Synergy between Speaker Recognition and Speech Recognition

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Reporting on joint work with:

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Speech Recognition & Speaker Recognition

Opposing goals:

- Invariance to speaker differences (ASR)
- Invariance to what was said (speaker recognition)
- □ (Largely) separate research communities
- ASR (and ASU) have always relied on speaker modeling
 - Speech/nonspeech segmentation
 - Diarization / speaker tracking
 - To help in feature normalization & model adaptation

□ What can ASR do for speaker modeling ?



ASR & Speaker Recognition (2)

Recent years have seen increasing ASR use in state-of-the-art speaker recognition

- NIST speaker recognition evaluation
- Telephone data (mostly)
- Long (conversation-length) data samples

Goal here:

- Overview of what's been done
- Incite interest among ASR researchers
- Point out challenges



"Generative" Speaker Verification

- GMM-UBM (Reynolds et al.)
- Models cepstral features
 - Feature normalization / mapping
- **Training**:
 - Train "background model" on a large population
 - "Speaker model" obtained via MAP-adaptation to enrollment data

Testing:

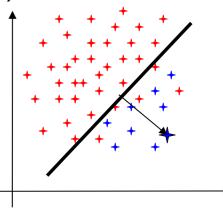
- Log-likelihood ratio between speaker and background model
- Threshold for decision (accept / reject)





"Discriminative" Speaker Verification

- □ Mostly based on SVMs (Campbell et al.)
- Each conversation side = one point in feature space
- SVM trained to separate target from background samples
- Score = distance from test sample to decision hyperplane
- Linear kernel functions work well for most features tried to date
- Crucial step: how to map variable-length speech sample into fixed-length vector



- Target training sample(s)
- + Background samples

5

Test sample



How Can ASR Help?

Phonetic / text conditioning

Modeling "speaking style"

- Pronunciation
- Lexico-grammatical choice
- Prosodic patterns
- □ ASR "by-product" features
 - MLLR-SVM features

Challenges



Phonetic Conditioning

- Condition cepstral features on phone or word identities
- Removes within-speaker variability due to phonetic content
 - More like text-dependent speaker verification
- Possibly focuses features on regions of greater inter-speaker variability
 - E.g., discourse markers

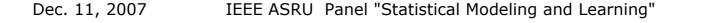
Explored by MIT-LL, Dragon, ICSI, et al.



Speaking Style Modeling

Pronunciation modeling (many variants)

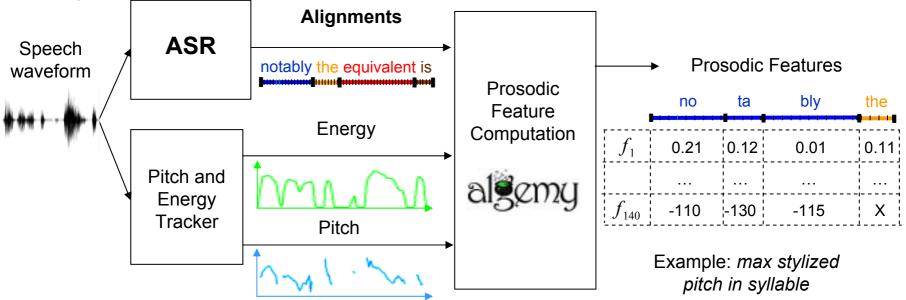
- Phone N-gram frequency SVM vectors (Campbell)
- Greatly enhanced by lattice decoding (Hatch et al.)
- Lexical & grammatical choice (Doddington)
 - Word N-gram frequency vectors
 - Distinguish "slow" from "fast" pronunciations for frequent words (Tur et al.)
- Prosodic modeling (Adami, Shriberg et al.)
 - Syllable-based energy, duation, and pitch features
 - Enhanced by lexical constraints





Prosodic Speaker Modeling

- SNERFs: Syllable-level Non-Uniform Extraction Region Features
- Compute a set of (140) duration, pitch and energy features on each syllable
- Transformations to fixed-length vectors using Fisher score (Ferrer et al.)





Recognizer-internal Features

- Idea: speech recognizer by-products encode speaker-specific information
 - Results of recognizer modeling inter-speaker variability
- Examples:
 - Sub-word unit duration modeling (Ferrer et al., Eurospeech '03)
 - Speaker adaptation (MLLR) transforms (Eurospeech '05, IEEE Trans. ASLP '07)



MLLR Speaker Adaptation

Speech recognizer adapts speaker-independent model to best fit test speaker



- Adaptation transform estimated by Maximum Likelihood Linear Regression (MLLR)
 - Maximizes likelihood of test data under recognition hypothesis
- Transform rotates and shifts Gaussian means (= matrix + vector)



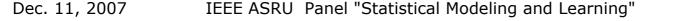
MLLR-SVM Speaker Recognition

- Idea: MLLR transform encapsulates what makes target speaker different from the "average speaker"
- Transforms are based on detailed, sequential speech models (unlike std. cepstral speaker models)
- Use transform coefficients as feature vector (after suitable normalization)

Refinements:

- Combine transforms for different phone classes
- Combine transforms relative to different recognition models

Model feature vectors with support vector machines (SVMs)





Results (on NIST SRE'06)

System	%EER
Cepstral GMM	4.75
Cepstral Polynomial SVM	5.07
Gaussian Supervector SVM	4.15
MLLR SVM	4.00
State/word duration GMM	16.03 / 22.24
Word + duration N-gram SVM	23.46
Prosodic SVM	10.41
Combination	2.59

□ Note: MLLR and prosodic SVM best 2-system combination

Challenges

- Novel recognizer-based features
 - Non-linear adaptation transforms ?
- Need fast, accurate ASR for variable, "unexpected" conditions
 - Noisy environments
 - Variable channels
 - Nonnative speakers
- Mapping of ASR-based features across languages
- How to compare English to non-English ASR features (bilingual speakers) ?

