Probabilistic Feature Transformation for Channel Robust Speaker Verification

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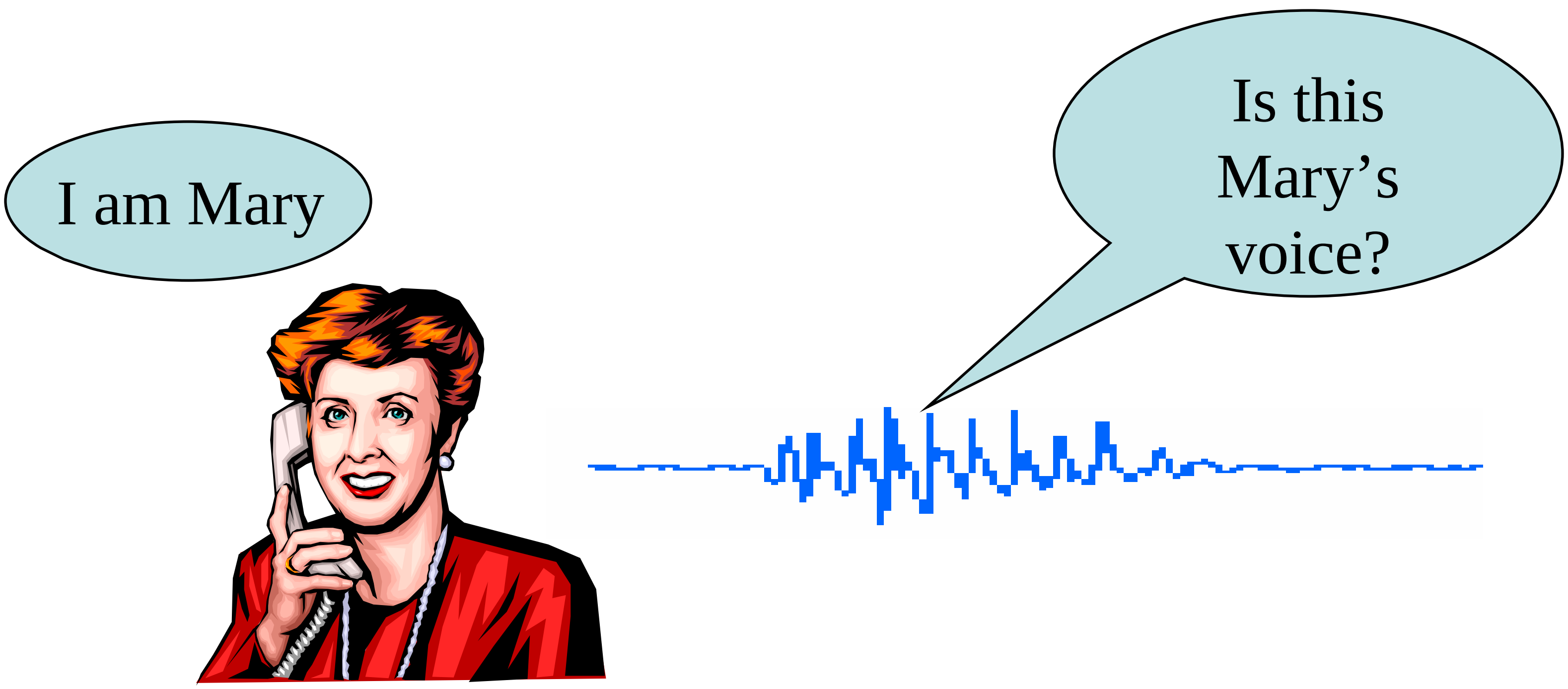
Outline

- What is Speaker Verification
- Challenge in Speaker Verification and How to Deal With it
- Feature Transformation
  - Blind Methods
  - Non-Blind Methods
- Evaluations on NIST2000 Dataset
- Results and Conclusion

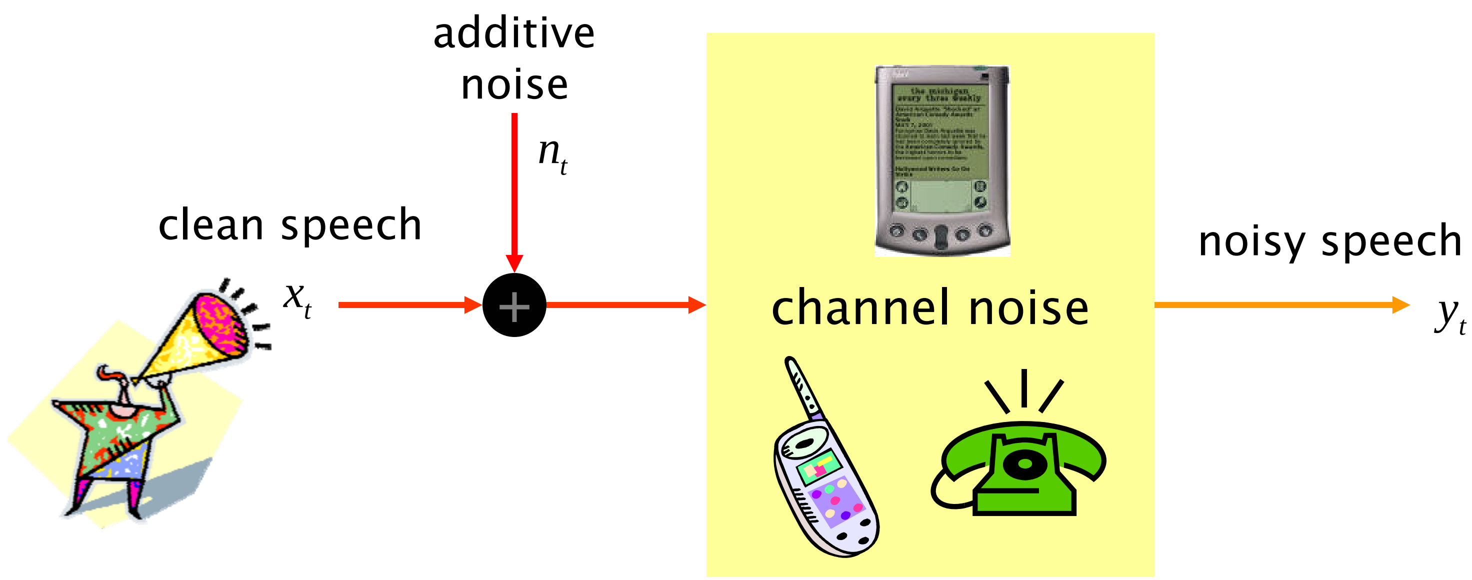
What is Speaker Verification?

- To verify the identify of a claimant based on his/her own voices

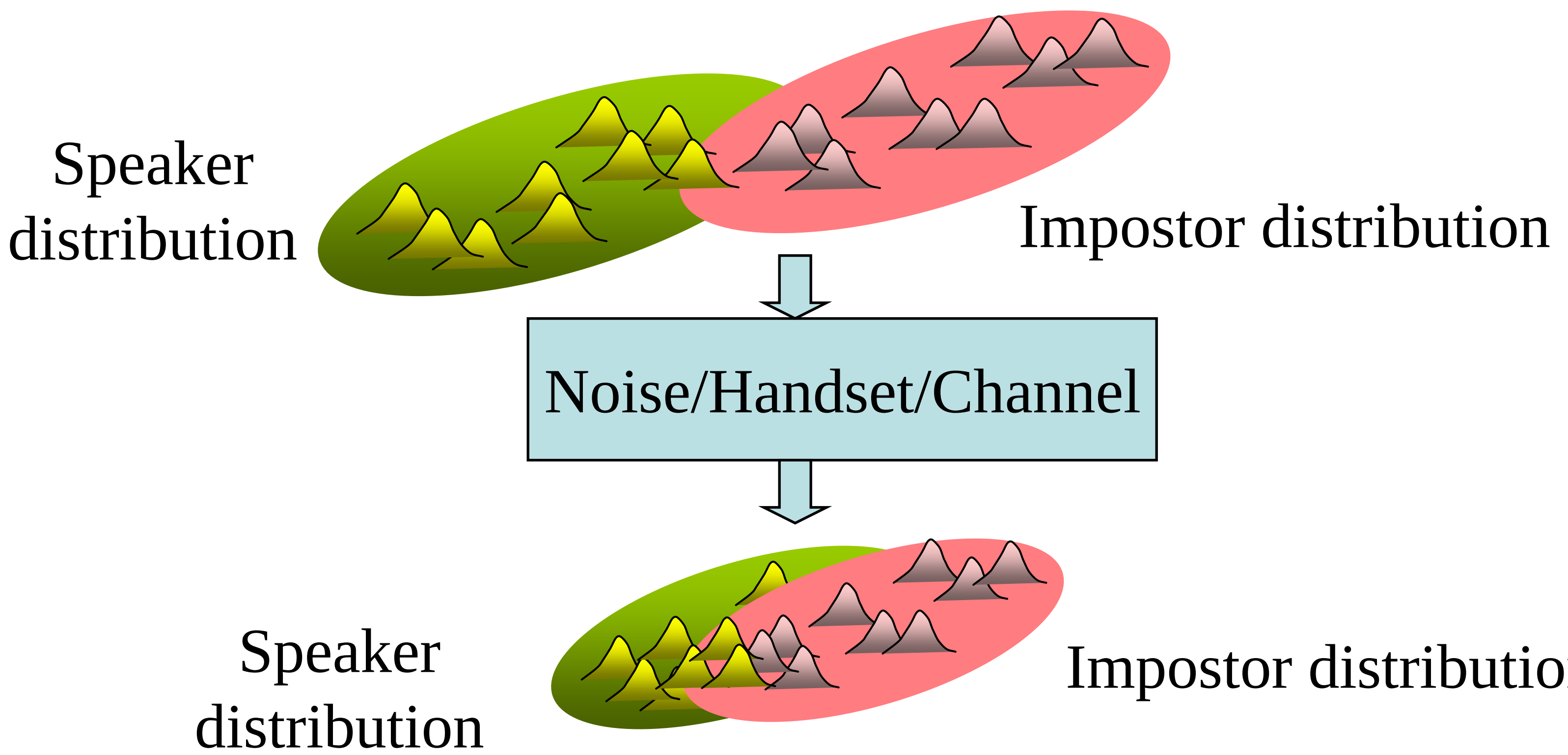


Challenges in Speaker Verification

- Handle distortion of speech signal due to background noise
- Handle distortion of speech signal due to handsets / transducers



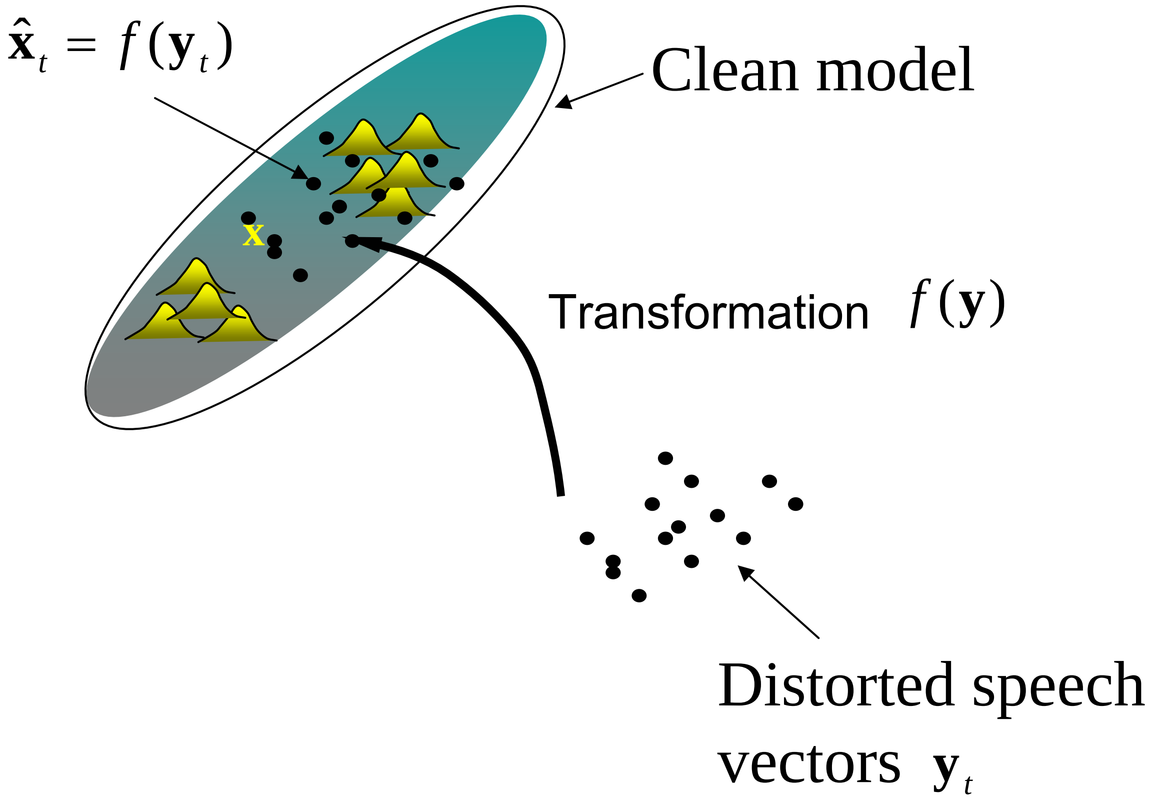
Effect of Noise/Channel on Speech Features



Problem: Noise and channel effect will make the speech of the true speaker and impostors less discriminative.

How do We Deal with the Challenge?

- Feature transformation aims to reduce the effects of channel- and handset-distortion by transforming distorted features to bring them closer to the clean speech models.

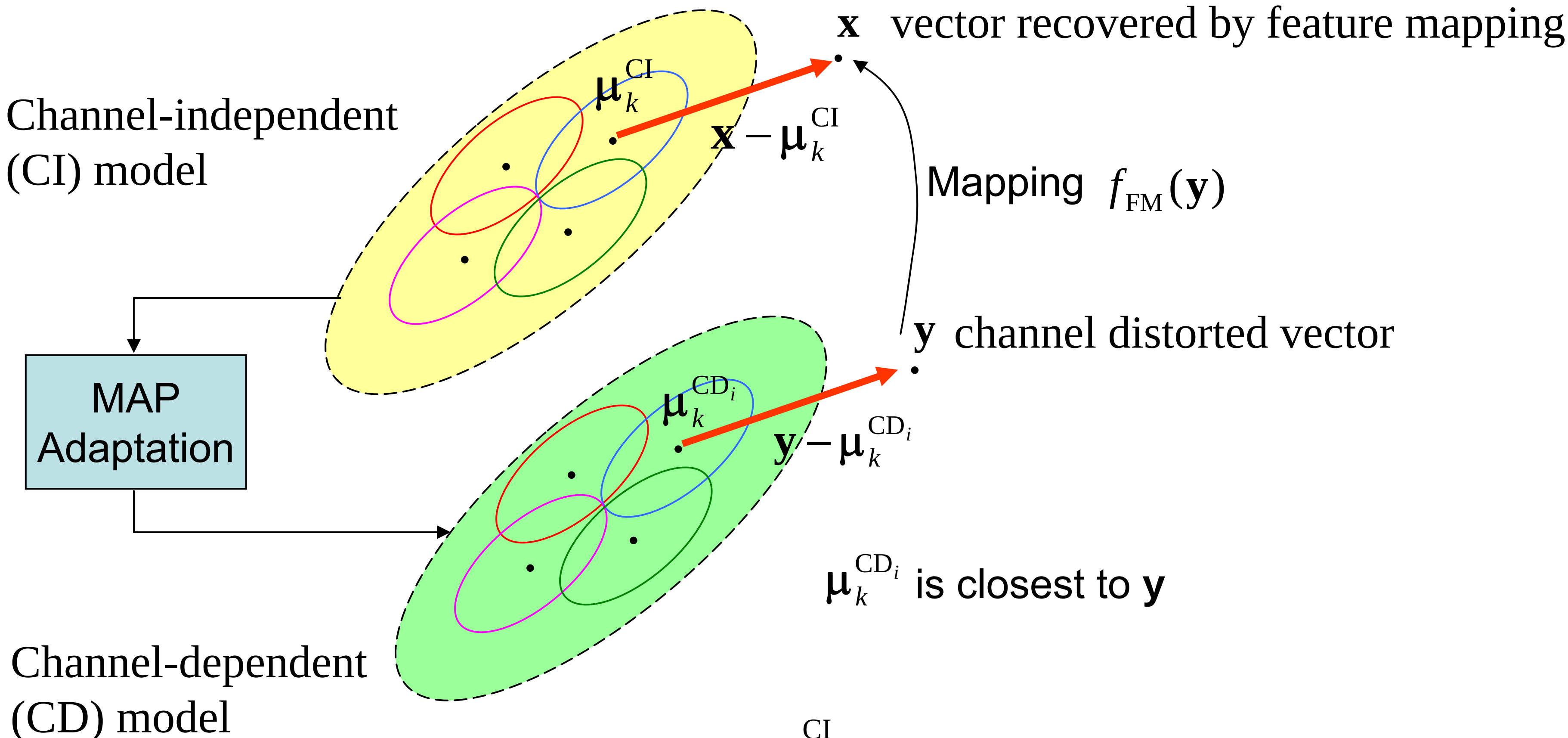


Type of Feature Transformation

- Non-blind compensation – based on a priori knowledge of the all possible channels
  - Feature Mapping (FM), by Reynolds (2003)
  - Probabilistic feature mapping (PFM), proposed in this paper
  - Fast probabilistic feature mapping (fPFM), proposed in this paper
  - Stochastic feature transformation (SFT), by Mak & Kung (2002)

- Blind compensation – without a priori knowledge of the channel characteristics
  - Cepstral Mean Subtraction (CMS), by Atal (1974)
  - Blind stochastic feature transformation (BSFT), by Yiu, Mak and Kung (2004, 2005)
  - Fast BSFT (fBSFT), proposed in this paper

Feature Mapping (Non-Blind)

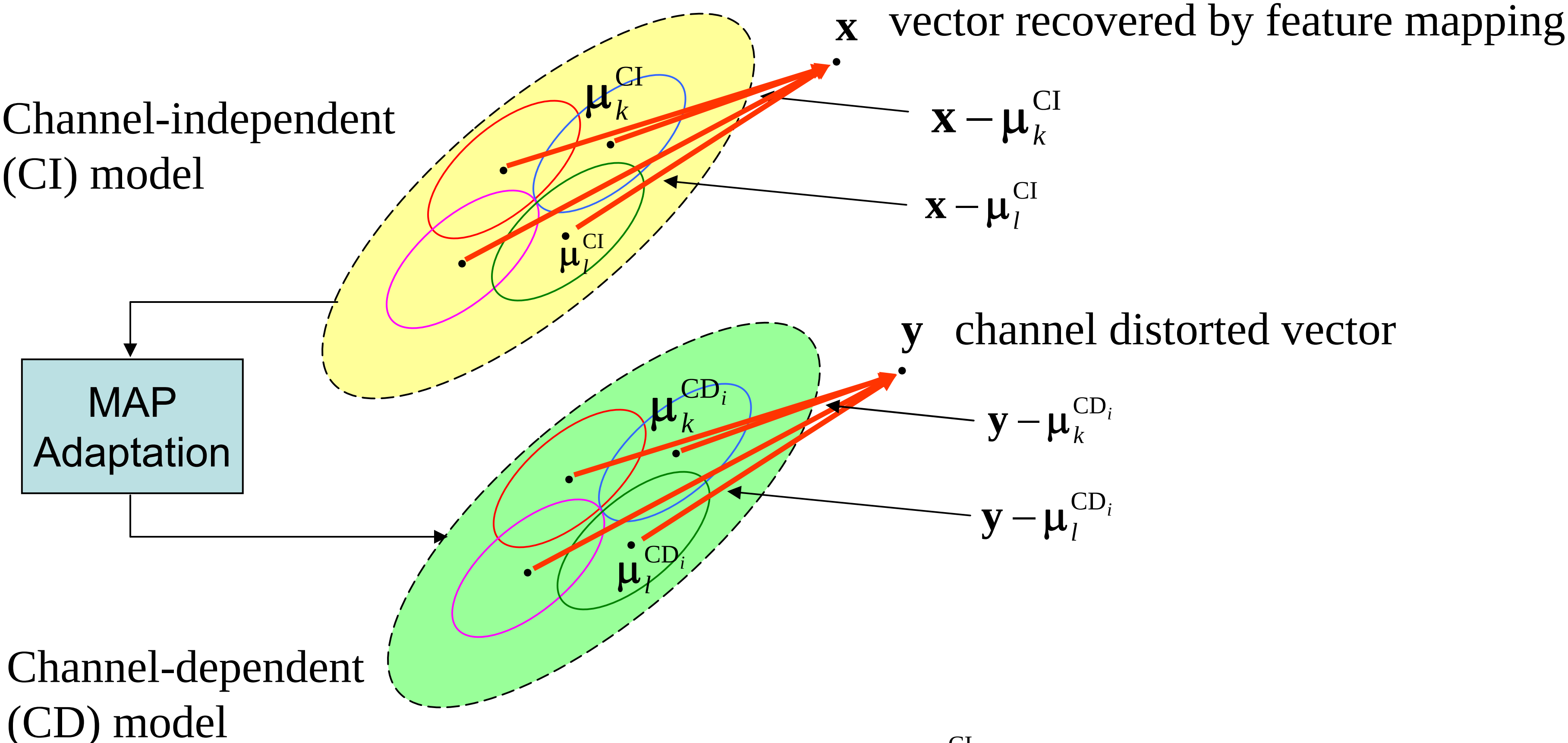


$$\mathbf{x}-\mu_k^{\mathrm{CI}} = \left(\mathbf{y}-\mu_k^{\mathrm{CD}_i}\right)\frac{\sigma_k^{\mathrm{CI}}}{\sigma_k^{\mathrm{CD}_i}}$$

account for the difference in variance

$$\Rightarrow \mathbf{x} = f_{\mathrm{FM}}(\mathbf{y}) = \left(\mathbf{y}-\boldsymbol{\mu}_k^{\mathrm{CD}_i}\right)\frac{\boldsymbol{\sigma}_k^{\mathrm{CI}}}{\boldsymbol{\sigma}_k^{\mathrm{CD}_i}}+\boldsymbol{\mu}_k^{\mathrm{CI}}$$

Probabilistic Feature Mapping (Non-Blind)

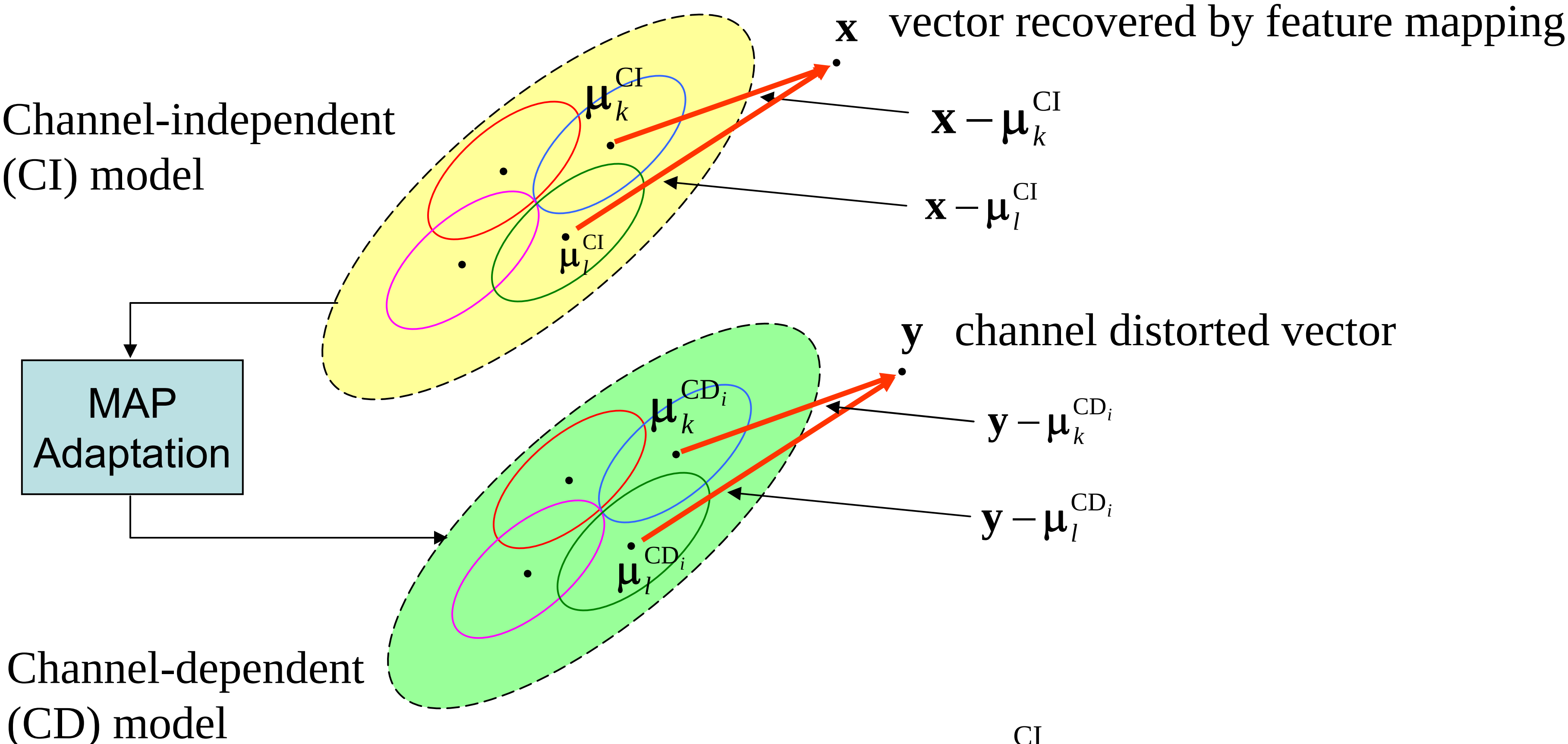


$$\sum_{j=1}^{M} P(j\,|\,\mathbf{y})\left(\mathbf{x}-\boldsymbol{\mu}_j^{\mathrm{CI}}\right) = \sum_{j=1}^{M} P(j\,|\,\mathbf{y})\left(\mathbf{y}-\boldsymbol{\mu}_j^{\mathrm{CD}_i}\right)\frac{\boldsymbol{\sigma}_j^{\mathrm{CI}}}{\boldsymbol{\sigma}_j^{\mathrm{CD}_i}}$$

$$\Rightarrow \mathbf{x} = \sum_{j=1}^{M} P(j\,|\,\mathbf{y})\left[\left(\mathbf{y}-\boldsymbol{\mu}_j^{\mathrm{CD}_i}\right)\frac{\boldsymbol{\sigma}_j^{\mathrm{CI}}}{\boldsymbol{\sigma}_j^{\mathrm{CD}_i}} + \boldsymbol{\mu}_j^{\mathrm{CI}}\right]$$

$$P(j\,|\,\mathbf{y}) = \frac{\pi_j^{\mathrm{CD}_i}\, p(\mathbf{y}\,|\,\boldsymbol{\mu}_j^{\mathrm{CD}_i}, \Sigma_j^{\mathrm{CD}_i})}{\sum_{l=1}^{M} \pi_l^{\mathrm{CD}_i}\, p(\mathbf{y}\,|\,\boldsymbol{\mu}_l^{\mathrm{CD}_i}, \Sigma_l^{\mathrm{CD}_i})}$$

Fast Probabilistic FM (Non-Blind)



$$\sum_{j\in C} P(j\,|\,\mathbf{y})\left(\mathbf{x}-\mu_j^{\mathrm{CI}}\right) = \sum_{j\in C} P(j\,|\,\mathbf{y})\left(\mathbf{y}-\mu_j^{\mathrm{CD}_i}\right)\frac{\sigma_j^{\mathrm{CI}}}{\sigma_j^{\mathrm{CD}_i}}$$

$$\Rightarrow \mathbf{x} = \sum_{j\in 1} P(j\,|\,\mathbf{y})\left[\left(\mathbf{y}-\mu_j^{\mathrm{CD}_i}\right)\frac{\sigma_j^{\mathrm{CI}}}{\sigma_j^{\mathrm{CD}_i}} + \mu_j^{\mathrm{CI}}\right]$$

$$P(j\,|\,\mathbf{y}) = \frac{\pi_j^{\mathrm{CD}_i}\, p(\mathbf{y}\,|\,\mu_j^{\mathrm{CD}_i},\Sigma_j^{\mathrm{CD}_i})}{\sum_{l=1}^{M}\pi_l^{\mathrm{CD}_i}\, p(\mathbf{y}\,|\,\mu_l^{\mathrm{CD}_i},\Sigma_l^{\mathrm{CD}_i})}$$

Different Type of Feature Mapping

Feature Mapping

$$\mathbf{x} = \left(\mathbf{y} - \boldsymbol{\mu}_k^{\mathrm{CD}_i}\right)\frac{\boldsymbol{\sigma}_k^{\mathrm{CI}}}{\boldsymbol{\sigma}_k^{\mathrm{CD}_i}} + \boldsymbol{\mu}_k^{\mathrm{CI}}$$

$$k = \arg\max_{j=1}^{M} \boldsymbol{\pi}_j^{\mathrm{CD}_i}\, p(\mathbf{y} \mid \boldsymbol{\mu}_j^{\mathrm{CD}_i}, \Sigma_j^{\mathrm{CD}_i})$$

Probabilistic Feature Mapping

$$\Rightarrow \mathbf{x} = \sum_{j=1}^{M} P(j \mid \mathbf{y})\left[\left(\mathbf{y} - \boldsymbol{\mu}_j^{\mathrm{CD}_i}\right)\frac{\boldsymbol{\sigma}_j^{\mathrm{CI}}}{\boldsymbol{\sigma}_j^{\mathrm{CD}_i}} + \boldsymbol{\mu}_j^{\mathrm{CI}}\right]$$

$$P(j \mid \mathbf{y}) = \frac{\boldsymbol{\pi}_j^{\mathrm{CD}_i}\, p(\mathbf{y} \mid \boldsymbol{\mu}_j^{\mathrm{CD}_i}, \Sigma_j^{\mathrm{CD}_i})}{\sum_{l=1}^{M} \boldsymbol{\pi}_l^{\mathrm{CD}_i}\, p(\mathbf{y} \mid \boldsymbol{\mu}_l^{\mathrm{CD}_i}, \Sigma_l^{\mathrm{CD}_i})}$$

Fast Probabilistic Feature Mapping

$$\Rightarrow \mathbf{x} = \sum_{j \in C} P(j \mid \mathbf{y})\left[\left(\mathbf{y} - \boldsymbol{\mu}_j^{\mathrm{CD}_i}\right)\frac{\boldsymbol{\sigma}_j^{\mathrm{CI}}}{\boldsymbol{\sigma}_j^{\mathrm{CD}_i}} + \boldsymbol{\mu}_j^{\mathrm{CI}}\right]$$

where *C* contains the indexes of top-*C* Gaussians

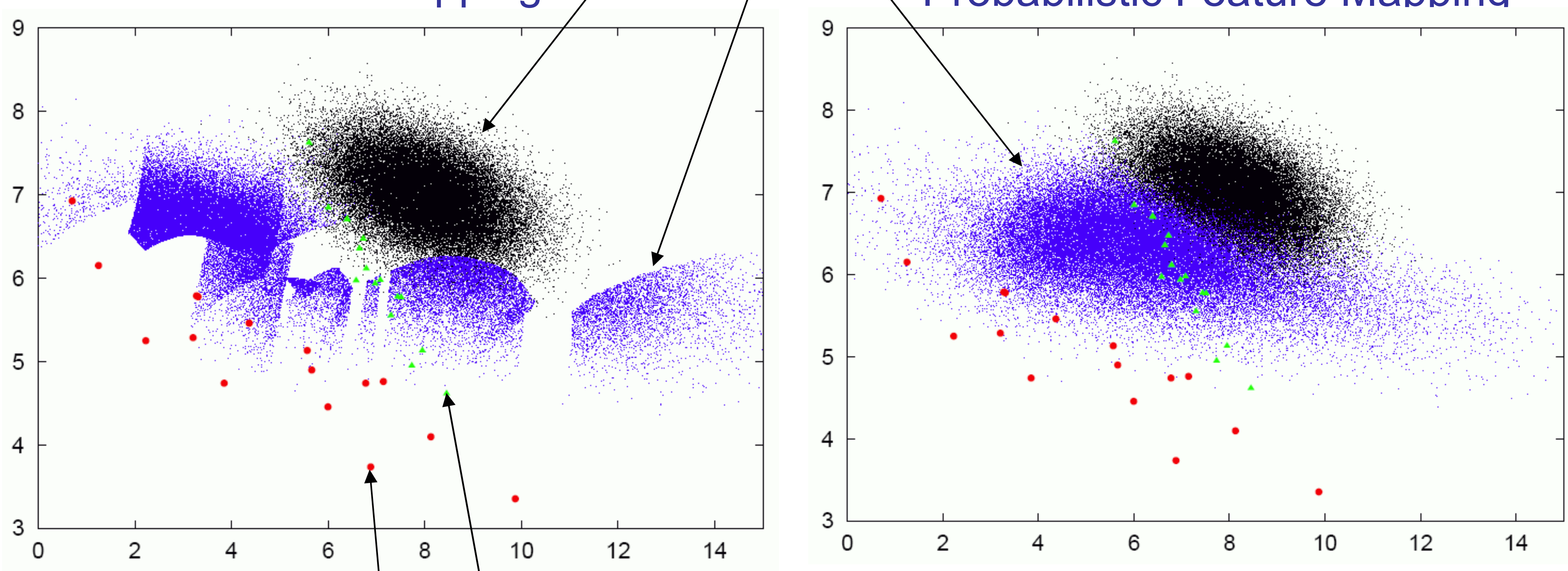
Clustering Effect of Feature Mapping

y: data from channel-dependent source

x: transformed features

Feature Mapping

Probabilistic Feature Mapping

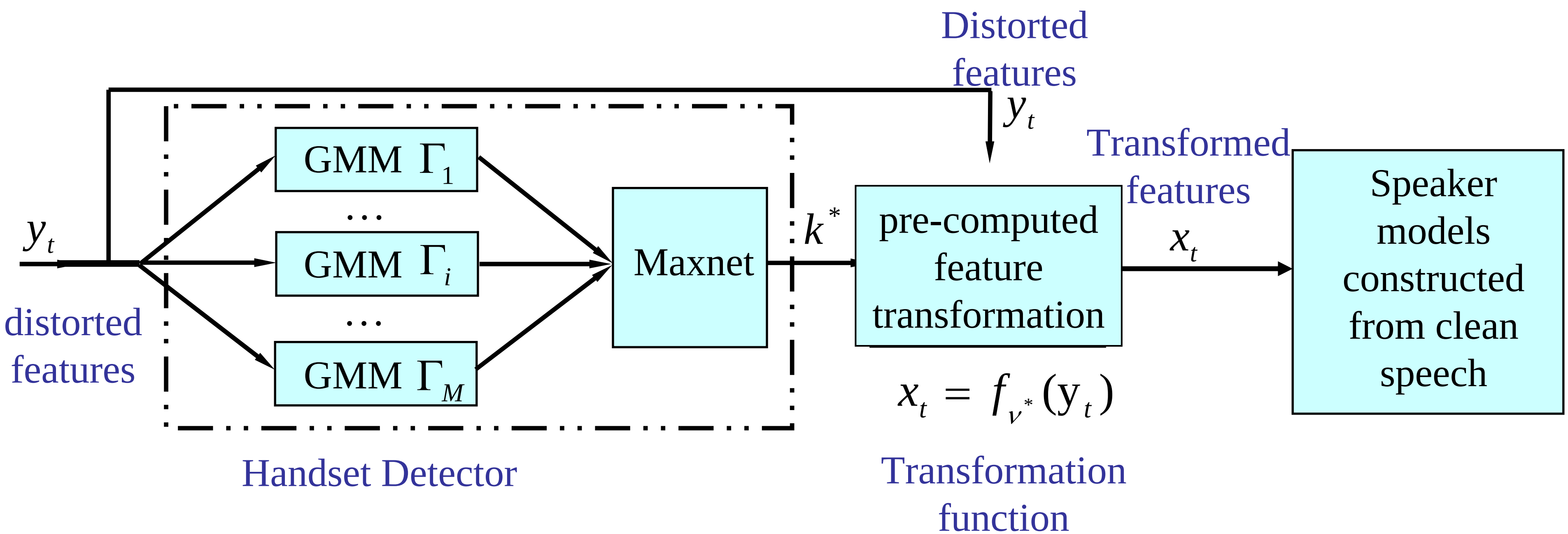


$\boldsymbol{\mu}_k^{\mathrm{CD}_i}$: Centers of channel-dependent model

$\boldsymbol{\mu}_k^{\mathrm{CI}}$: Centers of channel-independent root model

Stochastic Feature Transformation (Non-Blind)

Aim: To transform distorted features to fit the clean speech models using handset detection

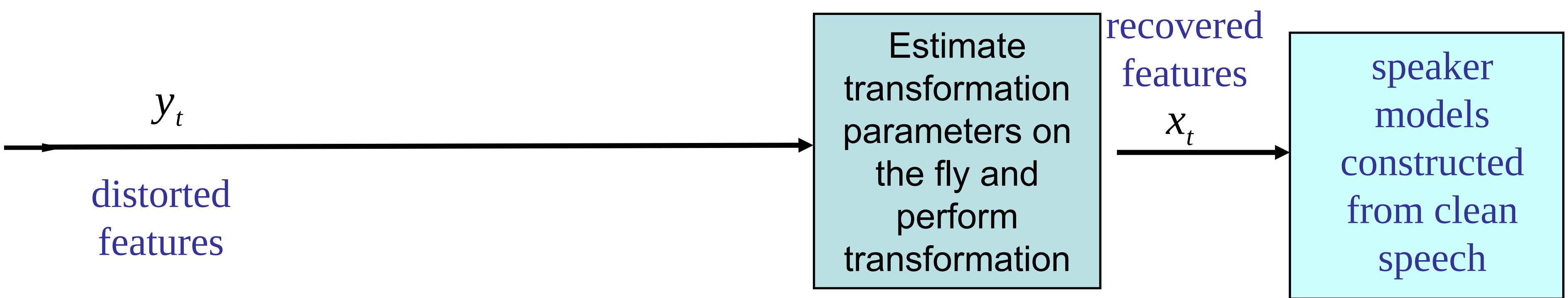


$$k^* = \arg \max_{k=1}^{H} \sum_{t=1}^{T} \log p(y_t \mid \Gamma_k)$$

Problem: The handset detector may not work for "unseen" handsets

Blind Stochastic Feature Transformation

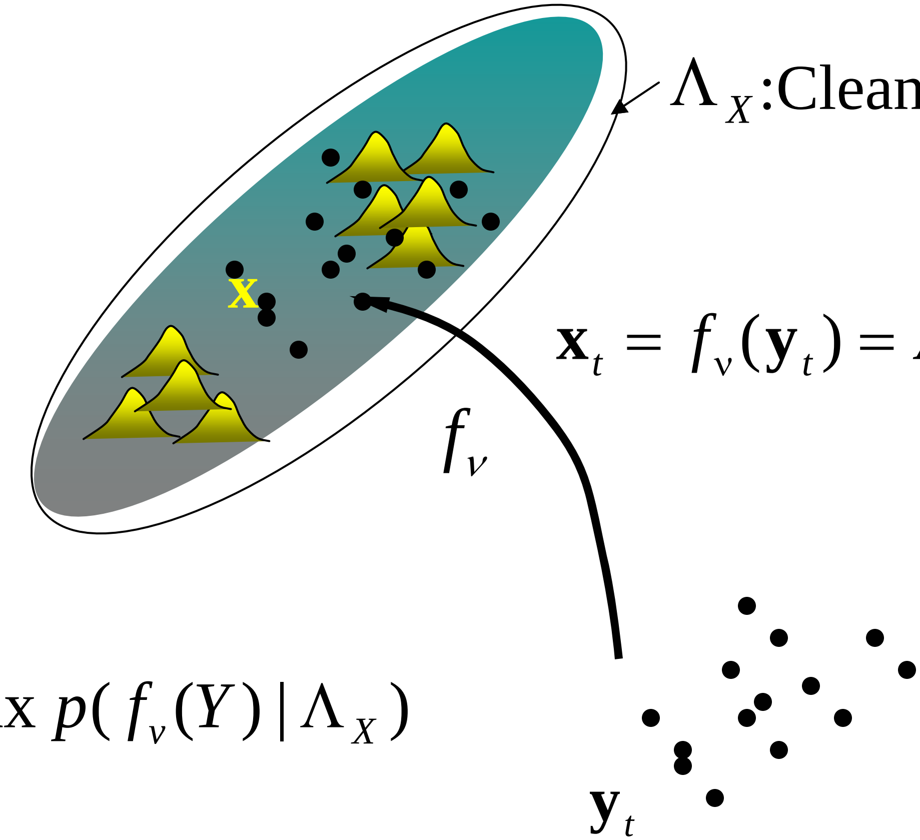
Aim: To transform distorted features to fit the clean speech models without handset detection



$$x_t = f_{\nu^*}(\mathrm{y}_t)$$

Blind Stochastic Feature Transformation

- Distorted speech vectors can be transformed to fit the clean speech model.



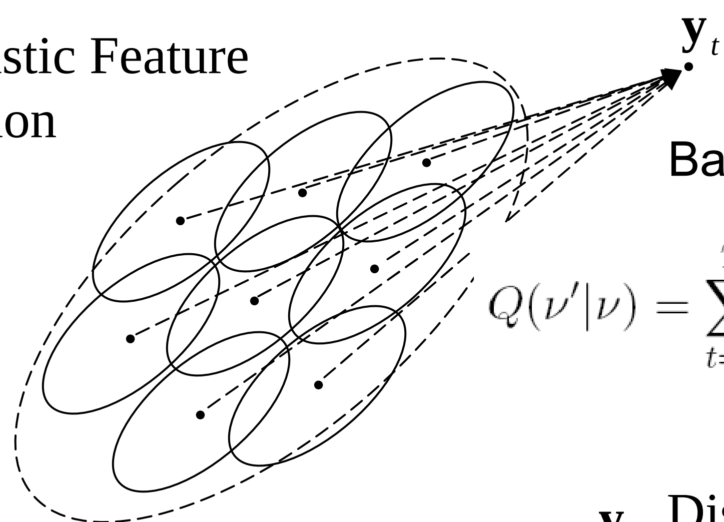
$$\mathbf{x}_t = f_\nu(\mathbf{y}_t) = A\mathbf{y}_t + \mathbf{b}$$

$$\{A, \mathbf{b}\} = \arg\max p(f_\nu(Y) \mid \Lambda_X)$$

Distorted speech vectors

Fast Blind Stochastic Feature Transformation

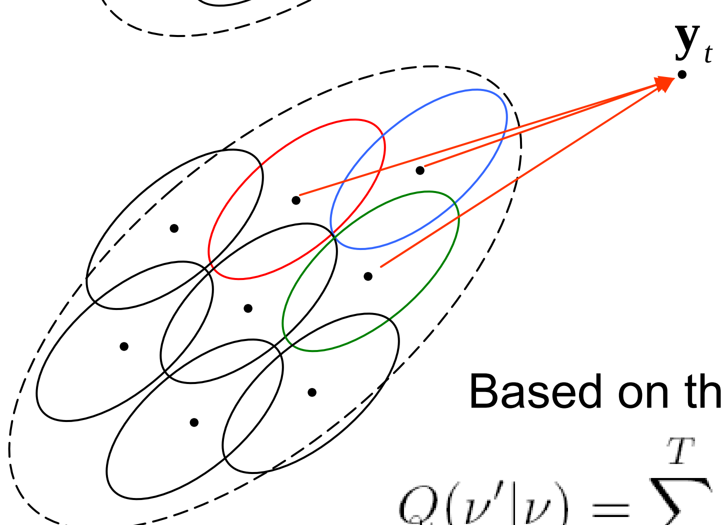
Blind Stochastic Feature Transformation



Distorted vector

Based on all Gaussians:

$$Q(\nu'|\nu) = \sum_{t=1}^{T} \sum_{j=1}^{M_c} h_j(f_\nu(\mathbf{y}_t)) \log \left\{ \frac{p(f_{\nu'}(\mathbf{y}_t)|\boldsymbol{\mu}_j, \Sigma_j)}{|J_{\nu'}(\mathbf{y}_t)|} \right\}$$



Distorted vector

Based on the top-C Gaussians only:

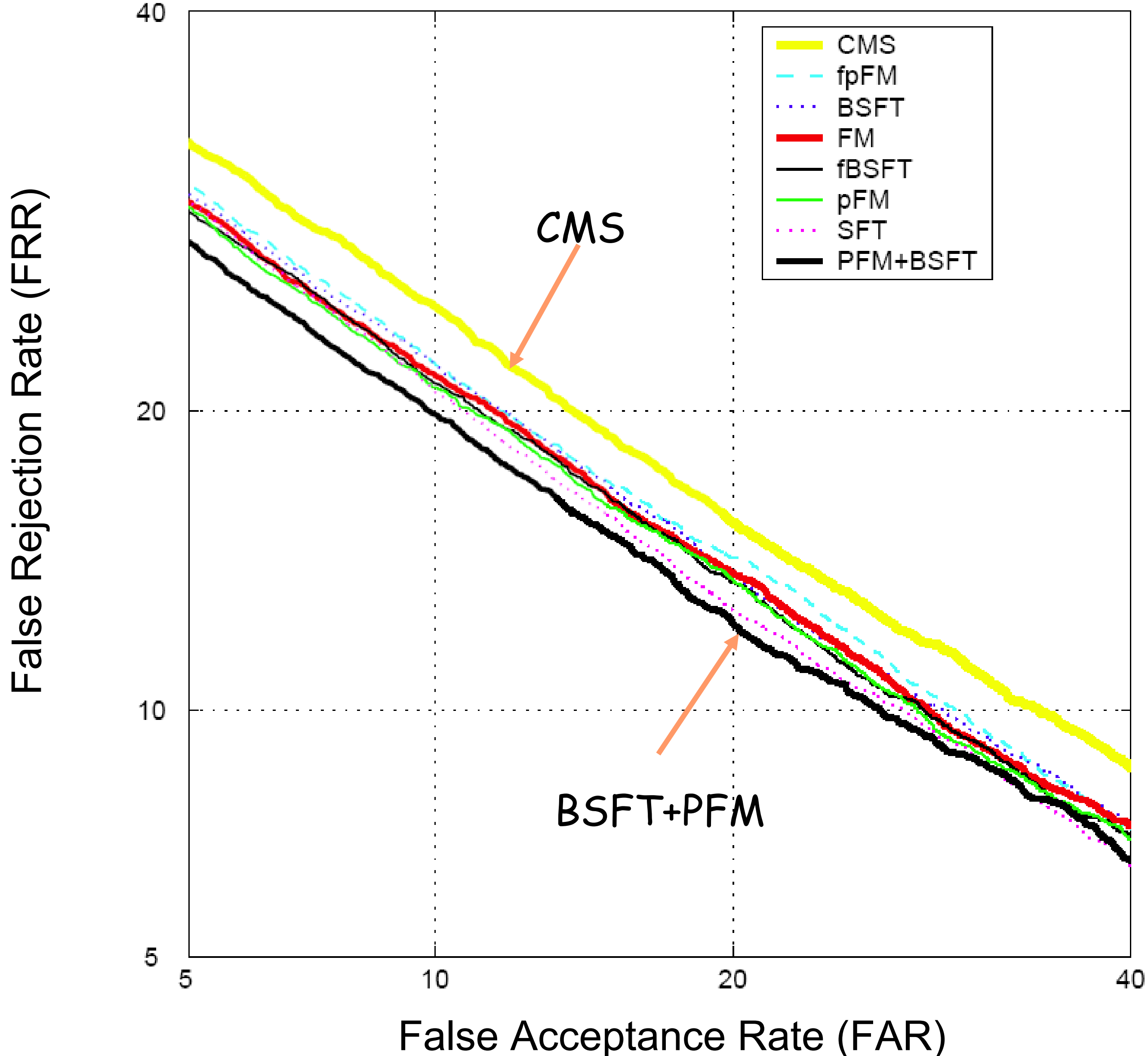
$$Q(\nu'|\nu) = \sum_{t=1}^{T} \sum_{j \in \mathcal{C}} h_j(f_\nu(\mathbf{y}_t)) \log \left\{ \frac{p(f_{\nu'}(\mathbf{y}_t)|\boldsymbol{\mu}_j, \Sigma_j)}{|J_{\nu'}(\mathbf{y}_t)|} \right\}$$

Fast Blind Stochastic Feature Transformation

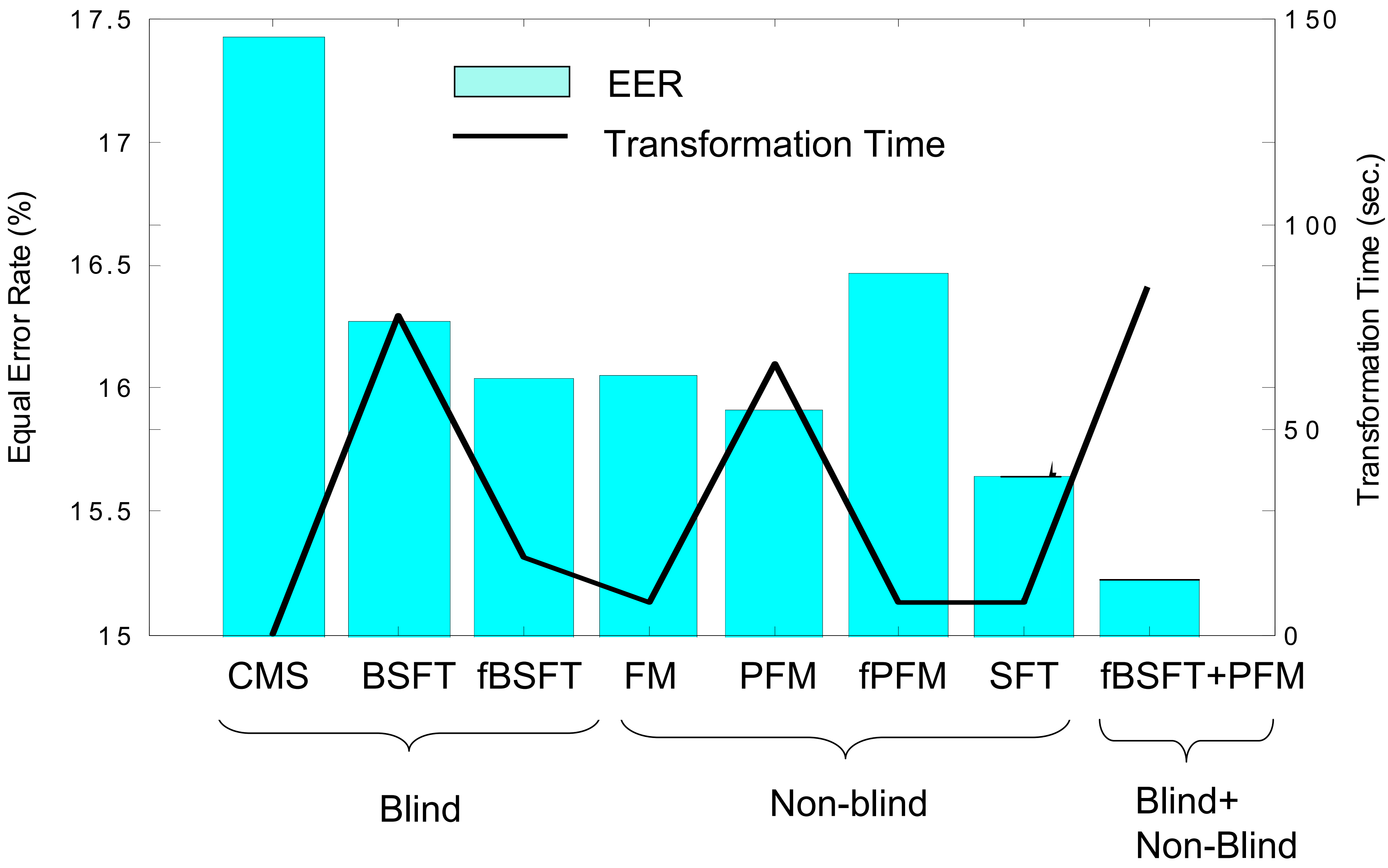
Experiments

- 2000 NIST speaker recognition evaluation set.
- 1003 target speakers (457 male and 546 female).
- Enrollment: approximately 1 minutes of speech.
- Verification: 6052 utterances (3026 male and 3026 female).
- Each verification utterance is evaluated against 11 hypothesized gender-matched speakers.
- For each gender, gender-dependent evaluation utterances from NIST99 were used to train a 1024-component gender-dependent universal background models (UBMs).
- Speaker and background models:
  - MFCC + ΔMFCC
  - Speaker models were adapted from the gender-dependent background model using MAP adaptation

Results: DET plots



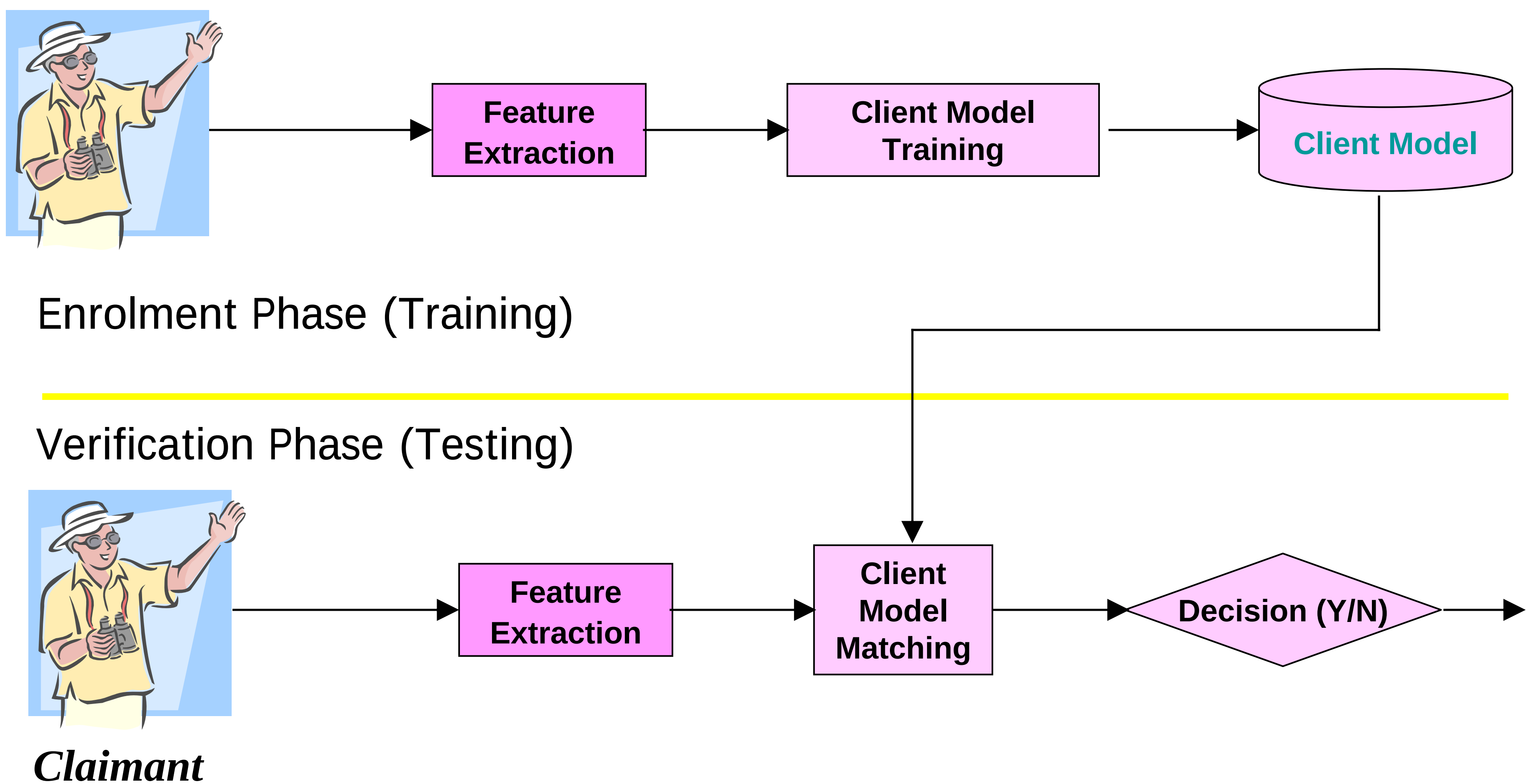
Results: EER & Transformation Time



Conclusions

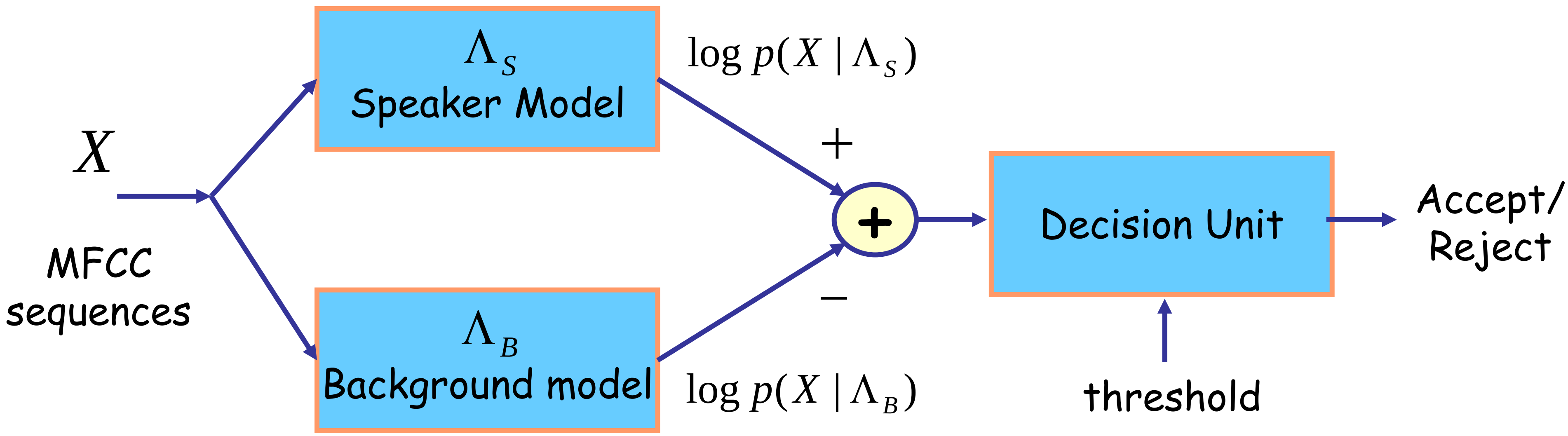
- Probabilistic feature map performs slightly better than feature map and that the fast approach can reduce computation time substantially.
- Among the approaches investigated, the fast BSFT (fBSFT) strikes a good balance between computational complexity and error rates.
- We advocate Fast BSFT for robust speaker verification because it achieves good performance without any a priori knowledge of the communication channel.

Biometric Verification



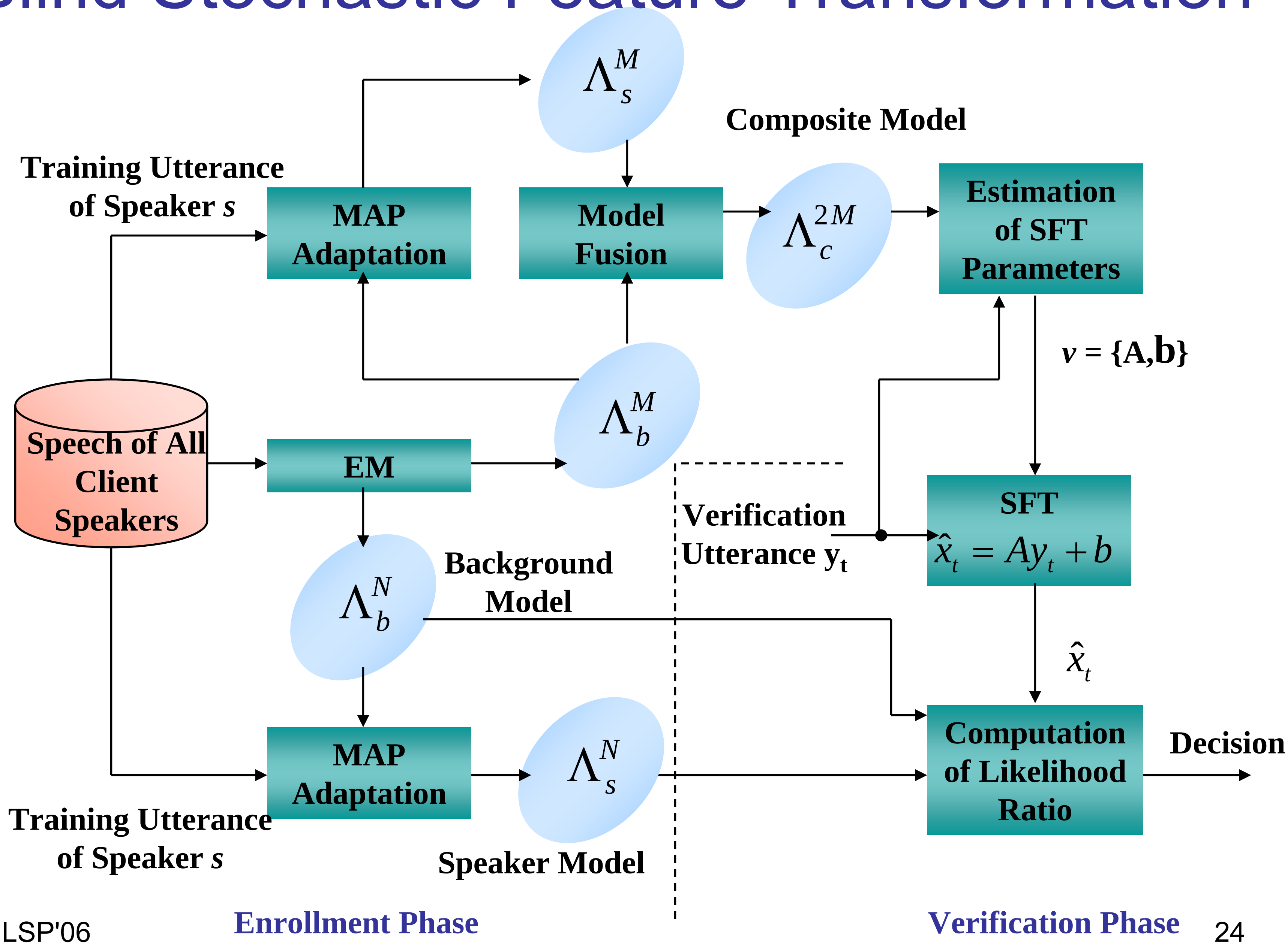
State-of-the-art Speaker Verification Systems

- Speaker verification is a biometric technology that aims to authenticate users via their voice patterns.



- The lack of robustness to channel variability and the acoustic mismatch between enrollment and verification conditions remain a major practical challenge.
- Currently, this problem is addressed by a technique called channel mismatch compensation.

Blind Stochastic Feature Transformation



Blind Stochastic Feature Transformation

- In BSFT, the transformed feature vector is
  $$\mathbf{x} = f_v(\mathbf{y}) = A\mathbf{y} + \mathbf{b}$$
- The auxiliary function is

$$Q(A',\mathbf{b}' \mid A\ ,\mathbf{b}) = \sum_{t=1}^{T}\sum_{j=1}^{M_c} h_j(f_\nu(\mathbf{y}_t))\log\left\{\frac{p(f_{\nu'}(\mathbf{y}_t)\mid \boldsymbol{\mu}_j,\Sigma_j)}{|J_{\nu'}(\mathbf{y}_t)|}\right\}$$

$$\frac{\partial Q(A',\mathbf{b}' \mid A\ ,\mathbf{b})}{\partial a_i'} = 0 \qquad \frac{\partial Q(A',\mathbf{b}' \mid A\ ,\mathbf{b})}{\partial b_i'} = 0$$

$$\Rightarrow \begin{cases} b_i' = \dfrac{p_i - q_i a_i'}{r_i} \\ \left(s_i - \dfrac{q_i^2}{r_i}\right) a_i'^2 + \left(\dfrac{q_i p_i}{r_i} - u_i\right) a_i' - T = 0 \end{cases}$$

Blind Stochastic Feature Transformation

$$p_i = \sum_{t=1}^{T} \sum_{j=1}^{M_c} h_j(f_\nu(\mathbf{y}_t))\boldsymbol{\mu}_{ji}\boldsymbol{\sigma}_{ji}^{-2}$$

$$q_i = \sum_{t=1}^{T} \sum_{j=1}^{M_c} h_j(f_\nu(\mathbf{y}_t))\mathbf{y}_{ji}\boldsymbol{\sigma}_{ji}^{-2}$$

$$r_i = \sum_{t=1}^{T} \sum_{j=1}^{M_c} h_j(f_\nu(\mathbf{y}_t))\boldsymbol{\sigma}_{ji}^{-2}$$

$$s_i = \sum_{t=1}^{T} \sum_{j=1}^{M_c} h_j(f_\nu(\mathbf{y}_t))\mathbf{y}_{ji}^{2}\boldsymbol{\sigma}_{ji}^{-2}$$

$$u_i = \sum_{t=1}^{T} \sum_{j=1}^{M_c} h_j(f_\nu(\mathbf{y}_t))\boldsymbol{\mu}_{ji}\mathbf{y}_{ti}\boldsymbol{\sigma}_{ji}^{-2}$$

- In the fast BSFT, the auxiliary function is

$$Q(A',\mathbf{b}' \mid A, \mathbf{b}) = \sum_{t=1}^{T} \sum_{j \in C} h_j(f_\nu(\mathbf{y}_t)) \log\left\{ \frac{p(f_{\nu'}(\mathbf{y}_t) \mid \boldsymbol{\mu}_j, \Sigma_j)}{|J_{\nu'}(\mathbf{y}_t)|} \right\}$$

where *C* contains the indexes of top-*C* Gaussians

Procedures for creating target speaker models for FM, PFM, and BSFT