Biometrics: Voice

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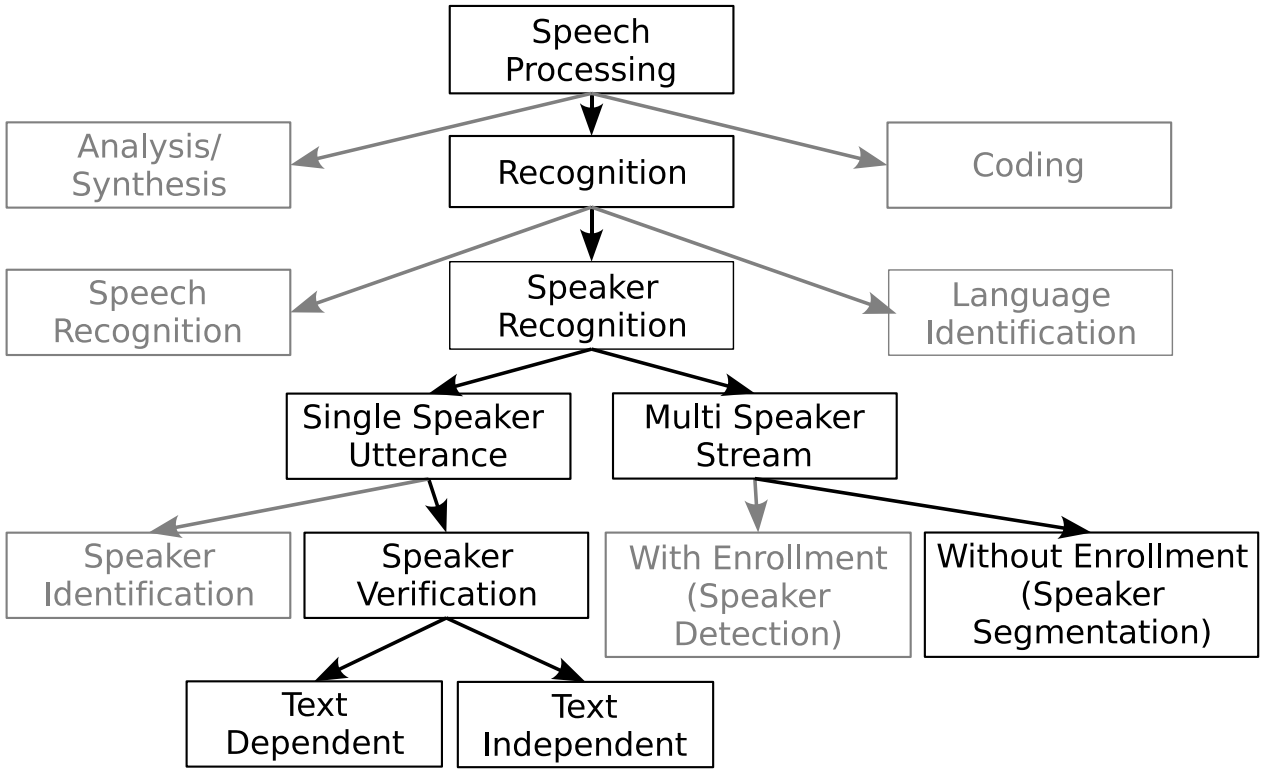
Outline

- Fundamentals
- Features - Preprocessing
- Pattern Matching Methods
- Air Traffic Control System
- Conclusion

Fundamentals and Preprocessing

Speech Processing



adapted from [5]

Fundamentals

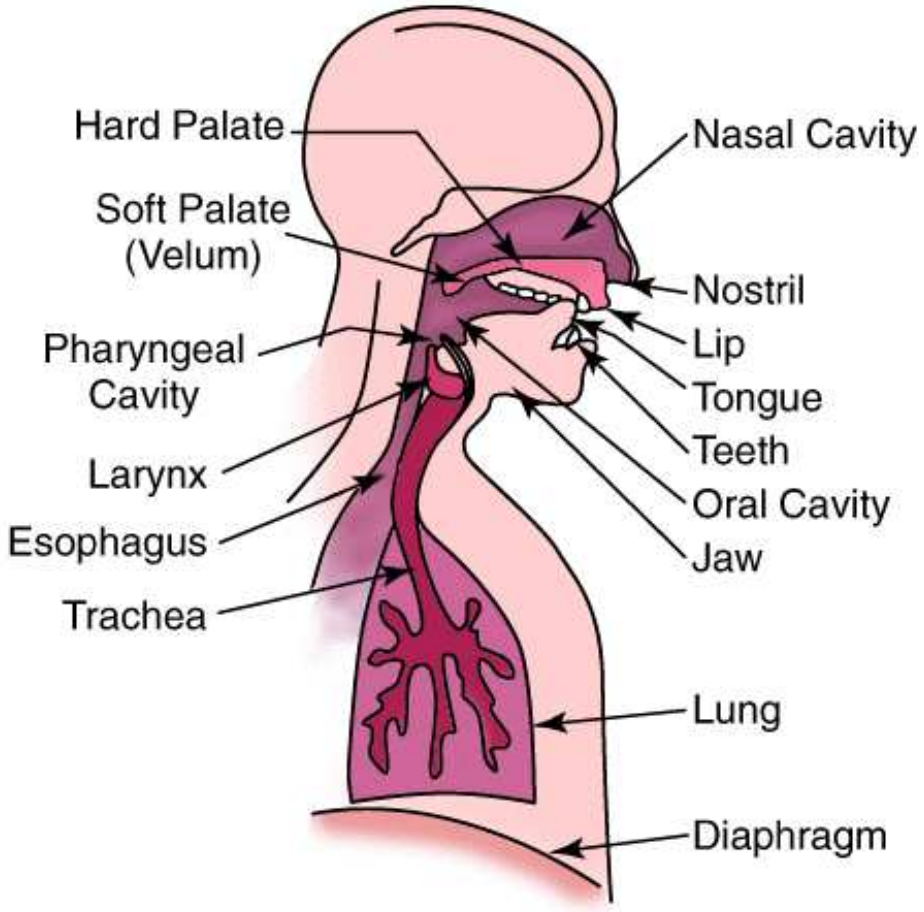
- Behavioral Biometrics - speakers identity can not be measured directly
- Speech carries 2 Informations:
  - Meaning of the message
  - Information about themselves as a person
- Speaker specific characteristics in signal
  - speaker's anatomy
  - physiology
  - linguistic
  - experience
  - mental state

Individuality in the sound system

- segmental component (e.g., mental lexicon, pronounced word)
- supra-segmental component (e.g., timing, stress pattern and intonation of a sequence)
- number and identity of segments used in the sound inventory

taken from [6]

Vocal Apparatus



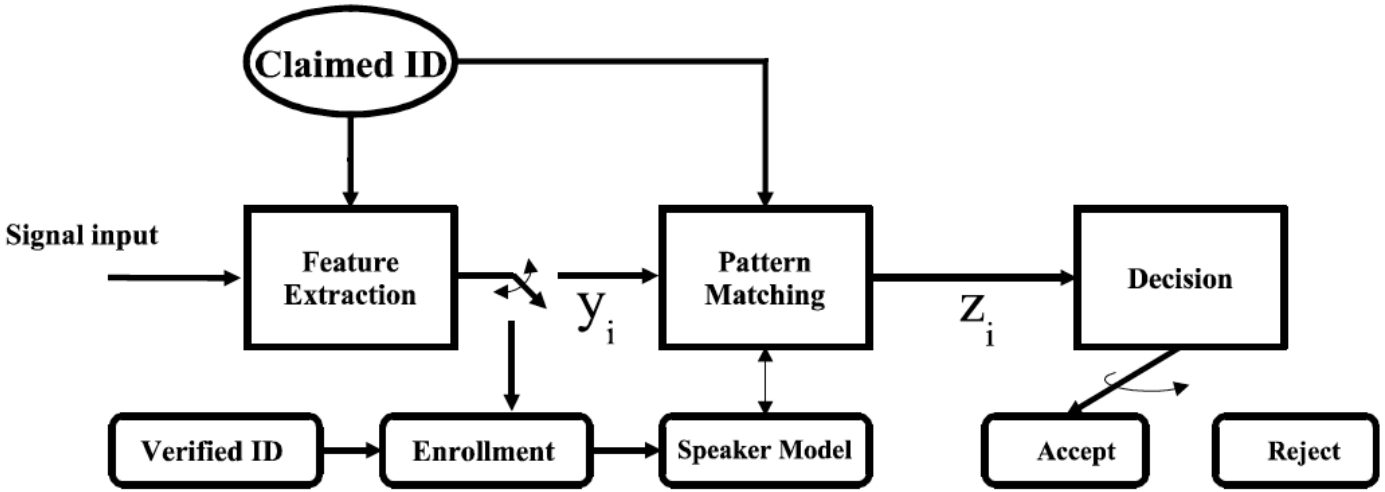
taken from [5]

Problems in Speaker Recognition

- Misspoken or misread prompted phrases
- Extreme emotional states (e.g., stress or duress)
- Time varying (intra- or intersession) microphone placement
- Poor or inconsistent room acoustics (e.g., multipath and noise)
- Channel mismatch (e.g., using different microphones for enrollment and verification)
- Sickness (e.g., head colds can alter the vocal tract)
- Aging (the vocal tract can drift away from models with age)

taken from [5]

Generic Speaker Verification

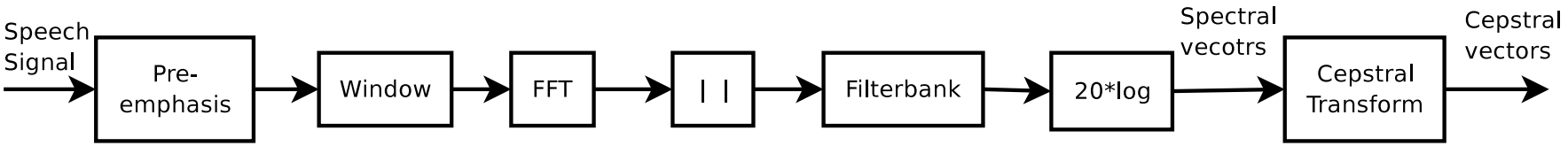


adapted from [7]

Features - Preprocessing

- Speech parameterization: Feature extraction from the speech signal
  - Cepstral coefficients
  - MFCC
  - Wavlet
  - LPCC, . . .
- Voice activity detection
- End point detection
- Feature normalization
- Dynamic information

Example Feature: Cepstral coefficients



taken from [7]

Pattern Matching Methods

Template Models

Definition of template: $\overline{x} = \frac{1}{N} \sum_{i=1}^{N} \boldsymbol{x}$, with N training vectors. Then a distance function can be defined as:

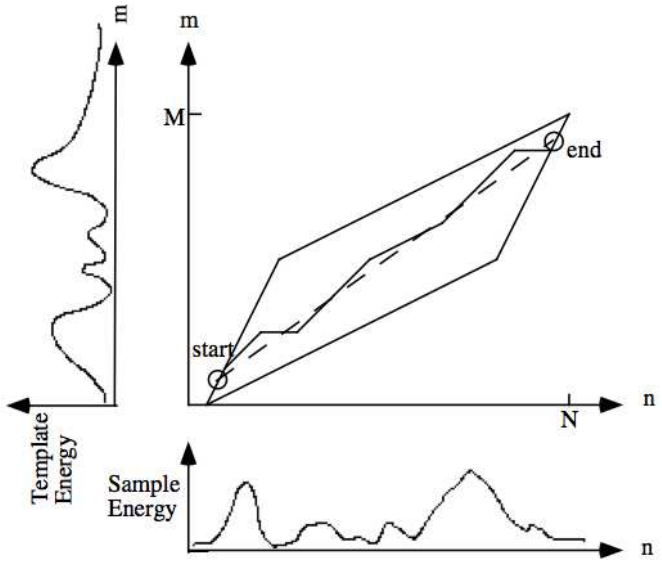
$$d(\boldsymbol{x}, \overline{\boldsymbol{x}}) = (\boldsymbol{x} - \overline{\boldsymbol{x}})^T \boldsymbol{W} (\boldsymbol{x} - \overline{\boldsymbol{x}}),$$

where $\boldsymbol{W}$ defines the chosen distance function.

Dynamic Time Warping

- Time-dependent methods
- Algorithm to compensate speaking rate variability
- Piece wise linear mapping of the time axis to align 2 signals and minimize z
- Text- dependent

The asymmetric match score z is given as: $z = \sum_{t=1}^{T} d(\boldsymbol{x}_t, \overline{\boldsymbol{x}}_{j(t)})$



Vector Quantization Source Modeling

- Time-independent
- Create a VQ code book as a collection of code words for each speaker by clustering
- No temporal information about the speaker used

The match score is defined as:

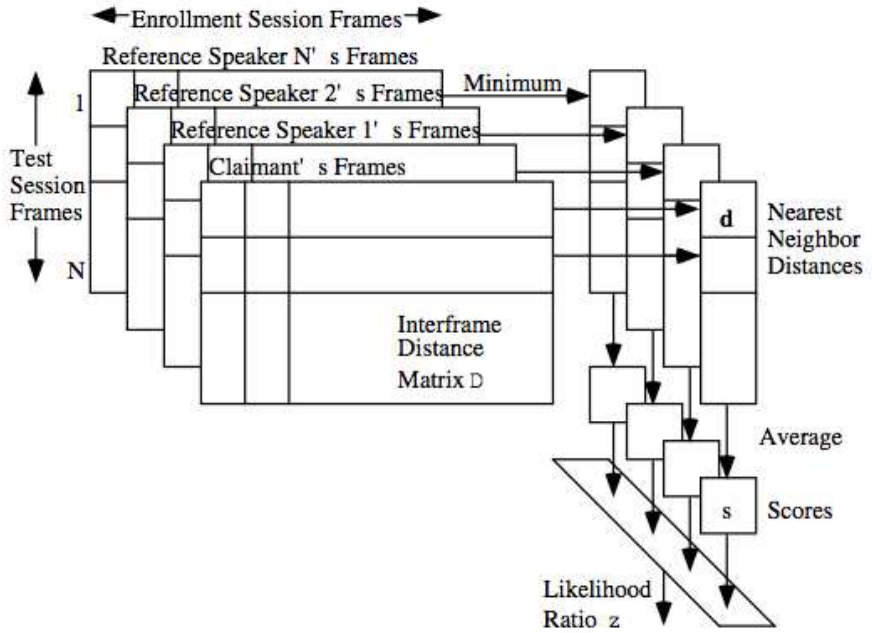
$$z = \sum_{t=1}^{T} \min \; d(\boldsymbol{x}_t, \overline{\boldsymbol{x}})$$

Nearest Neighbors

- Distance based classification by direct computation
- No models or data reduction by clustering
- Powerful method with high computational complexity

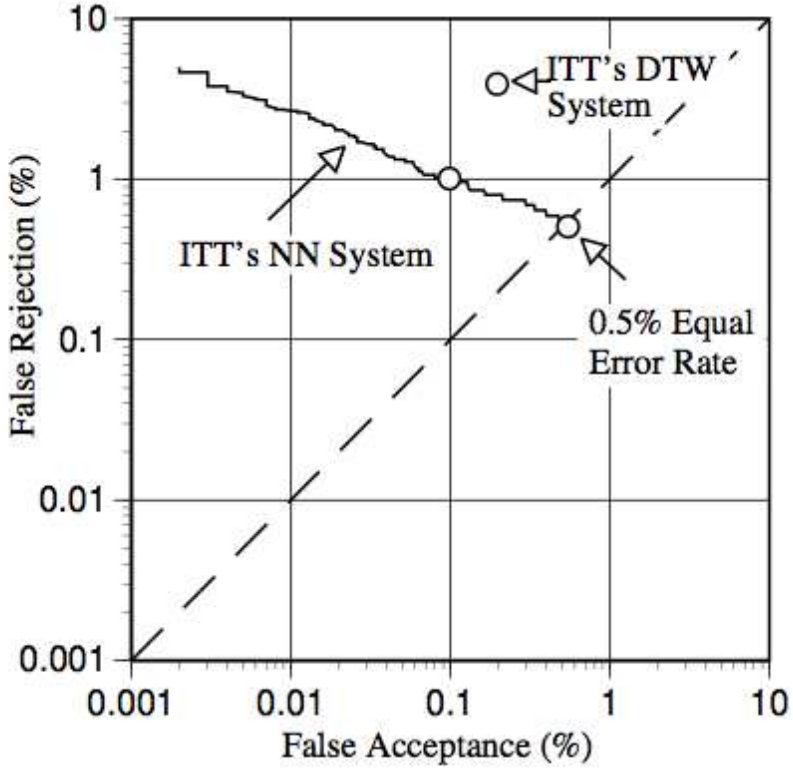
$$d(U,R) = \frac{1}{|U|}\sum_{\boldsymbol{u}_i \in U} \min_{\boldsymbol{r}_j \in R} |\boldsymbol{u}_i - \boldsymbol{r}_j|^2 + \frac{1}{|R|}\sum_{\boldsymbol{r}_j \in R} \min_{\boldsymbol{u}_i \in U} |\boldsymbol{u}_i - \boldsymbol{r}_j|^2$$

$$- \frac{1}{|U|}\sum_{\boldsymbol{u}_i \in U} \min_{\boldsymbol{u}_j \in U} |\boldsymbol{u}_i - \boldsymbol{u}_j|^2 - \frac{1}{|R|}\sum_{\boldsymbol{r}_i \in R} \min_{\boldsymbol{r}_j \in R} |\boldsymbol{r}_i - \boldsymbol{r}_j|^2$$



Performance

- YOHO database with 186 Subjects
- 9300 imposter trials
- DTW: 0.2% FA / 4 % FR; EER $\approx 1.5\%$
- NN: 0.1% FA / 1 % FR ; EER $\approx 0.5\%$

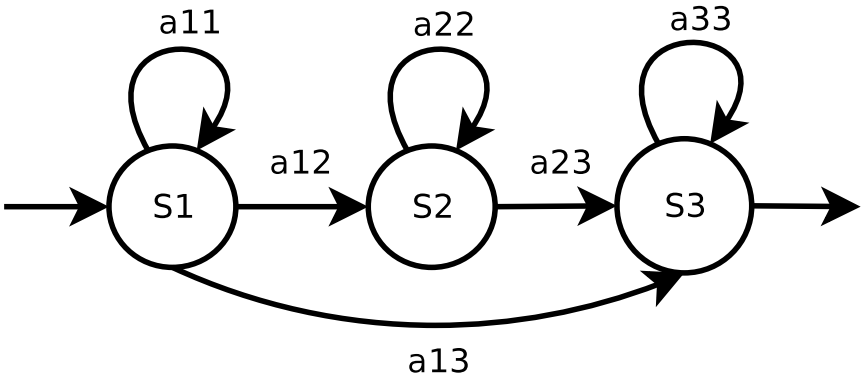


Stochastic Models

Hidden Markov Models

- Model represents a sequence of specific words
- Is a finite state machine, where each pdf $p(X|s_i)$ is associated with each state states are connected by a transition network with a given state transition probability $a_{ij} = p(s_i|s_j)$

$$p(\boldsymbol{x}|\lambda_i) = \sum_{\substack{\text{all state} \\ \text{sequences}}} \prod_{t=1}^{T} p(\boldsymbol{x}_t|s_t)\, p(s_t|s_{t-1})$$



EER $= 0.62\%$ @ $2.5s$ (YOHO, Che and Lin, 1995)

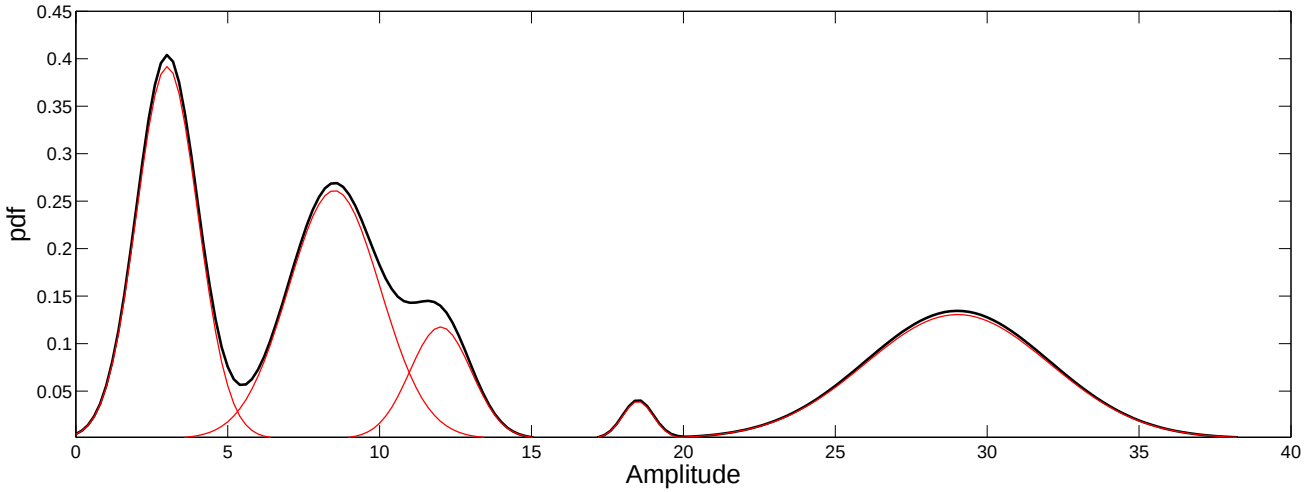
Gaussian Mixture Models

- Definition of a Gaussian Distribution

$$p_{\boldsymbol{x}}(\mu_c, \Sigma_c) = \frac{1}{(2\pi)^{D/2}|\Sigma_c|^{1/2}} \exp\Big[-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu_c})^T \Sigma_c^{-1}(\boldsymbol{x}-\boldsymbol{\mu_c})\Big]$$

- Weighted sum of C Gaussians to model target distribution

$$p(\boldsymbol{x}|\lambda) = \sum_{c=1}^{C} w_c \; p_{\boldsymbol{x}}(\mu_c, \Sigma_c)$$



GMM-UBM

- Define a Universal Background Model (UBM)
- Perform speaker adaptation
- Tight coupling between SD and UBM model
- UBM also used as cohort model
- EER $\approx 10\%$ (2048 components)

Speaker adaptation methods:

- Weighted sum combining
- Maximum a posteriori combining (MAP)

MAP adaptation:

$$\begin{aligned}
\mathbf{c}_{k,spk_{Comb}} &= [\beta_k^c \mathbf{c}_{k,spk} + (1-\beta_k^c)\mathbf{c}_{k,ubm}]\,\epsilon \\
\mu_{k,spk_{Comb}} &= \beta_k^\mu \mu_{k,spk} + (1-\beta_k^\mu)\mu_{k,ubm} \\
\mathbf{\Sigma}_{k,spk_{Comb}} &= \beta_k^\Sigma \mathbf{\Sigma}_{k,spk} + (1-\beta_k^\Sigma)(\mathbf{\Sigma}_{k,ubm} + \mu_{k,ubm}^2) - \mu_{k,spk_{Comb}}^2,
\end{aligned}$$

with $\beta_k^\rho = \frac{\mathbf{c}_{k,spk}}{\mathbf{c}_{k,spk}+r^\rho}$

and r^ρ the relevance factor. taken from [7]

Support Vector Machines

- Well suited for SV because of its binary nature of decision
- Construction of a boundary/hyperplane separating data sets
- Found optimum plane is a linear combination of a set of vectors (support vectors)
- For enrollment speaker and imposter data must be available
- Relaxation of linear separability condition to allow outliers
- Results in an EER : 0.59 % on the YOHO database

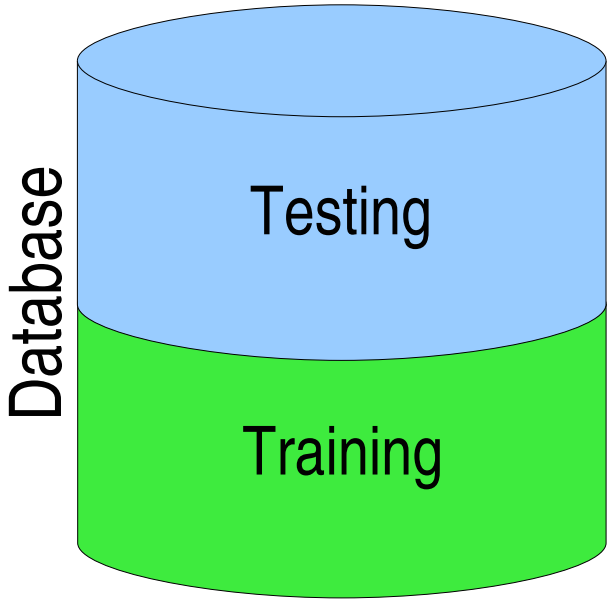
Performance for combined SVM-GMM system with non-linear kernel: EER $= 6.39\%$ (NIST 2006 SRE , 53966 tests, GMM-UBM baseline: 9.11%) [8]

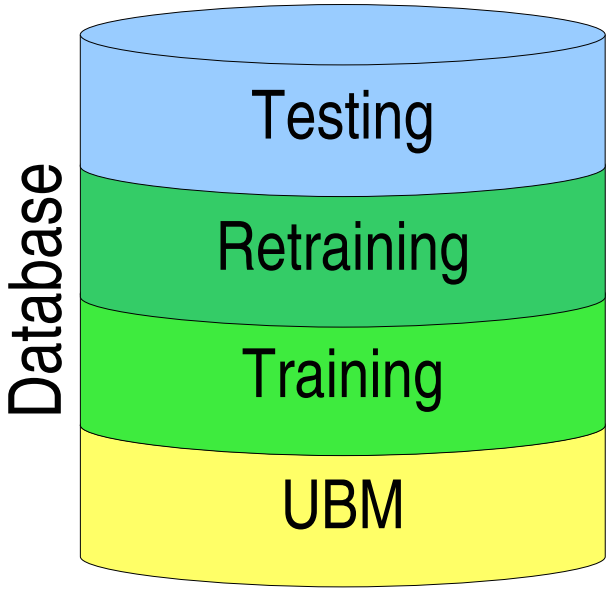
Air Traffic Control System Presentation

ATC System Presentation [9]

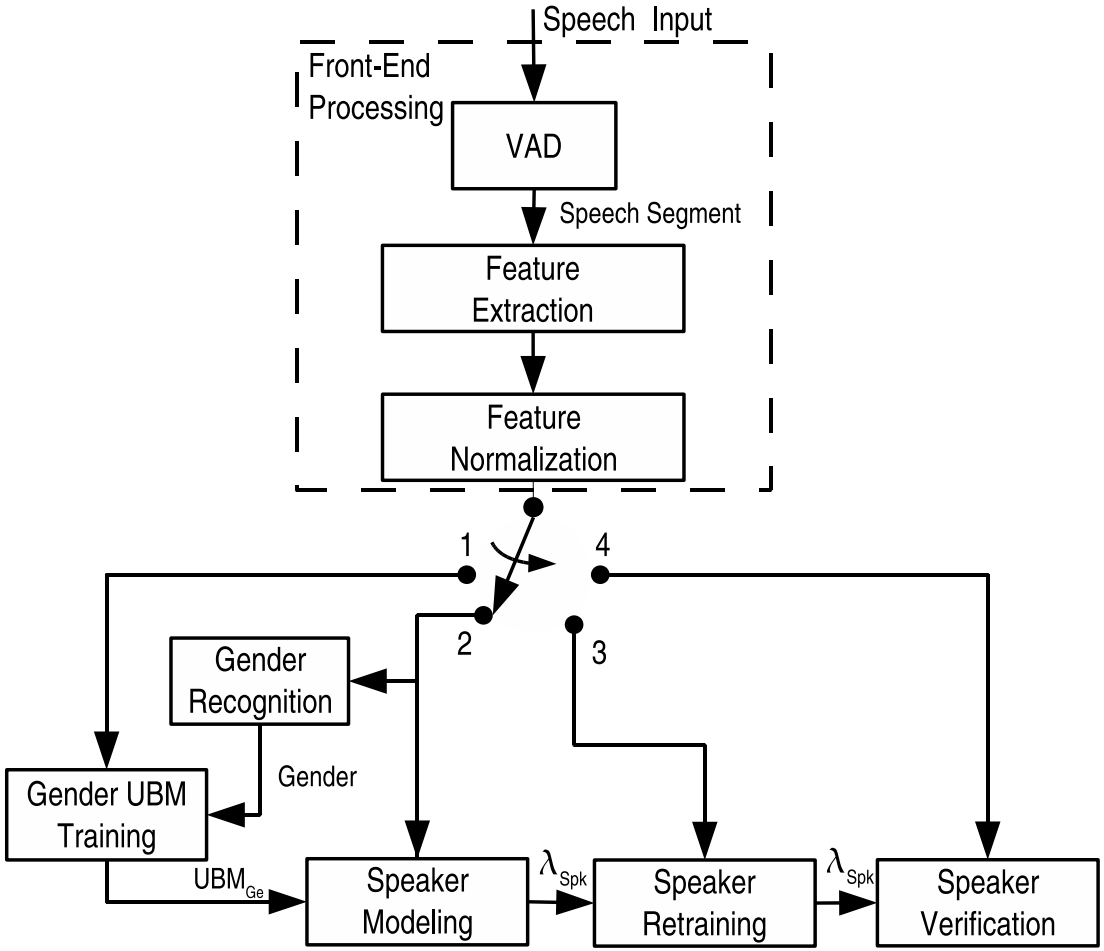
- Technical Requirements
  - AM channel with poor quality $\longrightarrow$ low SNR
  - *Narrow bandwidth in the region of 300 - 2500 Hz*
  - Real-time processing
- Speech Communication Specification
  - *Speaker turns on average only 5 seconds*
  - Hypothesized interval of uniform speaker through AIT
  - No offline speaker enrollment
  - By definition, start with reference speaker
  - Text-independent verification method used

System Pattern Recognition Approach





System Design



Databases

SPEECHDAT-AT: noisy telephone recordings

- Out of 100 speakers, 20 are marked as reference
- 6 utterances each are compared to the reference speaker
- $100*$ claimants $*6$ utterances each $*20$ reference $= 12000$ requests

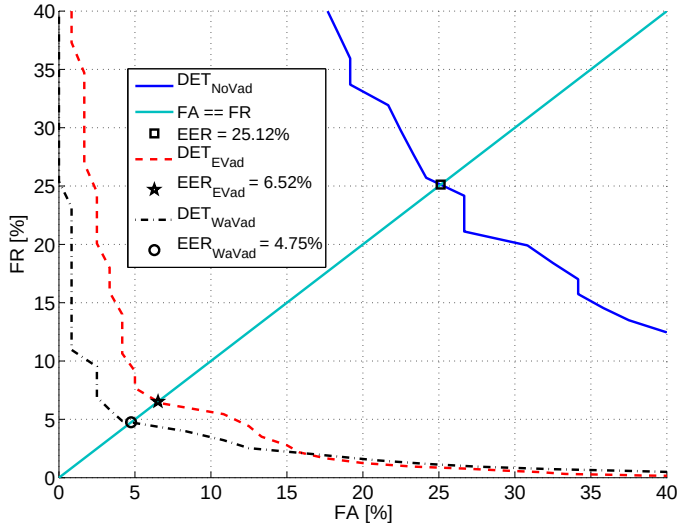
WSJ0: almost clean database (Broadcast)

- All speakers produce the same utterances
- Out of 45 speakers, 24 are marked as reference
- 12 randomly selected utterances each are compared to the reference speaker
- $45*$ claimants $*12$ utterances each $*24$ reference $= 12960$ requests

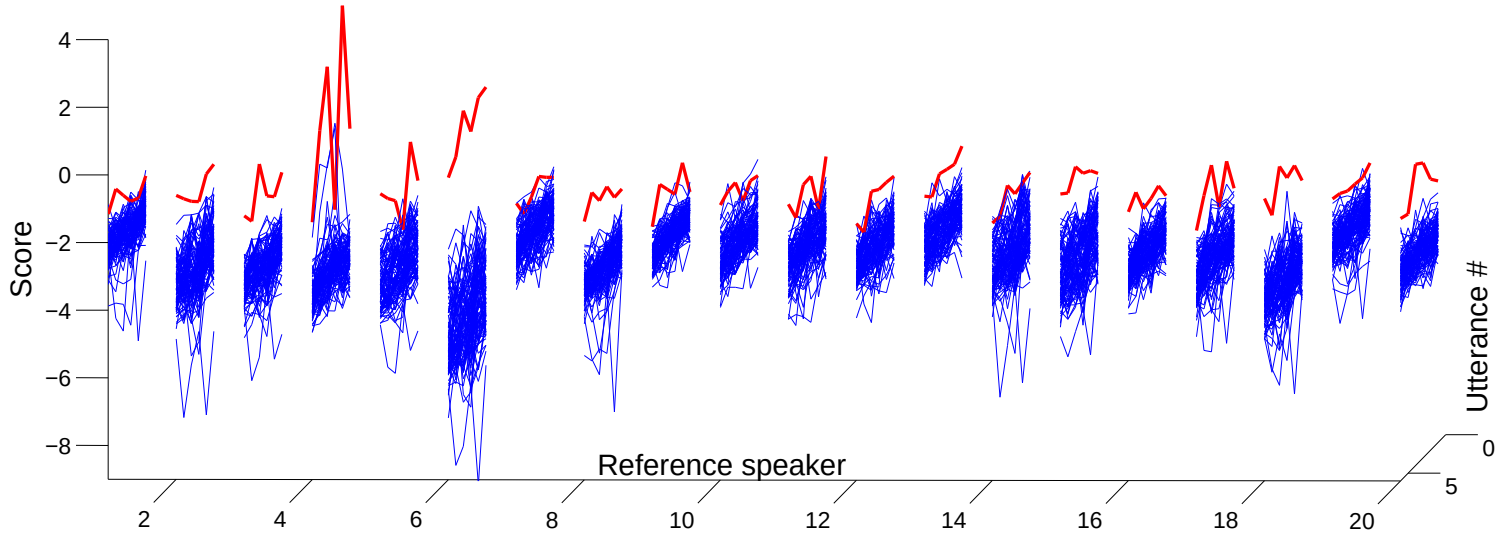
Results

DET. . . Detection error tradeoff curve
FA. . . False acceptance rate
FR. . . False rejection rate

EER . . . Equal error rate (FA == FR)



Speaker Score Distribution



Conclusion

- System to choose is application dependent
- EER depends on test (database) condition
- Most systems assume known end points
- Text-idependent systems are still a challenge

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