



SNR-Invariant PLDA with Multiple Speaker Subspaces



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Introduction

- Noise level variability can shift the i-vectors to different regions of the i-vector space, and i-vectors with similar SNRs tend to cluster together.
- This phenomenon limits the capability of SNR-invariant PLDA with a single speaker subspace.
- This paper proposes a new SNR-invariant PLDA model by introducing multiple speaker subspaces to the SNR-invariant PLDA model.
- Experiments on NIST 2012 SRE demonstrate the effectiveness of the proposed method compared with PLDA and SNR-invariant PLDA.

Background

Conventional PLDA: $\mathbf{x}_{ij}^k = \mathbf{m} + \mathbf{V}\mathbf{h}_i + \boldsymbol{\varepsilon}_{ij}^k$

Pool i-vectors from various background noise levels to train a PLDA model.

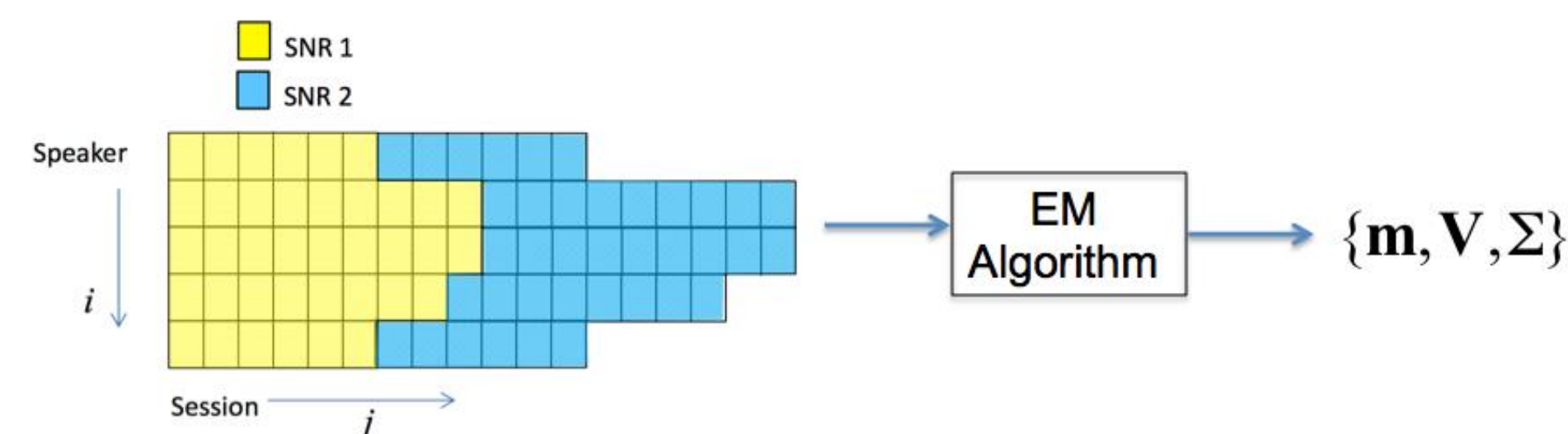


Fig.1: Training process of conventional PLDA.

SNR-invariant PLDA: $\mathbf{x}_{ij}^k = \mathbf{m} + \mathbf{V}\mathbf{h}_i + \mathbf{U}\mathbf{w}_k + \boldsymbol{\varepsilon}_{ij}^k$

I-vectors within the same SNR group share the same SNR factor \mathbf{w}_k ; the model is trained using the pooled data.

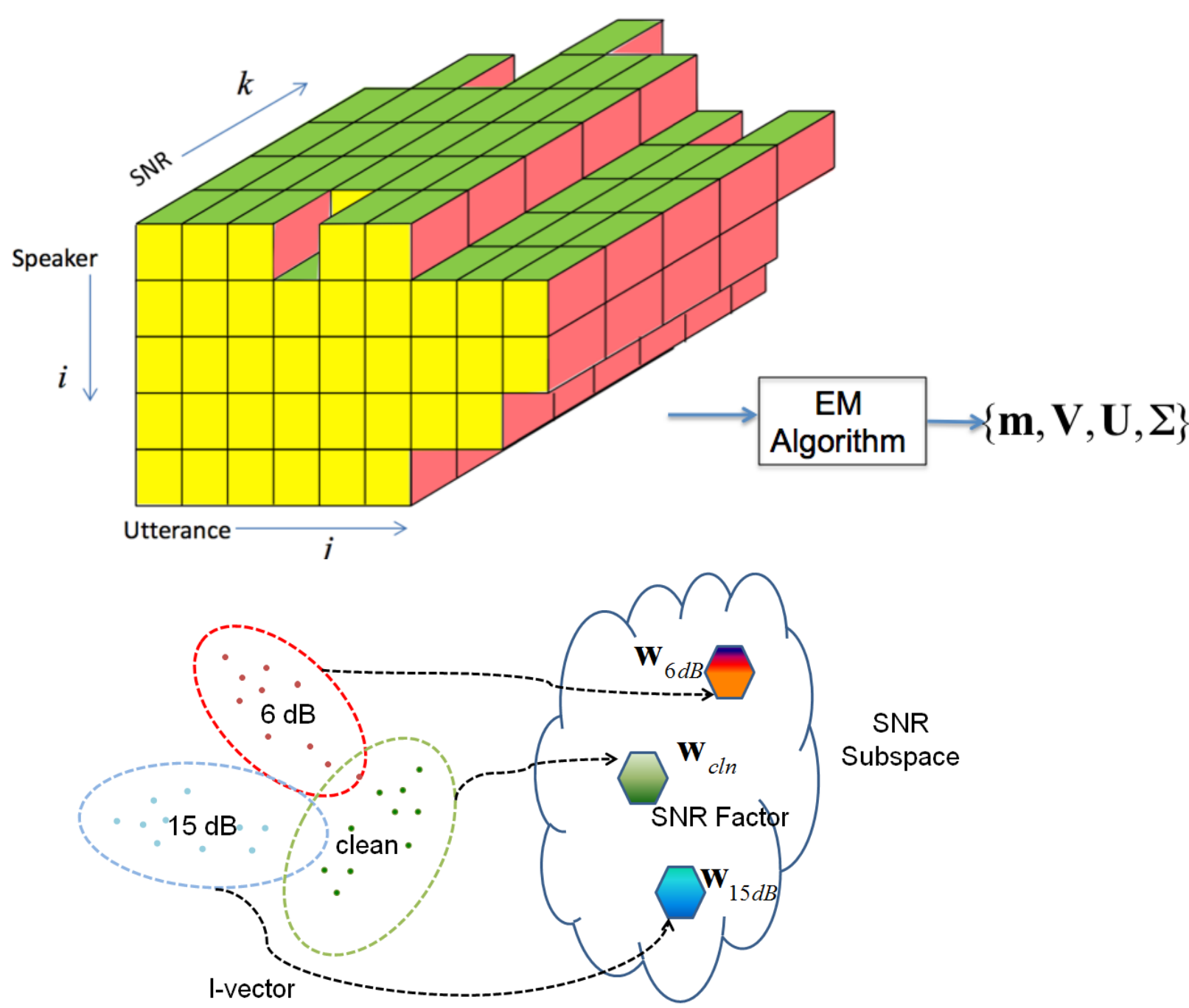


Fig.2: Training process of SNR-invariant PLDA.

Proposed Method

Assuming that speaker variability within a narrow range of SNR occurs in a unique speaker-subspace, multiple speaker subspaces are introduced.

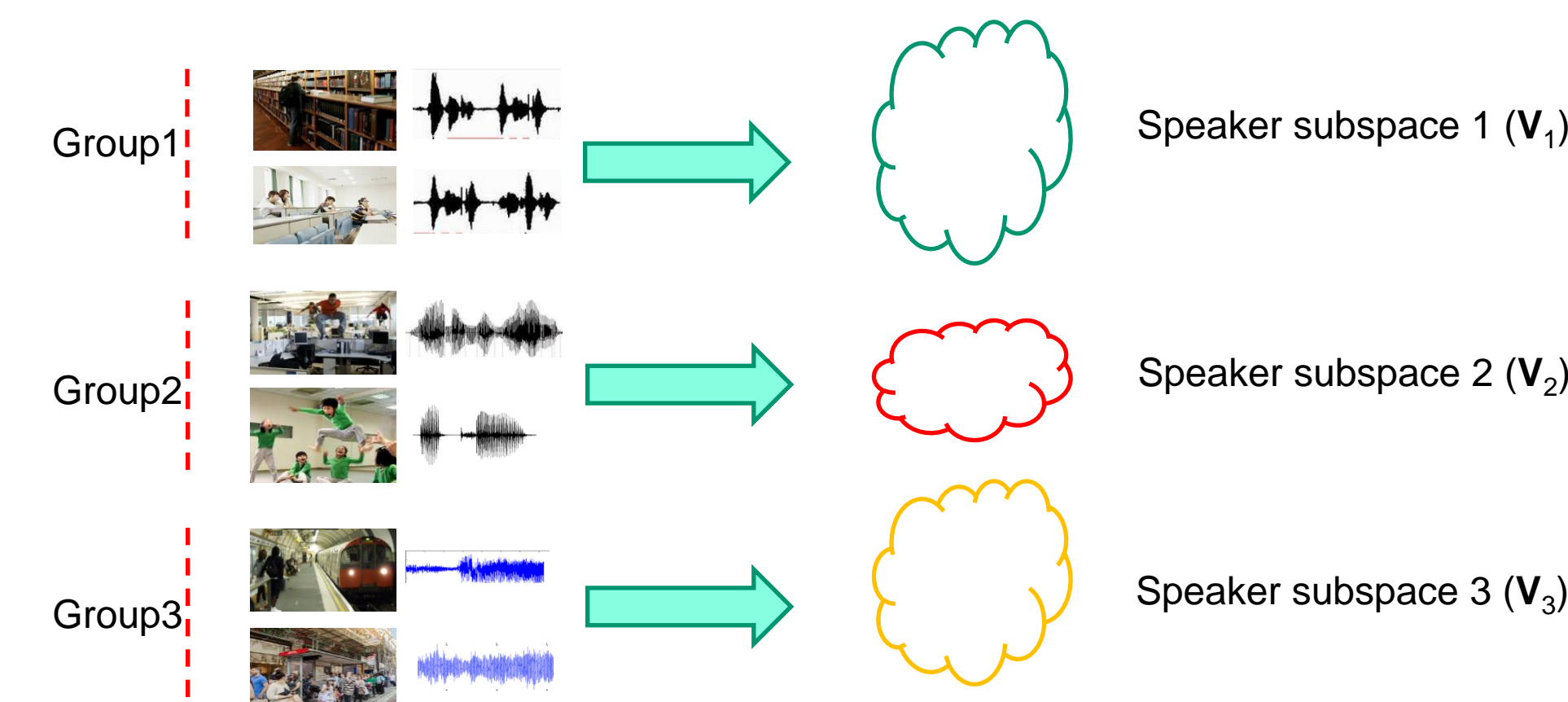


Fig.3: Multiple speaker subspaces in the proposed model.

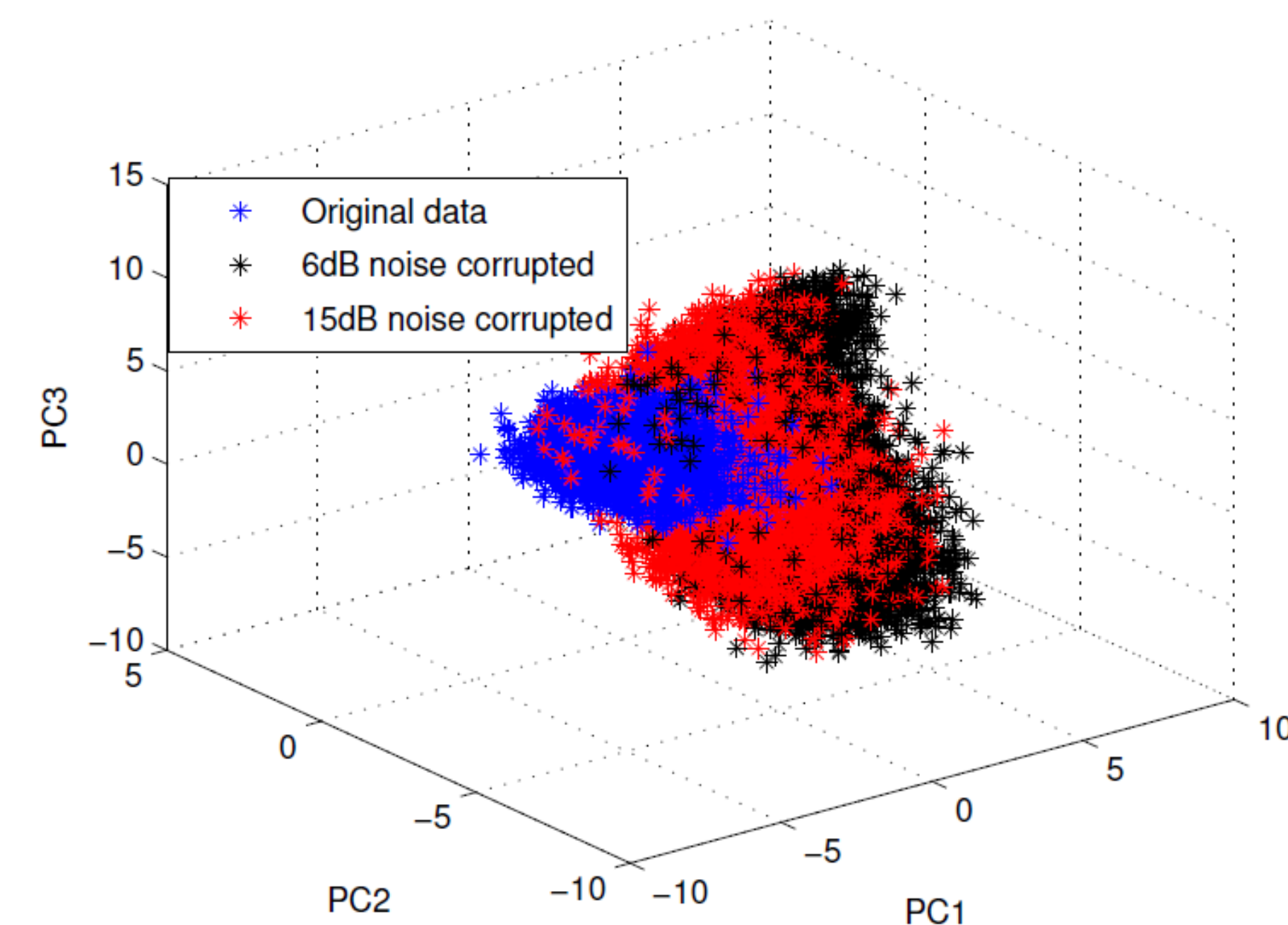


Fig.4: The mean-shift effect of i-vectors caused by different levels of background noise in the corresponding utterances. This figure displays the three groups of i-vectors on the first 3 principal components.

SNR Subgroups:

The training set is divided into multiple SNR subgroups according to the highest posterior probability with respect to a GMM trained using the SNRs of the training utterances.

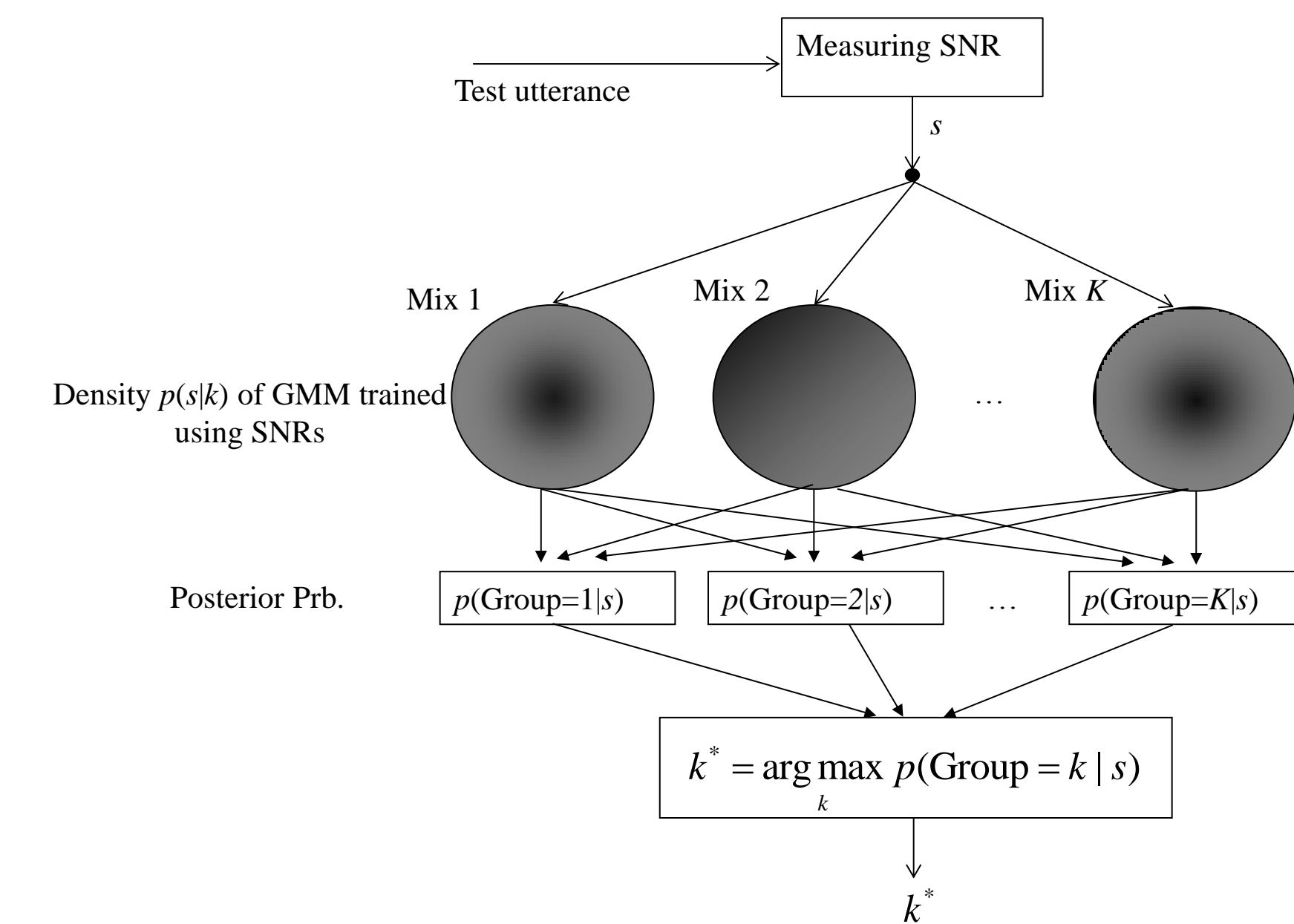


Fig.5: Determination of the SNR subgroup of a test utterance.

The proposed SNR-invariant PLDA:

$$\mathbf{x}_{ij}^k = \mathbf{m}_k + \mathbf{V}_k \mathbf{h}_i + \mathbf{U} \mathbf{w}_k + \boldsymbol{\varepsilon}_{ij}^k \quad \boldsymbol{\varepsilon}_{ij}^k \sim \mathcal{N}(\boldsymbol{\varepsilon} | \mathbf{0}, \boldsymbol{\Sigma}_k)$$

Auxiliary Function:

$$Q(\hat{\theta} | \theta) = \mathbb{E}_{\mathbf{h}, \mathbf{w}} \left[\sum_{i,k,j} \left(\ln \mathcal{N}(\mathbf{x}_{ij}^k | \mathbf{m}_k + \mathbf{V}_k \mathbf{h}_i + \mathbf{U} \mathbf{w}_k, \boldsymbol{\Sigma}_k) + \ln \mathcal{N}(\mathbf{h}_i | \mathbf{0}, \mathbf{I}) + \ln \mathcal{N}(\mathbf{w}_k | \mathbf{0}, \mathbf{I}) \right) \middle| \mathcal{X}, \theta \right]$$

$$\theta = \{\mathbf{m}, \mathbf{V}_k, \mathbf{U}, \boldsymbol{\Sigma}_k\}$$

EM-Step:

$$\langle \mathbf{h}_i | \mathcal{X} \rangle = (\mathbf{L}_i^1)^{-1} \sum_{k=1}^K \mathbf{V}_k^T \Phi_k^{-1} \sum_{j=1}^{H_i(k)} (\mathbf{x}_{ij}^k - \mathbf{m}_k)$$

$$\langle \mathbf{w}_k | \mathcal{X} \rangle = (\mathbf{L}_k^2)^{-1} \mathbf{U}^T \Psi_k^{-1} \sum_{i=1}^S \sum_{j=1}^{H_i(k)} (\mathbf{x}_{ij}^k - \mathbf{m}_k)$$

$$\mathbf{L}_i^1 = \mathbf{I} + \sum_{k=1}^K H_i(k) \mathbf{V}_k^T \Phi_k^{-1} \mathbf{V}_k$$

$$\mathbf{L}_k^2 = \mathbf{I} + M_k \mathbf{U}^T \Psi_k^{-1} \mathbf{U}$$

$$\Phi_k = \mathbf{U} \mathbf{U}^T + \boldsymbol{\Sigma}_k \quad \Psi_k = \mathbf{V}_k \mathbf{V}_k^T + \boldsymbol{\Sigma}_k$$

$$\mathbf{V}_k = \left\{ \sum_{i=1}^S \sum_{j=1}^{H_i(k)} [(\mathbf{x}_{ij}^k - \mathbf{m}_k)(\mathbf{h}_i | \mathcal{X})^T - \mathbf{U} \langle \mathbf{w}_k | \mathcal{X} \rangle^T] \right\} \left\{ \sum_{i=1}^S \sum_{j=1}^{H_i(k)} (\mathbf{h}_i \mathbf{h}_i^T | \mathcal{X}) \right\}^{-1}$$

$$\mathbf{U} = \left\{ \sum_{i=1}^S \sum_{k=1}^K \sum_{j=1}^{H_i(k)} [(\mathbf{x}_{ij}^k - \mathbf{m}_k)(\mathbf{w}_k | \mathcal{X})^T - \mathbf{V}_k (\mathbf{h}_i | \mathcal{X})^T] \right\} \left\{ \sum_{i=1}^S \sum_{k=1}^K \sum_{j=1}^{H_i(k)} (\mathbf{w}_k \mathbf{w}_k^T | \mathcal{X}) \right\}^{-1}$$

$$\boldsymbol{\Sigma}_k = \frac{1}{M_k} \sum_{i=1}^S \sum_{j=1}^{H_i(k)} [(\mathbf{x}_{ij}^k - \mathbf{m}_k)(\mathbf{x}_{ij}^k - \mathbf{m}_k)^T - \mathbf{V}_k (\mathbf{h}_i | \mathcal{X}) (\mathbf{x}_{ij}^k - \mathbf{m}_k)^T - \mathbf{U} \langle \mathbf{w}_k | \mathcal{X} \rangle (\mathbf{x}_{ij}^k - \mathbf{m}_k)^T]$$

$$\mathbf{m}_k = \frac{1}{M_k} \sum_{i=1}^S \sum_{j=1}^{H_i(k)} \mathbf{x}_{ij}^k$$

Likelihood Ratio Scores:

$$S_{LR}(\mathbf{x}_s, \mathbf{x}_t) = \ln \frac{p(\mathbf{x}_s, \mathbf{x}_t | \text{same-speaker})}{p(\mathbf{x}_s, \mathbf{x}_t | \text{different-speakers})}$$

$$= \ln \frac{\mathcal{N} \left(\begin{bmatrix} \mathbf{x}_s \\ \mathbf{x}_t \end{bmatrix} \middle| \begin{bmatrix} \mathbf{m}_{k_s} \\ \mathbf{m}_{k_t} \end{bmatrix}, \begin{bmatrix} \mathbf{A}_{k_s} & \mathbf{B}_{k_s k_t} \\ \mathbf{B}_{k_t k_s}^T & \mathbf{A}_{k_t} \end{bmatrix} \right)}{\mathcal{N} \left(\begin{bmatrix} \mathbf{x}_s \\ \mathbf{x}_t \end{bmatrix} \middle| \begin{bmatrix} \mathbf{m}_{k_s} \\ \mathbf{m}_{k_t} \end{bmatrix}, \begin{bmatrix} \mathbf{A}_{k_s} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{k_t} \end{bmatrix} \right)}$$

where

$$\mathbf{A}_{k_s} = \mathbf{V}_{k_s} \mathbf{V}_{k_s}^T + \mathbf{U} \mathbf{U}^T + \boldsymbol{\Sigma}_{k_s},$$

$$\mathbf{A}_{k_t} = \mathbf{V}_{k_t} \mathbf{V}_{k_t}^T + \mathbf{U} \mathbf{U}^T + \boldsymbol{\Sigma}_{k_t}, \text{ and}$$

$$\mathbf{B}_{k_s k_t} = \mathbf{V}_{k_s} \mathbf{V}_{k_t}^T.$$

Results

- Table1: Performance of PLDA, S-PLDA and Proposed multi-speaker subspace PLDA on CC4

Method	K	Male		Female	
		EER(%)	minDCF	EER(%)	minDCF
PLDA	-	3.39	0.325	3.10	0.354
S-PLDA	3	3.20	0.300	2.95	0.327
Proposed	2	3.31	0.302	3.09	0.333
	3	3.06	0.309	2.88	0.332
	4	3.12	0.316	2.84	0.339

- Table2: Performance of PLDA, S-PLDA and Proposed multi-speaker subspace PLDA on CC5

Method	K	Male		Female	
		EER(%)	minDCF	EER(%)	minDCF
PLDA	-	2.80	0.303	2.34	0.331
S-PLDA	3	2.80	0.302	2.37	0.319
Proposed	2	2.74	0.276	2.36	0.350
	3	2.80	0.278	2.31	0.325
	4	2.79	0.284	2.26	0.321

- Table3: Performance comparison of different SNR-invariant PLDA models on CC4

Model	Model Parameters	EER(%)	minDCF
1	$\theta = \{\mathbf{m}, \mathbf{V}, \mathbf{U}, \boldsymbol{\Sigma}\}$	3.20	0.300
2	$\theta = \{\mathbf{m}_k, \mathbf{V}_k, \mathbf{U}, \boldsymbol{\Sigma}_k\}$	3.06	0.309
3	$\theta = \{\mathbf{m}_k, \mathbf{V}, \mathbf{U}, \boldsymbol{\Sigma}\}$	3.30	0.305
4	$\theta = \{\mathbf{m}, \mathbf{V}_k, \mathbf{U}, \boldsymbol{\Sigma}_k\}$	3.15	0.308
5	$\theta = \{\mathbf{m}_k, \mathbf{V}, \mathbf{U}, \boldsymbol{\Sigma}_k\}$	3.57	0.319
6	$\theta = \{\mathbf{m}_k, \mathbf{V}_k, \mathbf{U}, \boldsymbol{\Sigma}\}$	2.81	0.332

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- N. Li and M. W. Mak, "SNR-invariant PLDA modeling in nonparametric subspace for robust speaker verification," *IEEE/ACM Trans. on Audio, Speech and Language Processing*, vol. 23, no. 10, pp. 1648–1659, 2015.
- P. Kenny, "Bayesian speaker verification with heavy-tailed priors," in *Proc. of Odyssey: Speaker and Language Recognition Workshop*, Brno, Czech Republic, June 2010.