Speaker Recognition

SRT project of Signal Processing

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Overview

Speaker Recognition

Identification of the person who is speaking by characteristics of their voice biometrics.

Primary Goal:

- **Accurate** and **Efficient Short** utterance speaker recognition.

Additional Goal:

- Scalability over large number of speakers.
- Low Latency Real-Time recognition
- A working Real-Time recognition system.

Content

VAD

Voice Activity Detection shall be applied for all signals as a pre-filter. We've tried 2 different approaches:

- Energy-Based:
  - Filter out the intervals with relatively low energy.
  - Work perfectly for high-quality recordings.
  - Sensitive to noise.
- Long-Term Spectral Divergence
  - Compare long-term spectral envelope with noise spectrum.
  - More robust to noise, used in our GUI.
  - *Efficient voice activity detection algorithms using long-term speech information, Ramırez, Javier, 2004*

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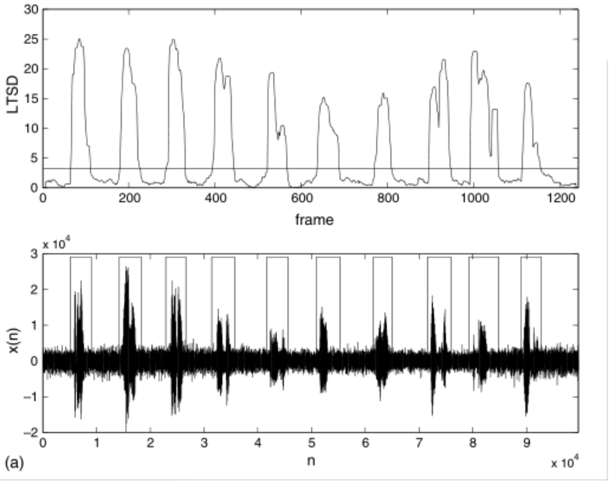
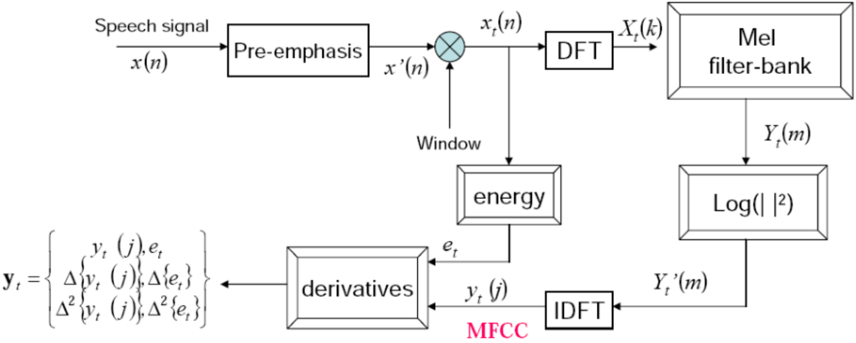
LTSD


LTSD
30
25
20
15
10
5
0
0
200
400
600
800
1000
1200
frame
x 10^4
3
2
1
0
−1
−2
x(n)
0
1
2
3
4
5
6
7
8
9
n
x 10^4
(a)

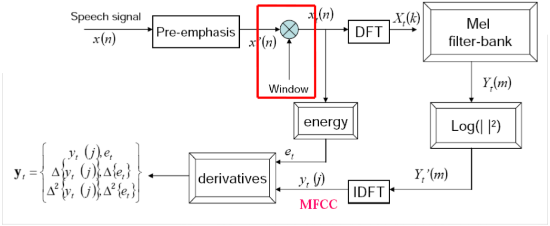
MFCC

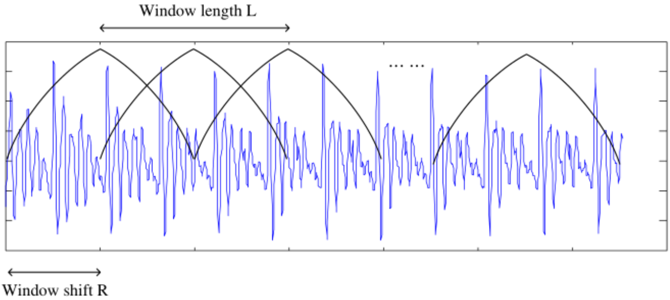
Mel-Frequency Cepstral Coefficients

Cepstral feature which closely approximates human auditory system's response. Commonly used feature for Speech/Speaker Recognition.

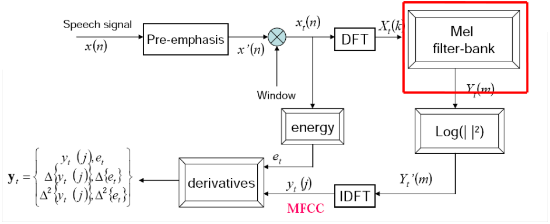


Windowing

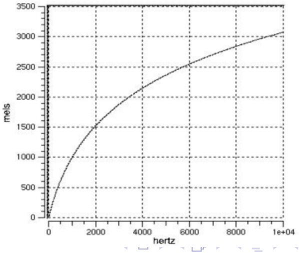

Speech signal
x(n)
Pre-emphasis
x'(n)
Window
x_t(n)
DFT
X_t(k)
Mel
filter-bank
Y_t(m)
Log(| |²)
Y_t'(m)
IDFT
y_t(j)
MFCC
energy
e_t
derivatives


Window length L
... ...
Window shift R

Mel-Scale



$$Mel(f) = 2595 \log_{10}(1 + \frac{f}{700})$$



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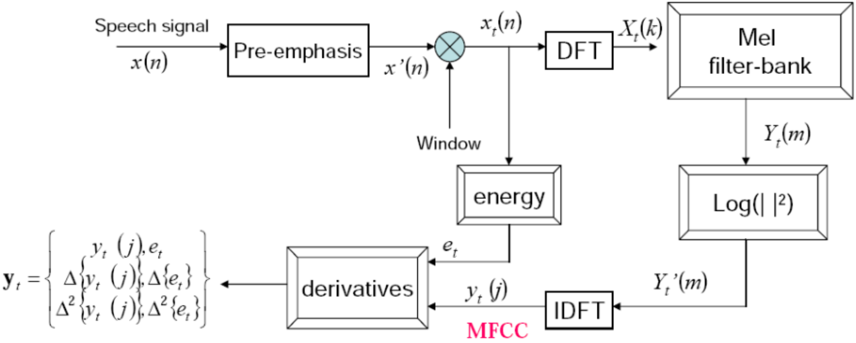

LPC

Linear Predictive Coding/Coefficients

Assumption

In a short period, the nth signal is a linear combination of previous p signals: $\hat{x}(n) = \sum_{i=1}^{p} a_i x(n-i)$

Minimize squared error $\mathrm{E}\left[\hat{x}(n) - x(n)\right]$ using Levinson-Durbin algorithm.

Use $a_1, \cdots, a_p$ as features.

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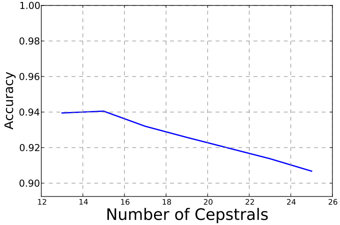
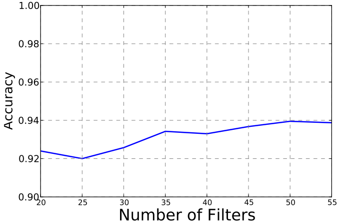
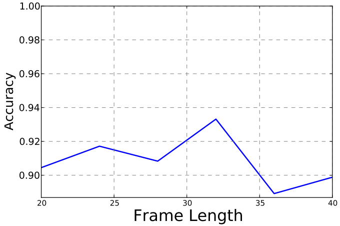
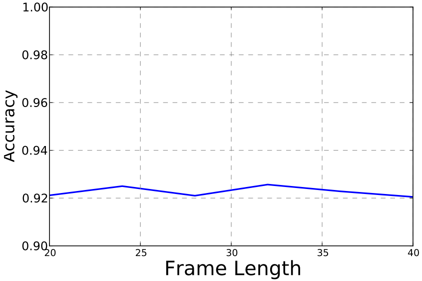


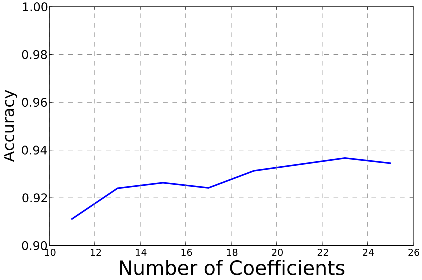




Best parameters in our cases:
Number of cepstrals: 15
Number of filters: 55
Frame length: 32ms

LPC Params



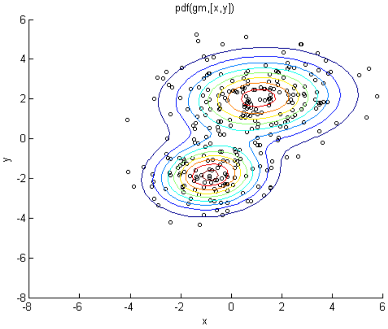


Best parameter in our cases:
Number of coefficients: 23
Frame length: 32ms

GMM

Gaussian Mixture Model is commonly used to model human's acoustic feature.

$$p(\theta) = \sum_{i=1}^{K} w_i \mathcal{N}(\mu_i, \Sigma_i)$$



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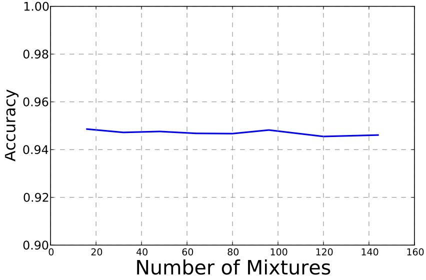

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Optimized GMM

- Basic GMM training: random initialize, estimate parameters with EM.
- Improvment: initialize with a parallel KMeansII.
- Improvment: parallel training implementation in C++.
- Compared to GMM from scikit-learn:

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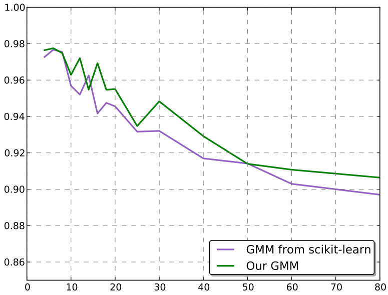

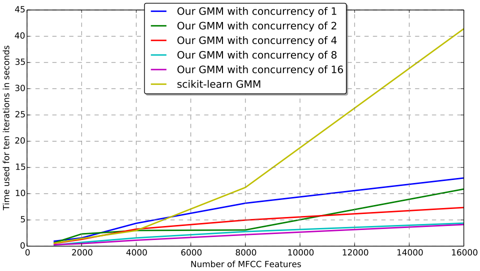

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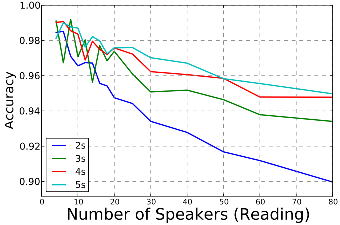
UBM

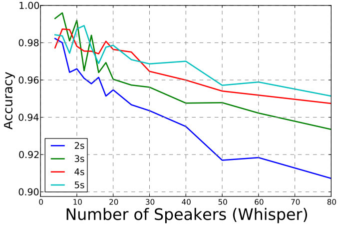
Universal Background Model is a GMM trained on giant datasets.
UBM can be used to:

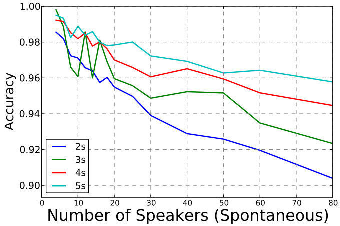
- Describe general acoustic feature of human.
- Reject the decision of GMM.
- Train adaptive GMM.

Reynolds, Douglas, et al, 2000,
Speaker verification using adapted Gaussian mixture models

GMM Results







Train duration: 20s
Random selected test utterance: 50
Each value in the graph is an average of 20 independent experiments.

CRBM

- **Restricted Boltzmann Machine** is a generative stochastic two-layer neural network.
- **Continuous RBM** extends RBM to real-valued inputs.
- RBM has the ability to reconstruct a layer similar to input layer. The difference between the two layers can be a used to measure the fitness of an input to the model.
- Therefore, RBM can be a substituion to GMM.

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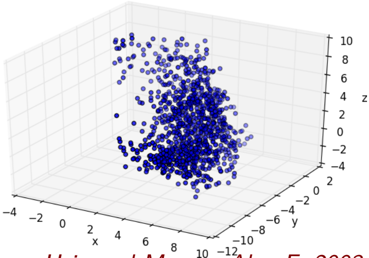

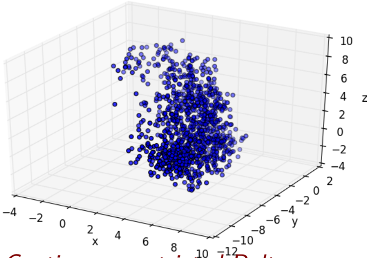

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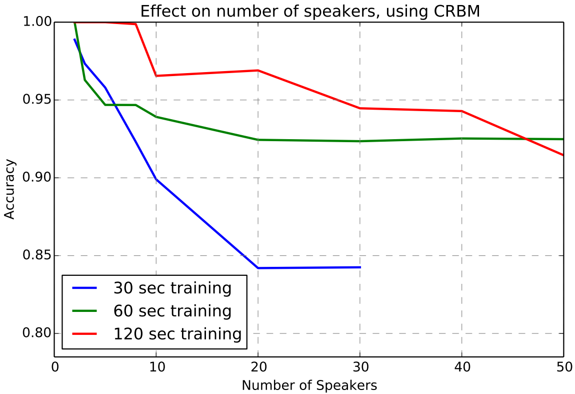
RBM Results

Results of CRBM, tested with 5 secs of utterance.



GUI Demo

Conclusion

- We implemented a faster GMM, also with better performance.
- Accuracy is kept even under short training and testing utterance.
- Our system is highly accurate, can almost response in real-time.
- 97% accuracy for 20$\sim$30 speakers, 95% for 70$\sim$80 speakers.

Thanks!