speaker recognition using gmm-ubm

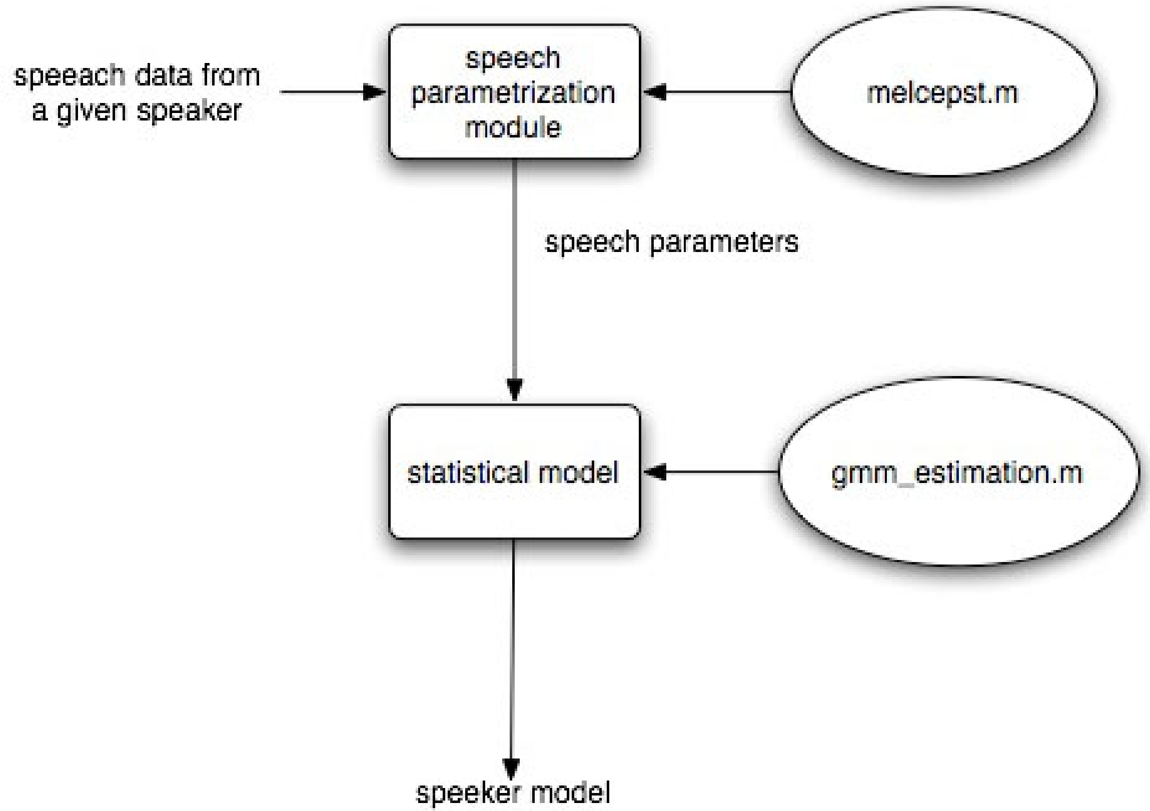
semester project presentation

OBJECTIVES OF THE PROJECT

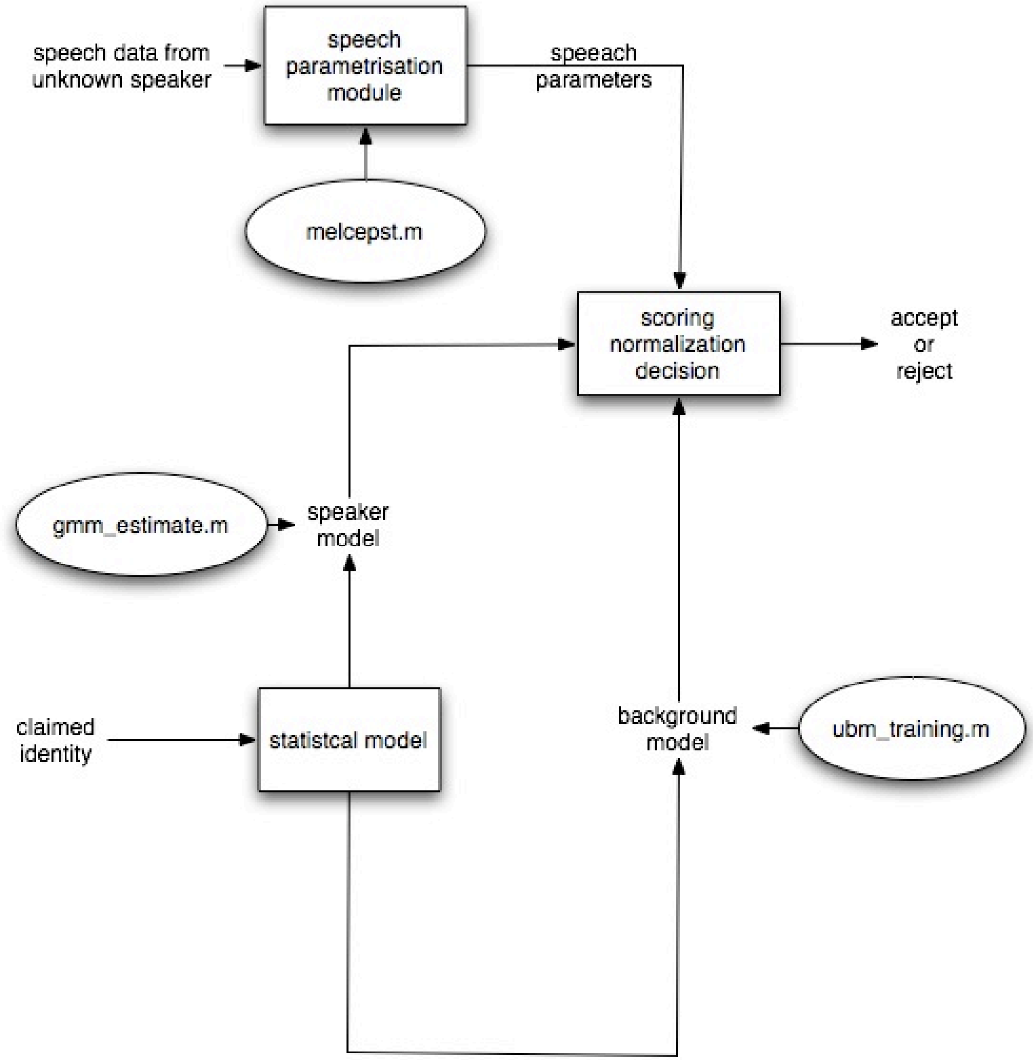
- study the GMM-UBM speaker recognition system
- implement this system with matlab
- document the code and how it interfaces with the rest of toolkit
- perform validation with different data (channel,content,etc)

Steps in speaker recognition using GMM

- feature extraction (transform the original signal in frequency domain)
- training (models the original voice using gaussian parameters)
- testing (calculate the "statistical distance" with each of the original models)



training phase


speech data from unknown speaker
speech parametrisation module
speeach parameters
melcepst.m
scoring normalization decision
accept or reject
gmm_estimate.m
speaker model
claimed identity
statistcal model
background model
ubm_training.m

test phase

LIKELIHOOD RATIO DETECTOR

- given a segment of speech Y
- implicit assumption : Y contains speech from only one speaker
- given a hypothesized speaker claimed identity S

Decision rule of likelihood ratio

- we take the hypothesis such as
- H0 :Y is from the hypothesized speaker S
- H1 :Y is not from the hypothesized speaker S
- we take H0 if $P(Y \mid H0)/P(Y \mid H1) > \theta$

log likelihood

- many advantages to take log likelihood
- a division become a subtraction
- a multiplication become an addition
- the equation before will be represent like
- $\log(P(Y \mid H0)) - \log(P(Y \mid H1)) > \log\theta$

GMM-UBM

- text independent speaker recognition
- read sound wave files
- melcepst extracts features
- training models with GMM
- training models with UBM
- decision, recognition based on likelyhood ratio

Gaussian mixture model (GMM)

- text independent verification
- not so expensive computation like HMM
- big phoneme or vocabulary database no needed
- HMM doesn’t shown advantage over GMM
- GMM training

GMM and EM algorithm

estimation step

compute the probability P(q(k)|x(n),θ) for each data point x(n) to belong the mixture q(k)

$$P(q_k \mid x_n, \theta) = \frac{P(q_k \mid \theta) \bullet p(x_n \mid q_k, \theta)}{p(x_n \mid \theta)} = \frac{P(q_k \mid \theta) \bullet p(x_n \mid u_k, \sum_k)}{\sum_j P(q_j \mid \theta) \bullet p(x_n \mid u_k, \sum_k)}$$

in the algorithm:

$$c(k) = P(q_k \mid \theta),$$

$$lBM(n,k) = \log p(x_n \mid q_k, \theta),$$

$$lB(k) = \log p(x_n \mid \theta),$$

$$gamm(n,k) = P(q_k \mid x_n, \theta)$$

maximization step

update the mean

$$u_k^{new} = \frac{\sum_{n=1}^{T} x_n P(q_k \mid x_n, \theta)}{\sum_{n=1}^{T} P(q_k \mid x_n, \theta)}$$

update the sigma

$$\sum\nolimits_k^{new} = \frac{\sum_{n=1}^{T} P(q_k \mid x_n, \theta)(x_n - u_k)(x_n - u_k)^T}{\sum_{n=1}^{T} P(q_k \mid x_n, \theta)}$$

update weight

$$P(q_k^{new} \mid \theta^{(new)}) = \frac{1}{T} \sum_{n=1}^{T} P(q_k \mid x_n, \theta)$$

- it’s a iterative algorithm
- input is feature x and M for number of mixture
- the probabilities follow gaussian distribution
- we evaluate the values of u,sigma and weight

UBM speaker verification procedure

- training UBM model(computation of θ)
- adapt each training feature to this model
- compute the log-likelihood(p(x|θubm))
- decision is based on the max likelihood

UBM training

- The UBM is a large GMM trained to represent the speaker-independent distribution of features
- The idea of using UBM is in order to capture the general characteristics of a population
- and then adapting it to the individual speaker
- Training uses EM algorithm

UBM adaptation

for mixture i, we compute

$$\Pr(\mathrm{i} \mid \mathrm{x_t}) = \frac{w_i p_i(x_t)}{\sum_{j=1}^{M} w_j p_j(x_t)}$$

we than use it to compute weight, mean and variance

$$n_i = \sum_{t=1}^{T} \Pr(i \mid x_t) x_t$$

$$E_i(x) = \frac{1}{n_i} \sum_{t=1}^{T} \Pr(i \mid x_t) x_t$$

$$E_i(x^2) = \frac{1}{n_i} \sum_{t=1}^{T} \Pr(i \mid x_t) x_t^2$$

the new coefficients are

$$w_i^{new} = [\alpha_{\mathrm{i}}^{\mathrm{w}} n_i / T + (1 - \alpha_{\mathrm{i}}^{\mathrm{new}}) w_i]\gamma$$

$$u_i^{new} = \alpha_{\mathrm{i}}^{\mathrm{m}} E(x)_i + (1 - \alpha_{\mathrm{i}}^{\mathrm{m}}) u_i$$

$$\sigma_i^{2new} = \alpha_{\mathrm{i}}^{\mathrm{v}} E(x^2)_i + (1 - \alpha_{\mathrm{i}}^{\mathrm{v}})(\sigma_i^2 + u_i) - u_i^{new}$$

In the GMM-UBM system we use a single adaptation coefficient for all parameters (α= n(i) /(n(i) + r)) with a relevance factor of r = 16

all above formula are took directly from Reynolds notes

the algorithm is valid

- the following experiments shows this algorithm is valid

the database

- IPSC03
- 73 speakers
- 3 wave files each speakers

TESTS

- UBM model composed by 14 people
- Comparisons with GMM
- 33 people detection
- we didn’t use any of these 33 people to train UBM parameters

different training size

- the gmm training and ubm adaption
- we split files on different size: 1/5,1/10,1/15,1/25,1/35

results

adapted UBM error rate

Split rate	1	1/5	1/10	1/15	1/25	1/35
FA	0.0066	0.0095	0.0142	0.0170	0.0303	0.0369
FR	0	0	0	0.0303	0.0303	0.0303
EER	0.0033	0.0047	0.0071	0.0237	0.0303	0.0336

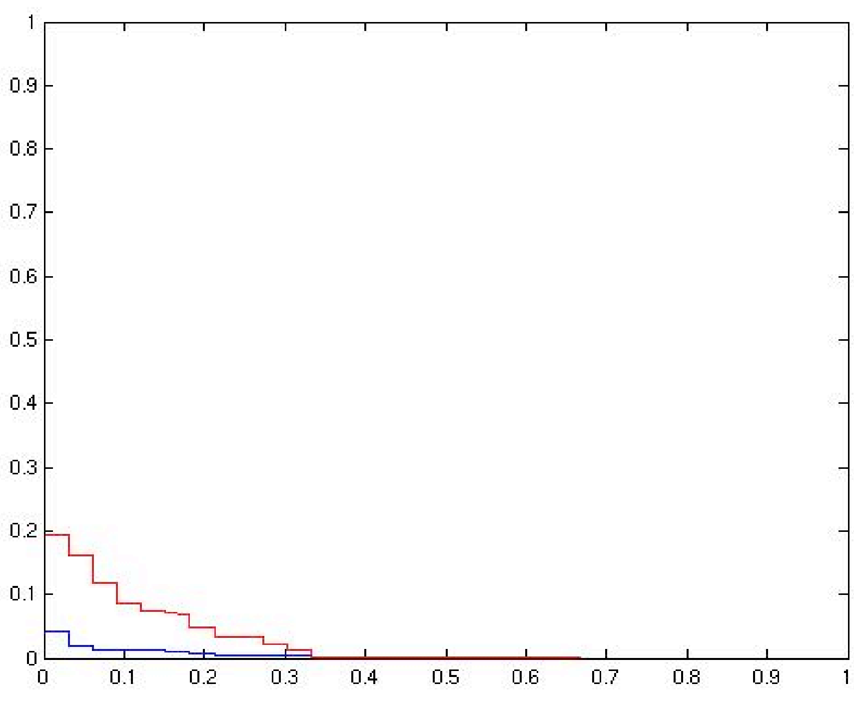
GMM classic error rate

Split rate	1	1/5	1/10	1/15	1/25	1/35
FA	0.0085	0.0189	0.0170	0.0379	0.0909	0.1847
FR	0	0.0303	0.0303	0.0303	0.0909	0.1818
EER	0.0043	0.0246	0.0237	0.0341	0.0909	0.1832

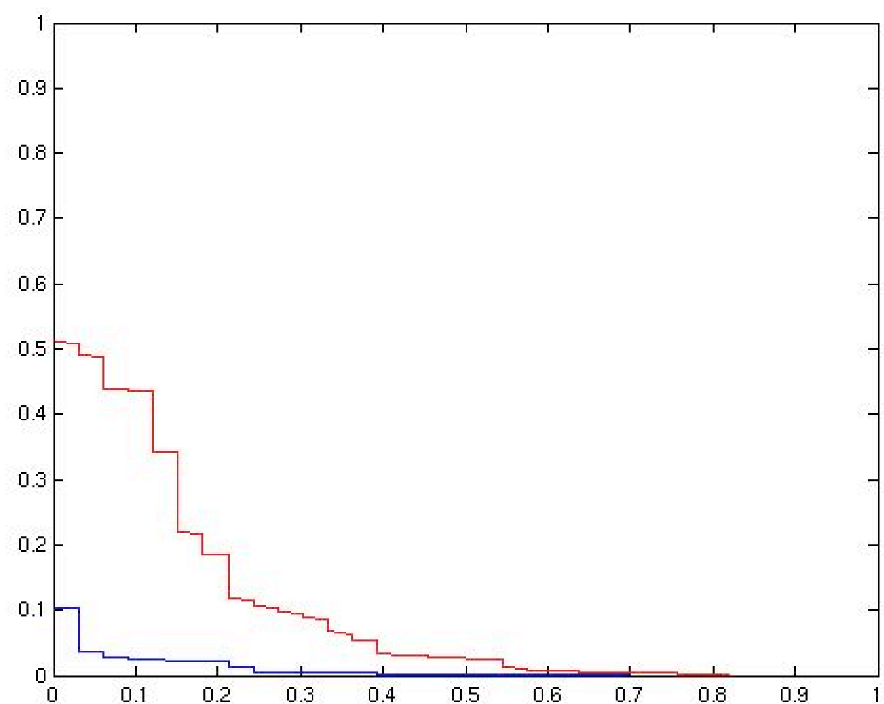
some DET curves

- UBM is blue color
- GMM is red color

6s training

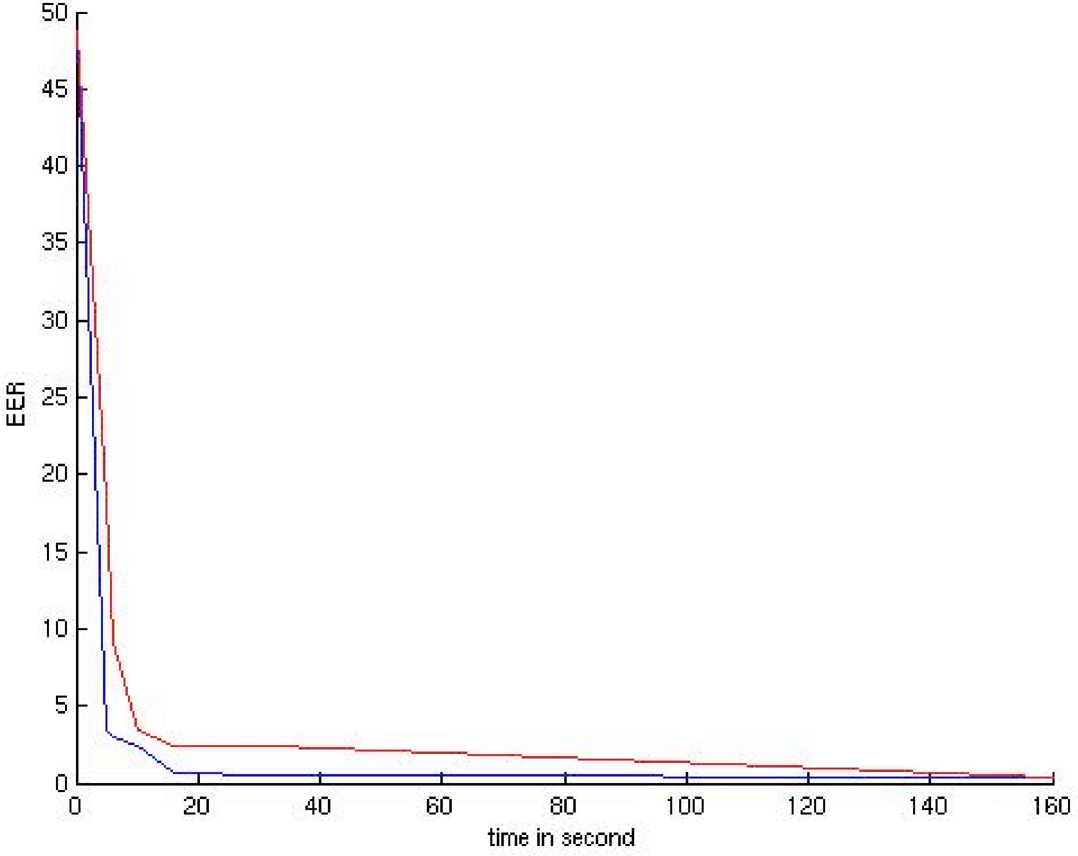


5s training



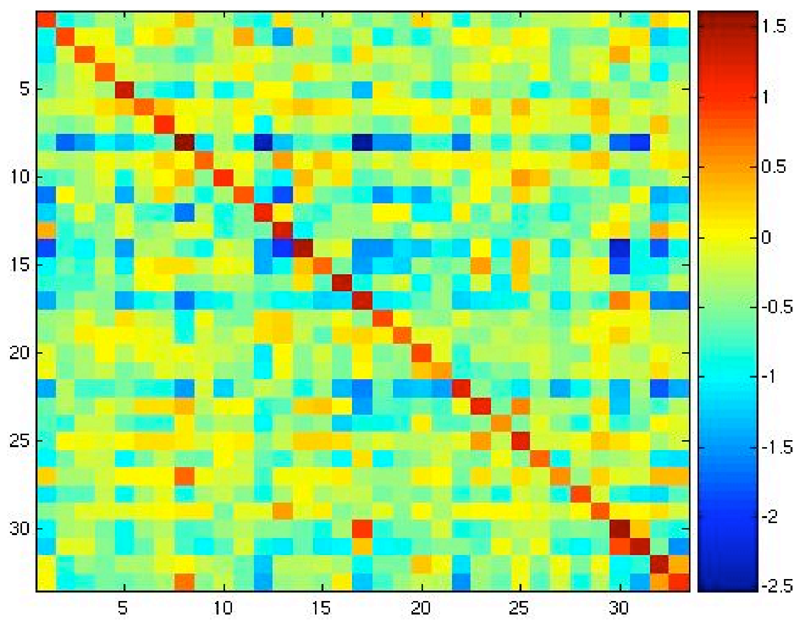
data length and EER

ubm
gmm

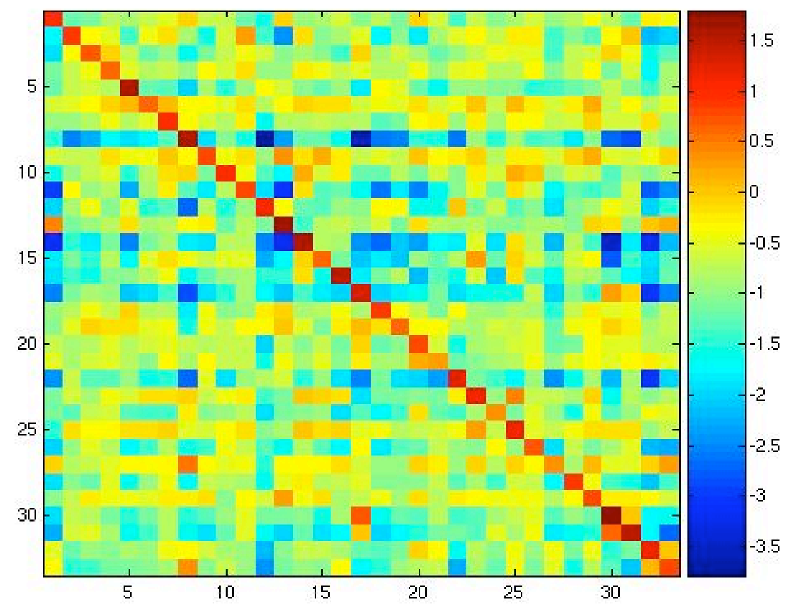


some images

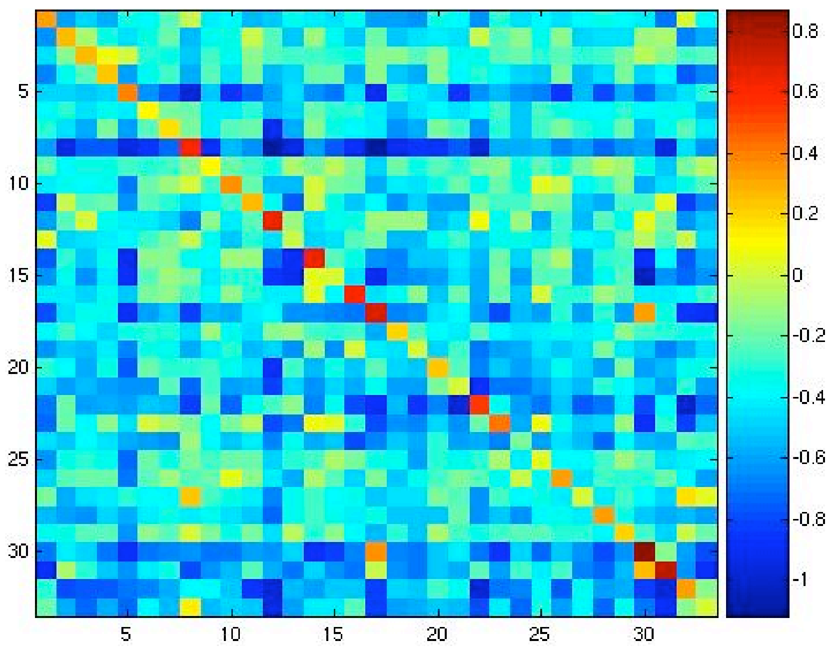
ubm 160s



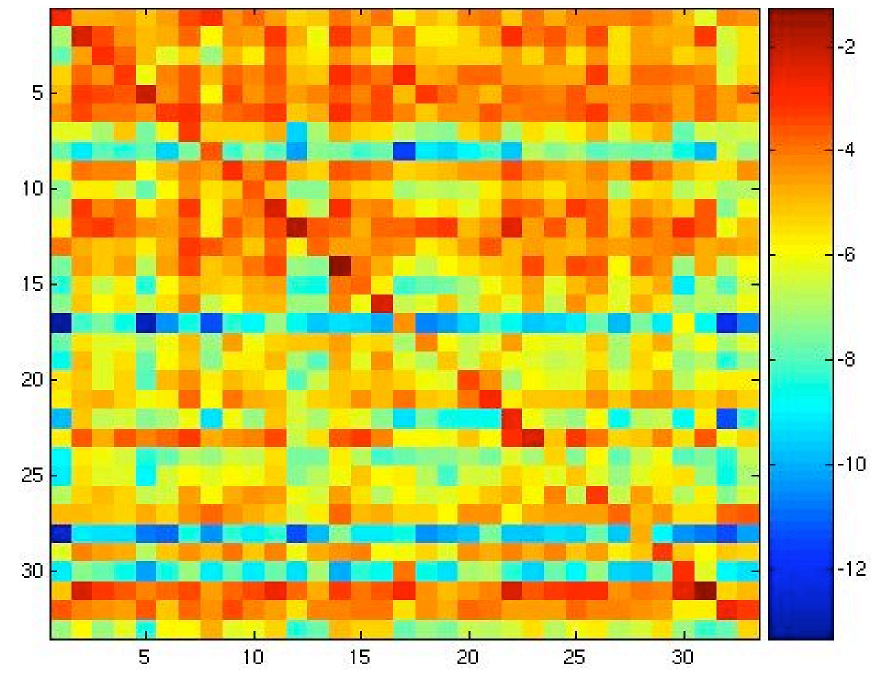
gmm 160s



ubm 5s



gmm 5s



results analysis

- the UBM seems better in our tests
- maybe the single channel, the population, and the speech content make the UBM more preferment in these tests

conclusion

- UBM adaptation is much more fast than GMM training
- the quality of UBM is much better than GMM when we have small training segments
- the detection computation time of UBM may longer than GMM