Bayesian Method in Speaker Verification

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Outline

- Speaker Verification System
- MAP adaptation of Speaker Model
- Experiment Setup, Conclusion and Future Work



Speaker Verification System

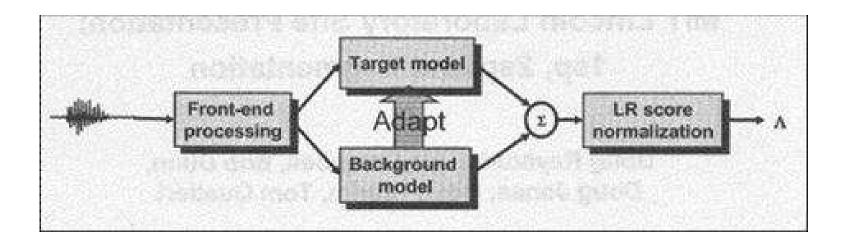


Speaker Verification System Framework

- Speaker Verification
 - Determines whether person is who they claim to be
 - User makes identity claim (one to one mapping)
- Three Main Components
 - Front-end processing (Feature Extraction)
 - Speaker and background modeling (Speaker Modeling)
 - Log-likelihood-ratio score normalization (Decision Making)



Speaker Verification System Framework (Cont.)





Speaker and Background Modeling

GMM (Gaussian Mixtures Model) represent static acoustic event distribution for each speaker

$$p(o_t|\Lambda) = \sum_{m=1}^{M} \frac{w_m}{(2\pi)^{\frac{d}{2}} |\Sigma_m|^{\frac{1}{2}}} \cdot e^{-\frac{1}{2}(o_t - \mu_m)^{\tau} \Sigma_m^{-1}(o_t - \mu_m)}$$

$$\sum_{m=1}^{M} w_m = 1 \quad \text{and} \quad w_m > 0$$

 Λ is used to represent speaker model parameters. w_m is the m^{th} weight of Gaussian mixture $\mathcal{N}(o_t; \mu_m, \Sigma_m)$ with mean μ_m and covariance matrix Σ_m .



Speaker Recognition Scoring

$$p(O|\Lambda) = p(o_1, o_2, \cdots, o_T|\Lambda) = \prod_{t=1}^{T} p(o_t|\Lambda)$$

The score (average *Log-Likelihood Ratio* (LLR)) of a given test segment *O* is computed as follow,

$$score = \frac{1}{T} \sum_{t=1}^{T} (\log p(o_t | \Lambda_{tar}) - \log p(o_t | \Lambda_{UBM}))$$

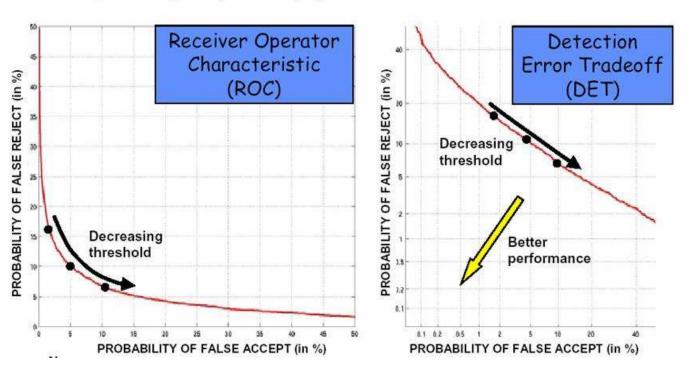
T is the length of the test segment, o_t is the feature vector at time t and $\Lambda_{\rm tar}$ and $\Lambda_{\rm UBM}$ are parameters of the target model and UBM (Universal Background Model) respectively.



Performance Measurement of Speaker Verification System

ROC and DET plots are used for performance measurement

Plot of Pr(miss) vs. Pr(fa) shows system performance DET plots Pr(miss) and Pr(fa) on normal deviate scale





MAP adaptation of Speaker Model



- EM training is reliable only when sufficient training data are available
- If only a small amount of training data, adaptation method will be used for model training.
- Background model is regarded as prior information for each speaker, speaker-specified training data are the observation samples, these two can be combined in the Bayesian framework.



Speaker model parameters to be estimated

$$\Lambda = (w_1, w_2, \cdots, w_M, \mu_1, \mu_2, \cdots, \mu_M, \Sigma_1, \Sigma_2, \cdots, \Sigma_M)$$

MAP estimation of speaker model parameters

$$\theta_{MAP} = \arg \max_{\theta} p(O|\Lambda)g(\Lambda)$$



Prior distribution of mixture weights is a conjugete density such as Dirichlet density

$$g(w_1, w_2, \cdots, w_M) \propto \prod_{m=1}^M w_m^{v_k-1}$$

where $v_k > 0$ are the parameters for the Dirichlet density. ^a



^aJ.-L. Gauvain and C.-H. Lee, "Maximum a Posterior Estimation for Multivariate Gaussian Mixture Observations of Markov Chains," IEEE Trans. Speech and Audio Processing, vol. 2, no. 2, pp. 291-298, April 1994.

• Prior distribution of (μ_m, Σ_m) is a normal_Wishart density

$$g(\mu_m, \Sigma_m) \propto |\gamma_m|^{(\alpha_m - p)/2}$$

$$\exp\left[-\frac{\tau_m}{2}(\mu_m - m_m)^t \Sigma_m(\mu_m - m_m)\right]$$

$$\exp\left[-\frac{1}{2}tr(u_m \Sigma_m)\right]$$

where $(\tau_m, m_m, \alpha_m, u_m)$ are the prior density parameters such that $\alpha_m > p-1, \tau_m > 0$, m_m is a vector of dimension p, and u_m is a p*p positive definite matrix.



Practical method for parameter adaptation only the mean vectors will be updated

$$\hat{\mu}_m = \alpha_m E_m(O) + (1 - \alpha_m) \mu_m$$



Experiment Setup, Conclusion and Future Work

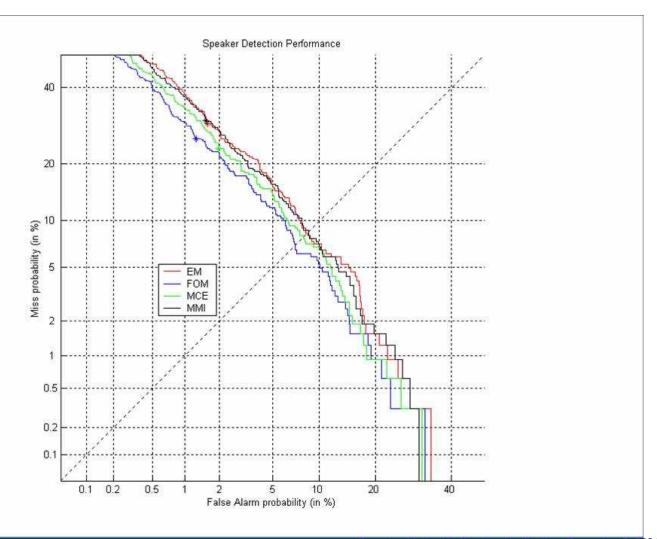


Experiment Setup

- 1996 NIST(National Institute of Standards and Technology) dataset was used for experiment,
- 225 Speakers in the Corpus
- 1 minutes for training and 15 second for testing for each speaker

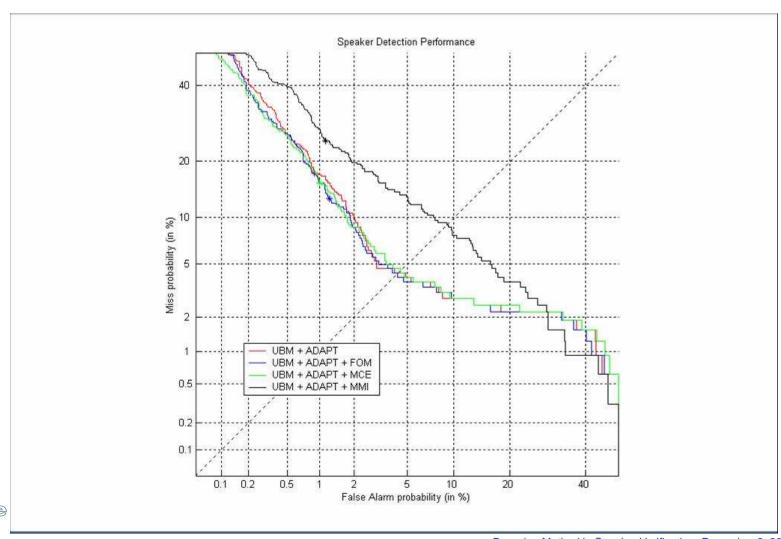


System Performance using EM Training





System Performance using MAP Adaptation





Future Work

- Acoustic features robust against noisy environment and different channels
- Incorporation dynamical acoustic features and prosodic features
- Higher level information
- novel probabilistic models for speaker modeling



Q & A

