Department of Systems Engineering and Engineering Management The Chinese University of Hong Kong

SEEM3510

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Introduction of speaker recognition

Biometric recognition

- Face
- Fingerprint
- Palmprint
- DNA
- Iris
- Signatures
- Voiceprint

. .









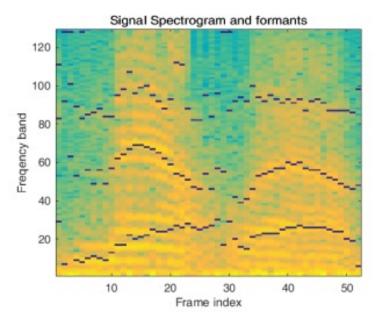
Why voice biometric

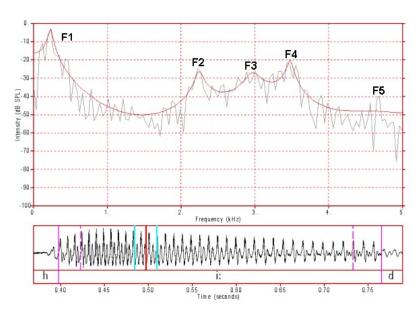


- An efficient and more natural choice for remote authentication
 - Local: fingerprint, face
- A low-cost and convenient approach to authentication
- Voice is the most natural signal not involving privacy issues

Spectrogram of the speech signals

How to detect a word("matlab")? spectrum(t, f) = STFT(wav(t))





- Convert Wave from time domain into frequency domain, using short Fourier fast transformation (STFT).
 - Resonance peaks
 - Harmonics frequencies fundamental frequency

Speaker recognition tasks

- Speaker recognition is the identification of a person from characteristics of voices (voice biometrics)
 - Verification or authentication: If the speaker claims to be of a certain identity and the voice is used to verify this claim, which is a 1:1 match task.
 - *Identification*: Determine an unknown speaker's identity with an utterance, which is a 1:N match task.

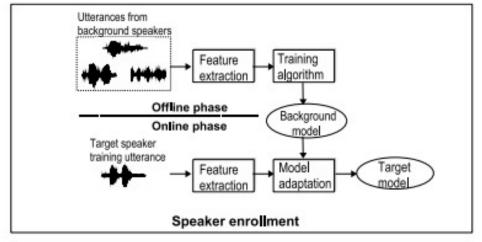


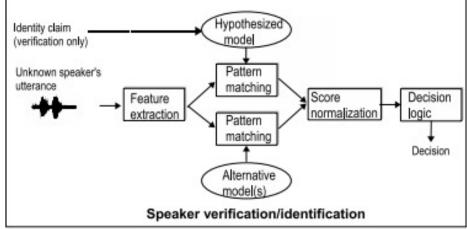


Speaker recognition system

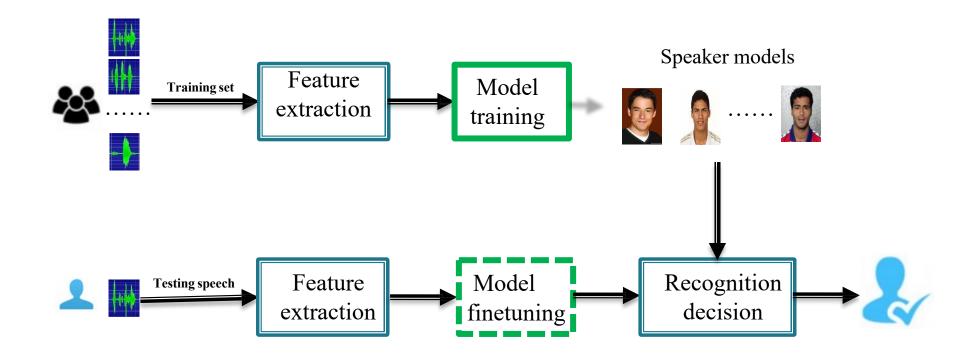
- Speaker enrollment (training)
 - Collect target speakers' information from their utterances to train the target recognizer models.
 - Train a background model based on all speakers' information.

- Speaker verification (test)
 - The feature vectors extracted from the unknown speaker's utterance are compared against the target speaker model(s) to give a similarity score.





Framework of speaker recognition



Features for speaker recognition

- High-level features
 - Phones, idiolect, accent, pronunciation
 - "uh-huh", "you know", "oh yeah", etc.
 - Can be learned from familiar people
- Prosodic feature
 - Pitch, rhythm
- Short-term spectral
 - Spectrum (e.g. MFCC, filter bank)
 - Easy to extract, small amount
 - Vulnerable to noise and channels

- + Robust against channel effects and noise
- Difficult to extract
- A lot of training data needed
- Delayed decision making
- + Easy to extract
- + Small amount of data necessary
- + Text- and language independence
- Real-time recognition
- Affected by noise and mismatch

High-level features

Phones, idiolect (personal lexicon), semantics, accent, pronunciation

Prosodic & spectrotemporal features

Pitch, energy, duration, rhythm, temporal features

Short-term spectral and voice source features

Spectrum, glottal pulse features

Learned (behavioral)

Socio-economic status, education, place of birth, language background, personality type, parental influence

Physiological (organic) Size of the vocal folds, length and dimensions of the vocal tract

Universal background model combined with Gaussian Mixture model: GMM-UBM

- Universal background model (UBM) is first trained with the Expectation Maximization (EM) algorithm from a large number of speakers as GMMs.
 - When enrolling a new speaker to the system, the parameters of the UBM are adapted to the feature distribution of the new speaker.
 - The adapted model

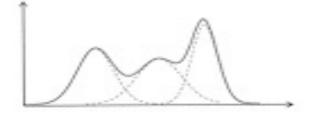
$$P(X \mid \lambda^{ubm}) = \sum_{i=1}^{C} \overline{w}_{i} \mathbf{N} \left(X \mid \overline{\mu}_{i}, \overline{\Sigma}_{i}\right)$$

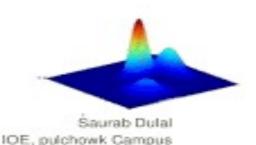
$$\lambda^{ubm} = \left\{ \overline{w}_i, \overline{\mu}_i, \overline{\Sigma}_i \right\}$$

X:input features

i: gaussian component

GMM Gaussian mixture models





Reynolds, D., Quatieri, T., and Dunn, R. Speaker verification using adapted gaussian mixture models. Digital Signal Processing 10, 1 (January 2000), 19–41

GMM-UBM: speaker adaptation

Given the enrollment samples with T frames, and UBM parameters

$$X^{k} = \left[X_{1}^{k}, X_{2}^{k}, ..., X_{T}^{k}\right] \qquad \lambda^{ubm} = \left\{\overline{w}_{i}, \overline{\mu}_{i}, \overline{\Sigma}_{i}\right\}$$

- Using maximum a posteriori (MAP) method
 - Align each frame into different Gaussian components

$$P\left(\lambda_{i}^{ubm} \mid X_{t}^{k}\right) = \frac{\overline{w}_{i} N\left(X_{t}^{k} \mid \overline{\mu}_{i}, \overline{\Sigma}_{i}\right)}{\sum_{i'=1}^{M} \overline{w}_{i'} N\left(X_{i'}^{k} \mid \overline{\mu}_{i'}, \overline{\Sigma}_{i'}\right)}, i = 1, ..., C$$

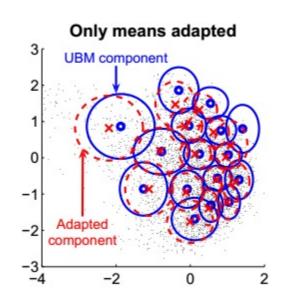
 Compute the zero, first, and second statistics, and then update the means of the Gaussian Components as the target model

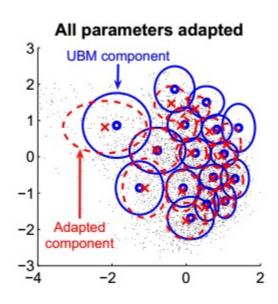
$$\tilde{\mu}_{i}^{k} = \frac{\sum_{t=1}^{T} P\left(\lambda_{i} \mid X_{t}^{k}\right) X_{t}^{k}}{\sum_{t=1}^{T} P\left(\lambda_{i} \mid X_{t}^{k}\right)}; \quad \mu_{i}^{k} = \left(1 - \alpha\right) \overline{\mu}_{i} + \alpha \tilde{\mu}_{i}^{k}, i = 1, ..., C$$

Super-vector Methods

- Gaussian supervector: By stacking the d-dimensional mean vectors of a K-component adapted GMM into a vector.
 - it becomes possible to directly quantify and remove the unwanted variability from the supervectors.
 - Data dimension reduction: PCA, NAP, LDA, PLDA...

$$M = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_C \end{bmatrix}$$





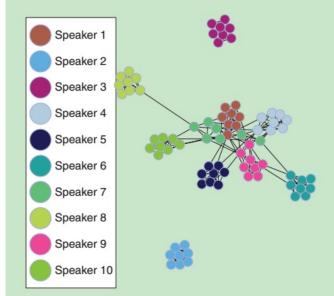
i-vector and total variability space

For i-vector, observing the fact that the channel factors also contain speaker-dependent information, the speaker and channel factors were combined into a single space termed the total variability space.

$$M = m + Tw$$

- T: the total variable space
- w: the i-vector
- m is the UBM supervector
- Cosine Similarity

$$D(w_1, w_2) = \frac{w_1^T w_2}{\|w_1\| \|w_2\|}$$



[FIG9] A graphical representation of 79 utterances spoken by ten individuals collected from the NIST SRE 2004 corpus. The i-vector representation is used for each segment; the plot is generated using GUESS, an open-source graph exploration software [123] that can visualize higher-dimensional data using distance 12 measures between samples.

Different tasks:

- **Text independent**: no constraint on the text
- Text dependent: fixed passphrase,
 - e.g. 'Hey Siri'
- **Text constrained**: fixed vocabulary,
 - e.g. randomly prompted *digit strings* (e.g. Please say 672193)

- Advances during last decade have enabled reliable authentication:
 - Text dependent with short fixed passphrases in clean scenarios
 - Text independent with relative long utterances (tens of seconds)

Speaker recognition applications

- Military intelligence: initial application
- Criminal verification:
 - corroborate the voice samples for forensic analysis
- Transaction authentication
 - Telephone banking: China Construction Bank (CCB)
 - Call center: Voicevault
 - Mobile app: log in with voiceprint
- e-Signatures: Call Center integration
 - https://vimeo.com/134044022



Example with Echo

- Dialogues, Meeting minutes,
 - Who speak
 - Teach Amazon Echo to Recognize Your Voice -

YouTube



Challenges for speaker recognition / verification

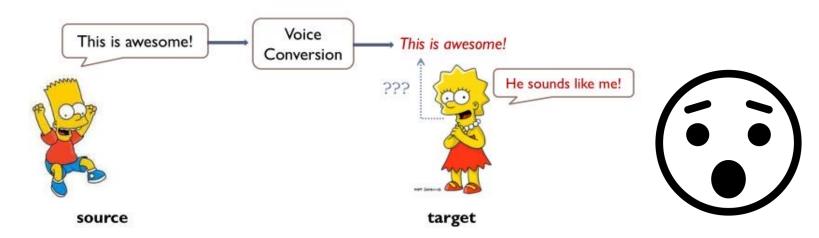
- Multi-channel
- Multi-speaker
- Noisy Environment
- Time-varying (or ageing)
 - Age or health problems
 - Emotions
- Short utterance
- Speech Spoofing
 - the impersonation of another person or the presentation of a prerecorded or synthesized speech signals

Challenges from speech spoofing

How about replay attack?



- or speech synthesis, or voice conversion.
- This AI Clones Your Voice After Listening for 5 Seconds YouTube
- MOS Test 1 (liusongxiang.github.io)



Thank you.