

Recursive Whitening Transform for Speaker Recognition on Language Mismatched Condition

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Abstract

- Main issue of SRE 16 is language mismatch compensation
- On conventional i-vector extraction, whitening transformation is primary step for normalizing i-vector
- While the whitening transformation is done using in-domain dataset on both training and test dataset, the training dataset always remained as un-whitened because of language mismatches
- We propose recursive whitening transformation approach to remove the un-whitened residual components by using subcorpora dataset
- Conventional domain mismatch compensation techniques were used to compare (IDVC, DICN)
- For experiments, 4 different i-vectors (GMM, DNN, Sup-GMM, BNF-GMM)
- While state-of-art i-vector extraction based on phonetically aware model does not showed advantages on language mismatched condition, proposed approach shows effectiveness on evaluation of SRE16

SRE 16 dataset

Statistics

Cotogony	Labela	Numbers of			
Category	Labeis	Utt.	Spk.		
Training	Available	64000>	6400>		
Training	X	200	20		
Enrollment	Available	120	20		
Test	Available	1207	20		
	Training Enrollment	Training Available Training X Enrollment Available	Training Available 64000> Training X 200 Enrollment Available 120		

English : SRE04~10, SWB Minor : Cebuano, Mandarin

- Performance evaluation
 - ➤ Equal Error Rate (EER)
- >_{min}DCF16-1
- >_{min}DCF16-2

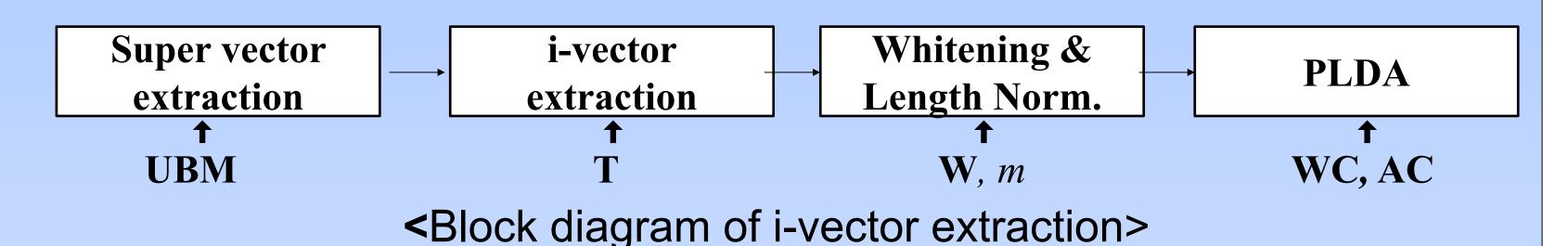
ID	C_{Miss}	$C_{FalseAlarm}$	P _{Target}				
1	1	1	0.01				
2	1	1	0.005				
<sde16 cost="" parameters=""></sde16>							

SRE16 Cost parameters>
min Cprimary

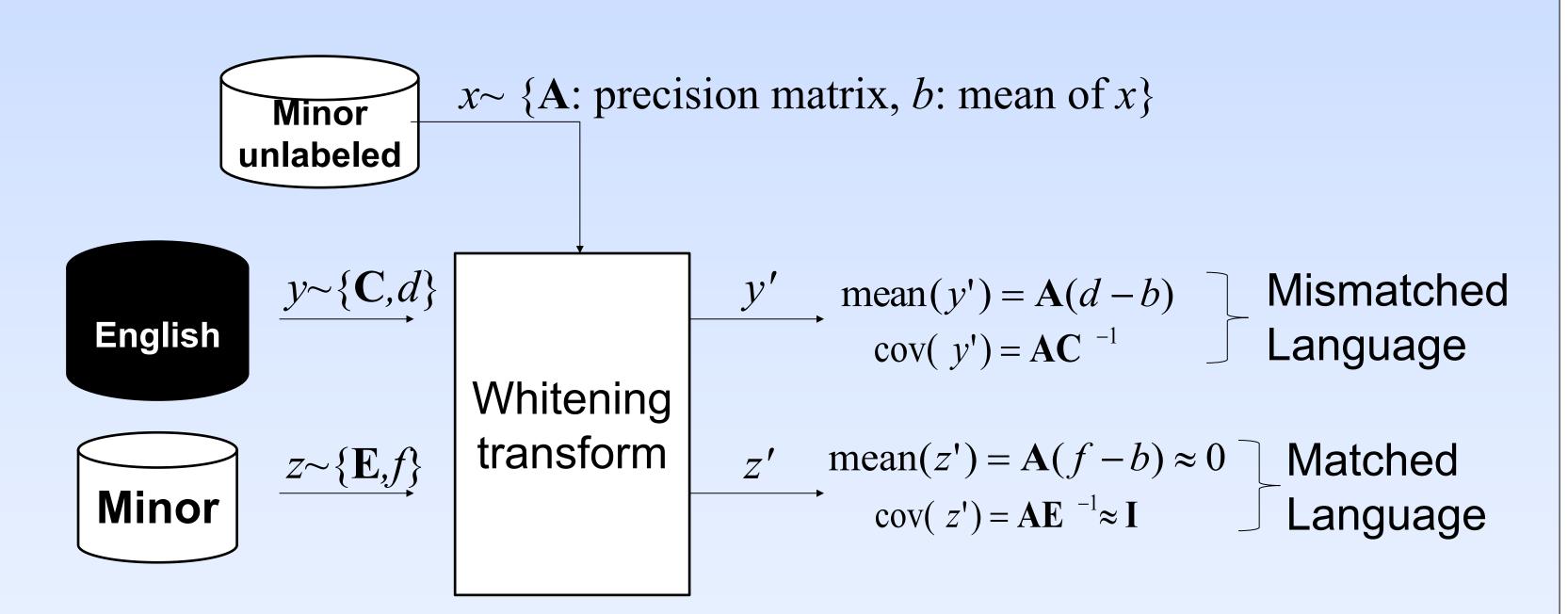
min primary
= (_{min}DCF16-1 + _{min}DCF16-2) / 2

Conventional approach

i-vector extraction

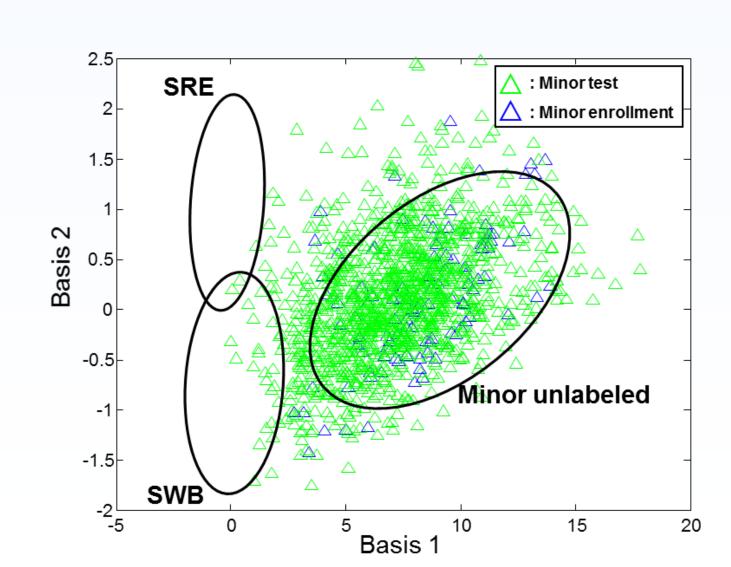


Whitening transform and residual component



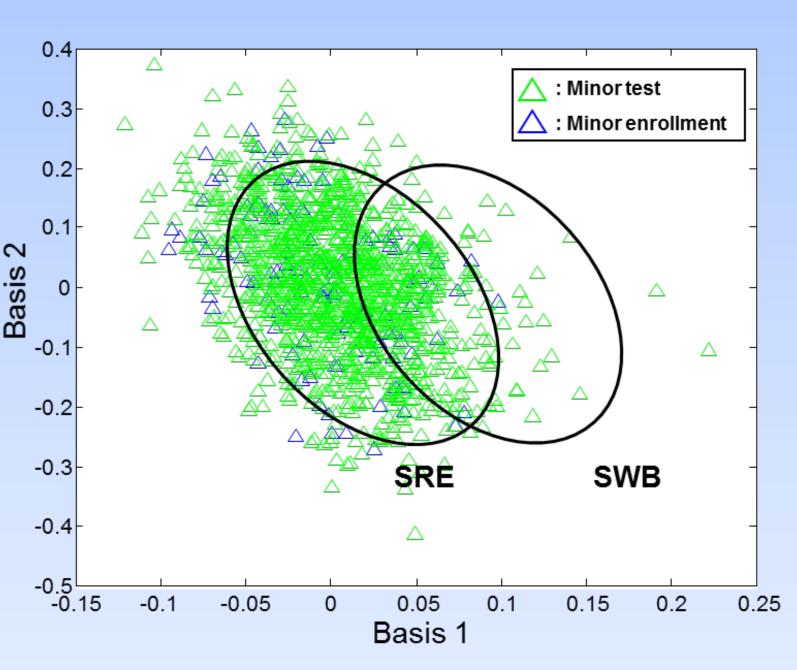
Whitening transform	Compensation techniques	EER	DCF16-1	DCF16-2	min C primary
	_	21.0232	0.8217	0.8598	0.8407
minor	IDVC	21.0957	0.8223	0.839	0.8306
	DICN	21.0853	0.8193	0.8722	0.8457
	-	19.361	0.866	0.8978	0.8819
English	IDVC	19.0452	0.8605	0.8841	0.8723
	DICN	19.5112	0.8630	0.9036	0.8833

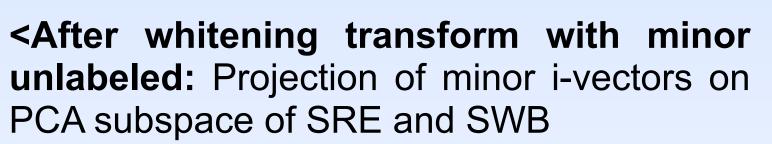
<Baseline performance on SRE16 minor test>

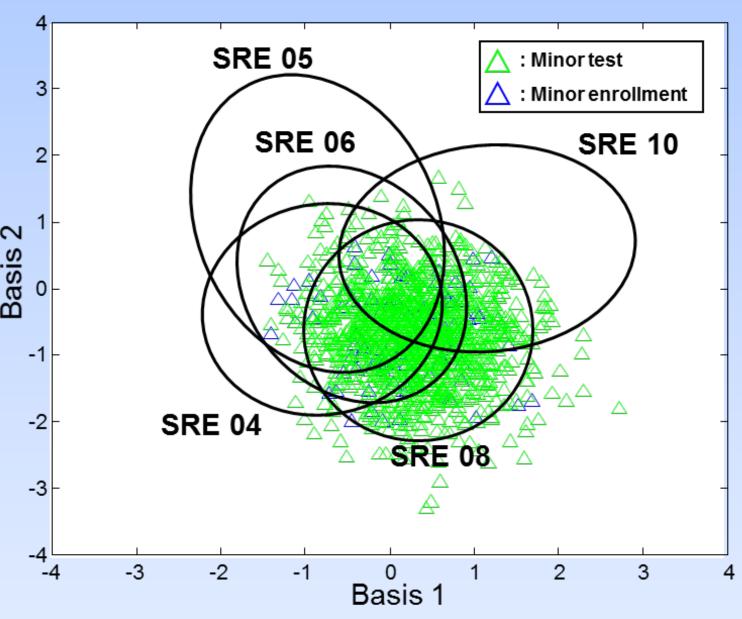


<Projection of minor i-vectors</p>
on PCA subspace of SRE, SWB and Minor unlabled dataset from training category>

Recursive whitening







<After whitening transform twice with minor unlabeled and SRE: Projection of minor i-vectors on PCA subspace of SRE04~10>

• Recursive Whitening transformation using sub-corpora

Sub-corpora Level <i>i</i>	Sub-corpora (sub-corpora index <i>j</i>)	Recursively whitened i-vector at each level i
0	Minor unlabeled dataset (1)	$f_0(\omega)$
1	SRE(1), SWB(2)	$f_{1}(\omega)$
2	SRE04(1), SRE05(2), SRE06(3), SRE08(4), SRE10(5), SWB2 p1~p3(6~8), SWB2 c1~c2(9,10)	$f_2(\omega)$

➤ Determine which sub-corpora is closest

$$J_{i} = \underset{j \in \{1,\dots,K\}}{\operatorname{arg\,max}} p(f_{i-1}(\omega) \mid \boldsymbol{\theta}_{ij})$$

➤ Whitening with the closest sub-corpora

$$f_i(\omega) = \eta \left(S_i(J_i) \cdot f_{i-1}(\omega) - \mu_i(J_i) \right)$$

Experiment

- i-vector extraction systems
 - > GMM-UBM
 - 2048 comp. GMM-UBM, 60-dim MFCC
 - > DNN-UBM
 - Time delay NN for acoustic model
 - DNN-UBM is estimated with 5567 comp.
 - > Supervised GMM-UBM (SGMM-UBM)
 - Phonetically-aware supervised GMM-UBM
 - with 5567 comp. using TDNN post.

 > Bottleneck feature based GMM-UBM (BNF-UBM)
 - DNN layer structure for 1500-1500-80-1500
 - 3rd layer(80 dim) for GMM-UBM estimation
- Common Back-end
 All i-vector was extracted in 600 dim.
- > PLDA parameter were estimated using SRE04~10 with 400 eigenvoice

	Sub-corpora for whitening		Compen-	EFD	DCE1C 1	DCE1C 2		
	Level 0	Level 1	Level 2	sation	EER	minDCF16-1	minDCF16-2	min C _{primary}
Conventional	Minor			-	21.02	0.8217	0.8598	0.8407
(Level 0	Minor			IDVC	21.10	0.8223	0.839	0.8306
recursive whitening)	Minor			DICN	21.08	0.8193	0.8722	0.8457
Level 1	Minor	SRE		-	17.48	0.7358	0.7556	0.7457
recursive	Minor	SRE		IDVC	17.01	0.7198	0.7504	0.7351
whitening	Minor	SRE		DICN	17.33	0.7204	0.7518	0.7361
Level 2	Minor	SRE	SRE-08	-	17.92	0.7085	0.7447	0.7266
recursive	Minor	SRE	SRE-08	IDVC	17.21	0.7123	0.7474	0.7298
whitening	Minor	SRE	SRE-08	DICN	17.33	0.7233	0.7465	0.7349

<Performance evaluation on SRE16 minor language using DNN-UBM i-vector>

i-vector Extraction	Conv	ventional (l	evel 0)	vel 0) Level 1 recursive whiteni		vhitening
System Name	EER	$_{ m min}C_{ m primary}$	$C_{ m primary}$	EER	$_{ m min}C_{ m primary}$	C_{primary}
GMM-UBM	21.91	0.8068	0.8271	18.93	0.7155	0.7293
DNN-UBM	21.21	0.8267	0.8428	19.12	0.6862	0.7043
SGMM –UBM	21.23	0.8099	0.8426	20.05	0.7251	0.7461
BNF-UBM	23.94	0.8973	0.9215	20.19	0.7557	0.7824
Fusion of 4 sub-systems	17.01	0.7179	0.7313	15.67	0.6478	0.6727

<Performance evaluation on SRE16 minor language using multiple i-vector system>

Conclusion

- Recursive whitening transformation is relatively simple, but powerful approach to deal with language mismatched condition
- By result, the approach gradually remove un-whitened residual component
- Robustness on challenge condition where in-domain dataset is extremely small