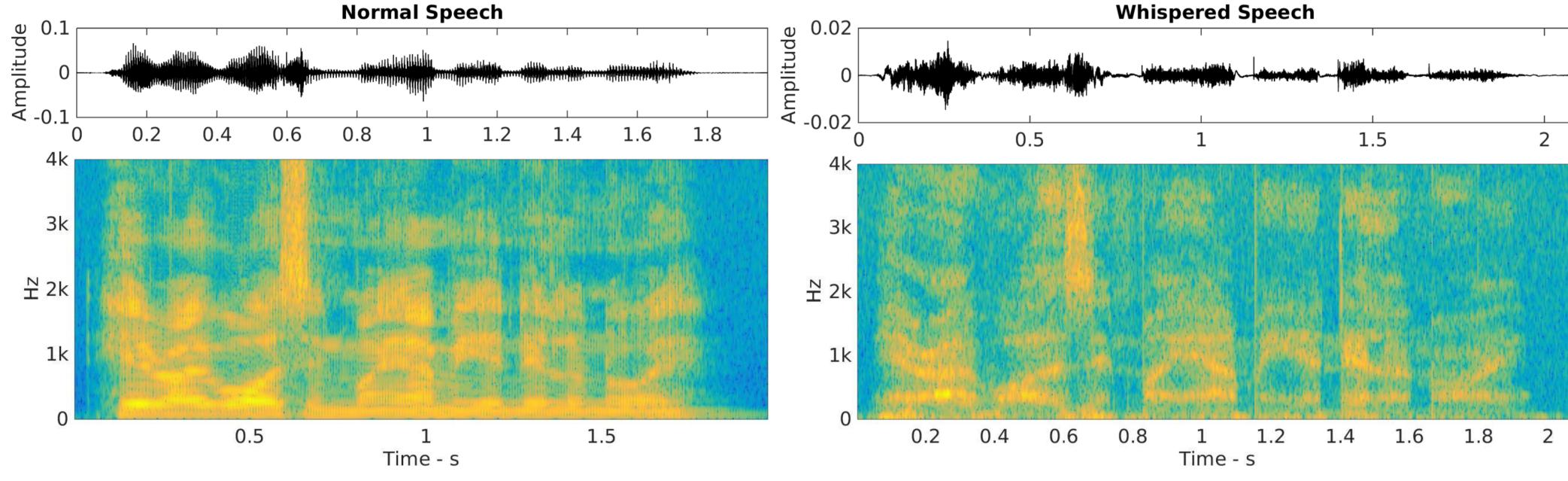
INTRODUCTION Normal speech Vocal effort Variation Whispered speech Speaker Claiming an identity

Whispered speech specific characteristics



- Lack of fundamental frequency.
- Formant shifts towards higher frequencies.
- Lower and flatter power spectral density.
- •64 low level descriptors (LLDs): spectral, prosody and voice quality were compared and 56 showed to be statistically different.

Mismatch between training data and what the model encounters in real life.

HOW TO ADDRESS THIS PROBLEM?

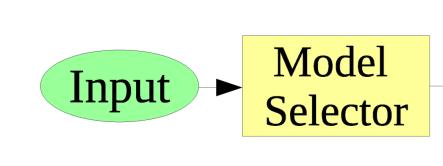
Three approaches have shown to be useful in related areas:

) Feature mapping:

- Compensate for the lack of data during enrollment
- Compensate for the differences during testing

2) Multiple model recognizer:

Requires significant amounts of data to train the models.

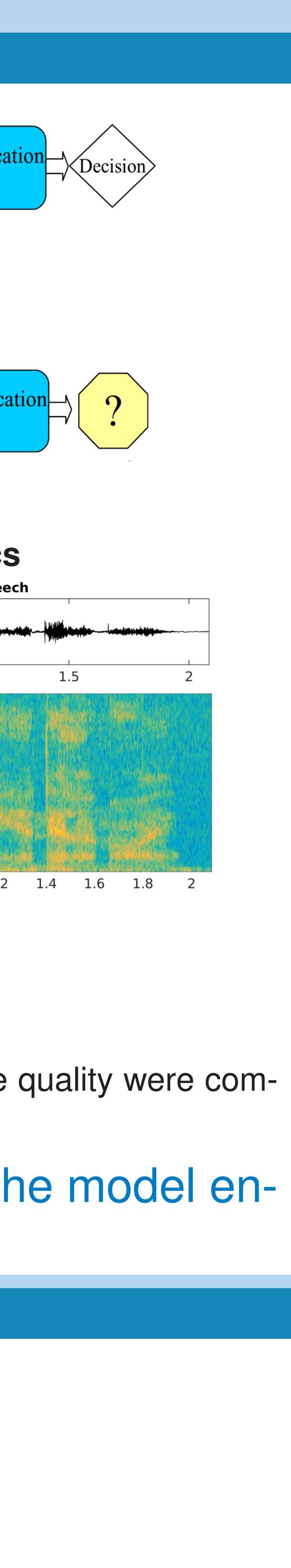


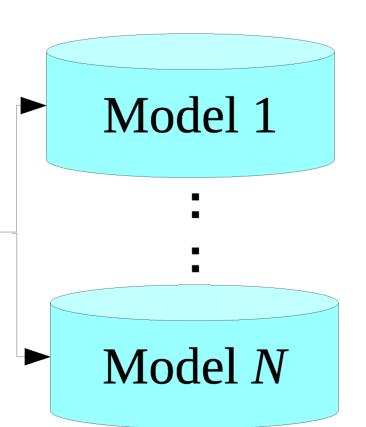
3) Multi-style models:

During parameter estimation and enrollment combination of normal speech and small amounts of speech of varying vocal efforts is used.

Feature Mapping, Score-, and Feature-Level Fusion for Improved Normal and Whispered Speech Speaker Verification Milton Sarria-Paja, Mohammed Senoussaoui, Douglas O'Shaughnessy and Tiago H. Falk

Institut National de la Recherche Scientifique (INRS-EMT), University of Quebec, Montréal (QC) - Canada





EXPERIMENTAL SETUP

Databases

Database	Num. of speakers		recordings/speaker Norm. Whsp.		
	Female	Male	Norm.	Whsp.	
TIMIT	192	438	10		
wTIMIT	24	24	450	450	
CHAINS	16	20	37	37	

Task design

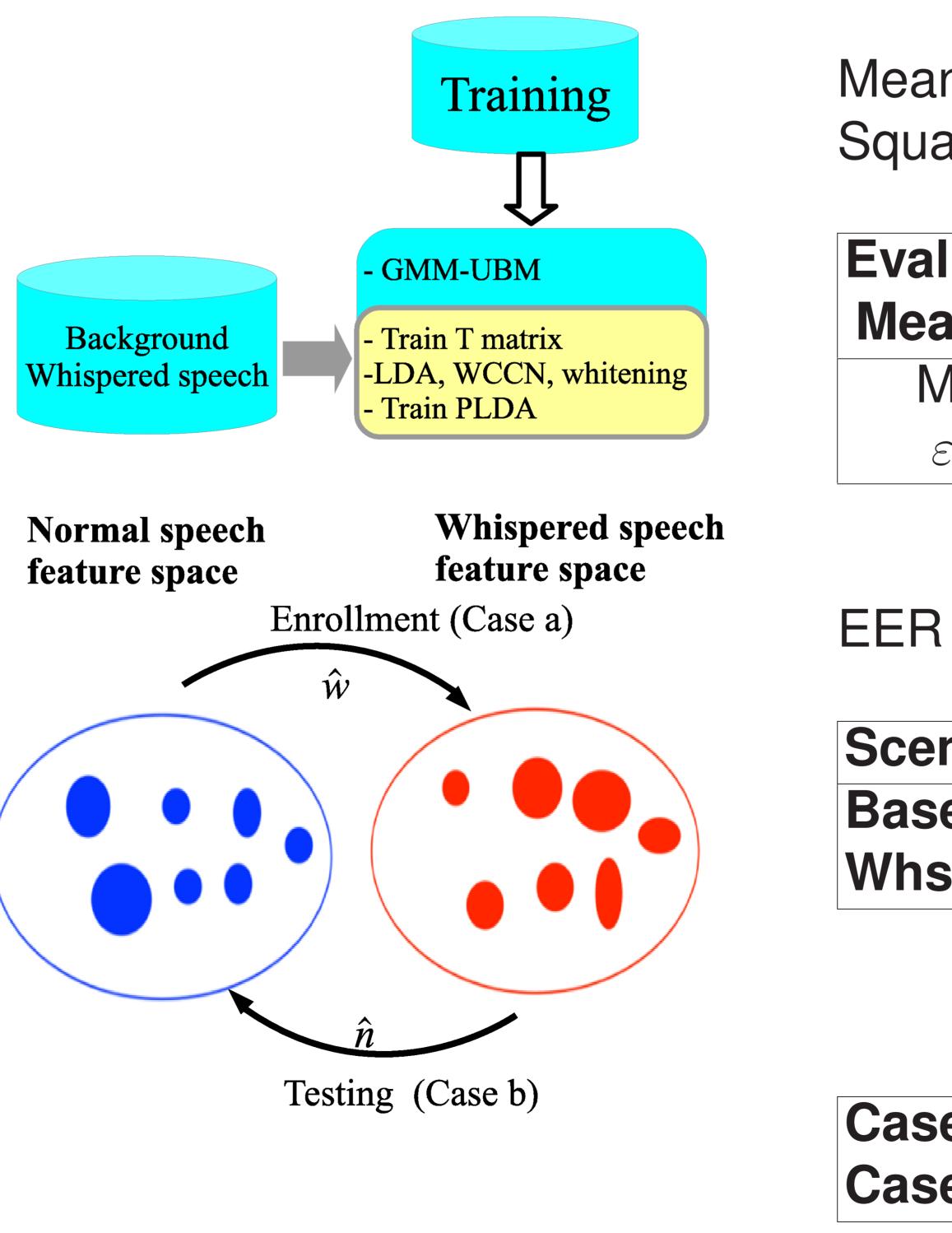
	Num. of speakers/Database		Total record.		
	TIMIT	wTIMIT	CHAINS	norm	whsp
UBM estimation	462	0	0	3696	0
T matrix estimation	462	14	0	9996	6300
Enrollment	100	24	36	1280	480
Testing	100	24	36	320	120

SV system parameters:

PLDA/i-vectors based system with: UBM $C = \{64, 128, 256, 512\}$. T matrix $D = \{200, 300, 400\}$.

FEATURE MAPPING

Two approaches are evaluated: DNN and GMM based mappings



A direct mapping between whispered and normal speech features does not seem to help reducing error rates when testing with whispered speech (Except Case b using GMM). The mappings cannot transform effectively speaker specific characteristics associated with identity affected while whispering.

Mean Cepstral Distance and Root Mean Square Error

luation	Norm	to Whsp	Whsp	to Norm
asures	GMM	DNN	GMM	DNN
ACD	13.84	12.78	13.96	12.75
arepsilonrms	0.644	0.596	0.649	0.595

EER comparison with the baseline system

nario	Norm	Whsp
eline	3.13	27.35
sp in dev. set	4.06	19.15
•		•

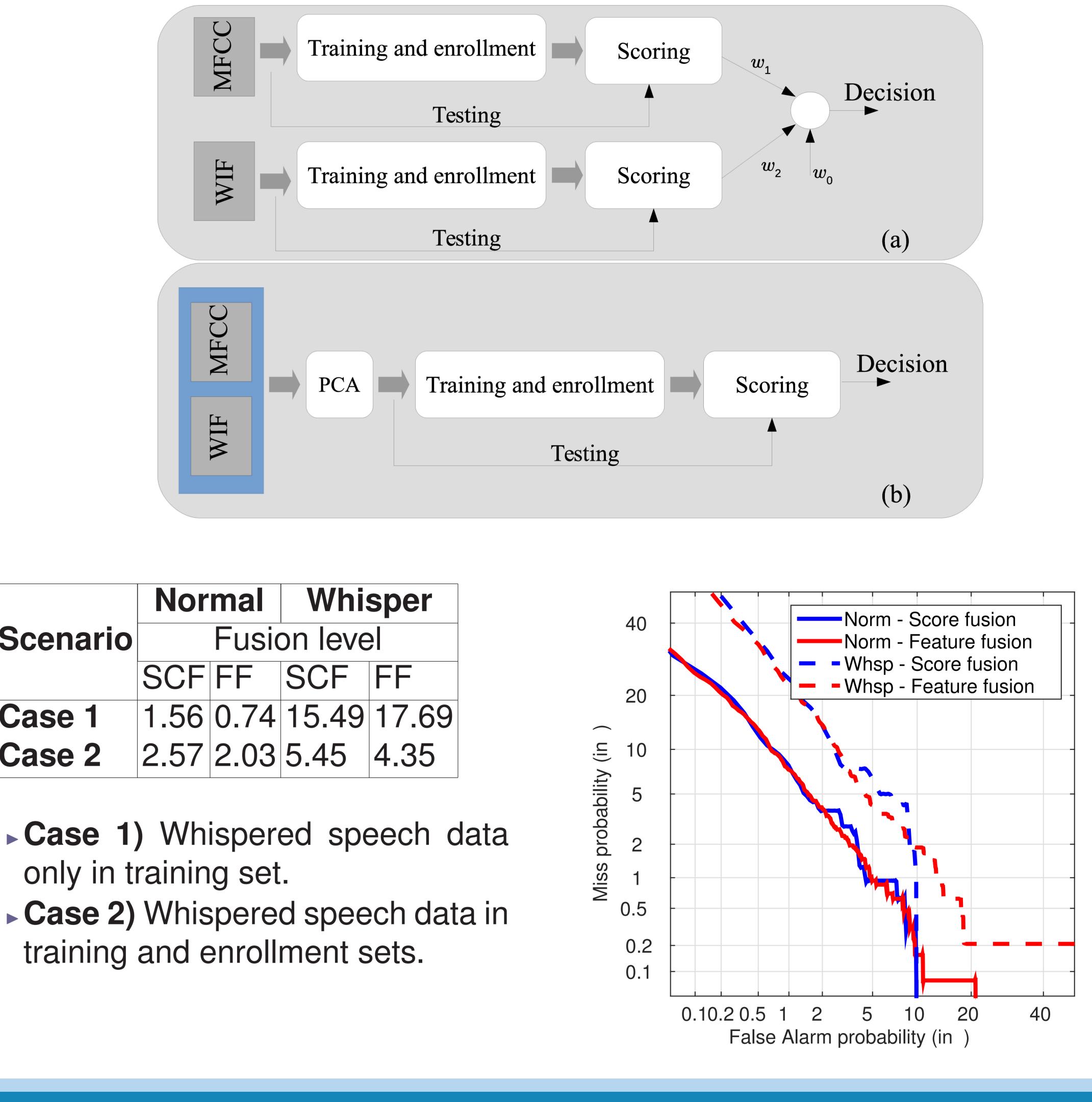
e	a
e	b

Feature Mapping					
GMM DNN GMM DNN					
			20.00		
			21.07		

MULTI-STYLE MODELS

Addition of whispere training and enrollm a cost: \Rightarrow

To compensate for the losses:



	Normal			
Scenario		Fusio	Dr	
	SCF	FF	S	
Case 1	1.56	0.74	1	
Case 2	2.57	2.03	5	

- only in training set.
- training and enrollment sets.

CONCLUSION







ed speech during	SV system	Norm	Whsp
nent comes with	Baseline/PLDA	2.93	28.00
	Multy-Style/PLDA	5.56	8.90

Include complementary features. Explore fusion schemes: Fusion at the scoring level - SCF (a) and Fusion at the frame level - FF (b).

Two different approaches were compared in order to reduce error rates for SV with whispered speech while maintaining performance with normal speech.

Multi-style models are the least computationally expensive and most effective way to achieve significant error rate reductions.

Our approach to compensate multi-style models is to include AM-FM based features and use fusion schemes at the frame level and at the scoring level.

Finally, it is observed that features that rely on instantaneous phase information add complementary speaker identity information.