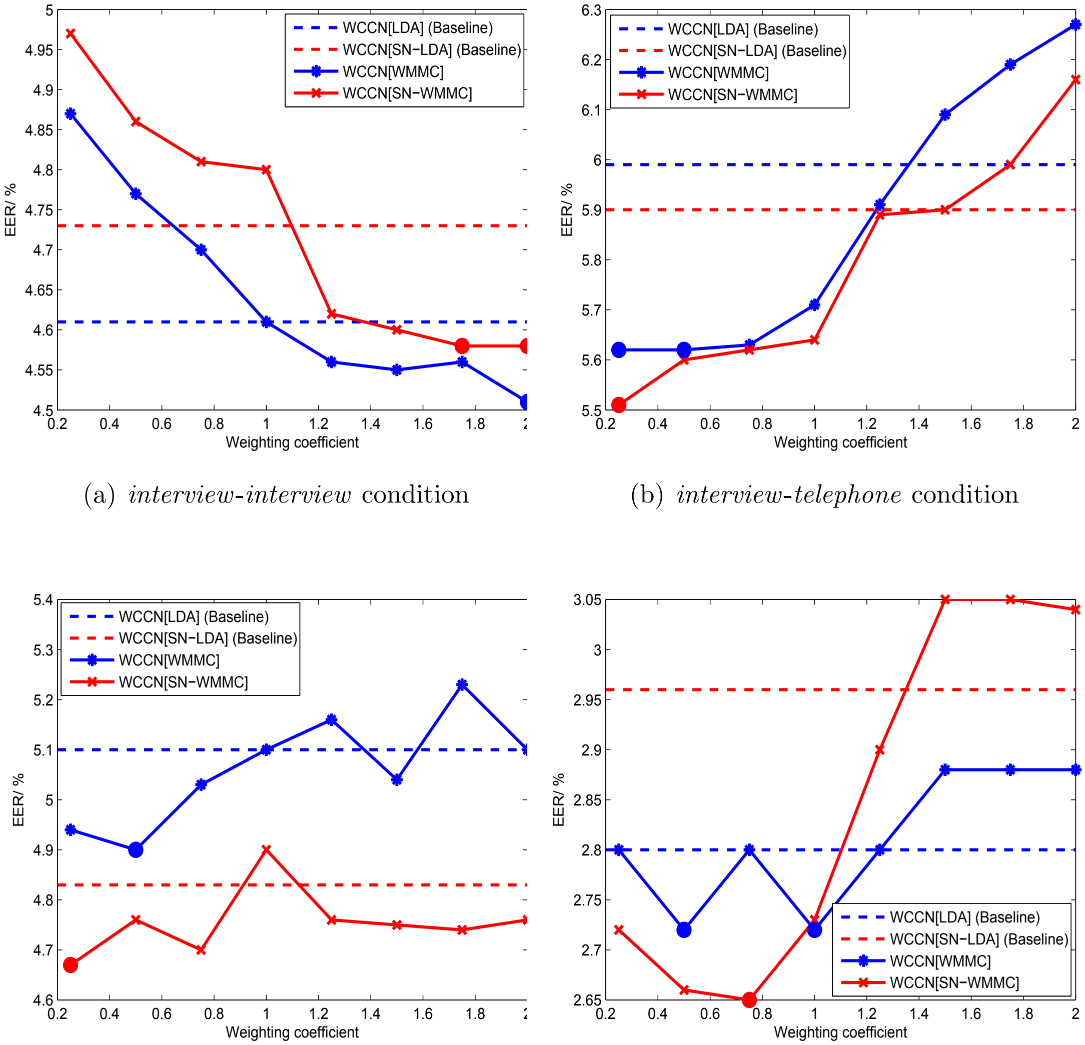
5.3.2 Training weighted channel compensation techniques

Before the weighted channel compensated techniques WMMC and WLDA (as well as SN-WMMC and SN-WLDA) can be evaluated against the traditional LDA (and SN-LDA) approaches, the best parameterizations of these techniques must be determined.

Choosing the WMMC weighting coefficient

The WMMC and SN-WMMC approaches have the flexibility to change the importance of the within- and between-class scatters, and those performances were analysed at different levels of the influence of within-class scatter ($\boldsymbol{S}_w$) based on manual weighting coefficients (W) in Equation 5.1.

WMMC and SN-WMMC were trained on NIST 2004, 2005 and 2006 SRE corpora as well as Switchboard II as described in Chapter 4. In order to find the optimum weighting coefficients, the evaluation was done with the NIST 2008 short2 - short3 evaluation condition [99]. The EER performance of WCCN[WMMC] and WCCN[SN-WMMC] across different train-test sources at different weighting coefficients is shown in Figure 5.4. It can be clearly seen with the aid of



(a) *interview-interview* condition

(b) *interview-telephone* condition

(c) *telephone-microphone* condition

(d) *telephone-telephone* condition

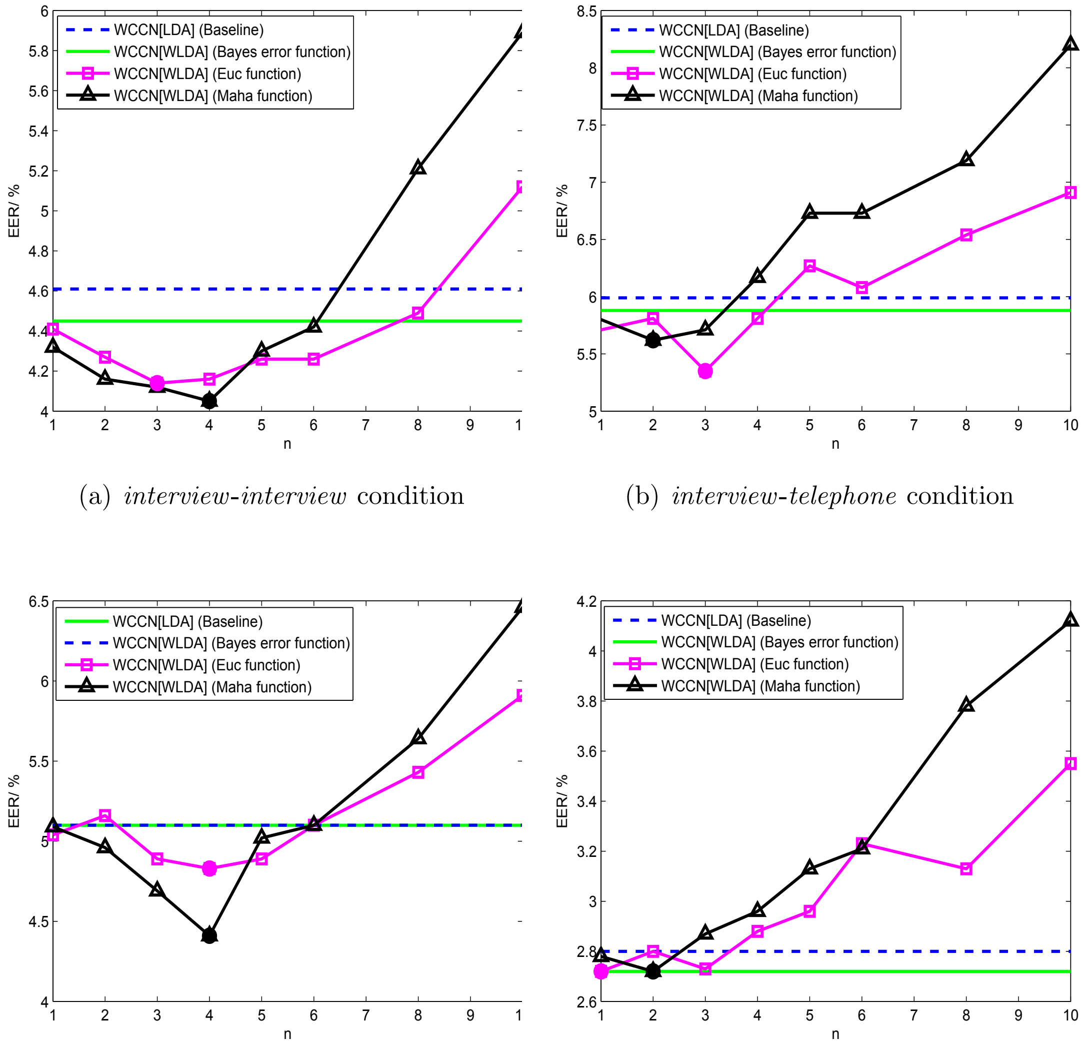
Figure 5.4: *Comparison of EER values of WCCN[WMMC] and WCCN[SN-WMMC] approaches at different weighting coefficients in different enrolment and verification conditions.*

Figures 5.4 (b) and (d) that when the weighting coefficient is increased around above 1, and therefore the level of influence of within-class scatter is increased, telephone speech verification condition performance goes down below baseline performance, suggesting that, for this condition, the within- and between-class scatter variances are equally important. However, when the level of influence of within-class scatter is increased around above 1, the system achieves better performance than baseline on *interview-interview* condition (Figure 5.4 (a)), as the within-class scatter variance plays a major role in the higher channel variation present in interview speech. The best values of WMMC weighting coefficients for all conditions were highlighted using a larger circle symbol in Figure 5.4, and these values will be used in future experiments within this chapter.

Choosing the WLDA weighting functions

The importance of weighted between-class scatters on LDA and SN-LDA estimations will be analysed in this section. WLDA and SN-WLDA approaches were trained on same data as WMMC and SN-WMMC approaches, which is clearly explained in Chapter 4. The performance of these approaches were analysed with respect to these weighting functions: Bayes error, Euclidean distance and Mahalanobis distance. While the Bayes error weighting function is not a parameterized approach, the Euclidean and Mahalanobis distance functions are constructed as monotonically decreasing functions, where the degree of order (n) is used to change the sensitivity of the weighting function to the underlying distance, where a higher order indicates more sensitivity. The Euclidean and Mahalanobis distance weighting functions were analysed at different degree of orders (n) to see the effect on between-speaker separability. In order to find the optimum value of n, the evaluation was done NIST 2008 short2 - short3 evaluation condition[99]. This analysis is shown in Figure 5.5 for WLDA and Figure 5.6 for SN-WLDA.

It can be clearly seen with the aid of both Figures 5.5 and 5.6 that when the degree of order increases above a certain level, around 4 for WLDA and 2 for SN-WLDA, the performance goes down in all enrolment and verification conditions, as the weighting functions with higher degree of orders reduces the quality of between-class scatter variance. The weighting functions with higher degree of orders fail to



(a) *interview-interview* condition

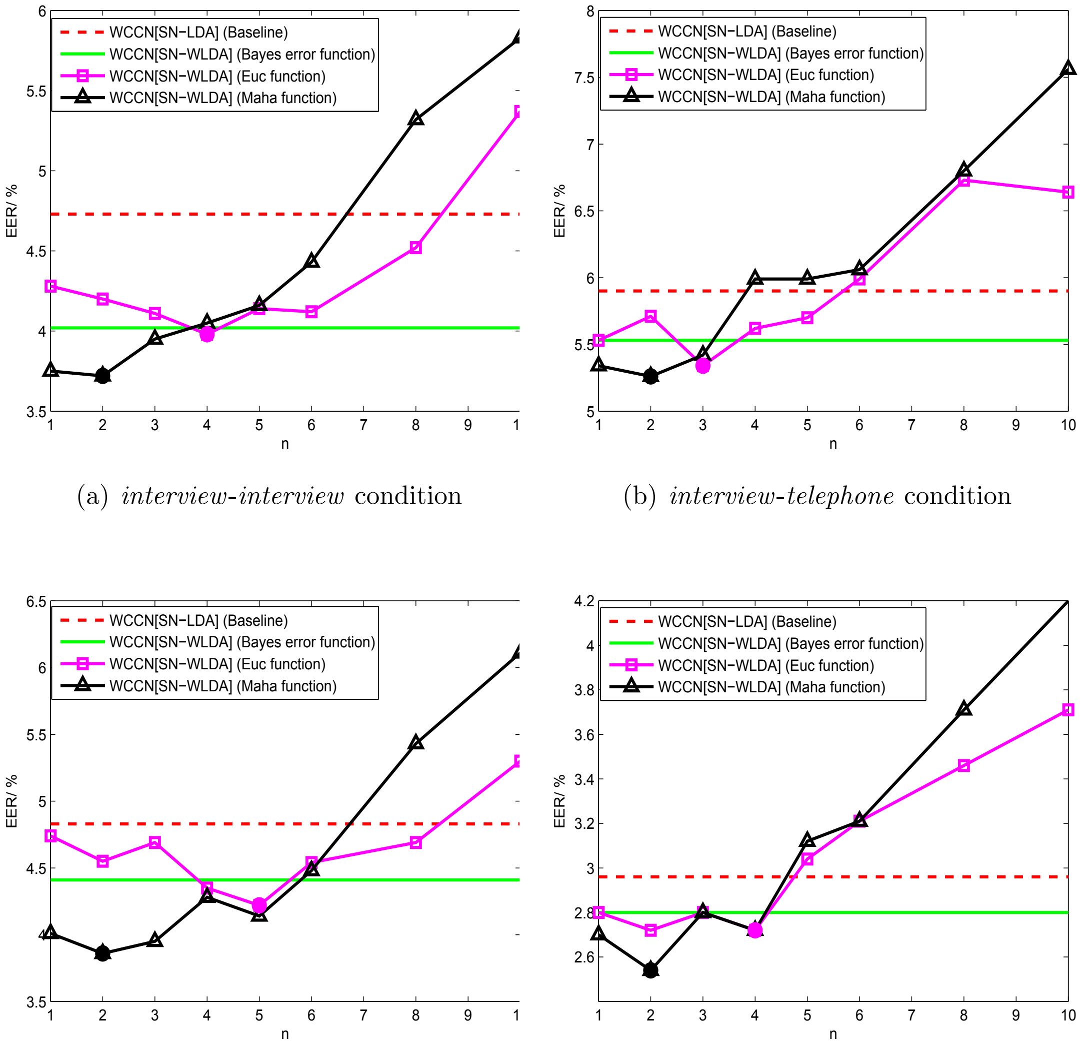
(b) *interview-telephone* condition

(c) *telephone-microphone* condition

(d) *telephone-telephone* condition

Figure 5.5: *Comparison of EER values of WCCN[WLDA] approach based on Euclidean and Mahalanobis distance weighting functions at different n values in different enrolment and verification conditions. Note that in (c), the baseline and Bayes error curves overlap and cannot be visually separated.*

alleviate the dominant role of the outlier classes. If the interview and microphone speech verification conditions are closely looked at (Figure 5.5 (a) and 5.5 (c), Figure 5.6 (a) and 5.6 (c)), the WLDA and SN-WLDA approaches achieved better performance than baseline systems over the wide range of degree of orders choice.



(a) *interview-interview* condition

(b) *interview-telephone* condition

(c) *telephone-microphone* condition

(d) *telephone-telephone* condition

Figure 5.6: *Comparison of EER values of WCCN[SN-WLDA] approach based on Euclidean, Mahalanobis distance weighting functions at different n values in different enrolment and verification conditions.*

Even through the Bayes error weighting function is a non-parametric approach, the Bayes error WLDA and SN-WLDA approaches achieved reasonably better performance over the baseline approaches.

Table 5.2: *Comparison of WCCN[WMMC] and WCCN[WLDA] systems against the WCCN[LDA] system on the common set of the 2008 NIST SRE short2-short3 and 2010 NIST SRE core-core conditions.*

(a) *NIST 2008 short2-short3 condition*

System	*Interview-interview*		*Interview-telephone*		*Telephone-microphone*		*Telephone-telephone*	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Baseline system								
WCCN[LDA]	4.61%	0.0228	5.99%	0.0293	5.10%	0.0222	2.80%	0.0134
Weighted MMMC system								
WCCN[WMMC]	4.51%	0.0231	5.62%	**0.0287**	4.90%	0.0223	**2.72%**	0.0135
Weighted LDA system								
WCCN[WLDA(Bayes)]	4.45%	0.0221	5.88%	0.0295	5.10%	0.0221	**2.72%**	0.0132
WCCN[WLDA(Euc)]	4.14%	0.0199	**5.35%**	**0.0287**	4.89%	**0.0213**	2.73%	**0.0128**
WCCN[WLDA(Maha)]	**4.05%**	**0.0198**	5.62%	0.0291	**4.69%**	0.0218	**2.72%**	0.0130

(b) *NIST 2010 core-core condition*

System	*Interview-interview*		*Interview-telephone*		*Interview-microphone*		*Telephone-telephone*	
	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}
Baseline system								
WCCN[LDA]	7.13%	0.0295	5.45%	0.0240	4.27%	0.0198	3.81%	0.0154
Weighted MMMC system								
WCCN[WMMC]	7.25%	0.0311	5.45%	0.0256	4.24%	0.0199	**3.54%**	0.0173
Weighted LDA system								
WCCN[WLDA(Bayes)]	7.10%	0.0292	5.39%	0.0239	4.22%	**0.0197**	3.81%	0.0153
WCCN[WLDA(Euc)]	6.97%	**0.0290**	5.33%	**0.0238**	4.27%	0.0201	3.83%	**0.0152**
WCCN[WLDA(Maha)]	**6.85%**	0.0291	**5.27%**	0.0239	**3.97%**	0.0201	4.10%	0.0153

5.3.3 Comparing all techniques

Weighted channel compensation techniques were finely tuned in the previous section. In this section, weighted and unweighted channel compensation techniques are compared to identify the best channel compensation approach. Tables 5.2 (a) and 5.2 (b) present the results comparing the performance of WCCN[WMMC] and WCCN[WLDA] against the baseline system, WCCN[LDA], on the common set of the 2008 NIST SRE short2-short3 and 2010 NIST SRE core-core conditions. The WCCN[WMMC] and WCCN[WLDA] results were presented with optimized weighting parameters, as detailed in the previous section.

Initially, if the performance between the WMMC and LDA approaches is compared on NIST 2008 short2-short3 condition, the WMMC technique achieved over 2% relative improvement in EER over LDA on all training and testing conditions,

Table 5.3: *Comparison of WCCN[SN-WMMC] and WCCN[SN-WLDA] systems against the WCCN[SN-LDA] system on the common set of the 2008 NIST SRE short2-short3 and 2010 NIST SRE core-core conditions.*

(a) *NIST 2008 short2-short3 condition*

System	***Interview-interview***		***Interview-telephone***		***Telephone-microphone***		***Telephone-telephone***	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Baseline system								
WCCN[SN-LDA]	4.73%	0.0235	5.90%	0.0278	4.83%	0.0208	2.96%	0.0136
Source-normalized WMMC system								
WCCN[SN-WMMC]	4.58%	0.0231	5.51%	0.0266	4.67%	0.0206	2.65%	0.0136
Source-normalized WLDA system								
WCCN[SN-WLDA(Bayes)]	4.02%	0.0196	5.53%	0.0251	4.41%	0.0184	2.80%	0.0130
WCCN[SN-WLDA(Euc)]	3.98%	0.0190	5.34%	0.0262	4.22%	0.0203	2.72%	0.0130
WCCN[SN-WLDA(Maha)]	**3.72%**	**0.0178**	**5.26%**	**0.0249**	**3.86%**	**0.0179**	**2.54%**	**0.0125**

(b) *NIST 2010 core-core condition*

System	***Interview-interview***		***Interview-telephone***		***Interview-microphone***		***Telephone-telephone***	
	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}
Baseline system								
WCCN[SN-LDA]	7.27%	0.0302	5.02%	0.0239	4.52%	0.0202	3.78%	0.0155
Source-normalized WMMC system								
WCCN[SN-WMMC]	7.29%	0.0294	5.20%	0.0238	4.56%	0.0203	3.95%	**0.0154**
Source-normalized WLDA system								
WCCN[SN-WLDA(Bayes)]	6.61%	0.0280	**4.59%**	0.0217	4.02%	**0.0193**	3.68%	0.0155
WCCN[SN-WLDA(Euc)]	6.85%	0.0288	4.72%	0.0225	**3.85%**	0.0198	3.94%	0.0165
WCCN[SN-WLDA(Maha)]	**6.44%**	**0.0272**	4.66%	**0.0210**	3.98%	0.0194	**3.67%**	0.0156

by finely tuning the required influence of within- and between-class scatter variances. However, the WMMC technique hasn't shown consistent improvement over LDA on NIST 2010 core-core condition as the required influence of within- and between-class scatter variances were finely selected from NIST 2008 data set.

Secondly, it can be clearly seen that, by taking advantage of the speaker discriminative information, the WLDA techniques have shown over 8% improvement in EER on the NIST 2008 interview and microphone speech verification conditions compared to the LDA approach. The WLDA techniques have also shown 10% improvement in EER on the NIST 2008 *interview-telephone* condition over the LDA approach. The WLDA techniques have not shown great improvement over LDA and WMMC in *telephone-telephone* condition, because most of the telephone-speech speaker means are closely situated and equally distributed due to channel similarities. When the performance of WLDA approaches are compared against the baseline LDA approach on the NIST 2010 core-core condition, there is an improvement, but further improvements can be achieved if the weighting functions coefficients and LDA dimension were selected from the NIST 2010 dataset.

In Tables 5.3 (a) and 5.3 (b), the advantage of source-normalization (SN) is taken, and the results are presented comparing the performance of WCCN[SN-WMMC] and WCCN[SN-WLDA] against the baseline system, WCCN[SN-LDA], on the common set of the 2008 NIST SRE short2-short3 and 2010 NIST SRE core-core conditions. The WCCN[SN-WMMC] and WCCN[SN-WLDA] results were presented with optimized weighting parameters, as detailed in the previous section.

Similarly to Table 5.2, it can be clearly seen that, by capturing the source variation as well, as finely tuning the influence of within- and between-class scatter variations, the SN-WMMC technique does show over 3% improvement in EER for NIST 2008 interview and microphone verification and over 6% improvement in EER for NIST 2008 telephone verification over the SN-LDA approach. However, the SN-WMMC technique hasn't shown consistent improvement over SN-LDA on NIST 2010 core-core condition, as the required influence of within- and between-class scatter variances were finely selected from the NIST 2008 data set.

When the performance of SN-WLDA to SN-LDA is compared, it can be clearly seen that, by extracting the discriminatory information between pairs of speakers as well as capturing the source variation information, the Mahalanobis distance SN-WLDA shows over 20% improvement in EER for NIST 2008 interview and microphone verification and over 10% improvement in EER for NIST 2008 telephone speech verification. If the SN-WLDA approach is closely looked at with several weighting functions, the Mahalanobis distance SN-WLDA showed greater improvement over the Euclidean distance-based SN-WLDA, as the Mahalanobis distance weighting function was used to alleviate the dominant role of the outlier classes as well as it was calculated based on source dependent within-class scatter variance and it has more speaker discriminant information. The Bayes error weighting function is also based on source-dependent within-class scatter variance, however, it hasn't shown improvement over the Mahalanobis distance SN-WLDA as it is a non-parametric weighting function. If the SN-WLDA approach is compared against a baseline approach, SN-LDA, the SN-WLDA approach shows over 10% improvement in EER on NIST 2010 *interview-interview* and *interview-microphone* conditions. The improvements over baseline suggest that the optimal parameter values are robust for other datasets as well. However, if the optimal parameters are selected on the same data set by looking at the performance, the performance would be better than when optimal parameters are trained on a different data set.

Overall, when the performance of WLDA is compared with SN-WLDA (refer to Table 5.2 and Table 5.3), SN-WLDA achieved better performance than the WLDA in all the enrolment and verification conditions, as the SN-WLDA approach captures the source variation information and also extracts the discriminatory information between pairs of classes.

5.3.4 Score-level fusion channel compensation analysis

Several novel channel compensation techniques, including WMMC, SN-WMMC, WLDA and SN-WLDA were investigated in combination with WCCN previously. However, multiple channel compensation approaches, combined using score-level fusion to extract speaker complementary information, have not yet been investigated. In this section, the score-level fused approach is investigated to combine all the source-normalize channel compensation approaches, including SN-LDA,

Table 5.4: *Comparison of score-level fusion systems on the common set of the NIST 2008 SRE short2-short3 and NIST 2010 SRE core-core* interview-telephone *conditions.*

Fused system ($a_1S_1 + a_2S_2 + a_3S_3 + a_4S_4 + a_5S_5 + b$)	**FoCal weights tuned on 2008**								
WCCN[SN-LDA] (a_1)	1.00	–	–	–	–	-0.66	–	–	–
WCCN[SN-WMMC] (a_2)	–	1.00	–	–	–	1.38	0.86	0.98	1.21
WCCN[SN-WLDA(Bayes)] (a_3)	–	–	1.00	–	–	0.46	0.33	–	–
WCCN[SN-WLDA(Euc)] (a_4)	–	–	–	1.00	–	0.54	0.49	0.52	–
WCCN[SN-WLDA(Maha)] (a_5)	–	–	–	–	1.00	1.07	1.12	1.30	1.57
Constant (b)	–	–	–	–	–	-5.36	-5.37	-5.35	-5.29
NIST 2008 SRE short2-short3 *interview-telephone* condition									
EER	5.90%	5.51%	5.53%	5.34%	5.26%	**5.16%**	5.26%	5.26%	5.34%
DCF	0.0278	0.0266	0.0251	0.0262	0.0249	**0.0230**	0.0235	0.0237	0.0235
NIST 2010 SRE core-core *interview-telephone* condition									
EER	5.02%	5.20%	4.59%	4.72%	4.66%	4.59%	**4.47%**	4.48%	**4.47%**
DCF_{old}	0.0239	0.0238	0.0217	0.0225	0.0210	**0.0207**	0.0208	0.0208	0.0208

SN-WMMC and SN-WLDA to extract the complementary speaker information. Score-level fusion is implemented using the FoCal toolkit [6], to optimize linear regression parameters. The fusion weights were learned using scores from the NIST 2008 short2 - short3 evaluation condition [99] and the fusion system was experimented on NIST 2010 core - core evaluation condition [100].

It can be clearly seen from Tables 5.2 and 5.3 that each individual system hasn't shown much improvement on the *telephone-telephone* condition. So, it is unlikely to expect improvement on fusion results on the *telephone-telephone* condition. The *interview-telephone* condition was chosen to analyse the score-level fusion approach, as *interview-telephone* condition has shown least performance over other enrolment and verification conditions in the previous experiments. Table 5.4 presents results comparing the performance of score-level fused approaches on a common set of NIST 2008 short2-short3 and NIST 2010 core-core *interview-telephone* conditions. The score fused system has shown improvement over individual systems on both NIST 2008 short2-short3 and NIST 2010 core-core *interview-telephone* conditions, which suggests that the fused weights are not optimistically biased for a given corpus. For score fusion experiments, initially all the source-normalized channel compensation approaches are fused together, and each step the least contribution system is cut off. By using this approach, it is found that WCCN[SN-WMMC] and WCCN[SN-WLDA(Maha)] were the two best systems to fuse together. For NIST 2010 evaluations, the weighted channel compensation approaches, including SN-WMMC and SN-WLDA were trained using the same optimized parameters, which were obtained from Figures 5.4 and 5.6. The improvements over baseline suggest that the optimal fusion parameter values are robust for other datasets as well.

It is also clear that the source-normalized channel compensation approach fused system provides over 8% improvement in DCF over the best single approach, WCCN[SN-WLDA(Maha)], on NIST 2008 short2-short3 *interview-telephone* condition, as all the source-normalized fused system extracts complementary speaker information. If the fusion weights are looked at closely, the contribution of the WCCN[SN-WMMC] approach is greater compared to weighting functions based WCCN[SN-WLDA], as all the weighting functions based WCCN[SN-WLDA] approaches are correlated, and the WCCN[SN-WMMC] approach has more complementary speaker information.

5.4 Chapter summary

In this chapter, advanced channel compensation techniques were introduced for the purpose of improving i-vector speaker verification performance in the presence of high intersession variability using the NIST 2008 and 2010 SRE corpora. The i-vector approach performance with/ without standard channel compensation techniques, such as WCCN-only, LDA and SN-LDA, was analysed. Subsequently, channel compensation approaches, WMMC and SN-WMMC, were introduced as an alternative to LDA and SN-LDA approaches that help to change the level of influence of within- and between-class scatter variances on WMMC or SN-WMMC estimations. Based upon the results, it is believed that SN-LDA techniques can be replaced with SN-WMMC for both mismatch conditions. However, WMMC and SN-WMMC investigations can't be further extensively investigated with weighted between-class scatters, since within-class scatter and weighted between-class scatters are in different scales.

Then, WLDA and SN-WLDA channel compensation approaches were introduced. Weighted between-class scatters were used to calculate the WLDA and SN-WLDA approach. By taking advantage of the weighted pairwise Fisher criterion, these WLDA and SN-WLDA techniques can take advantage of the speaker discriminative information present in the pairwise distances between classes that are not available to traditional LDA and SN-LDA techniques. Through evaluations performed on the NIST 2008 SRE data, SN-WLDA respectively achieved 20% and 8% improvement over standard SN-LDA on *interview-interview* and *telephone-telephone* conditions. SN-WLDA system also achieved over 7% improvement on both mis-matched conditions. It was also found that Mahalanobis distance SN-WLDA shows considerable improvement over Euclidean and Bayes-error SN-WLDA, as the Mahalanobis distance weighing function is calculated based on source dependent within-class scatter variance and it increases the between speaker (class) separability more than other weighting functions.

Lastly, score-level fusion of different channel compensation approaches were investigated to extract more complementary speaker information than existing individual and sequential channel compensation approaches. Based upon the NIST 08 and 10 evaluation condition results, it is believed that the score-level fusion of several weighting functions based SN-WLDA + WCCN-only approach can be used to extract more complementary speaker information than existing approaches.

Chapter 6

PLDA Speaker Verification and Channel Compensation Approaches

6.1 Introduction

In this chapter, PLDA speaker verification is investigated with advanced channel compensation techniques. Recently, the length-normalized GPLDA system has become a state-of-the-art speaker verification system. Some years ago, Kenny [51] found that HTPLDA and GPLDA approaches can be used to model the speaker and channel part within the i-vector space, and this has been shown to provide an improved speaker verification performance over CSS i-vector speaker verification systems [8, 51, 88]. It was also found that HTPLDA approach achieved significant improvement over GPLDA, concluding that i-vector features are better modelled by heavy-tailed distribution due to the frequent presence of outliers in the i-vector space [51]. Recently, Garcia-Romero *et al.* [29] have introduced the length-normalized GPLDA approach as an alternative to the HTPLDA approach, and that has shown similar performance to the HTPLDA approach.

Matejka *et al.* [69] have investigated the dimensionality reduction using LDA before PLDA modelling, and that has shown an improvement on *telephone-telephone* (enrolment-verification) condition. However, this approach of transforming the i-vector space before PLDA modelling has not yet been investigated under mismatched and interview conditions. More importantly, the investigation of more advanced channel compensation approaches would be of considerable value to improving length-normalized GPLDA-based speaker verification systems. The first aim of this chapter is to analyse the advanced channel compensated i-vector features with PLDA modelling for the purpose of improving speaker verification performance in the presence of high inter-session variability.

Another major problem is that in mismatched conditions, a large number of sessions per speaker data is required to adequately compensate the intra-speaker variance. However, it is hard to collect a large amount of session data. Thus, the second aim of this chapter is to analyse the length-normalized GPDLA system performance when a length-normalized GPLDA model is trained using the limited session variability data. It is hypothesised that when limited session data is available, a median-based LDA approach would be better than a mean-based LDA approach. Novel median fisher discriminator (MFD) and weighted MFD (WMFD)-based dimensionality reduction techniques are introduced to the GPLDA speaker verification system to improve the performance in limited session data conditions. It is difficult to evenly collect different types of data, including telephone and microphone speech data in practice. It is also known that microphone speech data has more channel variations than telephone speech data, as it was recorded from multiple auxiliary microphones. A larger amount of microphone speech is required to adequately model the PLDA approach. However, a substantial amount of telephone speech data can be collected through NIST databases, but microphone speech data is harder to acquire [98, 99, 100]. Several novel approaches are introduced in the i-vector feature and PLDA model domain to improve the PLDA speaker verification performance in a limited microphone condition. In the i-vector feature domain, pooled and concatenated total-variability approaches are investigated to improve the speaker verification performance in scarce microphone conditions. In the PLDA model domain, a novel approach is introduced to GPLDA to estimate reliable model parameters as a linearly weighted model taking more input from the large volume of available telephone data and smaller proportional input from limited microphone data.

6.2 Channel compensated i-vector GPLDA

I-vector feature extraction and PLDA model parameter estimations were thoroughly detailed in Chapter 3, and the framework of length-normalized speaker verification system was detailed in Chapter 4 where raw i-vectors were used as features for PLDA modelling.

In this chapter, a length-normalized GPLDA speaker verification system was chosen to study the newly proposed techniques as it is more computationally efficient approach than the HTPLDA speaker verification system while providing a similar or better level of performance. It is hypothesized that rather than attempting to model the speaker and channel variability on original i-vector space, an effective approach is to model the session and speaker variability on channel compensated i-vector features. A block diagram of extracting channel compensated i-vectors is shown in Figure 6.1 where a sequential approach is used to compensate the channel variation, as in the previous chapter, it was found that sequential channel compensation approach is better than individual channel compensation ap-

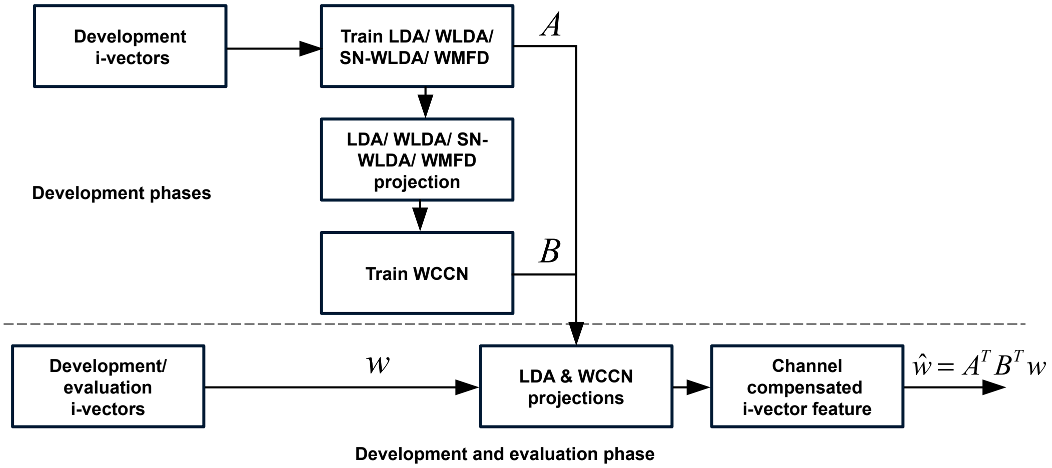

Development i-vectors
Train LDA/ WLDA/ SN-WLDA/ WMFD
A
LDA/ WLDA/ SN-WLDA/ WMFD projection
Development phases
Train WCCN
B
Development/ evaluation i-vectors
w
LDA & WCCN projections
Channel compensated i-vector feature
$\hat{w} = A^T B^T w$
Development and evaluation phase

Figure 6.1: *A block diagram of extracting channel compensated i-vector features.*

proaches. For the dimension reduced i-vector features GPLDA system, channel compensated i-vector features ($\hat{\mathbf{w}}$) are used for GPLDA modelling, instead of traditional i-vector features ($\mathbf{w}$).

The dimension-reduced PLDA approach considerably reduces computational complexity, as the PLDA modelling and scoring are estimated on reduced space (150) rather than full i-vector space (500). The length-normalization approach was detailed in the Section 3.4.3, and it is applied on development and evaluation data set prior to GPLDA modelling. For GPLDA experiments, it was assumed that the precision matrix ($\mathbf{\Lambda}$) is full rank and the eigenchannel ($\mathbf{U}_2$) was removed from Equation 3.29 as it was found that PLDA speaker verification didn't show any major improvement with eigenchannels, so removing them provided a useful decrease in computational complexity [29].

Table 6.1: *Comparison of SN-WLDA projected length-normalized GPLDA system against the standard length-normalized GPLDA, WCCN[LDA] and WCCN[SN-LDA] projected length-normalized GPLDA systems on the common set of the 2008 NIST SRE short2-short3 and 2010 NIST SRE core-core conditions.*

(a) *NIST 2008 short2-short3 condition*

System	***Interview-interview***		***Interview-telephone***		***Telephone-microphone***		***Telephone-telephone***	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Baseline system								
Standard GPLDA	5.05%	0.0264	5.43%	0.0275	4.08%	0.0204	2.63%	0.0136
WCCN[LDA]-GPLDA	4.29%	0.0214	5.51%	0.0254	4.35%	0.0195	2.63%	0.0126
WCCN[SN-LDA]-GPLDA	4.15%	0.0210	5.25%	0.0249	3.88%	0.0189	2.72%	0.0124
SN-WLDA projected length-normalized GPLDA system								
WCCN[SN-WLDA(Bayes)]-GPLDA	3.91%	0.0189	**4.96%**	0.0233	3.81%	0.0171	**2.39%**	**0.0118**
WCCN[SN-WLDA(Euc)]-GPLDA	3.89%	0.0196	5.27%	**0.0227**	**3.73%**	0.0174	2.47%	0.0124
WCCN[SN-WLDA(Maha)]-GPLDA	**3.61%**	**0.0174**	5.16%	0.0228	3.74%	**0.0157**	2.47%	0.0119

(b) *NIST 2010 core-core condition*

System	***Interview-interview***		***Interview-telephone***		***Interview-microphone***		***Telephone-telephone***	
	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}
Baseline system								
Standard GPLDA	7.21%	0.0338	4.84%	0.0239	4.56%	0.0244	3.39%	0.0167
WCCN[LDA]-GPLDA	6.76%	0.0292	4.41%	0.0220	4.10%	0.0196	3.41%	0.0152
WCCN[SN-LDA]-GPLDA	6.91%	0.0299	4.41%	0.0212	4.15%	0.0200	3.51%	0.0152
SN-WLDA projected length-normalized GPLDA system								
WCCN[SN-WLDA(Bayes)]-GPLDA	6.27%	0.0274	4.36%	0.0205	3.76%	0.0190	3.39%	0.0152
WCCN[SN-WLDA(Euc)]-GPLDA	6.37%	0.0285	4.35%	0.0202	**3.38%**	0.0190	3.56%	0.0144
WCCN[SN-WLDA(Maha)]-GPLDA	**5.94%**	**0.0262**	**4.10%**	**0.0193**	3.43%	**0.0182**	**3.25%**	**0.0143**

6.3 Channel compensated i-vector GPLDA

In the previous chapter, several novel channel compensation approaches were proposed to the CSS i-vector system, and it was found that the SN-WLDA approach is the best channel compensation approach when compared to the WMMC, WLDA and SN-WLDA approaches. In this chapter, it is hypothesized that if the SN-WLDA approach is applied to the i-vector features prior to the PLDA modelling, that could provide a better performance than both the CSS i-vector and standard PLDA-based speaker verification systems by providing additional compensation of channel variation over the existing approaches.

Results and discussion: The experimental protocol was detailed in Chapter 4. It was analysed how the SN-WLDA projected length-normalized GPLDA system performs over the baseline approaches, LDA and SN-LDA projected length-normalized GPLDA systems. Tables 6.1 (a) and 6.1 (b) present the results on the common set of the NIST SRE 2008 short-short3 and NIST SRE 2010 core-core conditions. If the SN-WLDA projected GPLDA is compared against a baseline approach, SN-LDA projected GPLDA, SN-WLDA projected GPLDA system shows over 14% improvement in EER for NIST SRE 2010 interview and microphone verification and over 7% improvement in EER for NIST SRE 2010 telephone verification, as it extracts the discriminatory information between pairs of speakers as well as capturing the source variation information.

Based upon all the experiments on NIST 2008 and NIST 2010 evaluations, it is believed that the improvements demonstrated throughout previous chapters of advanced channel compensation techniques for CSS-based i-vector speaker representation can also translate well into the length-normalized GPLDA approach. These research outcomes were published in Computer Speech & Language [45].

6.4 GPLDA with limited session data

In order to estimate reliable GPLDA model parameters, a considerable amount of session data per speaker is required; however, in a real world scenario, it is hard to collect a large amount of different session data from every speaker. To deal with this problem, in this section, initially the length-normalized GPLDA speaker verification performance is analysed when the GPLDA approach is modelled using the limited amount of session data, where a standard LDA approach is used to compensate the channel variation prior to GPLDA modelling. Subsequently, several channel compensation techniques, including WLDA and WMFD,

Table 6.2: *Comparison of LDA projected length-normalized GPLDA systems on common condition of NIST 2008 short2-short3 evaluation condition, when GPLDA is modeled using limited session variability data.*

No of data for	**Interview-interview**		**Interview-telephone**		**Telephone-interview**		**Telephone-telephone**	
GPLDA modeling	EER	DCF	EER	DCF	EER	DCF	EER	DCF
3 sessions/speaker	10.85%	0.0473	11.69%	0.0526	9.51%	0.0423	4.04%	0.0188
5 sessions/speaker	8.69%	0.0395	9.86%	0.0467	7.81%	0.0344	3.21%	0.0148
7 sessions/speaker	**8.00%**	**0.0361**	**8.29%**	**0.0430**	**7.00%**	**0.0307**	**2.55%**	**0.0143**

are introduced to the GPLDA speaker verification system to improve the speaker verification system performance in scarce session variability data scenario.

6.4.1 LDA projected GPLDA with limited session data

Table 6.2 presents the results, comparing the length-normalized GPLDA speaker verification performance when GPLDA is modelled with limited session data, where GPLDA was respectively modelled using 3, 5 and 7 sessions/ speaker data. A total of 1313 female and 1066 male speakers were used to train the GPLDA model. For this experiment, prior to GPLDA modelling, the standard WCCN[LDA] approach was used to compensate the channel variations. It can be clearly observed that when the number of sessions per speaker is reduced in training the GPLDA parameters, it significantly affects the speaker verification system's performance.

6.4.2 WLDA/ WMFD projected GPLDA with session data

Prior to GPLDA modelling, the WLDA approach can also be used as alternative to standard LDA approach. It is hypothesized that if a limited amount of session variability data is available, a standard LDA approach may not be a good estimate, and a WLDA approach can be used to extract more discriminant information from between pairs of speakers.

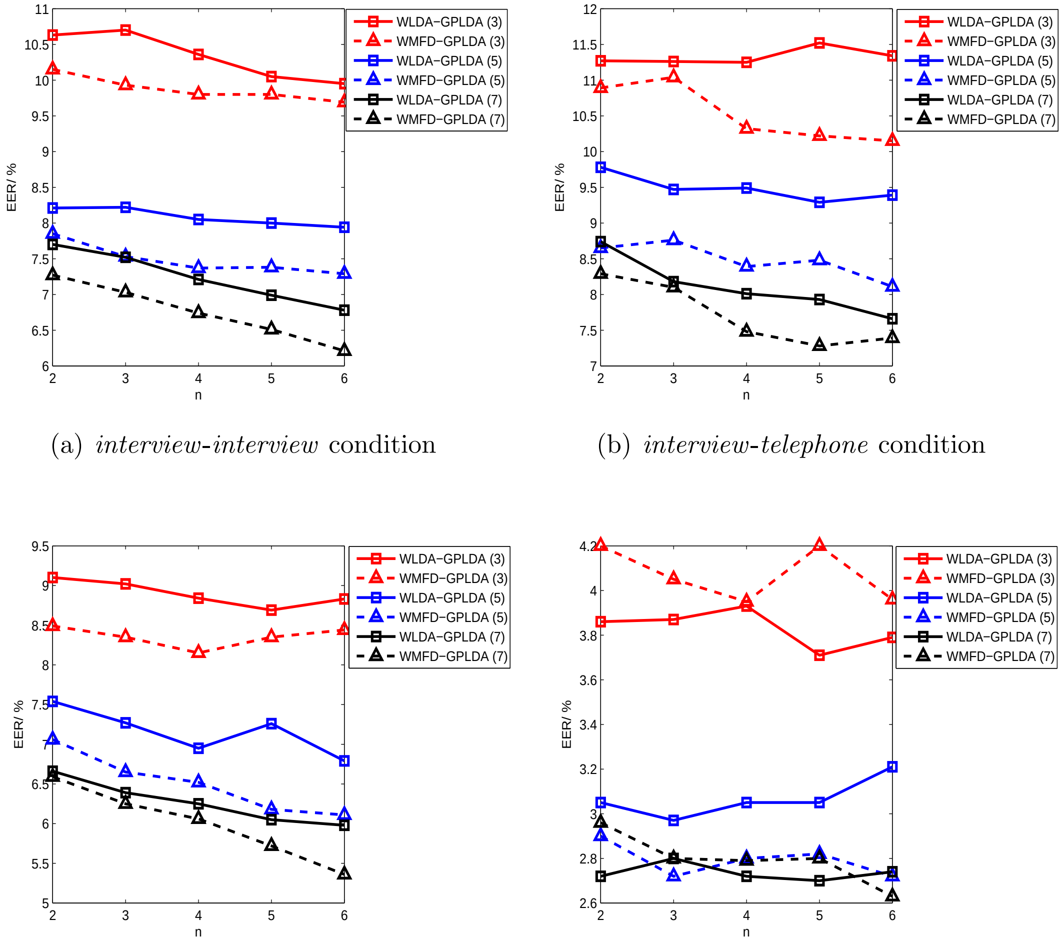
In addition, in the standard LDA approach, the speaker-mean i-vector plays a central role in the definition of the between-class and within-class scatter matrices. Therefore, the accuracy of its estimate will have a substantial effect on the resulting projection directions of the LDA transformation. When each individual speaker has a limited number of session variability data, averaging these session variability data often leads to loss of useful speaker-discriminant information, and in this section, WMFD approach is introduced to attenuate this loss. Like the sample average, the median can also be used as an estimator for the central tendency. Moreover, it is generally considered that the median is a more robust estimator of the central tendency than the sample average when a limited amount of session variability data is available [113]. MFD estimation is based on the median-based between- and with-class scatter estimations, $\boldsymbol{S}_w^{median}$ and $\boldsymbol{S}_b^{median}$, and those can be calculated as follows,

$$\begin{aligned} \mathbf{S}_b^{median} &= \sum_{s=1}^{S} n_s(\bar{\mathbf{w}}_s - \bar{\mathbf{w}})(\bar{\mathbf{w}}_s - \bar{\mathbf{w}})^T, && (6.1) \\ \mathbf{S}_w^{median} &= \sum_{s=1}^{S}\sum_{i=1}^{n_s}(\mathbf{w}_i^s - \bar{\mathbf{w}}_s)(\mathbf{w}_i^s - \bar{\mathbf{w}}_s)^T && (6.2) \end{aligned}$$

where S is the total number of speakers, n_s is number of utterances of speaker s. The median i-vectors, $\bar{\mathbf{w}}_s$ for each speaker is estimated by individually estimating the median for each column, and $\bar{\mathbf{w}}$ across all speakers are defined by

$$\begin{aligned} \bar{\mathbf{w}}_s &= Median(\{\mathbf{w}_1^s, \mathbf{w}_2^s, \mathbf{w}_3^s ... \mathbf{w}_{n_s}^s\}) && (6.3) \\ \bar{\mathbf{w}} &= \frac{1}{N}\sum_{s=1}^{S} n_s\bar{\mathbf{w}}_s && (6.4) \end{aligned}$$

where N is the total number of sessions. The median-based weighted between-class matrix ($\mathbf{S}_b^{w-median}$) is estimated using Equation 5.3, where the mean i-vectors



(a) *interview-interview* condition

(b) *interview-telephone* condition

(c) *telephone-microphone* condition

(d) *telephone-telephone* condition

Figure 6.2: *Comparison of EER values of WLDA and WMFD projected GPLDA systems based on Euclidean weighting functions at different values of* n *in different enrolment and verification conditions.(number represents the number of sessions per speaker in legend)*

of a speaker are replaced with the median. Once the median between- and within-class estimations are calculated using Equations 6.1 and 6.2, MFD and WMFD can be estimated using similar approaches to LDA-based eigenvector decomposition.

The Euclidean distance weighting function WLDA and WMFD projected GPLDA approaches were analysed at different values of degree of order (n) to see the ef-

Table 6.3: *Comparison of WLDA and WMFD projected length-normalized GPLDA systems against standard LDA projected length-normalized GPLDA systems on common condition of NIST 2008 short2-short3 evaluation condition, where GPLDA is modelled using the limited session data.*

System	**Interview-interview**		**Interview-telephone**		**Telephone-interview**		**Telephone-telephone**	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
3 sessions/speaker								
LDA-GPLDA	10.85%	0.0473	11.69%	0.0526	9.51%	0.0423	4.04%	0.0188
WLDA-GPLDA	9.95%	0.0455	11.25%	0.0515	8.69%	0.0393	**3.71%**	0.0193
WMFD-GPLDA	**9.69%**	**0.0435**	**10.15%**	**0.0470**	**8.15%**	**0.0364**	3.95%	**0.0186**
5 sessions/speaker								
LDA-GPLDA	8.69%	0.0395	9.86%	0.0467	7.81%	0.0344	3.21%	**0.0148**
WLDA-GPLDA	7.94%	0.0379	9.29%	0.0451	6.79%	0.0303	2.97%	0.0157
WMFD-GPLDA	**7.29%**	**0.0350**	**8.11%**	**0.0402**	**6.11%**	**0.0271**	**2.72%**	0.0154
7 sessions/speaker								
LDA-GPLDA	8.00%	0.0361	8.29%	0.0430	7.00%	0.0307	**2.55%**	**0.0143**
WLDA-GPLDA	6.78%	0.0326	7.66%	0.0401	5.98%	**0.0265**	2.70%	0.0143
WMFD-GPLDA	**6.12%**	**0.0306**	7.39%	**0.0373**	**5.36%**	0.0268	2.63%	0.0149

fect on between-speaker separability with limited session variability data. These analyses are shown in Figure 6.2. It can be clearly observed with the aid of Figure 6.2 that when the value of n increases, it improves the speaker verification system performance in all the DET conditions, except *telephone-telephone* condition as weighting function increases the between-speaker separability, and when n is selected as 6, the system achieves the best performance. The best value of n was tuned on NIST 2008 short2 - short3 evaluation condition.

6.4.3 Overall performance comparison

Table 6.3 presents the results, comparing the performance of WLDA and WMFD-projected GPLDA systems against LDA-projected GPLDA systems on a common set of NIST 2008 short2 - short3 evaluation conditions. The WLDA-projected GPLDA system shows useful improvement over the LDA-projected GPLDA system on mismatched and *interview-interview* conditions as the WLDA approach effectively extracts more discriminant information from between pairs of speakers. Further, the WMFD-projected GPLDA system has shown over 10%

improvement in EER over the LDA-projected GPLDA system on mismatched and *interview-interview* conditions as median-based MFD estimation is more robust and extracts more discriminant information from between pairs of speakers. These research outcomes were published at the ICASSP conference in 2014 [43].

6.5 Analysis of GPLDA in limited microphone data conditions

A significant amount of speech data is required to develop a robust speaker verification system, especially in the presence of high intersession variability, such as microphone data conditions of the NIST development data. A large amount of telephone speech data is available in the NIST SRE databases; however, microphone speech data is scarce in this data set. In addressing these disparity data sources, researchers have pooled the telephone and microphone data for the development of modern state-of-the-art speaker verification systems such as the GPLDA approach [90]. In this chapter, a new approach is taken to estimate reliable GPLDA model parameters as a linear-weighted model, taking more input from the large volume of available telephone data and smaller proportional input from limited microphone data.

JFA, as originally proposed by Kenny [58], has evolved as a powerful tool in speaker verification to model the inter-speaker variability and to compensate for channel/ session variability in the context of high-dimensional GMM supervectors. Dominguez *et al.* [32] have previously investigated the JFA approach with limited microphone speech data. They have introduced several approaches, including joining matrices, pooled statistics and scaling statistics to avoid the data scarcity problem.

A few years ago, Senoussaoui *et al.* extended their i-vector work where they have analysed the CSS i-vector speaker verification approach with microphone speech [89]. They have introduced the concatenated total-variability approach to extract i-vector features from telephone and microphone sources where the total-variability approach is separately trained using telephone and microphone sources and concatenated to form a concatenated total-variability space [89].

Recently, Senoussaoui *et al.* [90] have analysed the HTPLDA approach with microphone data conditions. They applied a concatenated total-variability approach to extract useful speaker information from telephone and microphone speech data. However, there have been no investigations into how the length-normalized GPLDA model parameters can be explicitly modelled using both rich telephone and limited microphone speech data.

The main aim of this section is to explicitly model the GPLDA parameters using rich telephone and limited microphone sourced speech data in the PDLA model domain. Initially, in the i-vector feature domain, two different types of total-variability approaches, including pooled and concatenated approaches are analysed to extract the speaker information from telephone and microphone speech data; subsequently, in the PLDA model domain, pooled and linear-weighted approaches are investigated to effectively model the GPLDA parameters from telephone and microphone speech data.

6.5.1 I-vector feature domain investigations

The total-variability subspace is responsible for defining a suitable subspace from which i-vectors are extracted. The total-variability subspace should be trained in a manner that best exploits the useful speaker variability contained in speech acquired from both telephone and microphone sources. In this section, both

Table 6.4: *Performance comparison of pooled and concatenated total-variability approach-based LDA-projected GPLDA systems on NIST 08 short2-short3 and NIST 10 core-core conditions.*

(a) *NIST 08 short2-short3 condition*

Total-variability	**Interview-interview**		**Interview-telephone**		**Telephone-microphone**		**Telephone-telephone**	
approach	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Concatenated approach	5.21%	0.0266	6.27%	0.0314	4.82%	0.0240	2.87%	0.0156
Pooled approach	**4.29%**	**0.0214**	**5.51%**	**0.0254**	**4.35%**	**0.0195**	**2.63%**	**0.0126**

(b) *NIST 10 core-core condition*

Total-variability	**Interview-interview**		**Interview-telephone**		**Interview-microphone**		**Telephone-telephone**	
approach	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}
Concatenated approach	7.37%	0.0320	4.84%	0.0231	4.44%	0.0210	3.67%	0.0156
Pooled approach	**6.76%**	**0.0292**	**4.41%**	**0.0220**	**4.10%**	**0.0196**	**3.41%**	**0.0152**

the pooled and concatenated total-variability approaches are investigated with length-normalized GPLDA speaker verification.

Pooled total-variability approach: For the pooled total-variability approach, the total-variability subspace (${R_w}^{telmic} = 500$) is trained on telephone and microphone speech utterances together. The major advantage is that it's a simplified approach.

Concatenated total-variability approach: For the concatenated total-variability approach, the separate telephone-only total-variability subspace (${R_w}^{tel} = 400$) and microphone-only subspace (${R_w}^{mic} = 100$) are trained separately using telephone and microphone speech, and then both subspace transformations are concatenated to create a single total-variability space.

Results and discussion: Initially, the pooled and concatenated total-variability approaches were analysed with the LDA-projected GPLDA system to identify the better total-variability approach to extract i-vector features, the analysis of which shows greater variation from telephone and microphone sourced speech. Table 6.4 presents the results, comparing the performance of pooled and concatenated total-variability approaches-based LDA-projected GPLDA system, on NIST 08 short2 - short3 and NIST 10 core - core conditions. The pooled total-variability approach GPLDA system has shown considerable improvement over the concatenated total-variability approach GPLDA system. The results suggest that the influence of microphone speech data cannot be significantly increased by a concatenated total-variability approach. Based upon this outcome, the pooled total-variability based i-vector feature extraction approach will be used for the following section experiments.

6.5.2 PLDA model domain investigations

In this section, in the PLDA model domain, the pooled and linear-weighted approaches are investigated to estimate the proper GPLDA model parameters from rich telephone and scarce microphone speech data.

Pooled GPLDA parameter estimation: It is commonly believed that robust probabilistic parameters can be estimated if an adequate amount of speech data is available, and telephone and microphone speech is pooled together to create a large development data set in the pooled approach. The length-normalized GPLDA parameters, including mean ($\bar{\mathbf{w}}_{telmic}$), precision matrix ($\mathbf{\Lambda}_{telmic}$) and eigenvoice matrix ($\mathbf{U}_{1telmic}$) are estimated using telephone and microphone pooled data.

Linear weighted GPLDA parameter estimation: If sufficient amounts of telephone and microphone speech data are available, the pooled approach shouldn't have problem with estimating reliable GPLDA parameters; however, in

NIST conditions, while larger amounts of telephone-sourced speech are available, the same does not apply for microphone-sourced speech. In addition, telephone- and microphone-sourced speech have different behaviours, and if both are pooled together, the influence of microphone-sourced data could be lost against the large volume of telephone-sourced data. Thus, the pooled approach is unlikely to help to improve the speaker verification in microphone conditions.

It is hypothesized that a linear-weighted approach can be used to increase the influence of microphone speech data. Firstly, the GPLDA model parameters, including mean ($\bar{\mathbf{w}}_{tel}$), precision matrix ($\mathbf{\Lambda}_{tel}$) and eigenvoice matrix ($\mathbf{U}_{1tel}$) are estimated using telephone speech data. Similarly, the GPLDA model parameters, including mean ($\bar{\mathbf{w}}_{mic}$), precision matrix ($\mathbf{\Lambda}_{mic}$) and eigenvoice matrix ($\mathbf{U}_{1mic}$) are also estimated using microphone speech data as well. After that, a linear-weighted approach is used to combined the both telephone and microphone based parameters. The combined parameters can be estimated as follows,

$$\bar{\mathbf{w}}_{telmic} = \alpha\bar{\mathbf{w}}_{tel} + (1-\alpha)\bar{\mathbf{w}}_{mic} \tag{6.5}$$

$$\mathbf{\Lambda}_{telmic} = \alpha\mathbf{\Lambda}_{tel} + (1-\alpha)\mathbf{\Lambda}_{mic} \tag{6.6}$$

$$\mathbf{U}_{1telmic} = \alpha\mathbf{U}_{1tel} + (1-\alpha)\mathbf{U}_{1mic} \tag{6.7}$$

where α is a weighting parameter between 0.0 and 1.0 denoting the influence of the telephone parameters on the final weighted parameters.

Results and discussions: The experiments were carried out to identify the best length-normalized GPLDA model parameter estimation approach. Table 6.5 presents the results, comparing the performance of the linear-weighted GPLDA system against the pooled GPLDA system on NIST 08 and 10 standard evaluation conditions. If a limited amount of microphone speech data is pooled together with rich amount of telephone speech data (Female (1286 tel and 100 mic speakers), Male (1034 tel and 83 mic speakers)), it is believed that the influence of

Table 6.5: *Performance comparison of pooled and linear-weighted-based GPLDA modelling approaches on NIST 08 short2-short3 and NIST 10 core-core conditions.*

(a) *NIST 08 short2-short3 condition*

Weight (α)	**Interview-interview**		**Interview-telephone**		**Telephone-microphone**		**Telephone-telephone**	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Baseline system (Pooled approach)								
-	4.29%	0.0214	5.51%	0.0254	4.35%	0.0195	2.63%	**0.0126**
New approach (Linear weighted approach)								
1.0	4.23%	0.0194	**4.89%**	**0.0230**	3.74%	0.0169	**2.45%**	0.0139
0.9	4.10%	0.0184	5.07%	0.0233	3.68%	0.0167	2.47%	0.0140
0.8	**3.95%**	**0.0180**	4.97%	0.0235	**3.67%**	**0.0166**	2.62%	0.0142
0.7	4.04%	0.0184	5.16%	0.0246	3.72%	0.0173	2.72%	0.0148
0.6	4.18%	0.0190	5.34%	0.0263	4.14%	0.0187	2.80%	0.0151
0.5	4.43%	0.0203	5.81%	0.0283	4.55%	0.0208	2.98%	0.0154

(b) *NIST 10 core-core condition*

Weight (α)	**Interview-interview**		**Interview-telephone**		**Interview-microphone**		**Telephone-telephone**	
	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}
Baseline system (Pooled approach)								
-	6.76%	0.0292	4.41%	0.0220	4.10%	0.0196	**3.41%**	0.0152
New approach (Linear weighted approach)								
1.0	6.56%	0.0281	4.48%	0.0203	3.81%	0.0194	3.42%	**0.0148**
0.9	6.40%	**0.0274**	**4.04%**	**0.0200**	**3.80%**	**0.0190**	3.53%	0.0156
0.8	**6.36%**	0.0276	**4.04%**	0.0201	**3.80%**	0.0194	3.67%	0.0160
0.7	6.41%	0.0284	4.10%	0.0209	3.94%	0.0198	3.67%	0.0164
0.6	6.54%	0.0294	4.27%	0.0224	4.27%	0.0203	3.67%	0.0165
0.5	6.78%	0.0301	4.35%	0.0237	4.23%	0.0211	3.81%	0.0179

microphone speech would be reduced. In order to increase the influence of microphone data, the linear-weighted-based GPLDA approach was analysed for several values of weights (α) with each interval of 0.1. It can be clearly seen from the results shown in Table 6.5 that when the influence of microphone speech data is increased over telephone speech by selecting the α of 0.8, the system shows better performance in microphone speech conditions. However, as α is further reduced, the performance is reduced in both telephone and microphone speech conditions. This is because the microphone-estimated GPLDA parameters provide a poor estimate of the true parameters due to the scarcity of microphone data. Based upon this outcome, it is believed that if the amount of microphone is further increased, the speaker verification system could achieve further improvement in microphone conditions when the α is less than 0.8.

At the optimal α of 0.8, it can be clearly seen that the linear-weighted GPLDA approach shows over 9% relative improvement in DCF for NIST 2008 *interview-interview* and mismatched conditions, and over 5% relative improvement in EER for NIST 10 *interview-interview* and mismatched conditions. The outcomes of this research were published in proceedings of the Interspeech 2013 conference [42].

6.6 Chapter summary

In this chapter, initially, a length-normalized GPLDA system was analysed with an SN-WLDA channel compensation approach in order to effectively compensate the channel variation. The SN-WLDA projected GPLDA system has shown over 14% improvement in EER for NIST SRE 2010 interview and microphone verification and over 7% improvement in EER for NIST SRE 2010 telephone verification, as it extracts the discriminatory information between pairs of speakers as well as capturing the source variation information. It is believed that the improvements, demonstrated throughout the previous chapter on advanced channel compensation techniques for CSS-based i-vector speaker representation, can also translate well into the length-normalized GPLDA approach. The improvements suggest that a standard length-normalized GPLDA system can be replaced with a channel compensation-based length-normalized GPLDA system as it provides better performance as well as more computationally efficient approach.

Subsequently, the length-normalized GPLDA system was analysed when GPLDA was trained using a limited number of session data, and it was found that when number of sessions per speaker is reduced for GPLDA modelling, it considerably affects the speaker verification system's performance. The WLDA and WMFD approaches were introduced to a length-normalized GPLDA system, and the

WMFD-projected GPLDA system has shown over 10% improvement in EER over the LDA-projected GPLDA system on mismatched and *interview-interview* conditions, as median-based LDA estimation is more robust and extracts more discriminant information from between pairs of speakers. The improvements suggest that a WMFD-projected GPLDA approach would be a better approach than a standard GPLDA approach in limited session data conditions.

Lastly, an LDA-projected length-normalized GPLDA system was analysed with limited microphone data conditions. In the i-vector feature domain, pooled and concatenated total-variability approaches were analysed with the GPLDA system, and it was found that a pooled total-variability is a better approach than concatenated total-variability approach to extract speaker variation information from telephone and microphone-sourced speech. Subsequently, in the PLDA model domain, pooled and linear-weighted GPLDA modelling approaches were analysed to improve the speaker verification performance in microphone conditions where a pooled total-variability approach was used to extract i-vector features. The linear-weighted GPLDA approach has shown over 9% relative improvement in DCF for NIST 2008 *interview-interview* and mismatched conditions, and over 5% relative improvement in EER for NIST 10 *interview-interview* and mismatched conditions. It is believed that a linear-weighted GPLDA approach can be used to improve the speaker verification performance in limited microphone conditions.

Chapter 7

Short Utterance I-vector Speaker Verification

7.1 Introduction

In a typical speaker verification system, a significant amount of speech is required for reliable speaker verification evaluation (enrolment and verification) and development in the presence of large inter-session variability that has limited the widespread use of speaker verification technology in everyday applications. Reducing the required amount of speech, while obtaining satisfactory performance, has been the focus of a number of recent studies in state-of-the-art speaker verification design, including JFA, SVMs and i-vectors. These studies have shown that performance considerably degrades in very short utterances ($< 10s$) for all common approaches [46, 49, 59, 73, 104, 106].

As short utterance issues have not been completely solved yet, the second aim of this thesis is to improve the state-of-the-art speaker verification system performance in short utterance evaluation and development data conditions. These are important in development of automatic speaker verification system in real world applications. Though in recent times, CSS i-vector and PLDA approaches have become state-of-the-art speaker verification systems, these approaches have not been deeply analysed on short utterance conditions. This chapter is divided into two parts: (1) both CSS i-vector and PLDA-based speaker verification systems are individually analysed with short utterance evaluation and development data conditions, and (2) a number of novel techniques are also introduced to improve the performance of CSS i-vector and PLDA approaches.

7.2 CSS i-vector system on short utterances

Recently, CSS i-vector speaker verification approaches have attracted considerable attention from researchers as it is a computationally efficient and simplified approach. As the i-vector approach is based on defining only one variability space [19, 20], instead of the separate session variability and speaker spaces of the JFA approach, it is commonly believed that i-vectors will not lose significant speaker information in the session variability space [20]. It is also believed that this would be an added advantage to a short utterance speaker verification system [20]. Until now, several standard session variability compensation approaches have been introduced to long utterance CSS i-vector speaker recognition systems [20, 47, 71]. In addition, in the previous chapter, several advanced session variability compensation techniques have also been proposed for the long utterance i-vector speaker verification system. However, it has not been analysed with short utterance conditions. In this chapter, the CSS i-vector system is analysed with standard and advanced channel compensation approaches.

Lastly, the CSS i-vector system is also analysed with short utterance and limited development data conditions, and several novel approaches are introduced to improve the speaker verification performance in such conditions as in a real world scenario, it is hard to collect a large amount of development data as well as acquire long utterances. Subsequently, a novel SUN-LDA technique is introduced to improve the short utterance CSS i-vector system performance.

7.2.1 Source- and utterance-normalised LDA (SUN-LDA)

In this section, a novel session compensation approach, source and utterance-duration normalized LDA, is introduced for the purpose of improving the short utterance i-vector speaker verification system.

McLaren *et al.* [71] introduced the source-normalized between-class estimations to capture the source variation information. The influence of short utterance development data for channel estimation will be detailed in the following section. Based upon short utterance development data analysis and the fundamentals of source-normalized estimation, the source and utterance-duration normalized between-class estimations is introduced to capture the source variation information from full- and short-length development i-vectors. The telephone- and microphone-sourced utterance-duration normalized between-class scatters, $\mathbf{S}_b^{tel_{utt}}$, and $\mathbf{S}_b^{mic_{utt}}$ are defined as follows,

$$\mathbf{S}_b^{tel_{utt}} = \alpha_{tf}\mathbf{S}_b^{tel_{full}} + \alpha_{ts}\mathbf{S}_b^{tel_{short}} \tag{7.1}$$

$$\mathbf{S}_b^{mic_{utt}} = \alpha_{mf}\mathbf{S}_b^{mic_{full}} + \alpha_{ms}\mathbf{S}_b^{mic_{short}} \tag{7.2}$$

where $\mathbf{S}_b^{tel_{full}}$ and $\mathbf{S}_b^{mic_{full}}$ are individually estimated from telephone- and microphone-sourced full-length utterances using Equation 3.9. $\mathbf{S}_b^{tel_{short}}$ and $\mathbf{S}_b^{mic_{short}}$ are estimated using the telephone- and microphone-sourced short-length utterances respectively. α_{tf}, α_{mf}, α_{ts} and α_{ms} are respectively the weighting coefficients of telephone- and microphone-sourced full- and short-length between-class scatter estimations, and the importance of each source is analysed using the binary weighting coefficients. Two different types of SUN-LDA approaches are introduced: (1) SUN-LDA-pooled and (2) SUN-LDA-concat.

1. SUN-LDA-pooled

   Estimate the SUN-LDA-pooled matrix, $\mathbf{A}$, based on summation of telephone- and microphone-sourced utterance-duration normalized between-class scatter and standard within-class scatter matrix. The SUN-LDA-pooled matrix can be estimated as eigenvalue decomposition of,

   $$(\mathbf{S}_b^{tel_{utt}} + \mathbf{S}_b^{mic_{utt}})\mathbf{v} = \lambda \mathbf{S}_w \mathbf{v} \tag{7.3}$$

   Empirically 150 eigenvectors were selected for SUN-LDA-pooled training by performance.

2. SUN-LDA-concat

   Estimate the telephone- and microphone-sourced dependent LDA matrices separately for telephone- and microphone-sourced utterance-duration normalized between-class estimation. The telephone- and microphone-sourced dependent LDA matrices, $\mathbf{A}_{tel}$ and $\mathbf{A}_{mic}$, can be estimated as eigenvalue decomposition of,

   $$\mathbf{S}_b^{tel_{utt}}\mathbf{v} = \lambda \mathbf{S}_w \mathbf{v} \tag{7.4}$$

   $$\mathbf{S}_b^{mic_{utt}}\mathbf{v} = \lambda \mathbf{S}_w \mathbf{v} \tag{7.5}$$

   The SUN-LDA-concat matrix is formed by concatenating the telephone- and microphone-sourced LDA matrices, $\mathbf{A}_{tel}$ and $\mathbf{A}_{mic}$, which can be estimated as follows,

   $$\mathbf{A} = [\mathbf{A}_{tel}\mathbf{A}_{mic}] \tag{7.6}$$

   Empirically 100 and 50 eigenvectors were respectively selected for telephone- and microphone-sourced LDA estimations.

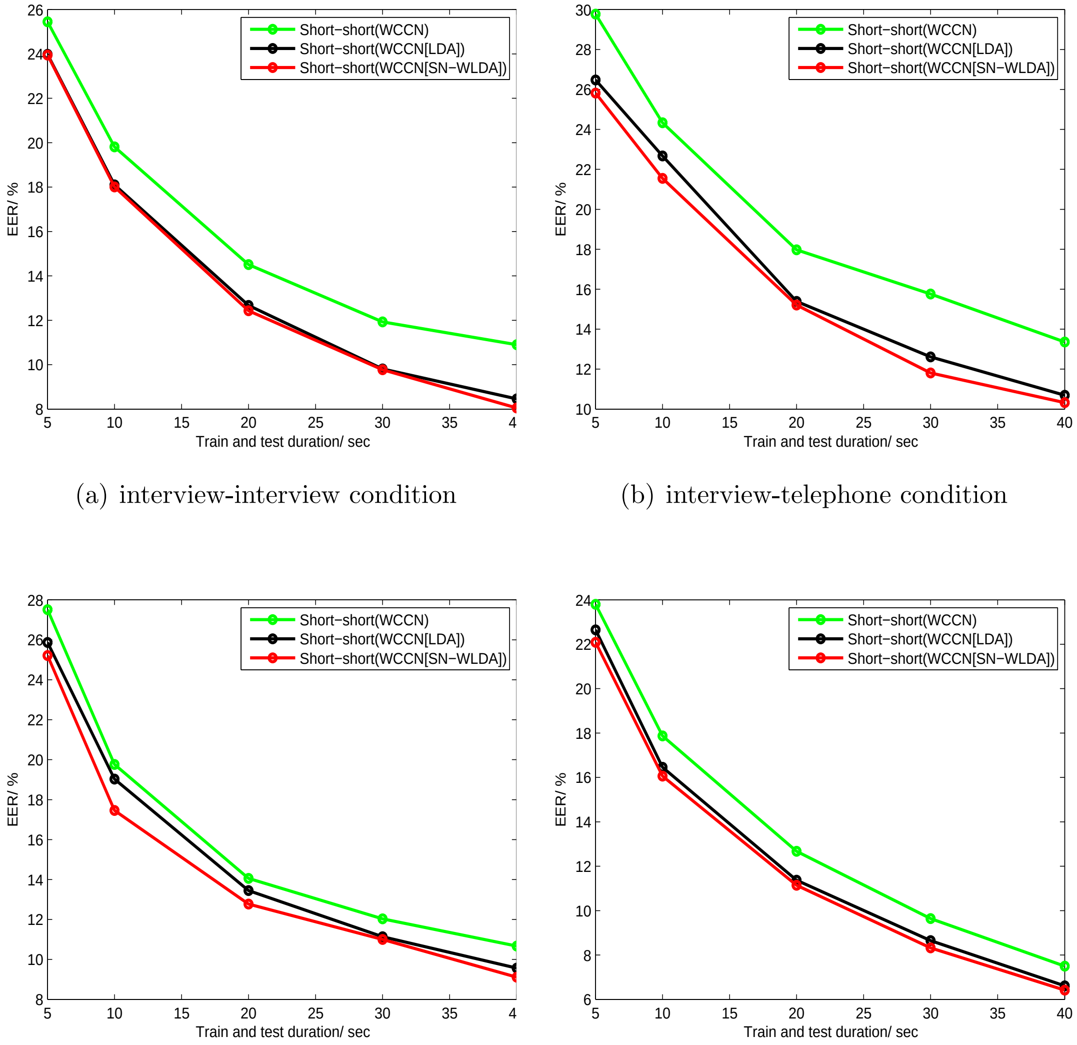
Table 7.1: *Performance comparison of baseline systems on NIST 2008 short2-short3 truncated 10sec - 10sec evaluation conditions.*

Approach	**Interview-interview**		**Interview-telephone**		**Telephone-microphone**		**Telephone-telephone**	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
WCCN	19.81%	0.0798	24.33%	0.0896	19.76%	0.0821	17.87%	0.0695
WCCN[LDA]	18.10%	**0.0767**	22.67%	0.0861	19.03%	0.0817	**16.46%**	**0.0679**
WCCN[SN-LDA]	**18.01%**	0.0771	**21.57%**	**0.0858**	**18.94%**	**0.0813**	16.56%	0.0683

7.2.2 CSS i-vector system results and discussion

The experimental protocol was detailed in Chapter 4. Initially, the standard and advanced session variability compensation approaches were analysed under short utterance evaluation conditions. After that, the i-vector performance was progressively analysed when the standard session variability compensation approach was trained using full- and short-length utterance development data. Finally, the newly proposed SUN-LDA-pooled and SUN-LDA-concat techniques were analysed with the i-vector speaker verification system.

Analysis of standard session variability compensation approaches: To serve as a baseline performance, standard inter-session variability compensation approaches, including WCCN, WCCN[LDA] and WCCN[SN-LDA] were investigated with a truncated 10 sec - 10 sec evaluation condition as shown in Table 7.1. The NIST standard condition development data (full-length) was used for inter-session variability compensation approach training. As had been previously shown by Dehak *et al.* [20], it is confirmed that the WCCN[LDA] provides an improvement over WCCN. As had also been previously shown by McLaren *et al.* [71], the results also confirm that WCCN[SN-LDA] provides an improvement over WCCN[LDA] on mis-matched conditions.



(a) interview-interview condition

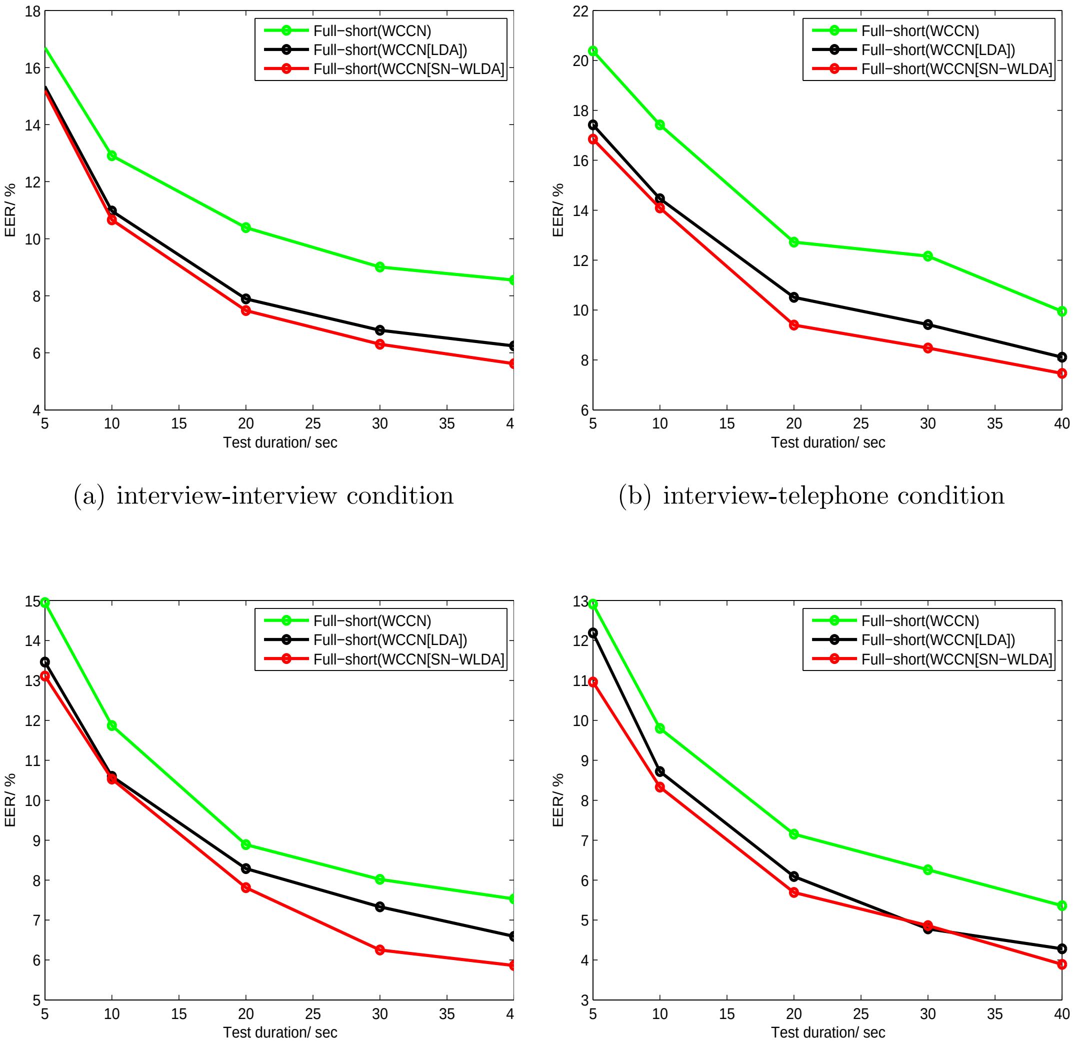
(b) interview-telephone condition

(c) telephone-microphone condition

(d) telephone-telephone condition

Figure 7.1: *Comparison of WCCN, WCCN[LDA] and WCCN[SN-WLDA] projected i-vector systems on the common subset of the 2008 NIST SRE short2-short3 truncated training and testing condition* (a) *interview-interview,* (b) *interview-telephone,* (c) *telephone-microphone, and* (d) *telephone-telephone.*

Analysis of advanced session variability compensation approaches:
The studies of the advanced channel compensation techniques on long-length utterance evaluation conditions have found in Chapter 5 that the WCCN[LDA] approach shows improvement over the WCCN approach, and the Mahalanobis



(a) interview-interview condition

(b) interview-telephone condition

(c) telephone-microphone condition

(d) telephone-telephone condition

Figure 7.2: *Comparison of WCCN, WCCN[LDA] and WCCN[SN-WLDA] projected i-vector systems on the common subset of the 2008 NIST SRE short2-short3 full length training and truncated testing condition* (a) *interview-interview,* (b) *interview-telephone,* (c) *telephone-microphone, and* (d) *telephone-telephone.*

distance weighting function SN-WLDA approach shows further improvement over the WCCN[LDA] approach, as the SN-WLDA approach captures more discriminant and source variation information. These techniques are investigated with a short-length utterance evaluation condition as shown in Figure 7.1. It can be clearly seen from Figure 7.1 that the WCCN[LDA] approach shows improvement over the WCCN approach with truncated training testing conditions, whereas the Mahalanobis distance weighting function-based SN-WLDA approach shows a little improvement over the WCCN[LDA] approach, as short training and testing utterances may not have enough speaker information to extract more speaker discrimination features using advanced channel compensation approaches.

Similarly to the short training and testing utterance analysis, the performance of the CSS i-vector system was also analysed with full-length training and truncated testing conditions. The performance comparison of the CSS i-vector system on full-length training and truncated testing condition is shown in Figure 7.2. When the testing utterance length decreases below 20 sec, the performance degrades at an increasing rate rather than in proportion with the utterance length in all the training and testing conditions, which suggests that at least 20 sec of speech is required to adequately model the i-vectors. Subsequently, when the testing utterance length reduces from 40 sec to 20 sec, the performance degrades slightly.

Subsequently, each channel compensation approach is individually studied on full-length training and truncated testing utterances. The results suggest that a WCCN[LDA] approach improves the performance over a WCCN approach. However, Mahalanobis distance weighting function WCCN[SN-WLDA] only shows a major improvement over WCCN[LDA] with a longer utterance testing condition. Based upon experiments conducted with both truncated training and testing and full-length training with truncated testing condition experiments, it is found that WCCN[LDA] is the best approach over WCCN for any length utterance conditions, and Mahalanobis distance weighting function WCCN[SN-WLDA] is the best approach for the longer utterance evaluation conditions.

Lastly, the CSS i-vector performance is compared using Figures 7.1 and 7.2 when evaluation is done on short-short and full-short evaluation conditions. When the

Table 7.2: *Performance comparison of WCCN[LDA] based i-vector systems on NIST 2008 short2 - short3 truncated 10 sec-10 sec evaluation conditions with full-, matched- and mixed-length utterance based WCCN training.*

WCCN training	**Interview-interview**		**Interview-telephone**		**Telephone-microphone**		**Telephone-telephone**	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Full-length	**18.10%**	**0.0767**	**22.67%**	**0.0861**	**19.03%**	**0.0817**	**16.46%**	**0.0679**
Matched-length	20.39%	0.0822	25.34%	0.0894	21.05%	0.0842	17.87%	0.0720
Mixed-length	19.57%	0.0804	24.44%	0.0879	20.38%	0.0823	17.30%	0.0708

utterance length reduces in short-short condition, the performance reduces at a higher increasing rate as the utterances reduce in length. This is because the short-short condition may not have enough speaker discriminant information on both enrolment and verification utterances, whereas in the full-short condition the enrolment utterances have enough speaker discriminant information, and verification utterances may not have enough speaker discriminant information.

Standard session variability compensation training using full- and short-length development data: In this section, short utterance i-vector performance is analysed when the inter-session variability approach, WCCN[LDA], is trained using full- and short-length development data. The NIST standard development data is used as full-length development data. For matched-length, the NIST standard condition development data is truncated into similar length of the evaluation condition. Full- and matched-length utterances are pooled together to create the mixed-length development data.

Table 7.2 presents the results comparing the WCCN[LDA] based i-vector performance with full-, matched- and mixed-length WCCN training on NIST 2008 truncated 10 sec-10 sec evaluation conditions. The results suggest that when short utterances are added to the development set for the WCCN training, it considerably affects the speaker verification performance as it deteriorates the quality

Table 7.3: *Performance comparison of SUN-LDA approach-based i-vector systems on truncated 10sec-10sec evaluation conditions.*

(a) *SUN-LDA-pooled vs LDA*

System				**Interview-interview**		**Interview-telephone**		**Telephone-microphone**		**Telephone-telephone**	
α_{tf}	α_{mf}	α_{ts}	α_{ms}	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Baseline approach (LDA_WCCN)											
-	-	-	-	18.10%	0.0767	22.67%	0.0861	19.03%	0.0817	16.46%	0.0679
Source and utterance-duration normalized approach (SUN-LDA-pooled_WCCN])											
1.0	1.0	1.0	1.0	18.04%	0.0764	21.37%	0.0857	18.75%	0.0790	16.56%	0.0670
1.0	1.0	0.0	1.0	18.34%	0.0766	21.47%	0.0859	18.68%	0.0811	16.56%	0.0681
1.0	1.0	1.0	0.0	17.98%	**0.0759**	21.22%	0.0858	18.60%	0.0783	**16.31%**	0.0667
1.0	1.0	0.0	0.0	**17.97%**	0.0761	21.47%	0.0859	18.87%	0.0807	16.48%	0.0674
1.0	0.0	1.0	0.0	18.06%	0.0774	**21.21%**	**0.0856**	**17.66%**	**0.0776**	**16.31%**	**0.0665**

(b) *SUN-LDA-concat vs LDA*

System				**Interview-interview**		**Interview-telephone**		**Telephone-microphone**		**Telephone-telephone**	
α_{tf}	α_{mf}	α_{ts}	α_{ms}	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Baseline approach (LDA_WCCN)											
-	-	-	-	18.10%	0.0767	22.67%	0.0861	19.03%	0.0817	16.46%	0.0679
Source and utterance-duration normalized approach (SUN-LDA-concat_WCCN)											
1.0	1.0	1.0	1.0	17.64%	**0.0760**	20.19%	0.0852	18.06%	0.0852	16.14%	0.0706
1.0	1.0	0.0	1.0	17.54%	0.0767	20.36%	0.0846	17.59%	0.0831	16.06%	0.0694
1.0	1.0	1.0	0.0	**17.29%**	0.0764	20.39%	0.0848	17.79%	0.0832	16.31%	0.0692
1.0	1.0	0.0	0.0	17.64%	**0.0760**	**19.91%**	**0.0841**	**17.39%**	0.0814	**15.82%**	0.0677
1.0	0.0	1.0	0.0	17.98%	0.0773	21.84%	0.0848	18.13%	**0.0798**	16.64%	**0.0654**

of intra-speaker variance. The purpose of the WCCN approach is to compensate the intra-speaker variance; however, it is believed that short utterance development set i-vectors have more intra-speaker variations due to phonetic content variations. Thus, it may not help to compensate the intra-speaker variation, and it would only affect speaker verification performance. These results demonstrate that full-length i-vectors are good enough to train the intra-speaker variance, and full-length i-vectors will only be used for intra-speaker variance estimations in the remaining of this chapter.

SUN-LDA analysis The influence of short utterance i-vectors for inter-speaker variance estimation is analysed in this section. It is believed that the short utterance development set i-vectors may not affect the quality of inter-speaker variation as they do not depend on phonetic contents. In order to capture the source variation information from full- and short-length i-vectors, two different types of SUN-LDA approaches, SUN-LDA-pooled and SUN-LDA-concat, are introduced.

Table 7.3 (a) and 7.3 (b) presents the results comparing the SUN-LDA-pooled and SUN-LDA-concat against traditional LDA on NIST 2008 truncated 10 sec-10 sec evaluation condition. As was previously hypothesized, the experiment results confirmed that the inclusion of short utterance development i-vectors (α_{ts} and α_{ms}) do not affect the speaker verification performance. If the influence of telephone- and microphone-sourced full- and short-length utterances is seen for SUN-LDA-pooled and SUN-LDA-concat estimations, it is clear that the inclusion of microphone-sourced short utterance i-vectors (α_{ms}) affects the speaker verification performance as microphone-sourced short utterance i-vectors may have more variations compared to telephone-sourced short utterance i-vectors. The SUN-LDA-pooled and SUN-LDA-concat approaches achieve a useful improvement over traditional LDA as they capture the source variation information from full- and short-length development set i-vectors. Further, SUN-LDA-concat shows improvement in EER over SUN-LDA-pooled as estimating the LDA matrices separately for telephone and microphone sources is better than a pooling approach. The best performance of SUN-LDA-concat is highlighted in Table 7.3 (b), and it is shown to have a relative improvement of 8% in EER for mis-matched conditions and over 3% for matched conditions over traditional LDA approaches. The outcomes of this research were published in the proceedings of the Interspeech 2013 conference [41].

7.3 PLDA system on short utterances

This section will focus on whether a recently proposed PLDA approach to speaker verification could form a suitable foundation for continuing research into short utterance speaker verification. The HTPLDA approach achieved a significant improvement over JFA on the standard NIST SRE conditions [51]; however, the robustness of GPLDA and HTPLDA to the limited speech resources in development, enrolment and verification is an important issue that has not been investigated yet. In the remainder of this chapter, the effects of limited speech data will be investigated using a PLDA approach. A brief history of GPLDA- and HTPLDA- based speaker verification system was described in Chapter 3.

For this investigation, both GPLDA and HTPLDA speaker verification systems were chosen, as these systems have not yet been analysed for short utterance evaluation and development data conditions. For this study, a length-normalised GPLDA approach wasn't considered as length-normalised GPLDA approach is equivalent to the HTPLDA approach. The PLDA speaker verification is divided into two categories by the data type: (1) telephone speech PLDA speaker verification system where telephone-sourced speech utterances are used to train a PLDA approach, (2) telephone and microphone speech PLDA speaker verification system where pooled telephone- and microphone-sourced speech is used to train a PLDA approach.

7.3.1 PLDA system results and discussion

Following is an experimental study regarding the impact of limited speech on PLDA speaker verification, divided into two sections: telephone speech only, then mixed condition speech. The telephone speech PLDA system is investigated with limited data conditions in the first section. Initially, experiments look at NIST standard conditions before progressively investigating on limited evaluation and development data conditions. In the second section, the telephone and microphone speech PLDA system is investigated with NIST standard and truncated

Table 7.4: *Comparison of GPLDA and HTPLDA systems with and without S-Norm on the common set of the 2008 NIST SRE standard conditions. (a) GPLDA (b) HTPLDA.*

(a) *GPLDA*

Evaluation	**Without Snorm**		**With Snorm**	
utterance lengths	**EER**	**DCF**	**EER**	**DCF**
short2-short3	4.20%	0.0204	**3.13%**	**0.0163**
10sec-10sec	19.94%	0.0837	**15.23%**	**0.0690**

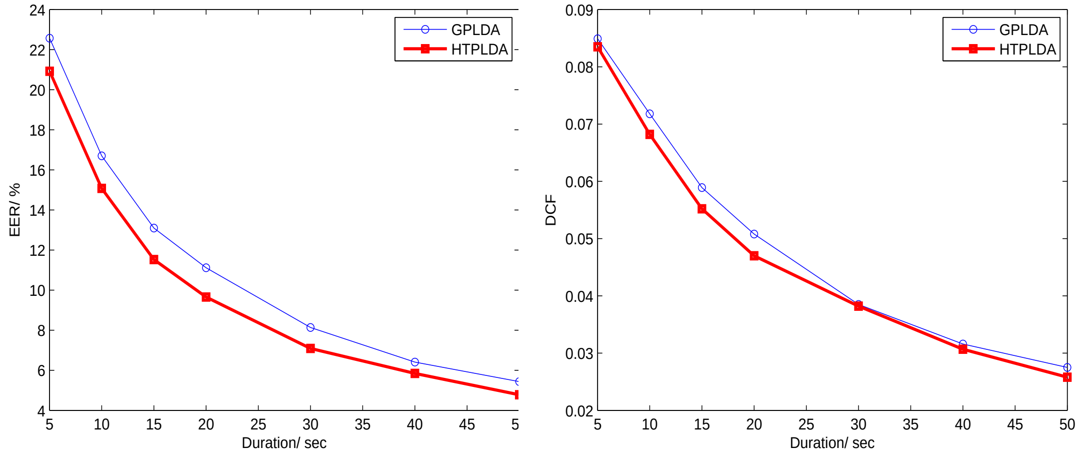
(b) *HTPLDA*

Evaluation	**Without Snorm**		**With Snorm**	
utterance lengths	**EER**	**DCF**	**EER**	**DCF**
short2-short3	**2.39%**	**0.0128**	2.47%	0.0151
10sec-10sec	16.14%	0.0741	**13.89%**	**0.0649**

conditions.

Telephone speech PLDA system: In this section, the speaker verification performance is analysed with regards to the duration of utterances used for both speaker evaluation (enrolment and verification) and score normalization and PLDA modelling during development. Two main questions can be raised when the PLDA system is analysed with limited development data conditions. Firstly, can the PLDA approach improve the performance of short utterance-based speaker verification system when the score normalization is trained with matched utterance length. Secondly, can the PLDA approach improve the performance of short utterance-based speaker verification when the PLDA is modelled with matched utterance length. These will be briefly analysed in this section. For telephone speech PLDA system, the total-variability subspace (${R_w}^{tel} = 500$) is trained from telephone-source speech development data.

Initially, the GPLDA and HTPLDA systems were investigated with NIST standard evaluation conditions using only telephone utterances. Table 7.4 presents



(a) EER

(b) DCF

Figure 7.3: *Comparison of GPLDA and HTPLDA systems at different lengths of active speech for each enrolment and verification condition*, (a) *EER and* (b) *DCF.*

results comparing the performance of the GPLDA and HTPLDA systems with and without S-Norm on the standard NIST SRE 08 evaluation conditions. As had been previously shown by Kenny [51], it is confirmed that the HTPLDA system provides an improvement over GPLDA. Similarly to Kenny's findings, it is also found that S-Norm improves the performance of the GPLDA system in both the *short2-short3* and the *10 sec-10 sec* enrolment-verification conditions. These results also indicate that while there appears to be limited advantage to score normalization in longer utterances, HTPLDA is improved by score normalization for shorter utterances.

In order to more closely examine the behaviour of PLDA speaker verification for short utterances, both the GPLDA and HTPLDA systems were evaluated for truncated evaluation data as shown in Figure 7.3. These results show that the HTPLDA system continues to achieve better performance than GPLDA for all the truncated conditions, although the difference is not as dramatic for DCF as for EER. Overall, the results show that as the utterance length decreases,

Table 7.5: *Performance comparison of GPLDA and HTPLDA systems with full and matched length score normalization data (a) GPLDA (b) HTPLDA.*

(a) *GPLDA*

Evaluation	**S-Norm development data**			
utterance	**Full length**		**Matched length**	
lengths	**EER**	**DCF**	**EER**	**DCF**
5 sec - 5 sec	22.57%	**0.0849**	**22.32%**	0.0855
10 sec - 10 sec	16.70%	0.0718	**16.65%**	**0.0716**
15 sec - 15 sec	13.10%	0.0589	**12.52%**	**0.0587**
20 sec - 20 sec	11.12%	**0.0508**	**11.04%**	0.0513

(b) *HTPLDA*

Evaluation	**S-Norm development data**			
utterance	**Full length**		**Matched length**	
lengths	**EER**	**DCF**	**EER**	**DCF**
5 sec - 5 sec	20.92%	0.0835	**20.76%**	**0.0828**
10 sec - 10 sec	**15.08%**	**0.0682**	**15.08%**	0.0692
15 sec - 15 sec	11.53%	**0.0552**	**11.37%**	0.0563
20 sec - 20 sec	9.66%	**0.0470**	**9.55%**	0.0480

performance degrades at an increasing rate, rather than in proportion with the reduced length. From these results, it is believed that HTPLDA provides a good choice for speaker verification in very short evaluation conditions.

Subsequently, the GPLDA and HTPLDA systems were also analysed with limited development data for both normalization and PLDA modelling. Table 7.5 presents the results, comparing the performance of the GPLDA and HTPLDA systems with full-length score normalization and matched-length score normalization data (where the score normalization data was truncated to the same length as the evaluation data). It was found that matched-length score normalization improves the EER performance of both PLDA systems across all truncated conditions, but doesn't show consistent improvement of DCF. These show that, rather than being a hindrance to normalization performance, limited development data (if matched in length), can improve normalization for speaker verification.

The GPLDA and HTPLDA systems were also investigated with limited PLDA

Table 7.6: *Performance comparison of GPLDA systems with full and matched length PLDA modelling data, HTPLDA systems with full and mixed length PLDA modelling data (a) GPLDA (b) HTPLDA.*

(a) *GPLDA*

Evaluation	**GPLDA development data**			
utterance	**Full length**		**Matched length**	
lengths	**EER**	**DCF**	**EER**	**DCF**
10sec - 10sec	16.70%	0.0718	**16.04%**	**0.0679**
20sec - 20sec	11.12%	0.0508	**10.63%**	**0.0490**

(b) *HTPLDA*

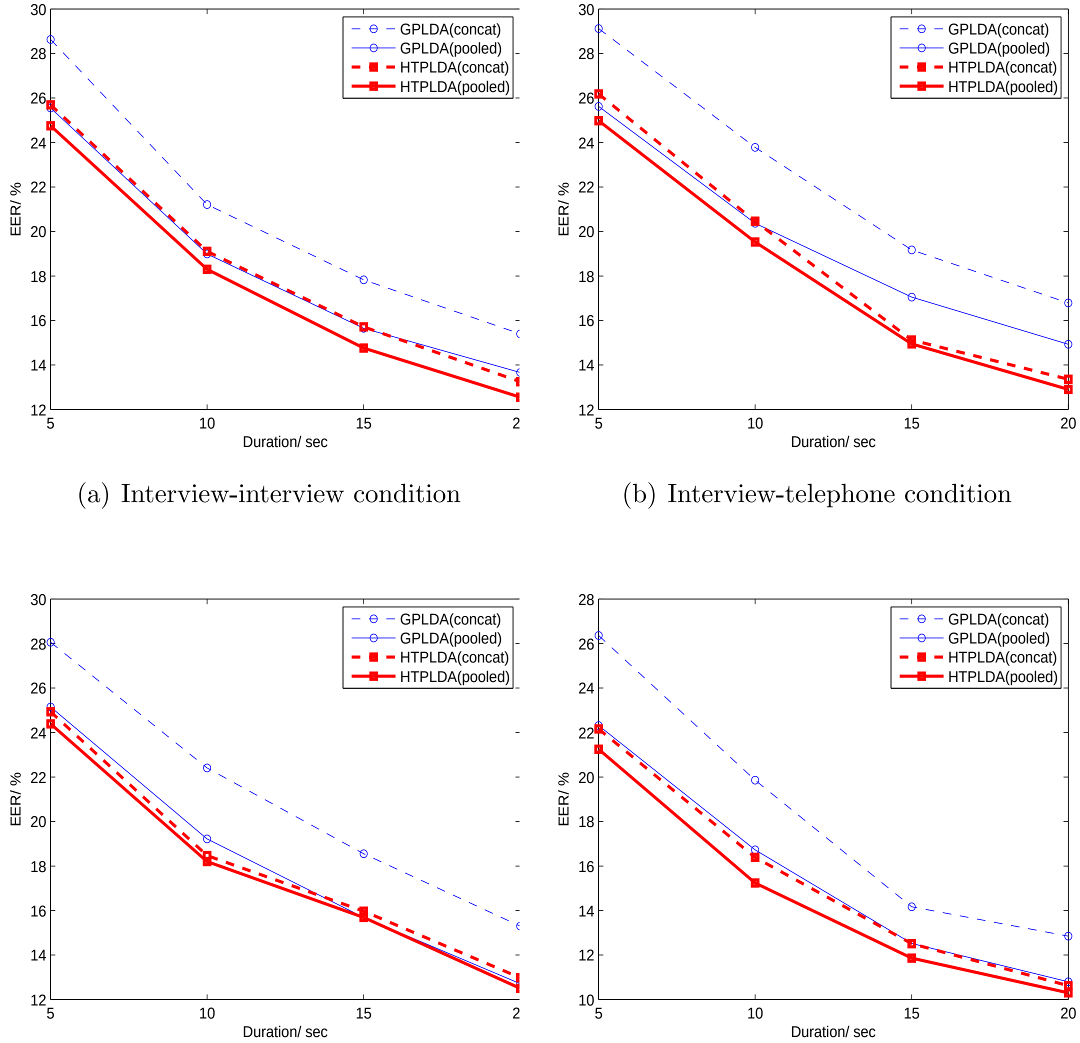
Evaluation	**HTPLDA development data**			
utterance	**Full length**		**Mixed length**	
lengths	**EER**	**DCF**	**EER**	**DCF**
10sec - 10sec	15.08%	0.0682	**13.67%**	**0.0639**
20sec - 20sec	9.66%	0.0470	**9.07%**	**0.0461**

modelling development data. Table 7.6 (a) presents the results of the GPLDA speaker verification system trained during development on full-length utterances and utterances with lengths matched to the evaluation conditions. These results suggest that when the GPLDA system is modelled with matched-length utterances, considerable improvement can be achieved over modelling based upon full-length utterances. When GPLDA modelling utterance's length are matched with short evaluation (enrolment and verification) utterance's length, there is no mismatch between GPLDA modelling development i-vector's behaviour and evaluation data (enrolment and verification) i-vector's behaviour. Because of these reasons, it is deemed to have achieved best performance.

When attempting to model the matched short utterances with HTPLDA, it was found that the i-vectors could not fit with a heavy-tailed distribution. Because of this difficulty and the improvement in GPLDA modelling with matched utterances, it is believed that this is an indication that short utterances in the i-vector space have less outliers than full-length utterances, and therefore are better modelled with Gaussian.

In order to still be able to take advantage of matching the development data with evaluation, an attempt was made to model the short-utterance HTPLDA system by including both matched and full-length utterances in the development data. This approach is shown as the 'Mixed' column in the Table 7.6 (b). It can be clearly seen that the mixed-length HTPLDA modelling provided improved speaker verification performance over the full-utterance modelling. It is also believed that, while matching the i-vector lengths does not appear to be feasible in HTPLDA modelling, the mixed-length modelling approach provides a closer match between development and evaluation, providing for an improvement in speaker verification performance in limited evaluation conditions.

Telephone and microphone speech PLDA system In this section, the impact of short utterance mismatched and matched *interview-interview* conditions with GPLDA speaker verification system was analysed. The EER performance of pooled and concatenated total-variability modelling for GPLDA and HTPLDA systems in limited evaluation data is shown in Figure 7.4. All results are presented with S-Norm applied. From the figure, it can be seen that the pooled total-variability approach provided improved performance, for both the GPLDA and HTPLDA speaker verification systems, across all lengths and channel conditions. These results also suggest that when the utterance length is reduced, the pooled total-variability approach improves the performance at an increasing rate. It has also been found that the pooled total-variability approach achieves considerable improvement on *telephone-telephone* and *interview-interview* matched conditions across all truncated evaluation data for the HTPLDA system. The outcomes of this research were published in proceedings of the Odyssey 2012 conference [48].



(a) Interview-interview condition

(b) Interview-telephone condition

(c) Telephone-interview condition

(d) Telephone-telephone condition

Figure 7.4: *Comparison of EER values of pooled and concatenated total-variability approach based GPLDA and HTPLDA systems at different lengths of active speech for each enrolment and verification condition,* (a) *interview-interview,* (b) *interview-telephone,* (c) *telephone-interview and* (d) *telephone-telephone.*

7.4 Chapter summary

The challenges of providing robust speaker verification for applications with access to only short speech utterances remains a key hurdle to the broad adoption of speaker verification systems. This chapter presented a study on the effects of limited speech data on CSS i-vector and PLDA speaker verification systems.

Initially, standard and advanced channel compensation approaches CSS i-vector speaker verification performance was analysed with short utterance evaluation condition, and found that the SN-WLDA advanced channel compensation approach has not shown much improvement over the standard channel compensation approach as short utterance data does not appear to have enough speaker discriminant information. The overall CSS i-vector speaker verification performance demonstrates that when the utterance length reduces, the performance reduces in an increasing rate rather than proportional.

Subsequently, CSS i-vector performance was also analysed when channel compensation approaches were trained using short utterance development data, and it was found that including the short utterance for intra-speaker variance affects the speaker verification performance; however, short utterances can be used to train the inter-speaker variance. Based upon this outcome, SUN-LDA was also introduced to improve the speaker verification performance in short utterance evaluation conditions.

Secondly, the PLDA approach was analysed with short utterance evaluation and development data. Experiments were conducted for telephone-only speaker verification, examining the performance of the GPLDA and HTPLDA systems compared with standard and truncated evaluation conditions. These experiments found that the HTPLDA system continued to achieve better performance than the GPLDA as the length of the truncated evaluation data decreased. The advantages of including short utterances in development were also investigated, finding that having short utterances available for normalization and PLDA modelling provided an improvement in speaker verification performance when compared to development in full-length data. This approach is very useful in real world speaker verification applications because the required development data can be reduced.

Chapter 8

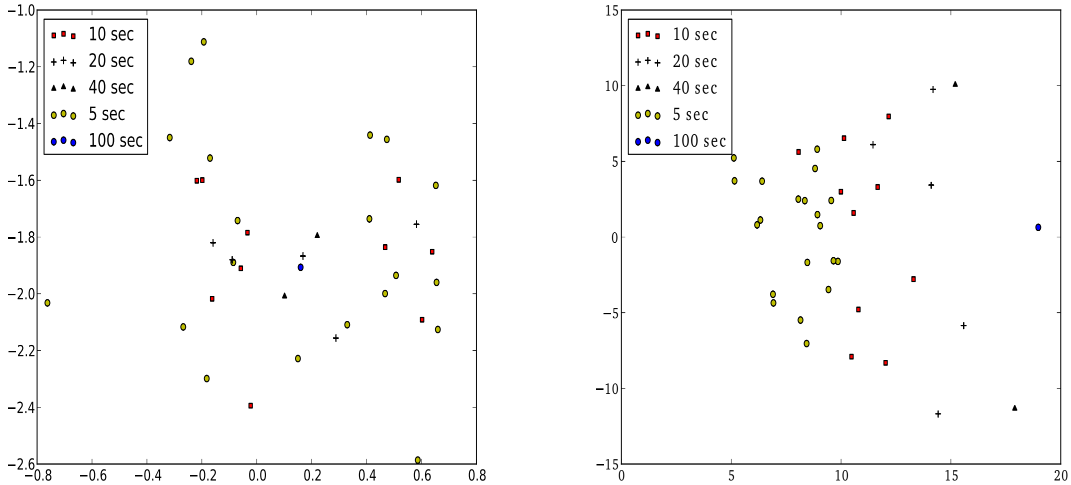
Short Utterance Variance Modelling and Compensation Techniques

8.1 Introduction

In the previous chapter, several channel compensation techniques were analysed with the short utterance CSS i-vector speaker verification system, and the PLDA speaker verification system was also studied with short utterances. However, these approaches have not helped to improve the performance of short utterance speaker verification significantly [46, 49, 104]. They restrict the design and use of the speaker verification systems in real world applications such as access control or forensics.

This chapter studies the shortcoming of short utterance i-vectors. The total-variability, or i-vector, approach has risen to prominence as the de-facto standard in recent state-of-the-art speaker verification systems due to its intrinsic capability to map an utterance to a single low-dimensional vector (the i-vector), turning a complex high-dimensional speaker recognition problem into a low-dimensional classical pattern recognition one. However, sight should not be lost of the fact that i-vectors are computed as point estimates of the hidden variables in a factor analysis model where the amount of available data plays an important role. Thus, i-vectors extracted from different durations should not be considered equal in reliability concerns. To address this issue, several approaches have been taken. Zhao *et al.* [114] have undertaken a variational-Bayes approach in order to integrate hidden factors of the model, avoiding the need for working on point estimates. More recently, Kenny *et al.* [59] have investigated how to quantify the uncertainty associated with the i-vector extraction process and propagated it into a PLDA classifier. Hasan *et al.* [34] have analysed the effect of short utterance i-vectors, finding that duration variability can be modelled as additive noise in the i-vector space, using a PLDA classifier.

Previous research studies had found that a collection of typical long utterance i-vectors contained variation due to two main sources of variation: changing speaker characteristics, and changing channel (or session) characteristics [20]. In this chapter, the limitations of short utterances are extensively studied with i-vector techniques and developed techniques to improve the speaker verification in short utterance evaluation conditions. Firstly, the shortcomings of short utterance i-vectors are investigated, by analysing the scatter plot of i-vector behaviour. Secondly, based on scatter plot analysis, the short utterance variance is introduced, defined as the inner product of difference between full-length and short-length i-vectors. Having captured the SUV, two techniques are introduced to attenuate the effect of the SUV, one based on CSS verification, the other on PLDA, designed to allow short utterances to provide a better representation of their full-length counterparts in i-vector speaker recognition.



(a) Original space

(b) PCA projected space

Figure 8.1: *Distribution of the first two dimensions of i-vector features of same speaker and session variability at varying utterance lengths:* (a) *Original space,* (b) *PCA projected space.*

8.1.1 Short utterance variation

In the previous chapter, it was found that when the utterance length reduces, the speaker verification performance reduces at an increasing rate rather than proportional, indicating that very short utterance i-vectors have a significant amount of uncertainty and the current state-of-the-art approaches fail to compensate completely for these uncertainties.

It is well known that typical full-length utterance i-vectors have speaker and session variation [54, 58]. However, it is hypothesized that i-vectors extracted from short utterances can also vary considerably with changes in phonetic content between i-vectors. Phonetic-content variation across a range of short utterances can be illustrated by comparing the most significant i-vector features as shown using the first two dimensions of the raw i-vectors in Figure 8.1(a), and of PCA-projected i-vectors in Figure 8.1(b). In the original space scatter plot, the two i-vector dimensions have just been randomly chosen and plotted, but there is no guarantee that these two dimensions show the larger variations. In order to see how the larger variation dimensions behave, the PCA plot was used. These plots show the variation in i-vectors captured from an identical full-length utterance (110400 from NIST2008 SRE), while the length over which the i-vectors are extracted is varied from 5 sec up to 100 sec.

As there are no speaker or session variations, one would expect the i-vectors extracted from 5 sec, 10 sec, 20 sec and 40 sec to all cluster closely around the full length (ie: 100 sec) i-vector. However as can be seen from scatter plots in Figure 8.1 this is not the case. As the i-vector extraction length is reduced from 40 sec to 5 sec, the points spread further apart. We hypothesize that this increase in spread is caused by the variation in phonetic content in the smaller speech lengths.

These plots clearly demonstrate that there is another source of variation (outside of speaker and session) when shorter utterances are used for i-vector extraction, which is believed to be largely related to the linguistic content of the short section of the utterance used for i-vector extraction. In traditional longer utterance i-vector extraction, this linguistic variation is averaged over a large variety of linguistic content, and can largely be ignored, but in short utterances it must be considered explicitly. This linguistic content variation is referred to as “short utterance variation”, and short utterance variance compensation techniques are introduced to adequately compensate this variation for short utterance i-vector extraction.

8.2 Short utterance variance normalization

In this section, short utterance variance normalization is introduced to compensate the short utterance variations present in CSS i-vector speaker verification. As has been demonstrated previously, short utterances cannot provide adequate information for reliably extracting speaker i-vectors when compared to longer utterances, but it is believed that the mismatch between shorter utterances and their longer counterparts can be compensated to improve the performance of short utterance speaker verification.

In order to capture the uncertainty in short utterances, a large set of development data is used to truncate each utterance to produce short utterances. The short utterance variance matrix , $\mathbf{S}_{SUV}$, can be calculated as the inner product of the difference between the full and short-length i-vectors, ie:

$$\mathbf{S}_{SUV} = \frac{1}{N}\sum_{n=1}^{N}(\mathbf{w}_n^{full} - \mathbf{w}_n^{short})(\mathbf{w}_n^{full} - \mathbf{w}_n^{short})^T \tag{8.1}$$

where $\mathbf{w}^{full}$ and $\mathbf{w}^{short}$ are respectively full- and short-length i-vector features. N is the total number of sessions.

Based upon the $\mathbf{S}_{SUV}$ estimation, the SUVN approach is introduced to compensate the utterance variation between short- and full-length utterances, and the SUVN matrix, $\mathbf{D}_1$, is calculated using the Cholesky decomposition of $\mathbf{D}_1\mathbf{D}_1^T = {\mathbf{S}_{SUV}}^{-1}$. The SUVN compensated i-vector ($\hat{\mathbf{w}}_{SUVN}$) is calculated as follows,

$$\hat{\mathbf{w}}_{SUVN} = \mathbf{D}_1\mathbf{w} \tag{8.2}$$

In the above approach, the SUVN technique is applied without a dimensionality reduction approach. However, session and utterance variation can be effectively compensated if it is applied on dimension-reduced space. By first transforming the i-vectors into a LDA-projected space, the combined SUVN[LDA] approach can provide further improvement over SUVN alone. In the SUVN[LDA] approach,

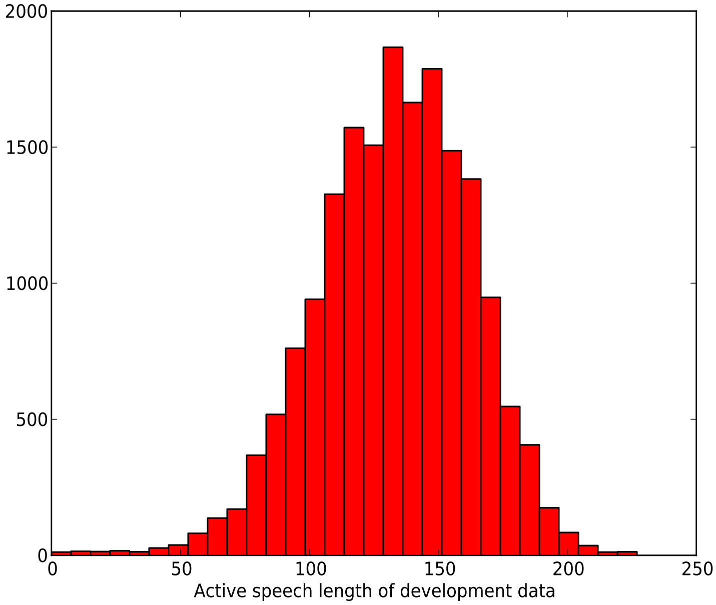


Figure 8.2: *Distribution of active speech length of NIST development data.*

first a LDA matrix, $\mathbf{A}$, is estimated as described previously in Chapter 5, and then the SUVN matrix is estimated on the LDA-projected subspace to compensate the utterance variation. The short utterance variance matrix, $\mathbf{S}_{SUV[LDA]}$, on the LDA projected space, is defined as follows,

$$\mathbf{S}_{SUV[LDA]} = \frac{1}{N}\sum_{n=1}^{N}(\mathbf{A}^T(\mathbf{w}_n^{full} - \mathbf{w}_n^{short}))(\mathbf{A}^T(\mathbf{w}_n^{full} - \mathbf{w}_n^{short}))^T \tag{8.3}$$

For $\mathbf{S}_{SUV[LDA]}$ estimation, the actual definition of what constitutes a full and/or short-length utterance needs to be established. The NIST 2004, 2005 and 2006 SRE corpora as well as Switchboard II were used as development data for SUV training, which includes 1386 female and 1117 male speakers. Looking at the distribution of active-speech length (utterance length after voice activity detection) across our development dataset shown in Figure 8.2, it can be seen that most utterances are over 100 sec. In order to provide a clear representation of a full-length utterance for this research, full-length was defined to be an 100-second

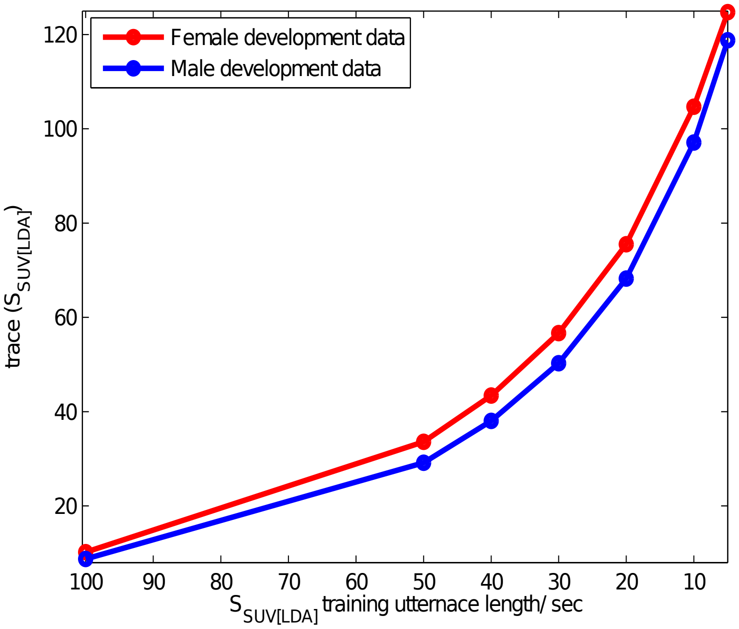


Figure 8.3: Variance captured in the $\mathbf{S}_{SUV[LDA]}$ matrix (measured using the trace) as the utterance lengths approach their full-length counterparts.

utterance, and development was therefore done accordingly on only development utterances over, or equal to, 100 sec in active-speech length, with all utterances trimmed to 100 sec of active speech. In order to capture the SUV, the short-utterances during development are represented by utterances trimmed to lengths of 5, 10, 30, 50, 90 and 99 sec of active-speech from the original utterances. One short utterance was extracted from the each original utterances.

The variation captured by SUV can be quantified simply using $trace(\mathbf{S}_{SUV[LDA]})$, and is shown in Figure 8.3. It is evident that when the utterance length used for $\mathbf{S}_{SUV[LDA]}$ training is reduced, the $\mathbf{S}_{SUV[LDA]}$ matrix captures more utterance variations due to the higher variation in linguistic content between individual utterances as utterance lengths are reduced.

The LDA projected SUVN matrix, $\mathbf{D}_2$, can be calculated using Cholesky de-

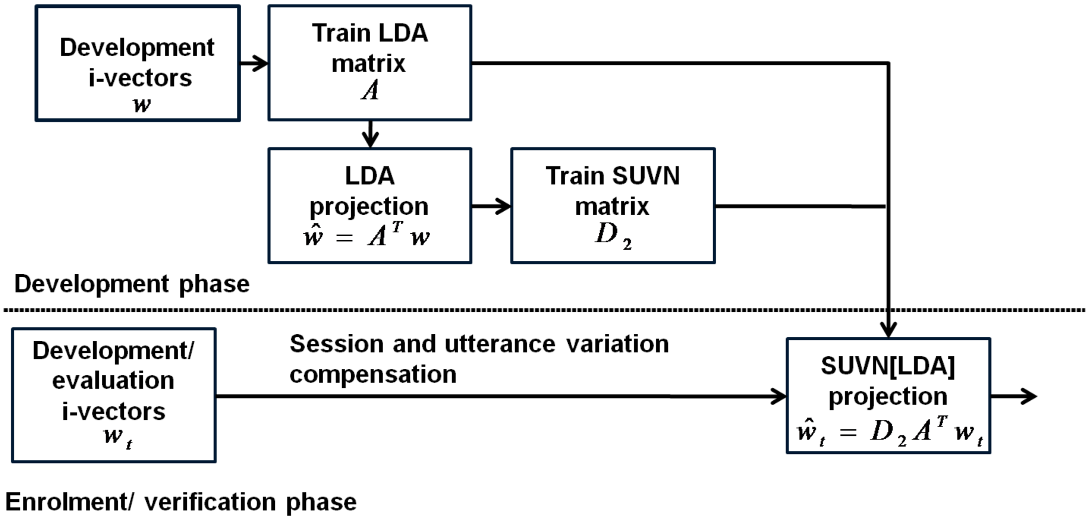

Development i-vectors w
Train LDA matrix A
LDA projection $\hat{w} = A^T w$
Train SUVN matrix D_2
Development phase
Development/ evaluation i-vectors w_t
Session and utterance variation compensation
SUVN[LDA] projection $\hat{w}_t = D_2 A^T w_t$
Enrolment/ verification phase

Figure 8.4: *A flow chart of SUVN[LDA] estimation.*

composition of $\mathbf{D}_2\mathbf{D}_2^T = \mathbf{S}_{SUV[LDA]}{}^{-1}$. The flow chart of SUVN[LDA] estimation is shown in Figure 8.4. The LDA projected utterance variation compensated i-vector ($\hat{\mathbf{w}}_{SUVN[LDA]}$) can be calculated as follows,

$$\hat{\mathbf{w}}_{SUVN[LDA]} \quad = \mathbf{D}_2\mathbf{A}^T\mathbf{w} \tag{8.4}$$

Similarly to the SUVN[LDA] approach outlined above, for the SUVN[SN-LDA] approach, after the i-vectors are first projected into session compensated SN-LDA space, a SUVN matrix is estimated to reduce the utterance variation.

By looking at the cosine distance scores between short (10 sec) and full (100 sec) utterance captured from the same utterance, as shown in Figure 8.5, it can be seen that while traditional LDA can decrease the cosine distance, much better performance can be obtained by SUVN[LDA] by taking advantage of the SUVN transformation.

It can also be clearly seen from Figure 8.5 that when the SUVN transformation is trained on 99 second short utterances (compared to the full-length of 100

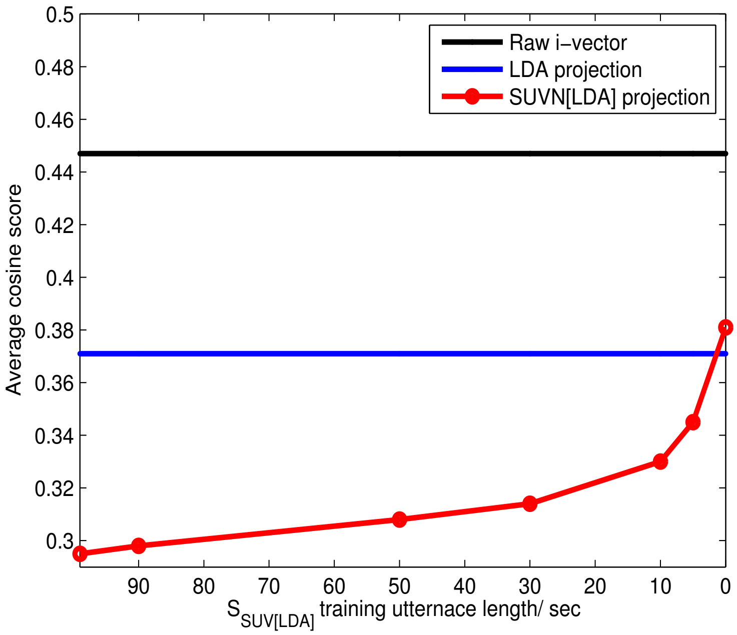


Figure 8.5: The similarity (measured in cosine distance score) between SUVN[LDA] projected full- and short-length utterances, under varying SUVN training length. Raw and LDA projected 10-second utterances are also included for comparison.

sec), both still have different linguistic content and the SUVN approach effectively compensates the utterance variation. When the SUVN training utterance length reduces further, though the $\mathbf{S}_{SUV[LDA]}$ matrix captures more utterance variance (refer Figure 8.3), the SUVN approach fails to compensate all the utterance variation as the Cholesky decomposition is applied to inverse of $\mathbf{S}_{SUV[LDA]}$ matrix, and it does not guarantee to compensate larger utterance variation.

8.2.1 Results and discussion

Baseline systems: The CSS i-vector system framework and experimental protocol were detailed in Chapter 4. The CSS i-vector and the standard GPLDA

Table 8.1: *Performance comparison of baseline systems on NIST 2008 truncated 10 sec-10 sec evaluation conditions. The best performing systems by both EER and DCF are highlighted across each column.*

(a) *CSS i-vector speaker verification*

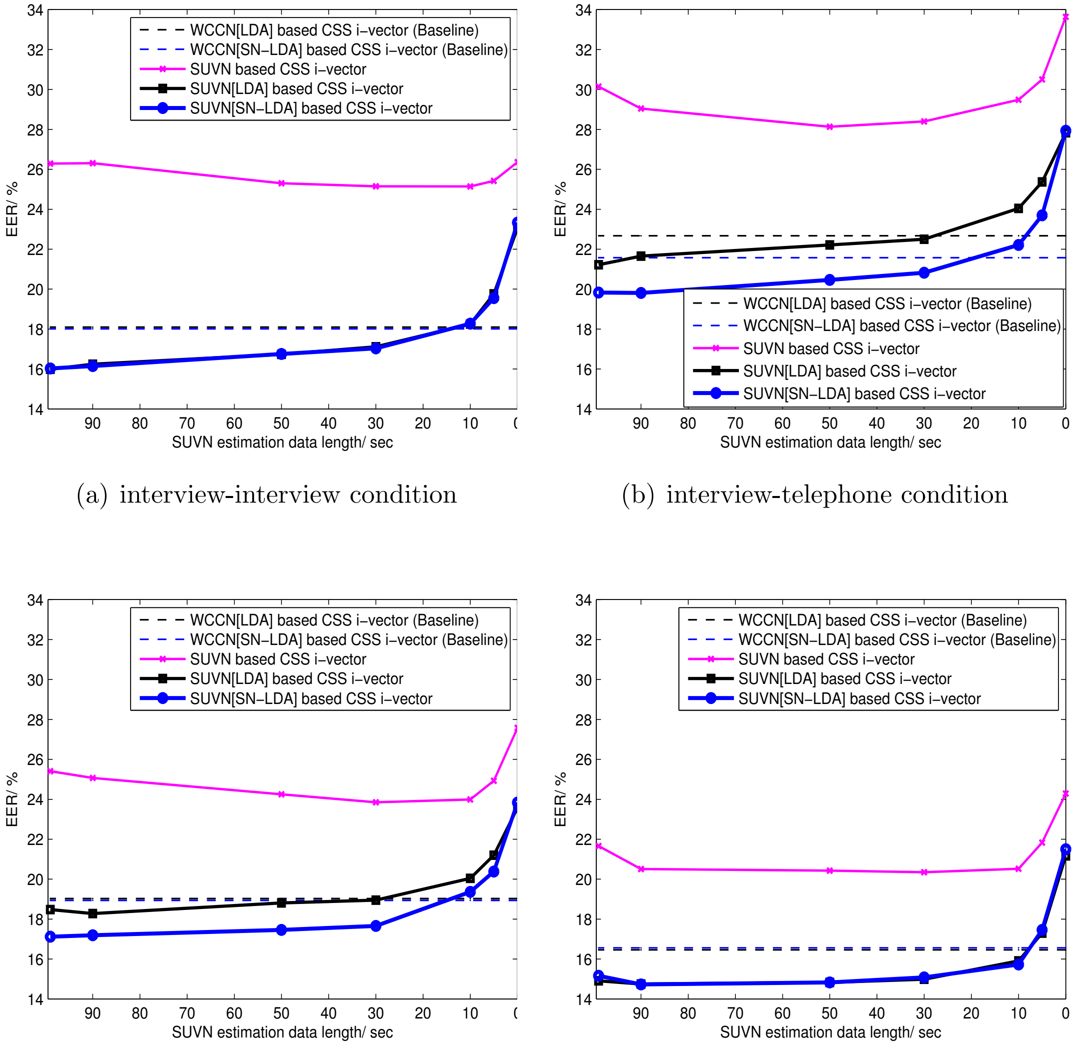
Approach	**Interview-interview**		**Interview-telephone**		**Telephone-microphone**		**Telephone-telephone**	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Uncompensated	25.51%	0.0923	32.70%	0.0975	26.41%	0.0880	23.48%	0.0805
WCCN	19.81%	0.0798	24.33%	0.0896	19.76%	0.0821	17.87%	0.0695
WCCN[LDA]	18.10%	**0.0767**	22.67%	0.0861	19.03%	0.0817	**16.46%**	**0.0679**
WCCN[SN-LDA]	**18.01%**	0.0771	**21.57%**	**0.0858**	**18.94%**	**0.0813**	16.56%	0.0683

(b) *GPLDA speaker verification*

Approach	**Interview-interview**		**Interview-telephone**		**Telephone-microphone**		**Telephone-telephone**	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Standard GPLDA	18.32%	0.0786	21.09%	0.0864	18.00%	0.0817	15.07%	0.0673
WCCN-GPLDA	18.36%	0.0786	21.09%	0.0864	18.00%	0.0816	**14.99%**	0.0674
WCCN[LDA]-GPLDA	**17.84%**	0.0769	20.38%	0.0843	17.72%	0.0809	15.80%	0.0664
WCCN[SN-LDA]-GPLDA	17.91%	**0.0767**	**20.09%**	**0.0838**	**17.66%**	**0.0807**	15.40%	**0.0661**

systems have been taken as our two baseline systems. The CSS i-vector systems, both with and without session variability compensation approaches; and the standard GPLDA approach, and session-compensated i-vector GPLDA approach were all evaluated to provide a reference as the baseline approaches perform in 10 sec-10 sec (enrolment-verification) evaluation conditions.

The performance comparison of CSS i-vector and GPLDA baseline systems for NIST 2008 truncated 10 sec-10 sec is shown in Table 8.1. As had been previously shown by Dehak *et al.* [20] for full-length utterances, it has been shown that the WCCN[LDA] CSS i-vector system provides an improvement over WCCN CSS i-vector system on shortened evaluation conditions as well. The results also confirm that the WCCN[SN-LDA] CSS approach provides an improvement over the WCCN[LDA] CSS approach on mismatched conditions, confirming and extending the full-length results shown by McLaren *et al.* [71]. However, the WCCN-projected GPLDA system has not shown any improvement over standard GPLDA as the full rank precision matrix, $\mathbf{\Lambda}$, in GPLDA, effectively models



(a) interview-interview condition

(b) interview-telephone condition

(c) telephone-microphone condition

(d) telephone-telephone condition

Figure 8.6: *Comparison of SUVN, SUVN[LDA] and SUVN[SN-LDA] against WCCN[LDA] and WCCN[SN-LDA] on the common subset of the 2008 NIST SRE truncated 10 sec-10 sec training and testing condition:* (a) *interview-interview,* (b) *interview-telephone,* (c) *telephone-microphone, and* (d) *telephone-telephone.*

the intra-speaker variance. However, the WCCN[LDA] and WCCN[SN-LDA] projected-i-vector GPLDA systems do show improvement over standard GPLDA system in mismatched conditions as the session variability compensation does

Table 8.2: *Comparison of the SUVN[LDA] and SUVN[SNLDA] systems against the WCCN[LDA] and WCCN[SN-LDA] systems on the common set of the 2008 NIST SRE truncated 10 sec-10 sec and 2010 NIST SRE truncated 10 sec-10 sec conditions. The best performing systems by both EER and DCF are highlighted down each column.*

(a) *NIST 2008 truncated 10 sec-10 sec condition*

System	***Interview-interview***		***Interview-telephone***		***Telephone-microphone***		***Telephone-telephone***	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Baseline (WCCN[LDA])	18.10%	0.0767	22.67%	0.0861	19.03%	0.0817	16.46%	0.0679
New approach (SUVN[LDA])	**15.99%**	0.0718	21.22%	0.0840	18.28%	0.0800	14.75%	**0.0618**
Relative improvement (%)	13.20%	6.82%	6.83%	2.50%	4.10%	2.13%	11.59%	9.87%
Baseline WCCN[SN-LDA]	18.01%	0.0771	21.57%	0.0858	18.94%	0.0813	16.56%	0.0683
New approach SUVN[SN-LDA]	16.03%	**0.0708**	**19.83%**	**0.0787**	**17.12%**	**0.0780**	**14.73%**	0.0620
Relative improvement (%)	10.99%	8.17%	8.07%	8.28%	9.61%	4.06%	11.05%	9.22%

(b) *NIST 2010 truncated 10 sec-10 sec condition*

System	***Interview-interview***		***Interview-telephone***		***Interview-microphone***		***Telephone-telephone***	
	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}
Baseline WCCN[LDA]	22.22%	0.0834	20.45%	0.0779	20.45%	0.0750	16.64%	0.0714
New approach SUVN[LDA]	**20.74%**	0.0798	20.45%	0.0756	**18.60%**	0.0708	14.55%	**0.0657**
Relative improvement (%)	6.66%	4.32%	0.00%	2.95%	9.05%	5.60%	12.56%	7.98%
Baseline WCCN[SN-LDA]	22.40%	0.0839	20.58%	0.0779	20.80%	0.0754	16.38%	0.0712
New approach SUVN[SN-LDA]	20.84%	**0.0796**	**19.17%**	**0.0727**	18.72%	**0.0697**	**14.41%**	0.0670
Relative improvement (%)	6.96%	5.13%	6.85%	6.68%	10.00%	7.56%	12.03%	5.90%

provide a benefit in this case.

Compensating short utterance variance using SUVN approach: In this section, experiments were conducted to examine whether our proposed short utterance variance normalization technique can improve over existing approaches for short utterance i-vector extraction. Initially, the SUVN, SUVN[LDA] and SUVN[SN-LDA] approaches were analysed against WCCN[LDA] and WCCN[SN-LDA] on NIST 2008 SRE truncated 10 sec-10 sec training and testing conditions. The SUVN compensation approach was trained using different short utterances lengths, from 0 sec to 99 sec, as shown being evaluated against 10 sec-10 sec training-testing conditions in Figure 8.6. The special case of 0 sec, indicates that the SUVN matrix is captured on full-length utterances and therefore estimated as the inner-product of the full-length (100 second) i-vectors. It can be observed in Figure 8.6 that when the SUVN compensation matrix is trained on short utterances above 90 sec, the SUVN[LDA] and SUVN[SN-LDA] approaches achieve the best performance as the SUVN approach effectively compensates the utterance variation even when SUVN is trained on almost similar sized full- and short-length utterances.

When the SUVN training reduces below the 10 sec length of the evaluation (train-test) utterances, even though the SUV matrix captures more utterance variance (as was seen in Figure 8.3), the SUVN approaches are not as effective in improving the speaker verification as the very short-length i-vector estimate has a significant amount of uncertainty, and Cholesky decomposition of $\mathbf{D}_2\mathbf{D}_2^T = \mathbf{S}_{SUV[LDA]}{}^{-1}$ cannot compensate the utterance variation adequately. This chapter only shows evaluation on 10 sec-10 sec conditions, but similar findings exist for other shortened evaluation data, with SUVN performance degrading considerably in all cases as the development lengths go below the evaluation lengths.

The performance of the SUVN[LDA] and SUVN[SN-LDA] systems depend heavily on the short utterance development data used for estimation of the SUVN transformation, and the best short utterance lengths were selected for SUVN[LDA] and SUVN[SN-LDA] estimation for each condition. Using the short-utterance lengths chosen from Figure 8.6 to provide the lowest EER, the results of the SUVN approaches against the baseline systems using 10sec-10sec train-test evaluation utterances across the NIST 2008 and NIST 2010 evaluation datasets are shown in Table 8.2. These results suggest that the SUVN[LDA] approach shows over 10% relative improvement over the WCCN[LDA] approach on *telephone-telephone* and *interview-interview* conditions as it adequately compensates the utterance variation between short and full-length utterances. The SUVN[SN-LDA] approach has also shown over 8% relative improvement when compared to the WCCN[SN-

LDA] approach in the *interview-telephone* and *telephone-microphone* mismatched conditions as it is compensating the utterance and source variation present. These results suggest that the traditional session variability compensation approaches, including WCCN[LDA] and WCCN[SN-LDA], should be replaced with the SUVN[LDA] and SUVN[SN-LDA] for short-utterance CSS speaker verification.

Subsequently, the SUVN approach was also analysed with GPLDA speaker verification; however our experiment studies have found that the SUVN[LDA] projected GPLDA system has failed to show improvement over the WCCN[LDA] projected GPDLA system as the full-rank precision matrix of GPLDA approach effectively reduces the mismatch between full- and short-length i-vectors.

8.3 Modelling the short utterance variance using GPLDA

An alternative approach to modelling the short utterance variance using PLDA is investigated in this section. In this section, length-normalized GPLDA approach was chosen instead of HTPLDA approach as length-normalized GPLDA is computationally efficient approach and it achieves similar performance as HTPLDA approach. Modelling the short utterance variance using GPLDA is based upon recent work by Hasan *et al.* [34], where they showed that duration variability can be considered as additive noise in the i-vector space, modelled using the PLDA approach. In this section, a similar approach is taken to model the short utterance variation on LDA and SN-LDA projected spaces. Length-normalized GPLDA approach was chosen for this analysis as it is computationally approach and achieves similar performance as HTPLDA approach.

As full-length utterances do not have significant utterance variations, utterance variation information is artificially added to full-length utterances and short utterance variance is modelled using the PLDA approach. The short utterance variance (SUV) matrix, $\mathbf{S}_{SUV}$, can be estimated using the Equation 8.1. The SUV decorrelated matrix, $\mathbf{D}_3$, is calculated using the Cholesky decomposition of $\mathbf{D}_3\mathbf{D}_3^T = \mathbf{S}_{SUV}$. A random vector with utterance variation information can be generated if random normally independently distributed vector, $\mathbf{d}$, with mean zero and variance one, is multiplied by SUV decorrelated matrix, $\mathbf{D}_3$. The SUV added full-length development vectors can be estimated as follows,

$$\mathbf{w}_{full_{SUV}} = \mathbf{w}_{full} + \mathbf{D}_3{}^T\mathbf{d} \tag{8.5}$$

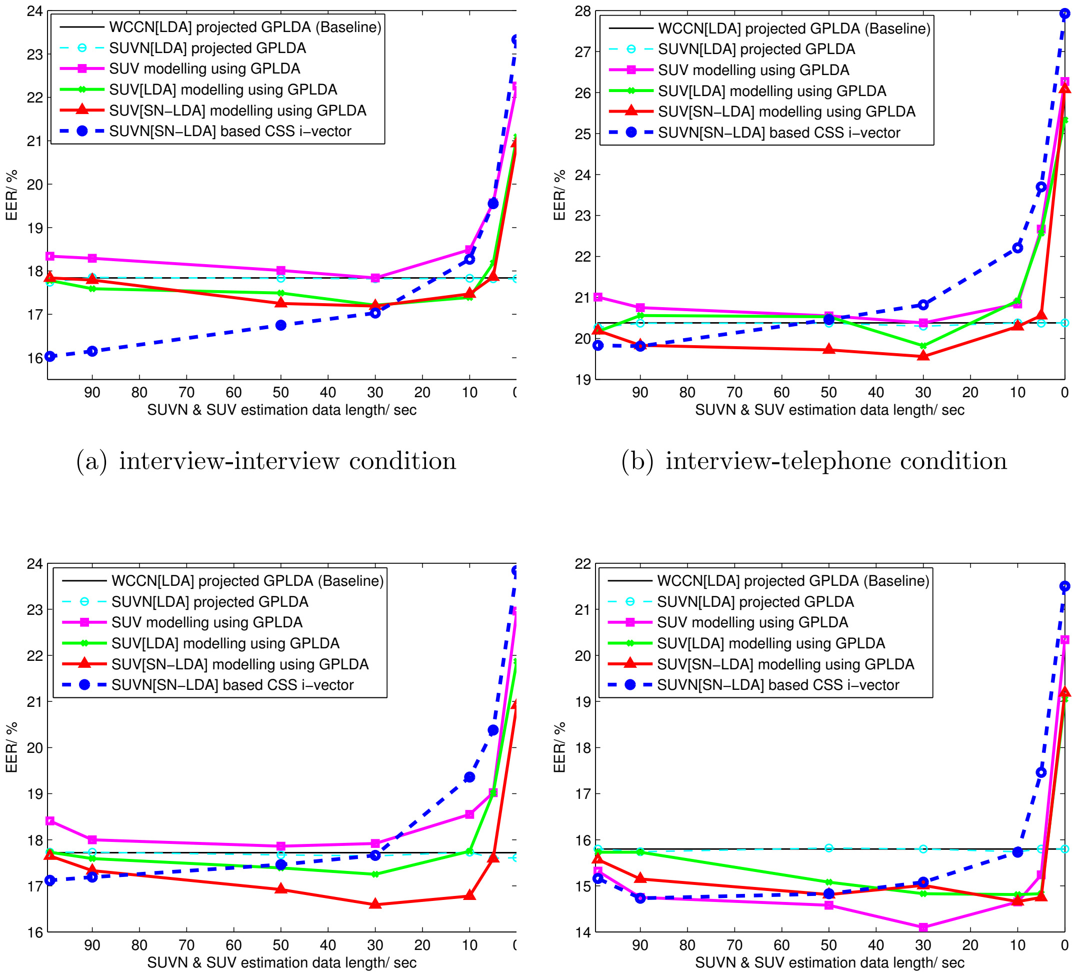
After SUV-added full-length i-vectors are extracted, the length-normalized GPLDA model parameters are estimated in the usual way as described in Chapter 3.

8.3.1 Modelling the SUV on LDA projection

As an extended work of Hasan *et al.* [34], the GPLDA modelling of SUV is analysed on LDA and SN-LDA projected space. Similarly to the extraction of SUV variation added full-length i-vectors, the SUV[LDA] variations-added full-length i-vectors can be extracted as follows,

$$\mathbf{w}_{full_{SUV[LDA]}} = \mathbf{A}^T\mathbf{w}_{full} + \mathbf{D}_4^T\mathbf{A}^T\mathbf{d} \tag{8.6}$$

The estimation of the LDA matrix, $\mathbf{A}$, is detailed in Chapter 3, and the short utterance variance matrix, $\mathbf{S}_{SUV[LDA]}$, on LDA projected space is estimation using Equation 8.3. The SUV decorrelated matrix, $\mathbf{D}_4$, is calculated using Cholesky decomposition of $\mathbf{D}_4\mathbf{D}_4^T = \mathbf{S}_{SUV[LDA]}$. The SUV[SN-LDA] variance added full-length i-vectors are also extracted in a similar way of SUV[LDA] variation-added full-length i-vectors. Once LDA or SN-LDA followed by SUV variation-added full-length vectors are extracted, the GPLDA model parameters are estimated as described in Chapter 3.



(a) interview-interview condition

(b) interview-telephone condition

(c) telephone-microphone condition

(d) telephone-telephone condition

Figure 8.7: *Comparison of SUV, SUV[LDA], SUV[SN-LDA] modelling using GPLDA approach against WCCN[LDA], SUVN[LDA] projected GPLDA and SUVN[SN-LDA] based CSS i-vector systems on the common subset of the 2008 NIST SRE truncated 10 sec-10 sec training and testing condition:* (a) *interview-interview,* (b) *interview-telephone,* (c) *telephone-microphone, and* (d) *telephone-telephone.*

8.3.2 Results and discussion

In this section, an alternative approach will be demonstrated extending upon the work of Hasan *et al.* [34], to show that the SUV GPLDA approach outlined in Section 8.3 can effectively model the short utterance variance in a GPLDA i-vector approach. The framework of GPLDA speaker verification and experimental protocol were detailed in Chapter 4.

A performance comparison of the SUV GPLDA approaches (SUV[LDA] and SUV[SN-LDA]), against GPLDA and session-compensated baseline GPLDA approaches (WCCN[LDA], SUVN[LDA]) is shown in Figure 8.7. The best-performing SUVN[LDA] CSS approach from the previous section is also included for comparison. From these results, it can be observed that SUV GPLDA approaches are shown to provide a clear improvement over the WCCN[LDA] and SUVN[LDA] GPLDA approaches on the matched telephone-telephone condition. On the other hand, the SUV[LDA] and SUV[SN-LDA] GPLDA approaches are shown to provide improvement over the WCCN[LDA] and SUVN[LDA] GPLDA approaches across all conditions when the GPLDA SUV process is trained using 30 sec utterances, allowing the GPLDA approach to explicitly model the short utterance variation and capture more speaker discriminant information.

It can be seen in Figure 8.7, that when the SUV training utterance length goes below 5 sec, speaker verification performance reduces drastically as very short utterance i-vectors have a large level of uncertainty and provide an unreliable estimate of the 'true' full-length i-vector. In addition, it is also observed that when the SUV training utterances are longer than 50 sec, the captured utterance variation reduces (as seen in Figure 8.3), and the lesser variation available between the short and full-length utterances produces a related reduction in speaker verification performance.

Table 8.3: *Comparison of SUV, SUV[LDA], SUV[SN-LDA] modelling using GPLDA approach against WCCN[LDA] projected GPLDA system on the common set of the 2008 NIST SRE truncated 10 sec-10 sec and 2010 NIST SRE truncated 10 sec-10 sec conditions. The best performing systems by both EER and DCF are highlighted down each column.*

(a) *NIST 2008 truncated 10 sec-10 sec condition*

System	***Interview-interview***		***Interview-telephone***		***Telephone-microphone***		***Telephone-telephone***	
	EER	DCF	EER	DCF	EER	DCF	EER	DCF
Baseline system								
WCCN[LDA]-GPLDA	17.84%	0.0769	20.38%	0.0843	17.72%	0.0809	15.80%	0.0664
Modelling utterance variation using GPLDA								
SUV modelling	17.84%	0.0718	20.38%	0.0840	17.92%	0.0739	**14.10%**	0.0644
Relative improvement (%)	0.00%	6.63%	0.00%	0.36%	-1.13%	8.65%	10.76%	3.01%
SUV[LDA] modelling	17.21%	0.0735	19.82%	0.0854	17.25%	0.0775	14.81%	**0.0617**
Relative improvement (%)	3.53%	4.42%	2.75%	-1.30%	2.65%	4.20%	6.27%	7.08%
SUV[SN-LDA] modelling	**17.19%**	**0.0697**	**19.56%**	**0.0804**	**16.59%**	**0.0715**	14.66%	0.0646
Relative improvement (%)	3.64%	9.36%	4.02%	4.63%	6.38%	11.62%	7.22%	2.71%

(b) *NIST 2010 truncated 10 sec-10 sec condition*

System	***Interview-interview***		***Interview-telephone***		***Interview-microphone***		***Telephone-telephone***	
	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}	EER	DCF_{old}
Baseline system								
WCCN[LDA]-GPLDA	21.51%	0.0844	19.84%	0.0787	19.70%	0.0757	16.55%	0.0701
Modelling utterance variation using GPLDA								
SUV modelling	**21.06%**	**0.0810**	19.12%	0.0775	**18.42%**	**0.0709**	**14.83%**	**0.0685**
Relative improvement (%)	2.09%	4.03%	3.63%	1.52%	6.50%	6.34%	10.39%	2.28%
SUV[LDA] modelling	21.37%	0.0822	**19.04%**	**0.0761**	18.69%	0.0729	14.96%	0.0686
Relative improvement (%)	0.65%	2.61%	4.03%	3.30%	5.13%	3.70%	9.61%	2.14%
SUV[SN-LDA] modelling	21.42%	0.0820	19.41%	0.0768	19.30%	0.0729	15.11%	0.0670
Relative improvement (%)	0.42%	2.84%	2.17%	2.41%	2.03%	3.70%	8.70%	4.42%

Similarly to the CSS i-vector results reported earlier, the performance of the SUV GPLDA approaches depend heavily on the length of the short utterance development data used for calculating the SUV-added GPLDA modelling, and the best short utterance lengths were selected for SUV, SUV[LDA] and SUV[SN-LDA] estimation for each condition. Using the short-utterance lengths chosen from Figure 8.7 that provide the lowest EER, the results of the SUV GPLDA approaches against the baseline systems using 10 sec-10 sec train-test evaluation utterances against the NIST 2008 and NIST 2010 evaluation datasets are shown in Table 8.3. It can be seen that the SUV GPLDA modelling approaches show an improvement over the baseline systems, as the SUV-added GPLDA approach can effectively model the short utterance variance. Based upon these results, it is believed that using SUV-added full-length utterances instead of full-length utterances for GPLDA modelling is a better approach for short utterance evaluation of GPLDA speaker verification. These research outcomes were published in Speech Communication journal [44].

8.4 Chapter summary

The performance of i-vector speaker verification systems degrades rapidly as the available amount of enrolment and/or verification speech decreases, limiting the utility of speaker verification in real world applications. This chapter proposes techniques to improve the performance of i-vector-based speaker verification systems, when only short speech utterances are available. This study has been based on two state-of-the-art, i-vector-based speaker recognition systems: the CSS i-vector and length-normalised GPLDA.

Previous research studies have found that a typical i-vector contains both speaker and session variation. In this chapter, the shortcomings of short utterance i-vector features were studied, and in the process, provided two major insights. The first insight is that, in addition to speaker and session variation, short utterance i-vectors also exhibit considerable utterance variation arising from differences in linguistic content, whereas long utterance i-vectors' linguistic variation can normally be averaged out over the length of the utterance. The second insight is that the utterance variation due to the differences in the linguistic content of short utterances can be learned using the development data of i-vectors. Based upon these observations, the concepts of SUVN and SUV have been introduced to compensate the session and utterance variations in CSS i-vector and PLDA speaker verification systems. The performance of the speaker verification systems with these utterance variation compensation techniques combined with various state-of-the-art session variability compensations have been investigated for short-duration speech.

There are two key recommendations arising from this research for i-vector speaker verification with short utterances: (i) when a CSS i-vector approach is used, the use of SUVN[LDA] and/or SUVN[SN-LDA] is recommended instead of standard session variability compensation approaches, such as WCCN[LDA] and/or WCCN[SN-LDA], (ii) when a PLDA approach is used, it is recommended that the use of WCCN[LDA] and/or WCCN[SN-LDA] followed by SUV modelling using PLDA. It is important in this implementation to artificially add utterance variation information to the full-length i-vectors for SUV modelling, as full-length short utterances do not, by definition, have any utterance variation.

Chapter 9

Conclusions and Future Directions

9.1 Introduction

This chapter provides a summary of the work presented in this dissertation and the conclusions drawn from it. The summary follows the three main research themes and areas of contribution identified in Chapter 1: compensating the training and testing mismatch, improving the speaker verification performance in limited development data and short utterance training/ evaluation data conditions.

9.2 Conclusions

9.2.1 Compensating the training and testing mismatch in CSS i-vector speaker verification

Chapter 5 studied the shortcoming of standard channel compensation approaches and introduced several novel advanced channel compensation approaches to improve the performance of CSS i-vector speaker verification.

In recent times, the CSS i-vector speaker verification approach has become one of the state-of-the-art approaches to speaker verification. As i-vectors are based on one variability space, previously several standard channel compensation approaches, including LDA, WCCN and NAP, have been proposed to compensate the channel variations. A question unanswered was that whether standard channel compensation approaches can be used to effectively compensate the channel variation or if there are any other methods that can be used to effectively compensate the channel variation.

The several novel advanced channel compensation approaches, including WMMC, WLDA, SN-WMMC and SN-WLDA were introduced to effectively compensate the channel variations and improve the performance of CSS i-vector speaker verification system.

- **WMMC and SN-WMMC approach:** In the LDA approach, the transformation matrix is calculated as the ratio of between-class scatter to within-class scatter, and the level of importance of within- and between-class scatters cannot be changed. The WMMC approach was introduced to change the level of importance of within- and between-class scatters by weighing coefficients. Subsequently, the SN-WMMC approach was introduced to CSS i-vector system. The studies in Chapter 5 found that a standard SN-LDA approach could be replaced with SN-WMMC as that captures the source variation and can be used to change the level of importance of within- and between-class scatters by weighing coefficients.

- **WLDA and SN-WLDA approach:** LDA cannot take advantage of the discriminative relationships between the class pairs which are much closer due to channel similarities, and the traditional estimation of between-class scatter matrix is not able to adequately compensate. The novel WLDA technique was introduced to overcome this problem, by weighting the distances between classes that are closer to each other higher to reduce class confusion. Several novel weighting functions, such as Euclidean, Mahalanobis and Bayes error were introduced to extract more discriminative information. Based upon the WLDA and SN-LDA concepts, a novel SN-WLDA approach was also introduced to the CSS i-vector system. Several source-dependent and source-independent weighting functions were introduced for CSS i-vector speaker verification, which should show an improvement in performance across both matched and mismatched enrolment/ verification conditions. The studies in Chapter 5 have found that SN-WLDA would be a better channel compensation approach than LDA, WMMC, SN-LDA, SN-WMMC, and a SN-WLDA-based CSS i-vector system would provide state-of-the-art performance.

- **Score-level fusion channel compensation analysis:** Several novel channel compensation techniques, including WMMC, SN-WMMC, WLDA and SN-WLDA were introduced above. It was also hypothesised that as different types of channel compensation approaches extract different discriminant information, fusion of these channel compensation approaches would provide an improvement. It was also found that fusion of SN-WLDA and SN-WMMC provide an improvement over individual approaches in mismatched and interview-interview conditions.

9.2.2 Compensating the channel variability using channel compensation and PLDA approach

Chapter 6 investigated the length-normalized GPLDA approach to improving the speaker verification performance in mismatched conditions. Subsequently, a novel SN-WLDA and GPLDA combined approach was introduced to improve performance. Further, a number of techniques were also introduced to improve GPLDA performance in limited session data conditions. Lastly, a novel linear-weighted approach was also introduced to improve the GPLDA performance in limited microphone speech conditions.

- **SN-WLDA projected GPLDA approach:** It was hypothesized that rather than attempting to model the speaker and channel variability on the original i-vector space, a more sophisticated attempt would model the session and speaker variability on channel compensated-i-vector features. In Chapter 5, it was found that SN-WLDA provides state-of-the-art channel compensation approach for CSS i-vector speaker verification. The studies in Chapter 6 found that a SN-WLDA-projected GPLDA approach would be the state-of-the-art approach, and standard length-normalized GPLDA could be replaced with an SN-WLDA-projected GPLDA approach.

- **Improving the GPLDA system in limited session data:** In adverse noise conditions, reliable GPLDA model parameters can be estimated when a considerable amount of session data is available; however, it is difficult to collect a large amount of session data. To deal with this problem, initially length-normalized GPLDA speaker verification performance was studied when a GPLDA approach is modelled using a limited number of session data, and it was found that limited session data considerably affects the speaker verification performance. Subsequently, several novel techniques, including WLDA and WMFD, were introduced to GPLDA speaker verification to improve the speaker verification performance in a scarce session variability data scenario.

- **Improving the GPLDA system in limited microphone data:** A significant amount of speech data is required to develop a robust speaker verification system, especially in the presence of the microphone data conditions as they contain large amounts of intersession variability. A large amount of telephone speech data is available in the NIST SRE databases; however, microphone speech data is scarce in this data set. In order to improve the speaker verification performance in limited microphone conditions, a new approach was introduced to estimate reliable GPLDA model parameters as a linear-weighted model, taking more input from the large volume of available telephone data and smaller proportional input from limited microphone data. This approach has shown improvement over a traditional pooled-based approach.

9.2.3 Extensive analysis of CSS i-vector and PLDA speaker verification systems on short utterances

Chapter 7 studied the CSS i-vector and PLDA speaker verification system with short utterance evaluation and development data conditions. Based upon the studies, a novel SUN-LDA approach was introduced to improve the CSS i-vector speaker verification on short utterance evaluation conditions.

- **CSS i-vector speaker verification system on short utterances:** The CSS i-vector speaker verification system was analysed in short utterance evaluation conditions and found that when the utterance length reduces, performance reduces in an increasing rate, rather than a proportional one. An advanced channel compensation approach, SN-WLDA, has not also shown any major improvement over a baseline approach as short utterance evaluation data may not have enough discriminant information; however, when the SN-WLDA was analysed with full training and short testing conditions, it showed an improvement over LDA baseline approach as sufficient discriminant information is available in the enrolment data.

- **Analysis of channel compensation approaches with short utterance development data:** The short utterance CSS i-vector speaker verification performance was analysed when channel compensation approaches were trained using the short utterance development data. It was found that when intra-speaker variance is trained using the short utterances, it considerably affects the CSS i-vector performance as short utterances have a large variation due to limited linguistic content, and it deteriorates the quality of intra-speaker variance. However, when short utterances are used for inter-speaker variance, it does not reduce the quality of inter-speaker variance. Based upon this analysis, a novel SUN-LDA approach was introduced to the CSS i-vector system and it has shown improvement over baseline approaches as it captures the source variation information from full- and short-length i-vectors.

- **PLDA speaker verification system on short utterances:** The GPLDA and HTPLDA approaches were analysed with short utterance evaluation data, and it was found that when the utterance length reduces, the performance reduces in increasing rate. Subsequently, GPLDA and HTPLDA approaches' performances were analysed when GPLDA and HTPLDA approaches were modelled using full and short utterances. It was found that when HTPLDA/ GPLDA is trained using short utterances, it has shown a significant improvement as a PLDA approach effectively models any variations. It was also found that when score normalization was trained using short-length utterances rather than full-length utterances, the PLDA approach has shown an improvement. Lastly, telephone and microphone-based speaker verification system was analysed with pooled and concatenated total-variability approaches, and it was found that a pooled approach is a better than a concatenated approach.

9.2.4 Short Utterance Variance Modelling and Compensation Techniques

Chapter 8 studied the shortcomings of short utterance i-vectors using the scatter plot analysis, and found that long-length utterance i-vectors may vary with speaker and channel variations, whereas short-length utterance i-vectors may vary with speaker, channel and utterance variations. A novel SUVN approach was introduced to the CSS i-vector system to compensate the channel and utterance variations, and this approach has shown an improvement over the baseline approach, WCCN[LDA] CSS i-vector system. Subsequently, it was also found that instead of compensating the short utterance variation, PLDA approach could alternatively be used to directly model the short utterance variance. The LDA and SN-LDA followed by SUV modelling using a PLDA approach has also shown to provide improvement over a standard GPLDA approach. The results suggest that the short utterance variance added full-length utterances, instead of full-length utterances, would be required for PLDA modelling in order to obtain an improved speaker verification performance.

9.3 Future work

We propose two main directions in which future research can be carried out: (1) Improving speaker recognition performance using weighted intra-speaker variance, and (2) Improving speaker recognition performance in the presence of channel noise.

9.3.1 Improving speaker recognition performance using weighted intra-speaker variance

In this research program, we have analysed weighted between-class estimation to increase the between-speaker variability. However, there has been no investigations to reduce the intra-speaker variance. We propose the introduction of weighted intra-speaker variance, to reduce intra-speaker variance using the following approaches:

- In an SN-WLDA-projected GPLDA system, SN-WLDA approaches were applied prior to the PLDA modelling, and this has also shown an improvement. In the future, it could be investigated how to incorporate the weighted between-speaker variance estimations within the PLDA modelling to capture discriminative information within pair of classes.

- In the limited session data-based GPLDA approach, when the speaker part hidden variable is estimated, averaging all the session data is used to compensate the session variations. However, if limited session data is available, averaging the session data is not a good option, and a median-based approach could be applied instead of averaging.

- In the limited microphone data-based GPLDA approach, it is hypothesized that instead of directly estimating the PLDA parameters on microphone data, estimating the PLDA parameters on telephone data and adapting these parameters to microphone data, and combining the telephone and microphone-based PLDA parameters using a linear-weighted approach, would be a good option.

9.3.2 Improving speaker recognition performance in the presence of channel noise

Due to the relatively clean conditions in which current speaker recognition is deployed, significant effort has not focused on speaker recognition in noisy channel conditions. In the future, speaker recognition system will need to operate in harsh environments encountered in forensic and wireless applications. In these conditions the effectiveness of the voice activity detection (VAD) stage at the front-end will be of importance and an accurate VAD will be a crucial factor in determining overall performance. Robust VAD has never been a large focus of state-of-the-art speaker recognition systems, with many systems (including our research) relying on simple energy-based metrics for separating speech from the background. To improve the robustness and performance of VAD for speaker recognition in mismatched noisy conditions in i-vector-based speaker recognition systems, a Baum-Welch statistics approach that integrates VAD directly into i-vector extraction could be used, thus reducing the error due to the front-end-effect of separate VAD. By allowing the i-vector extraction to focus on the sections of the utterance most likely to be clean speech, this approach will also allow for better calculation of short utterance i-vectors.

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