Noise Compensation for Subspace Gaussian Mixture Models

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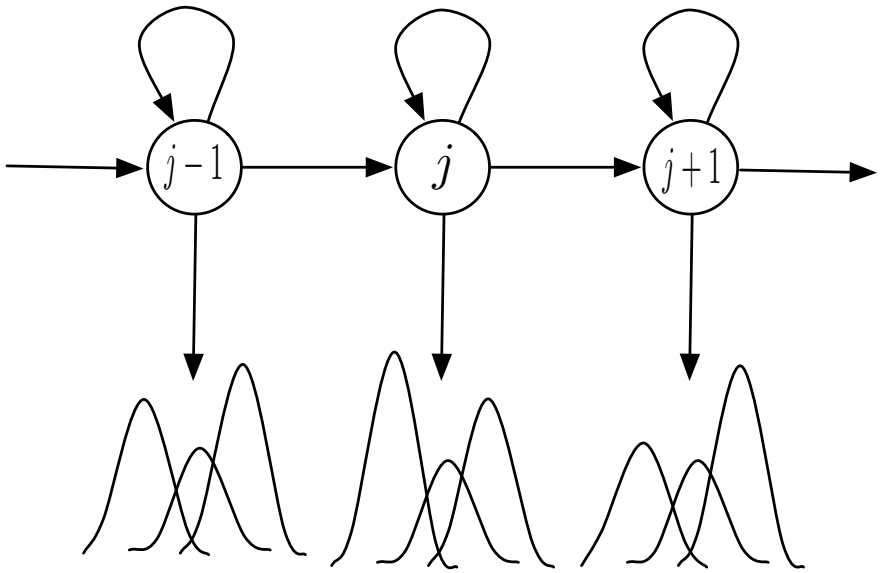
Joint work with KK Chin, A. Ghoshal and S. Renals

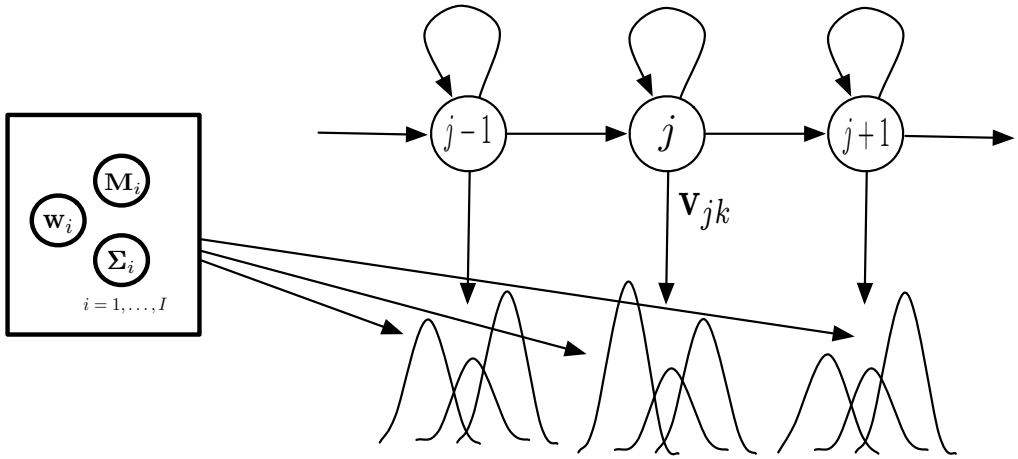
Outline

- Motivation
  - Subspace GMM (SGMM) works well in matched speech condition [Povey et al., 2011]
  - In mismatched condition (i.e. noise), the gain disappears
- Goal
  - Noise compensation for SGMM
- Method
  - Model space compensation
  - Joint uncertainty decoding (JUD) [Liao and Gales, 2005]

HMM-GMM acoustic model



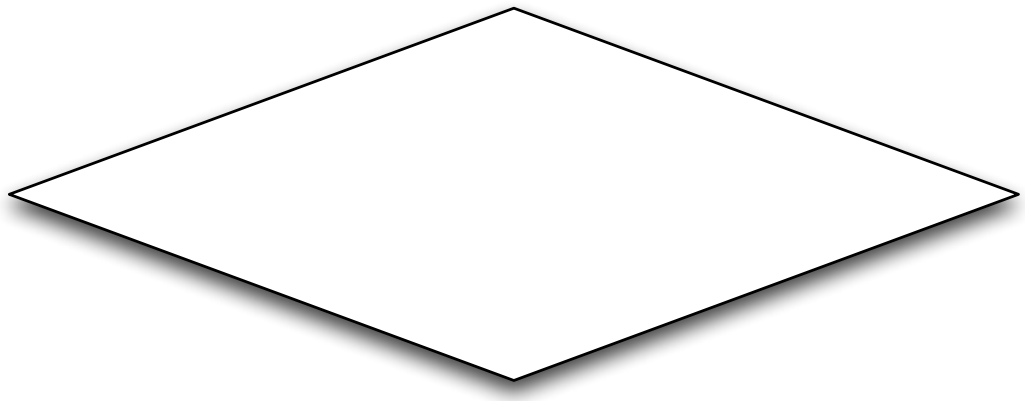
Subspace Gaussian Mixture Models [Povey et al., 2011]



- Global
  - $\mathbf{M}_i$ is the basis for means
  - $\mathbf{w}_i$ is the basis for weights
  - $\mathbf{\Sigma}_i$ is the covariance matrix
- State-dependent
  - $\mathbf{v}_{jk}$ is low dimensional vectors (e.g. 40dim)
  - Gaussian mean: $\boldsymbol{\mu}_{jki} = \mathbf{M}_i \mathbf{v}_{jk}$

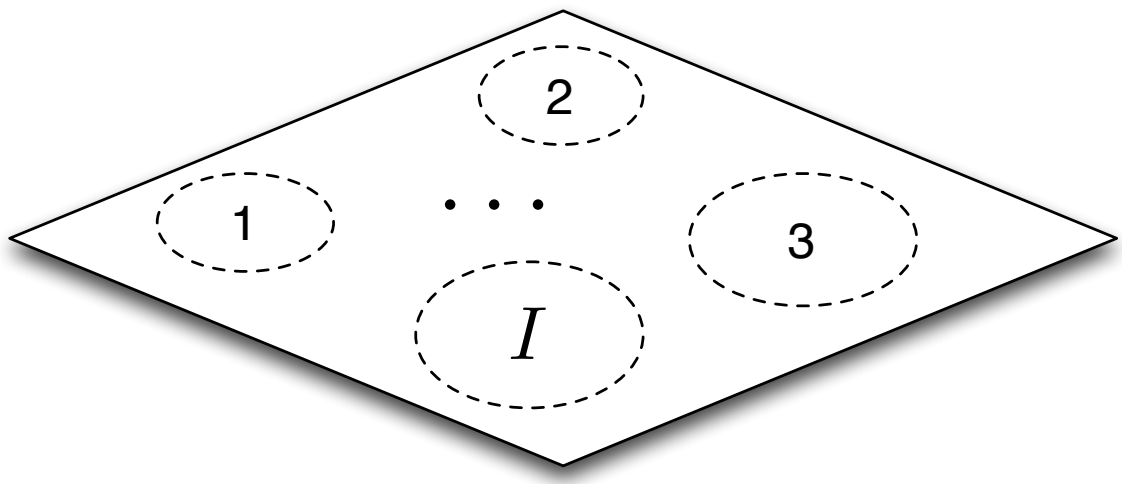
Subspace Gaussian Mixture Models

- More intuitively, suppose we have an acoustic space like this



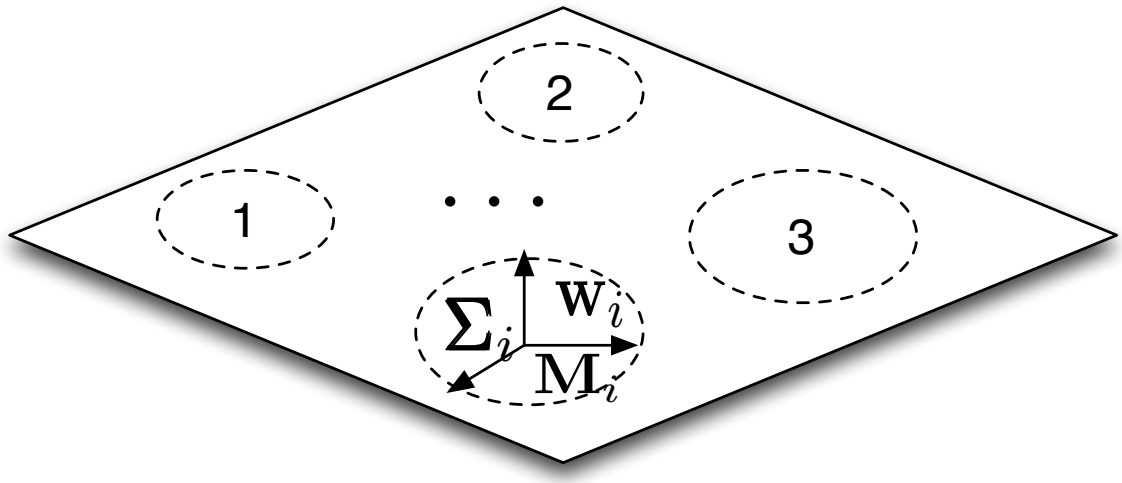
Subspace Gaussian Mixture Models

- We then partition the whole acoustic space into I regions.
- This can be done by learning a GMM using the training data.



Subspace Gaussian Mixture Models

- We then introduce some parameters to structure each region



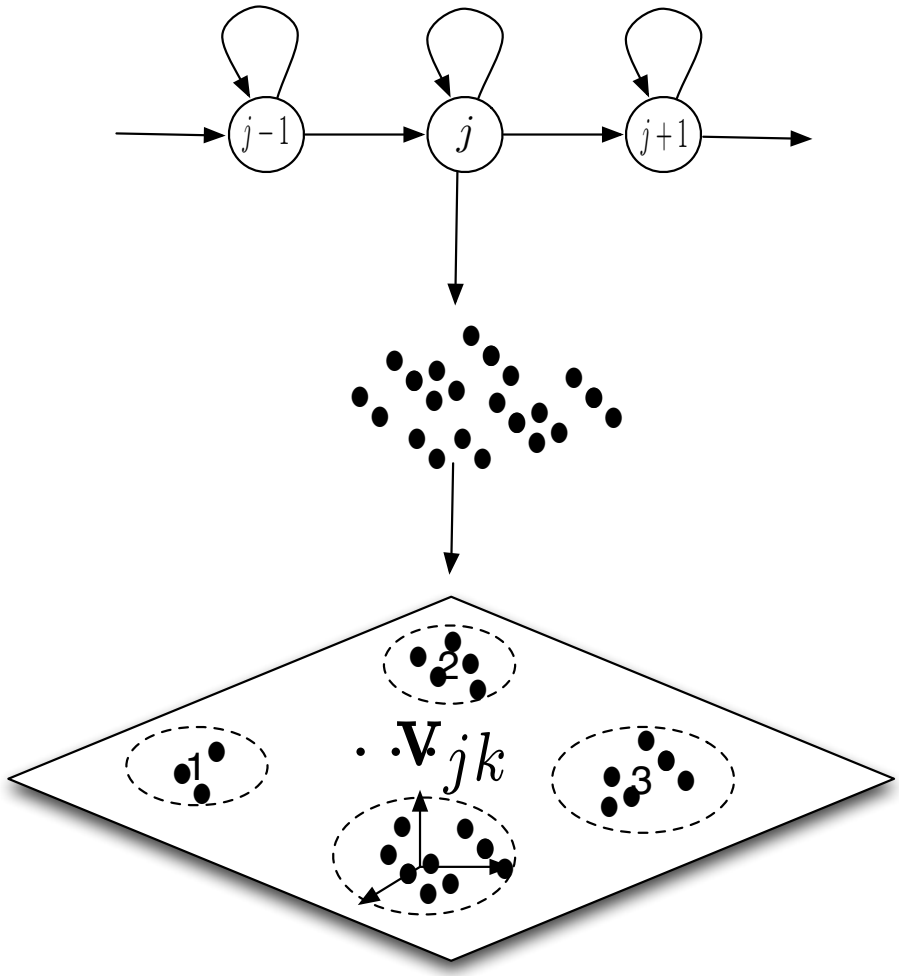
Σ_i - model the covariance of this region

$\mathbf{M}_i$ - span the basis for Gaussian mean

$\mathbf{w}_i$ - span the basis for Gaussian weight

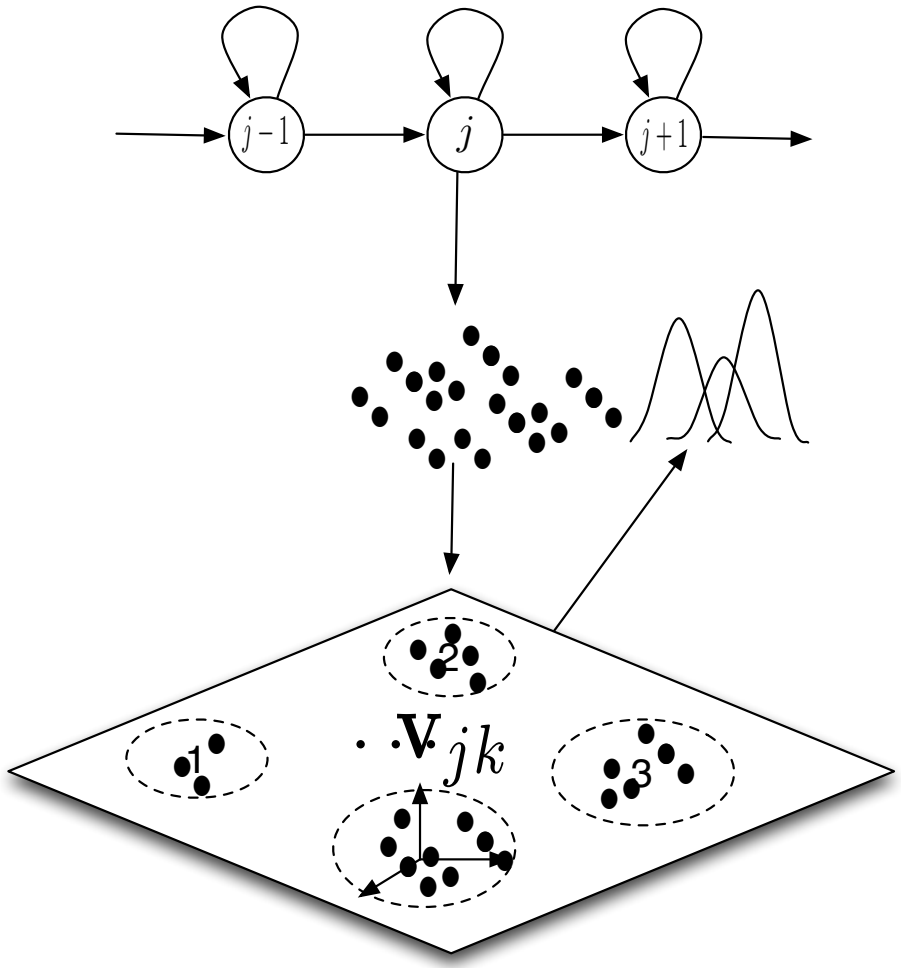
Subspace Gaussian Mixture Models

Given a class with some data, such as an HMM state



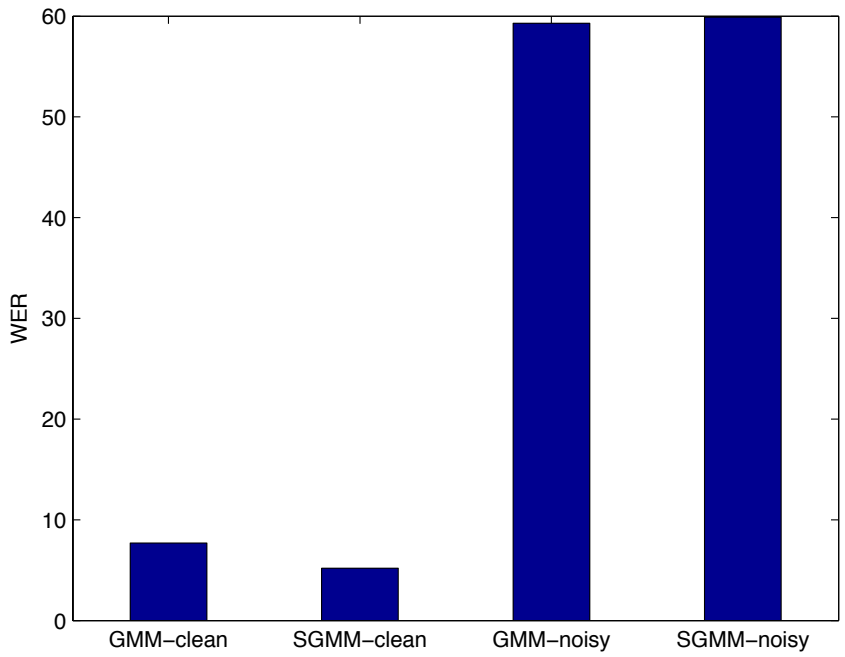
Subspace Gaussian Mixture Models

Then we learn a GMM for this class



Noise compensation

- Larger modelling power $\rightarrow$ higher recognition accuracy.
  - Our systems on Aurora 4, the #Gaussians is 6.4M (SGMM), vs. 50k (GMM).
  - SGMM vs. GMM $\rightarrow$ 5.2% vs. 7.7% on clean condition
  - SGMM vs. GMM $\rightarrow$ 59.9% vs. 59.3% on noisy condition
- Can we do noise compensation for SGMMs ?



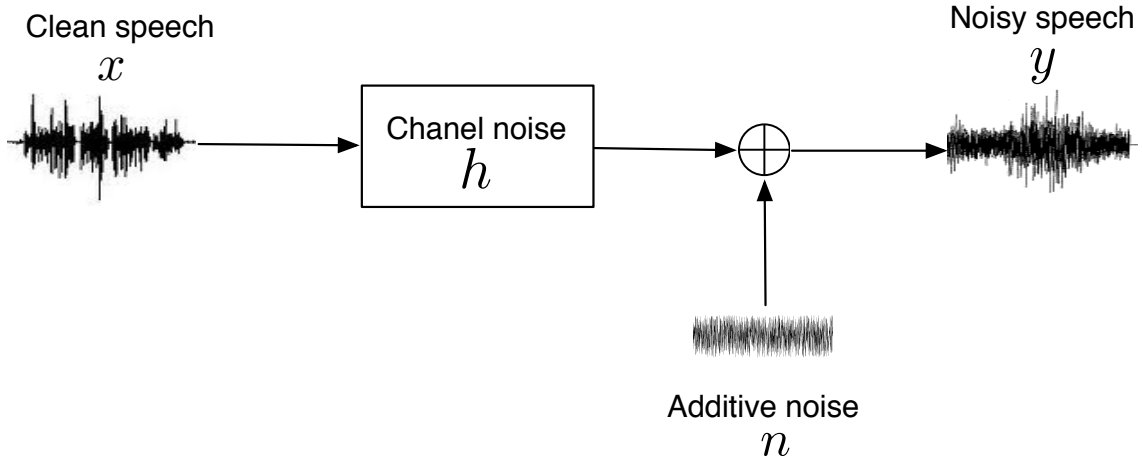
Noise compensation

There are numerous work on noise compensation for robust ASR [Deng, 2011]

- Feature domain
  - Spectral subtraction, cmn/cvn
  - Cepstral mean square error estimation
  - Algonquin
  - Splice
  - Feature space vector Taylor series (VTS)
- Model domain
  - MLLR, noise constraint MLLR
  - PMC, Data-driven PMC (DPMC), iterative DPMC
  - VTS, joint uncertainty decoding (JUD)
  - Linear spline interpolation (LSI)
  - Unscented transform (UT)
- Hybrid
  - Noise adaptive training

Noise compensation for SGMM

- Model space compensation for SGMM
- Not data-driven but using heuristic knowledge
- Mismatch function $\mathbf{y} = f(\mathbf{x}, \mathbf{h}, \mathbf{n}, \boldsymbol{\alpha})$ [Acero, 1990]
- $\boldsymbol{\alpha}$ denotes the phase term between noise and speech [Deng et al., 2004].



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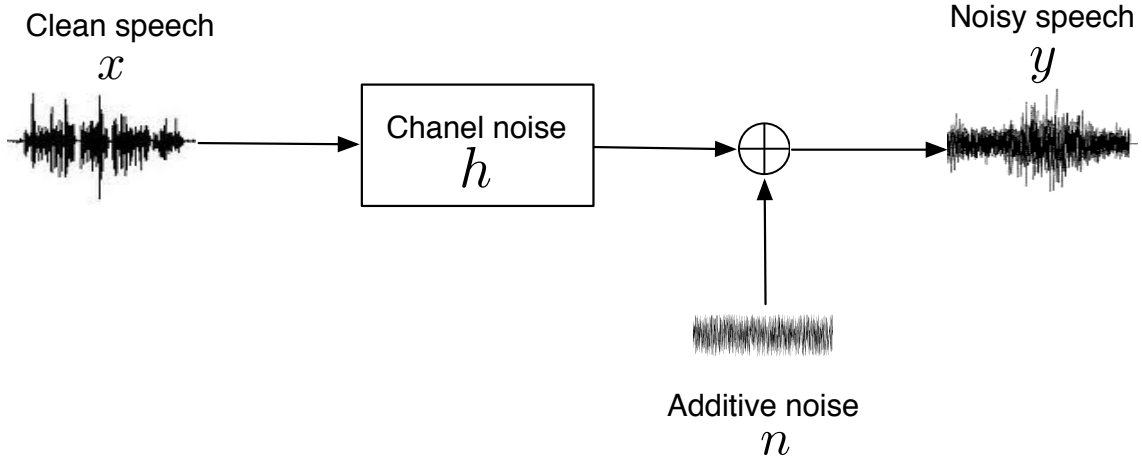

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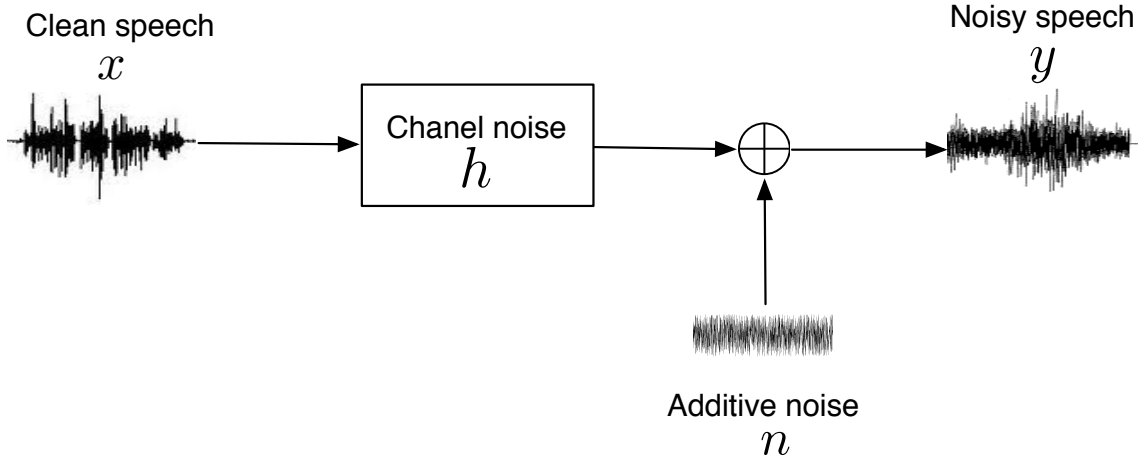

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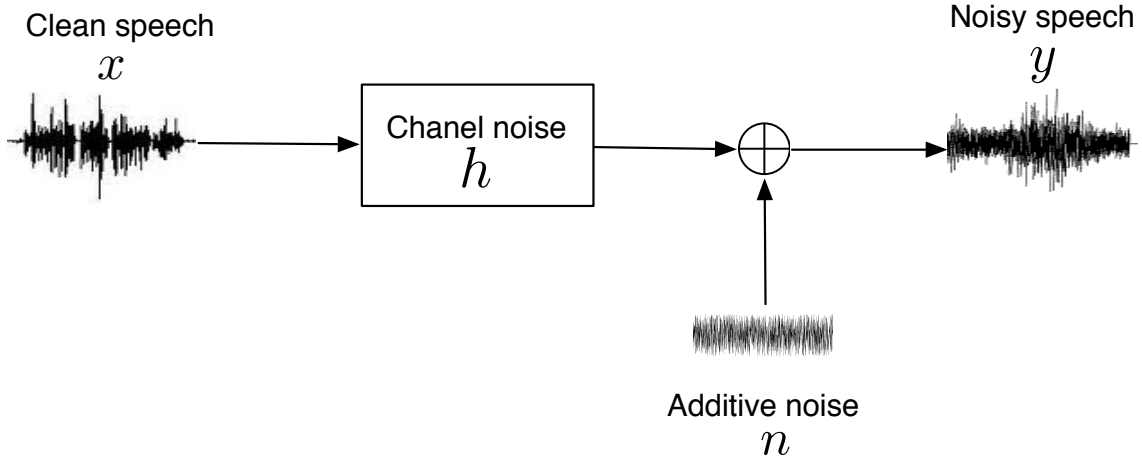

Noise compensation for SGMM

The mismatch function is

$$\begin{aligned}\mathbf{y} &= f(\mathbf{x}, \mathbf{h}, \mathbf{n}, \boldsymbol{\alpha}) \\ &= \mathbf{x} + \mathbf{h} + \mathbf{C}\log\Big[\mathbf{1} + \exp\left(\mathbf{C}^{-1}\left(\mathbf{n} - \mathbf{x} - \mathbf{h}\right)\right) \\ &\quad + \underbrace{2\boldsymbol{\alpha} \bullet \exp\left(\mathbf{C}^{-1}(\mathbf{n} - \mathbf{x} - \mathbf{h})/2\right)}_{\textit{phase term}}\Big]. \end{aligned} \tag{1}$$

where $\mathbf{C}$ be the DCT matrix.

Noise compensation

- Aim: estimate $\boldsymbol{\mu}_y$ and $\boldsymbol{\Sigma}_y$ for each Gaussian component.
- Difficulty: $\mathbf{y} = f(\mathbf{x}, \mathbf{h}, \mathbf{n}, \boldsymbol{\alpha})$ is highly nonlinear, no analytic solution!
- Solution: Vector Taylor series (VTS) approximation [Moreno et al., 1996]
- Cost: Real time factor > 100, memory $> 10G$ for (medium size) SGMM with 6.4M Gaussian
- Inelegant: Direct apply VTS will destroy the compact of structure of SGMMs

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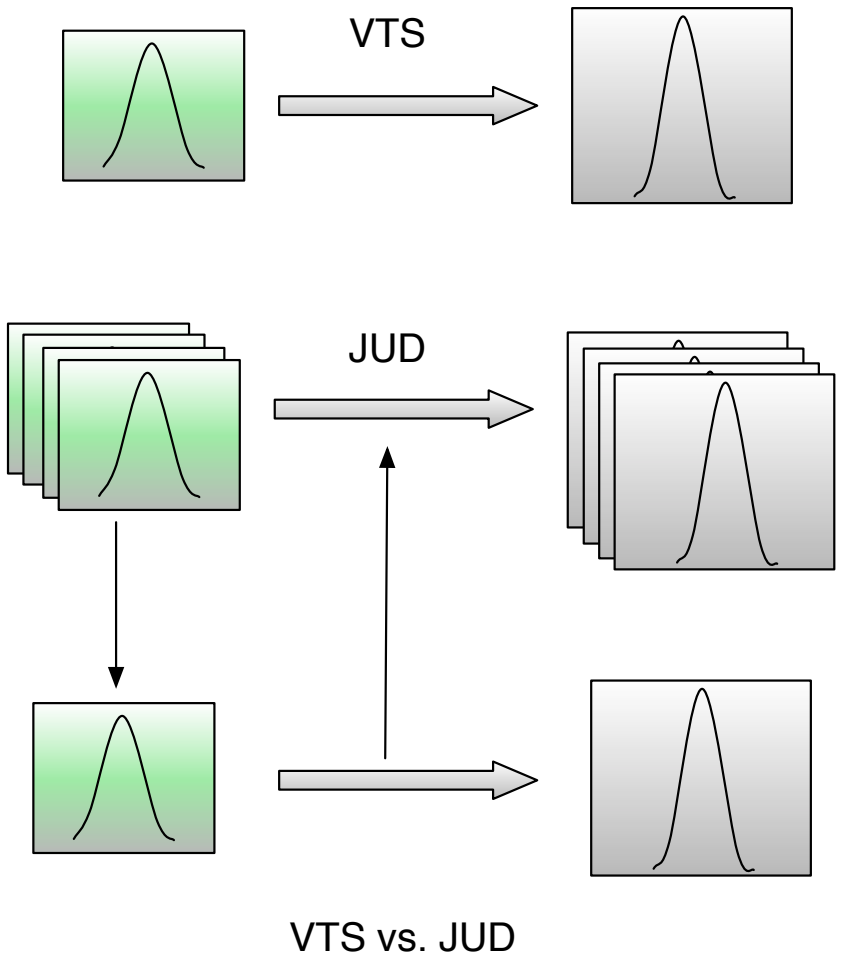
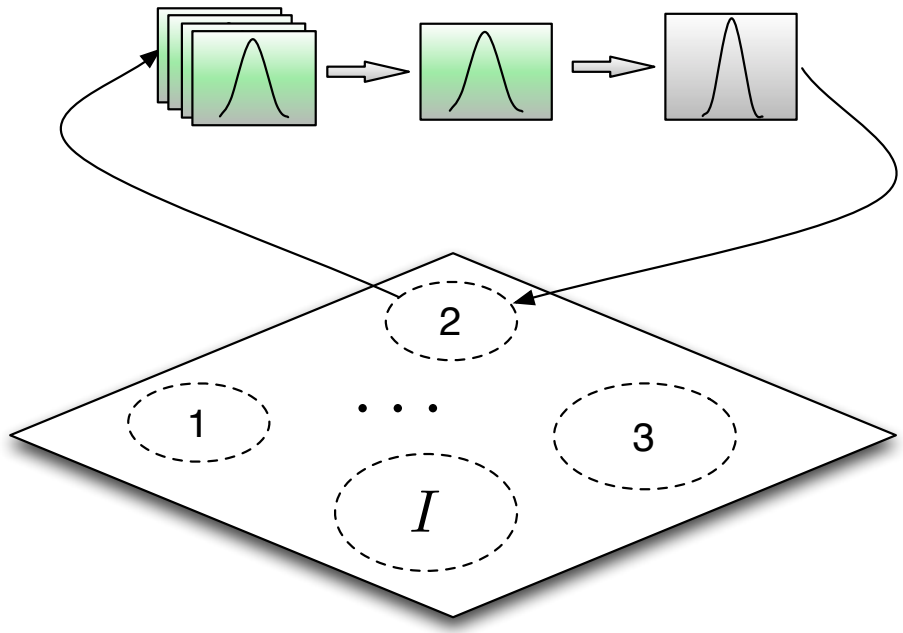
- Solution: Joint uncertainty decoding (JUD)



VTS vs. JUD

Noise compensation

- Applying JUD to SGMM

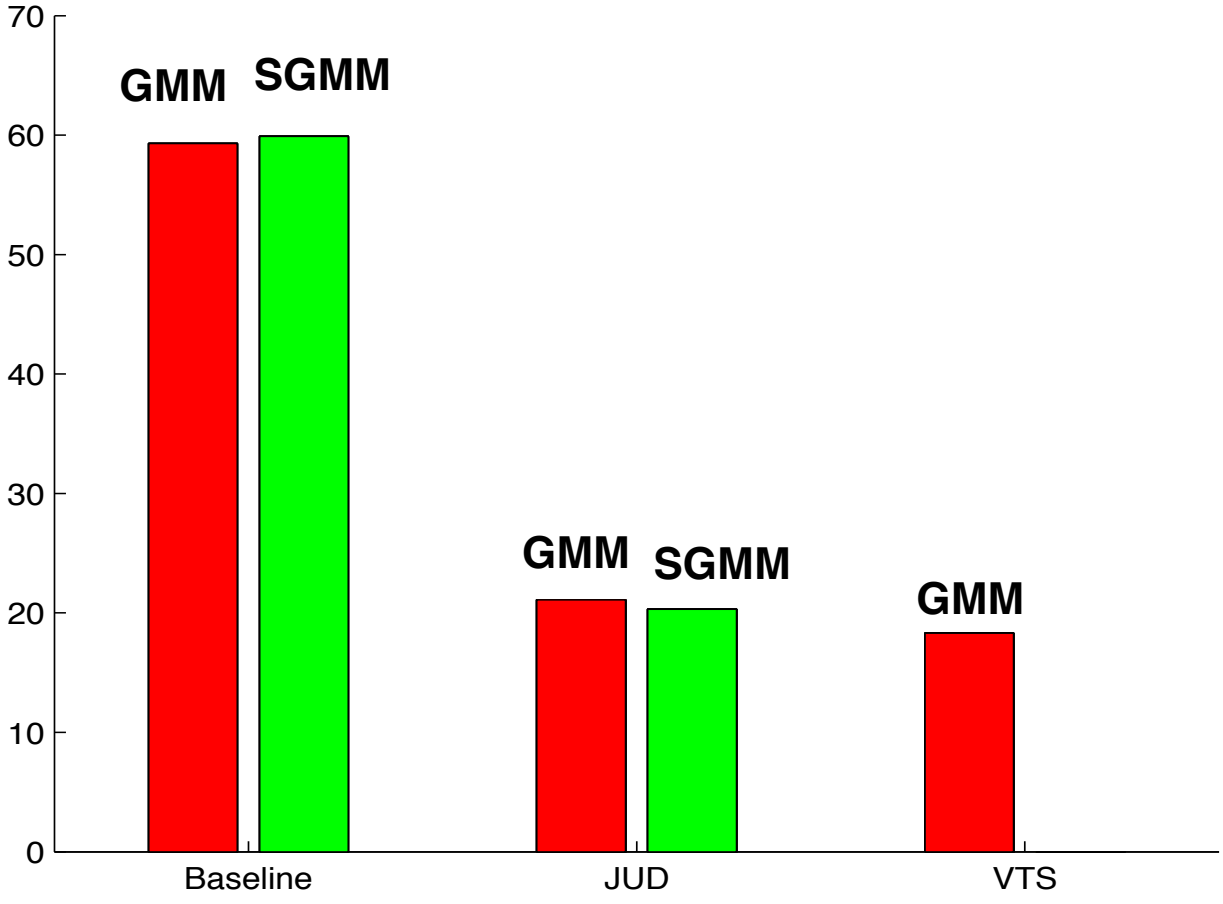


- Cost: Real time factor $\sim$ 10 for SGMM with 6.4M Gaussians

Experiments

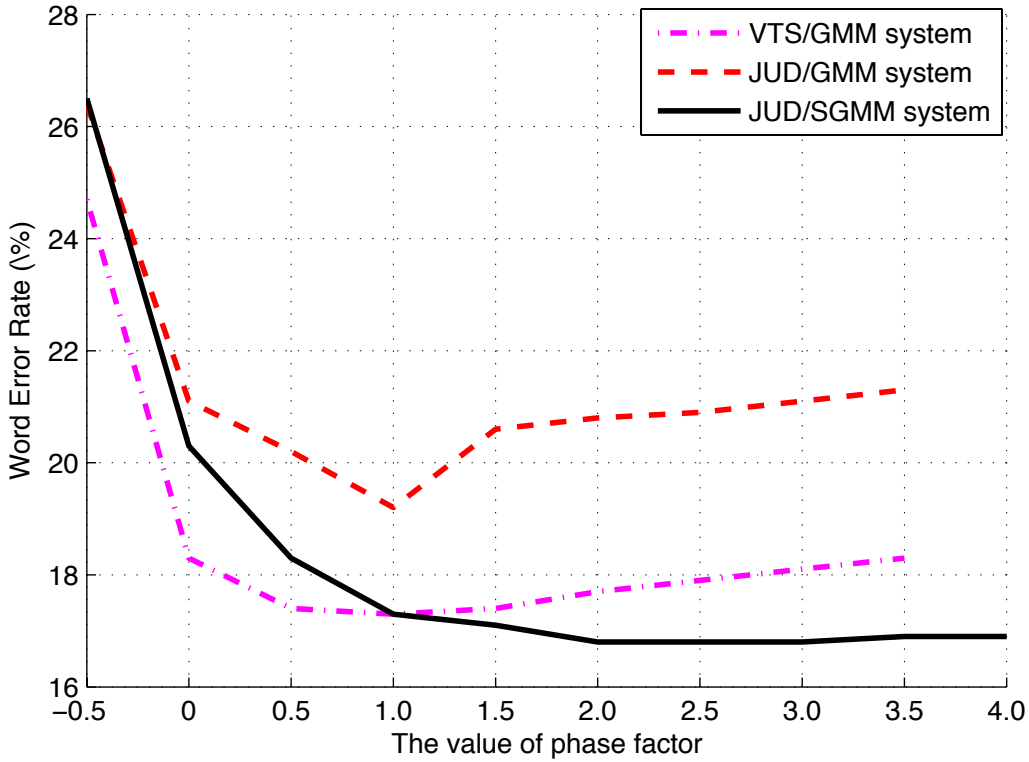
- Database
  - Aurora 4 dataset
  - Clean speech and noisy speech with SNR [5db - 15db]
  - Close-talking microphone and desk-mounted microphone
  - $\sim$ 15 hour training data
  - 330 testing utterances
- System configuration
  - 39dim MFCC
  - #triphone states: 3.1k (GMM) vs. 3.9k (SGMM)
  - #Gaussians: 50k (GMM) vs. 6.4M (SGMM)
  - #regression classes: 112 (GMM) vs. 400 (SGMM)

Noise compensation experiments



Experiments

Results by tuning the value of phase factors.



- JUD/SGMM system achieved 16.8% WER on Aurora 4 database

Remarks

- The phase term is very effective for noise compensation
- Similar improvements were also observed in other studies, e.g. [Li et al., 2009]
- The reasons maybe it can compensate for the linearization bias and performs domain compensation [Li et al., 2009]
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Conclusion

- SGMM is a promising alternative for acoustic modelling
- Noise compensation using JUD works well for SGMMs
- The phase term is particular effective for the noise compensation
- Future works will be on noise adaptive training, compensation in log-spectral domain.

Noise compensation

- With JUD, the marginal likelihood can be obtained as

$$p(\mathbf{y} \mid m) \approx |\mathbf{A}^{(r)}| \mathcal{N}\left(\mathbf{A}^{(r)}\mathbf{y} + \mathbf{b}^{(r)}; \boldsymbol{\mu}_m, \boldsymbol{\Sigma}_m + \boldsymbol{\Sigma}_b^{(r)}\right). \quad (2)$$

- The transformation is done in the feature space, applied to each frame
- Computation is saved since that the #frame $\ll$ #Gaussians
- The transformation should be diagonalized in GMM systems, but not in SGMM system since we used full covariance matrix

Experiments

Table: GMM systems with $\boldsymbol{\alpha} = \mathbf{0}$.

Methods	Clean	Avg
Clean model	7.7	**59.3**
MTR model	12.7	**26.9**
VTS	7.3	**18.3**
JUD	7.0	**21.1**

Table: SGMM systems with $\boldsymbol{\alpha} = \mathbf{0}$.

Methods	Clean	Avg
Clean model	5.2	**59.9**
MTR model	6.8	**22.2**
JUD	5.3	**20.3**

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