

The CRSS Systems for NIST SRE 2010

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Introduction

Systems Summary

- The CRSS system is a fusion of five SVM based systems [1] and one Joint Factor analysis system [3]
- The factor analysis based front end [1] is used as features for the SVM based systems

• Task focus

- We mainly focused on the core-core telephone train and test condition
- > We also submitted a system for the 10sec-10sec condition

Novel Elements

- New background selection strategy was employed
- Supervised Probabilistic Principal Component Analysis method was introduced

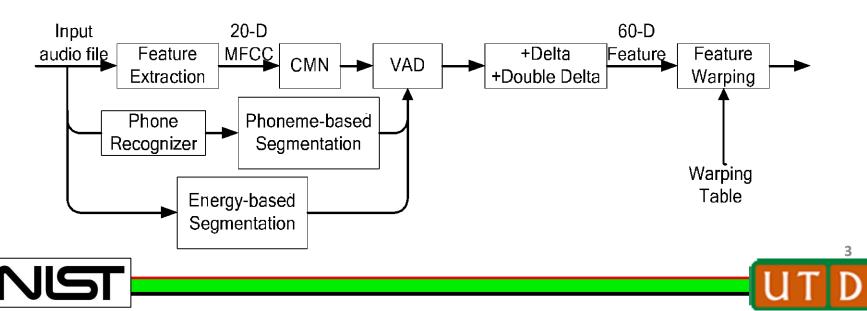




Feature Extraction

Algorithm Details

- > 60-dimension feature (19 MFCC with log energy + Δ + $\Delta \Delta$) using a 25 ms analysis window with 10 ms shift
- Used feature warping with a 3-s sliding window
- Used Hungarian phoneme recognizer [6] and simple energy based voice activity detection (VAD)
- This is the common acoustic front-end for all subsytems





System Components

UBM Training

- Gender dependent UBMs with 1024 mixtures
- NIST 2004, 2005, 2006 SRE data used for training
- > 20 iterations per mixture split (HTK toolkit)

• Factor Analysis (PPCA and SPPCA)

- Two different modeling approaches used:
 - Standard Probabilistic principal component analysis (PPCA) [2]
 - New technique: Supervised probabilistic principal component analysis (SPPCA) [4]
- Data: Switchboard II Phase 2 and 3, Switchboard Cellular Part 1 and 2, and the NIST 2004, 2005, 2006 SRE enrollment data
- Total 400 factors used





System Components

Channel Compensation

- Three techniques are used:
 - Linear Discriminant Analysis (LDA)
 - Nuisance Attribute Projection (NAP)
 - Within Class Covariance Normalization (WCCN)
- Training Data: NIST 2004, 2005, 2006 SRE enrollment data used for training the LDA, NAP and WCCN matrices

• SVM Training (SVM)

- > The cosine kernel was used for SVM.
- Background dataset consists of NIST SRE 2004, 2005, 2006, and the Switchboard II Phase 2 and 3, Switchboard Cellular Part 1 and 2, with a total of 12,763 utterances.
- Used only SRE 04 and 05 as background dataset for final submission







Impostor Selection

Proposed Method

- The idea is to find the best group of impostor speakers for enrollment speakers [4]
- Used SVM ranking algorithm to find the closest background set
- Used SVM-delta for selecting best background set for each enrollment speaker

$$\mathbf{w} = \sum_{i} \alpha_{i} y_{i} \mathbf{x}_{i} \qquad SVWeight_{i} = \sum_{k=1}^{n} \alpha_{ik}$$

 $SVMdelta_n = SVWeight_l - SVWeight_m \ (l < m)$



Score Normalization and Fusion

Score Normalization

- NIST SRE 2005 data was used for T-norm
- > The T-norm model is trained with a leave-one-out method
- No Z-norm was used in the SVM systems

Score Fusion

- Score fusion software based on Brummer et. al.'s FoCal toolkit was implemented [7]
- Linear logistic regression (LLR) method is used to train the fusion weights
- The score fusion software is designed to automate the process of choosing a fusion method for the best MinDCF value





The Subsystems

• SVM Based Subsystems:

- SVM-SPPCA-LDA
 SVM-PPCA-LDA
- SVM-SPPCA-NAP
- SVM-PPCA-NAP
- SVM-PPCA-LDA-BG
- GMM-UBM-JFA

Commonalities

- > All SVM systems utilize WCCN after LDA or NAP
- Only the system SVM-PPCA-LDA-BG uses the new background selection algorithm [5]





Joint Factor Analysis Subsystem

Subsystem Details

300 speaker factors and 100 channel factors was used

> Training data:

- Eigenvoice Matrix V: Switchboard II, Phases 2 and 3, Switchboard Cellular, Part 1 and 2; NIST 2005 and 2006 data
- Eigenchannel Matrix U: NIST 2004, 2005, and 2006 data
- Diagonal Matrix D: NIST 2004 data
- No score normalization was used in this case
- Notated as GMM-UBM-JFA in subsequent slides







Construction of the CRSS Submissions

Submission	Fused Subsystems	Submission	Fused Subsystems
CRSS_1	SVM-PPCA-LDA	CRSS_3	SVM-PPCA-LDA
	SVM-PPCA-NAP		
CRSS_2	SVM-PPCA-LDA		SVM-PPCA-NAP
	SVM-PPCA-NAP		SVM-SPPCA-LDA
	SVM-SPPCA-LDA		
	SVM-SPPCA-NAP		SVM-SPPCA-NAP
	GMM-UBM-JFA		SVM-PPCA-LDA-BG
	SVM-PPCA-LDA-BG		

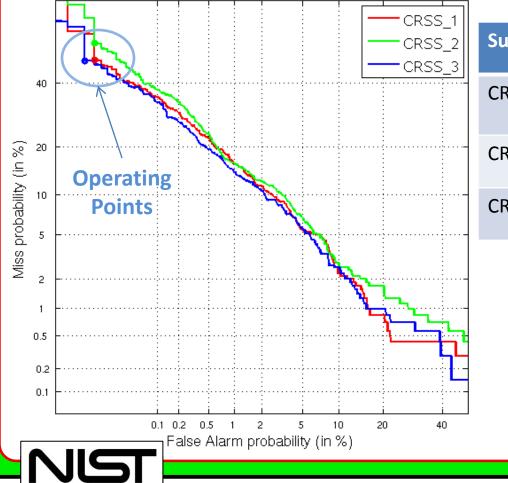








• Submission Performance (NIST 2010 SRE, core-core, Cond. 5)

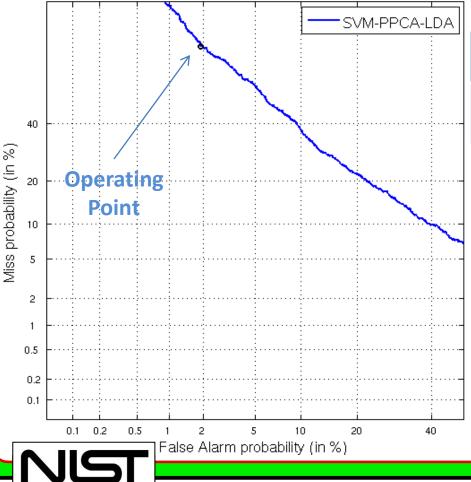


Submission	EER (%)	MinDCF
CRSS_1	5.225501	0.585491
CRSS_2	5.791149	0.646226
CRSS_3	5.264267	0.546166





• Submission Performance (NIST 2010 SRE, 10sec-10sec)



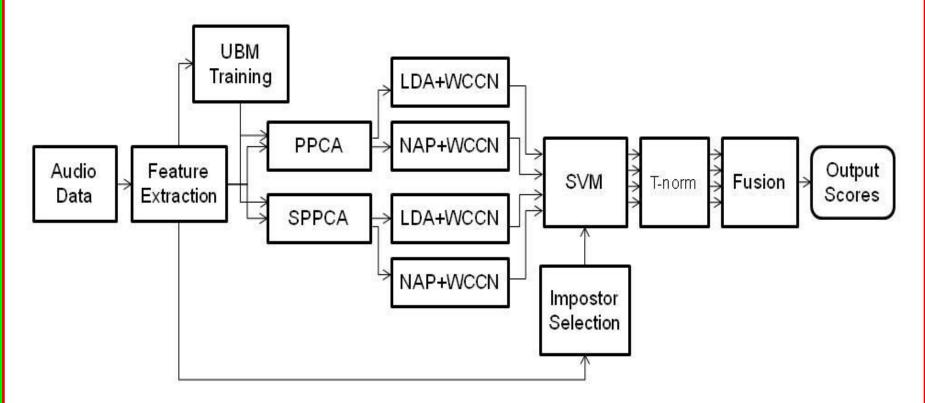
System	EER (%)	MinDCF
SVM-PPCA-LDA	21.119471	0.89685

- We used the SVM-PPCA-LDA system for 10sec case
- Paramater Tuning can further improve the performance



System Block Diagram

CRSS SVM Submission Architecture







Other Developments

ASR MLLR System

- ASR trained on Switchboard is used to generate MLLR transform matrices for speaker verification tokens
- The ASR employs PLP front-end and feature warping
- A global MLLR transform and broad phone-group transforms are estimated
- PCA is applied to reduce feature dimension and SVM is used as classifier
- Achieved 21.46% EER for SRE08 core tel-tel for male trials.
- PMVDR Features Based System
 - A GMM-UBM-MAP system was evaluated
 - > Achieved 13.103% EER for SRE08 core tel-tel for male trials.

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Requires further investigation





Computational Resources

Computational Resources

- System OS: High performance Rocks computing cluster running the CentOS Linux distribution
- CPU: The cluster comprises 18 HP Intel Quad-Core Xeon 2.33 GHz CPU's. Total 72 CPU cores
- ➢ RAM: 126 GB
- > Disks: A 4 TB external RAID disk array is used

CPU Execution Times

- Training: Requires 6.2771 mins for a 5 min utterance assuming a single CPU. Real time factor (RTF) = 1.2554
- Testing: Requires 4.6034 mins for a 5 min utterance assuming a single CPU. Real time factor (RTF) = 0.9207







- [1] N. Dehak, P. Kenny, R. Dehak, P. Ouellet, and P. Dumouchel, "Front-end Factor Analysis for Speaker Verification," *submitted to IEEE Transaction on Audio, Speech and Language Processing.*
- [2] M. Tipping and C. Bishop, "Mixtures of probabilistic principal component analyzers," *Neural computation, vol. 11, no. 2, pp. 443–482, 1999.*
- [3] P. Kenny, G. Boulianne, P. Ouellet, and P. Dumouchel, "Joint factor analysis versus eigenchannels in speaker recognition," *Audio, Speech, and Language Processing, IEEE Transactions on, vol. 15, no. 4, pp.* 1435–1447, May 2007.
- [4] Y. Lei and J. H. L. Hansen, "Speaker recognition using supervised probabilistic principal component analysis," in Proc. Interspeech'10 (Submitted), 2010
- [5] J. Suh, Y. Lei, and J. H. L. Hansen, "Best background data selection in SVM speaker recognition for new diverse evaluation data sets," in Proc. Interspeech'10 (Submitted), 2010.
- [6] P. Schwarz, P. Matejka, and J. Cernocky, "Hierarchical structures of neural networks for phoneme recognition," in Proc. IEEE ICASSP 2006, vol. 1, May 2006, pp. I–I.
- [7] Online: http://www.dsp.sun.ac.za/~nbrummer/focal/



