Speaker Change Detection

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Speaker Change Detection

Given a wave file, the aim is to find out instances of speaker change.

Motivation

- Diarization: It is the task of determining who spoke where (and what). Speaker change detection is preliminary processing step for diarization.
- Also, essential in applications like conference and meeting audio data indexing.

Literature Review

- Distance metrics based classification: Using a pair of sliding windows and computing the distance between their contents.
- Build speaker models: Identify each speaker accurately then instances of speaker ID change imply a change in speaker.

Issues with current methods

- Since we have no prior knowledge of speakers, there is no data to obtain an accurate speaker model a priori.
- For the system to be real time, we can't use data hungry clustering methods like GMM.

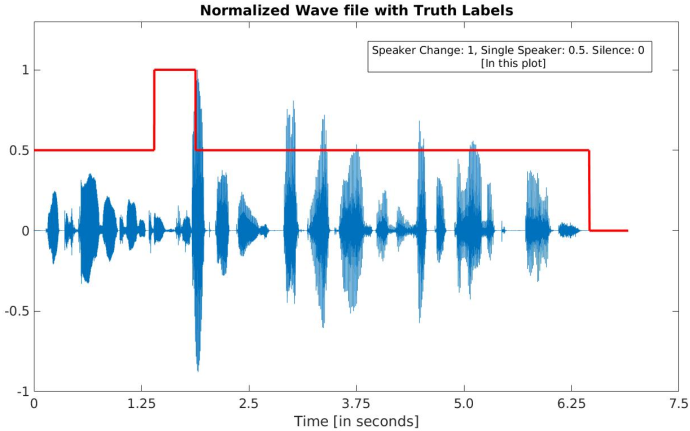
Dataset

- We used the TIMIT dataset, which consists of data from 630 speakers.
- From each speaker, we have a set of 10 sentences, and their corresponding phonetic transcriptions.
- Out of 10 sentences, 2 sentences are common to every speaker, 3 are unique to the speaker and other 5 are spoken by 7 speakers each.

Data Preparation

- We create three disjoint list of speakers, corresponding to training, validation and test sets. For each speaker we only use the diverse (spoken by individual) and compact (spoken by 7 speakers).
- First, from the phonetic transcriptions we find the speech regions of two random wave files.
- Since the wave files have some silence at the start and end of file, we concatenate the two wave files in a way ensuring there is no silence between the two speakers.

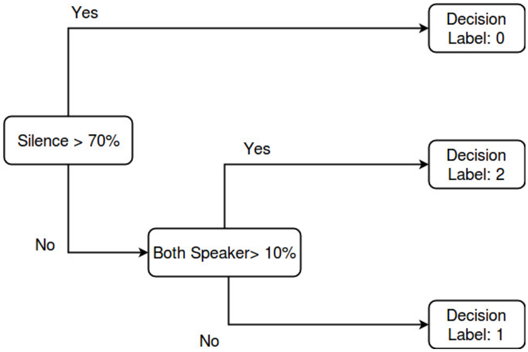
Wave file with truth labels



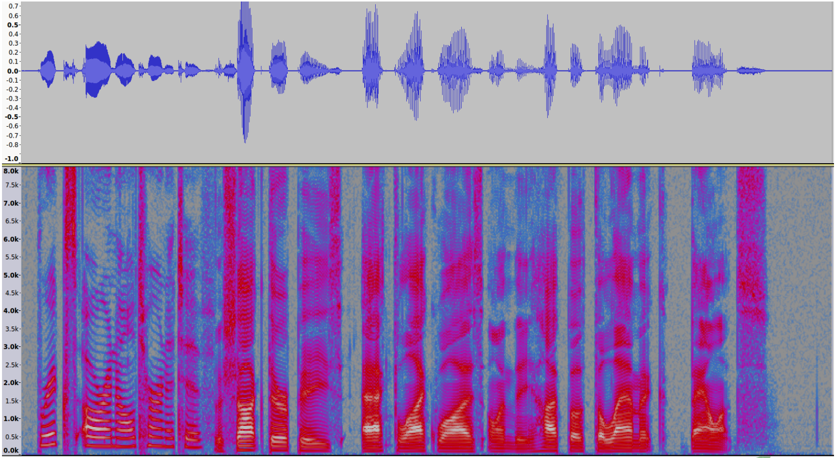
Labelling strategy

- The main issue in speaker change problem is how to obtain the ground truth.
- Since we always consider a non-zero length window to compute any feature, marking the change as instantaneous won't help.
- To take decision whether a frame is speaker change or not, we consider windows of 200 msec, 400 msec and 600 msec.

Labelling Strategy



Spectrogram and Wave File



Features and Approaches Tried

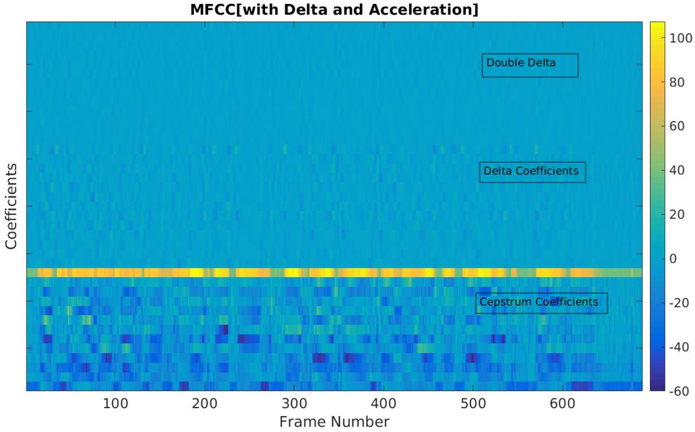
- The idea was to capture the subtle changes in the features, that occur when the speaker change occurs.
- Choosing the right window for decision is critical for detecting the change.

MFCC

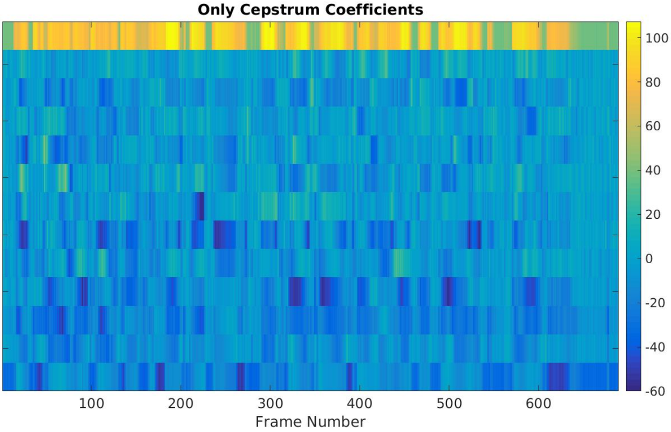
Steps to obtain MFCC:

- Frame the signal into short frames.
- For each frame calculate the periodogram estimate of the power spectrum.
- Apply the mel filterbank to the power spectra, sum the energy in each filter.
- Take the logarithm of all filterbank energies.
- Take the DCT of the log filterbank energies.
- Keep DCT coefficients 1-13, discard the rest.

MFCC-Delta-Acceleration

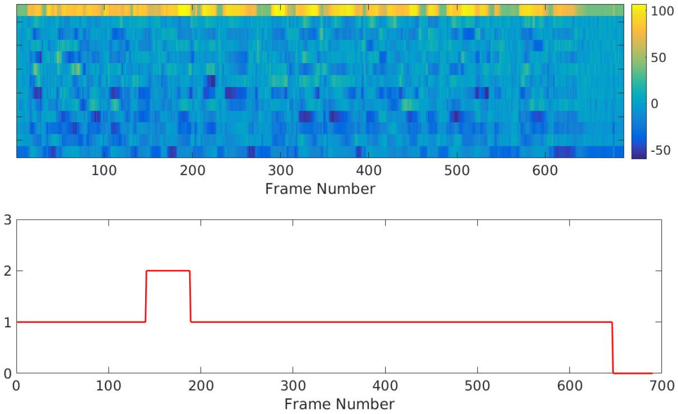


Only MFCC

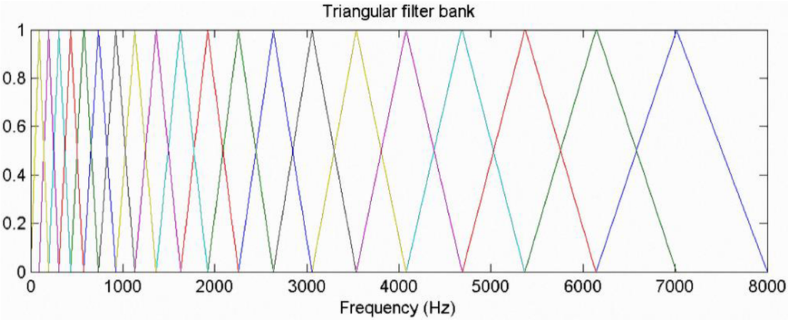


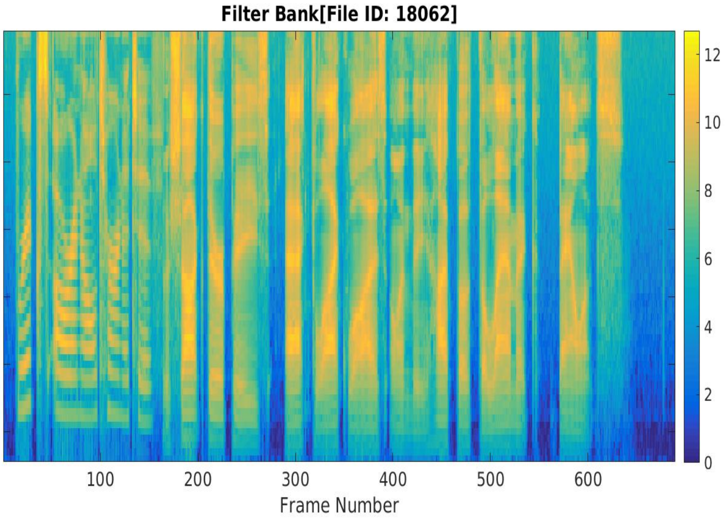
Only Cepstrum Coefficients
100
80
60
40
20
0
-20
-40
-60
100
200
300
400
500
600
Frame Number

MFCC with truth label



Mel Filter Bank

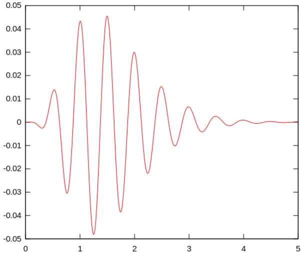



Filter Bank[File ID: 18062]
100
200
300
400
500
600
Frame Number
0
2
4
6
8
10
12

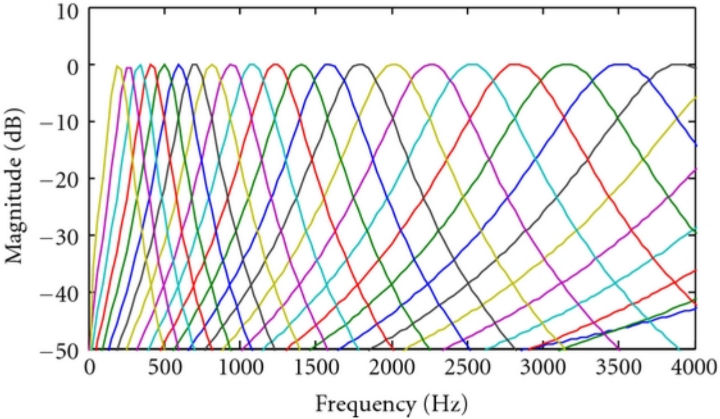
Gammatonegram

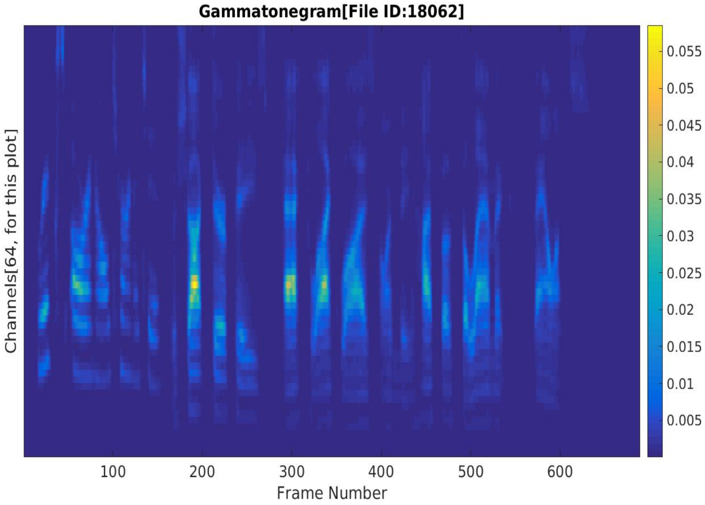
The gammatone filter models:

$$g(t) = at^{n-1} \exp^{-2\pi bt} \cos(2\pi ft + \phi)$$

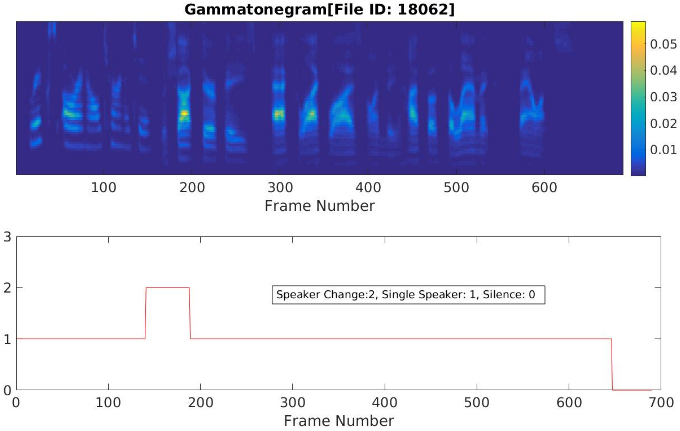


Gammatone Filterbank frequency response

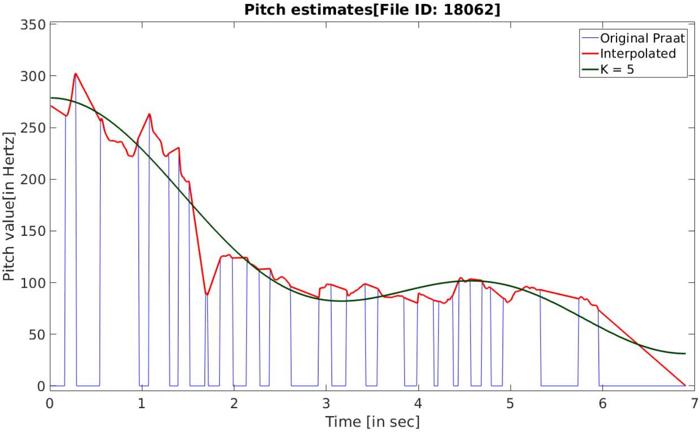



Gammatonegram[File ID:18062]
Channels[64, for this plot]
Frame Number
100
200
300
400
500
600
0.055
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005

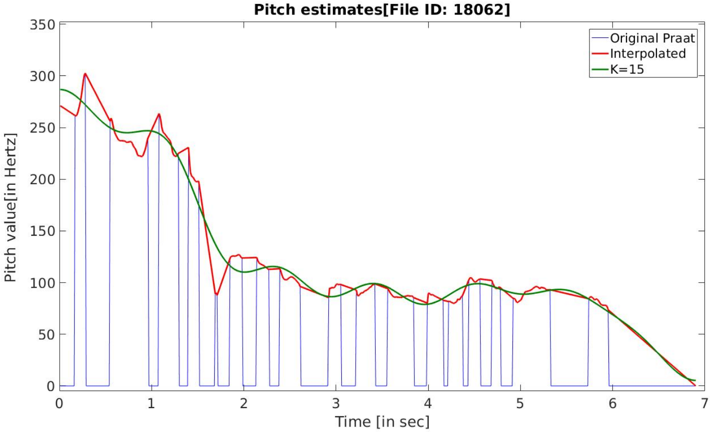
Gamma features with truth labels



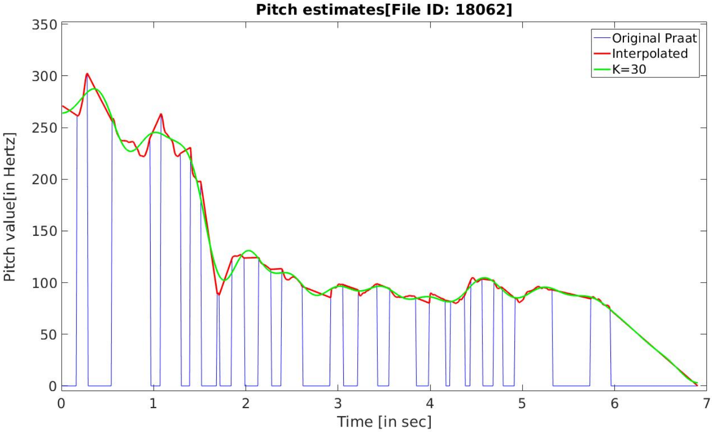
Pitch estimates (K=5)



Pitch estimates (K=15)



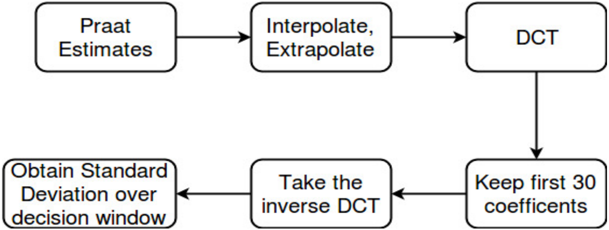
Pitch estimates (K=30)



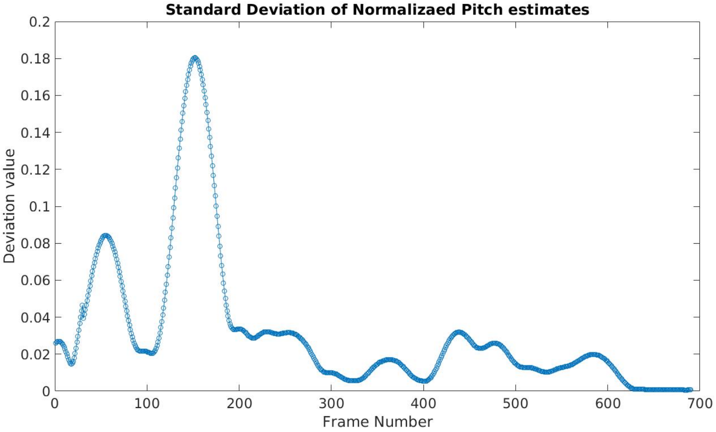
Steps used to obtain Pitch estimates

- First, using Praat pitch estimates are obtained for the given file, for a window of 25ms with a hop of 10ms
- For the regions where Praat can't estimate the pitch value, it gives "-undefined–" as its output. We change this undefined to zero.
- Next, we use linear interpolation and extrapolation on non-zero points, to obtain a continuous pitch estimate for the whole signal
- We take the DCT of the estimate, and zero out coefficients greater than 30, and take i-DCT to get smoothened pitch estimates
- Next, we take the standard deviation of the above obtained pitch estimates, over a window of 610 ms, with a hop of 10 ms.

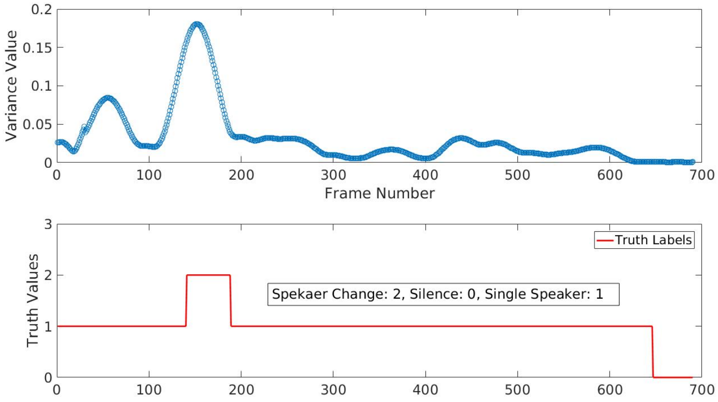
Steps Involved

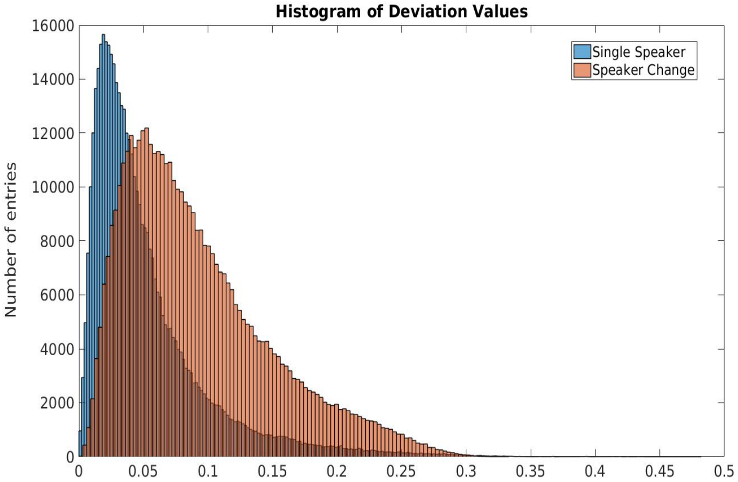


Deviation of Pitch estimates



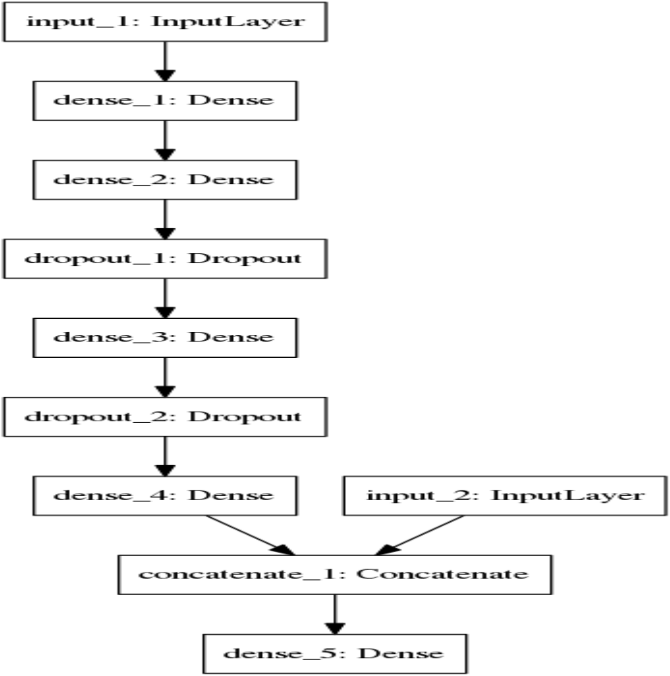
Deviation with ground truth labels




Histogram of Deviation Values
Single Speaker
Speaker Change
Number of entries
0
2000
4000
6000
8000
10000
12000
14000
16000
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5

Results[with DNN Classifier]

Context	Features	1 Speaker[Val Acc.]	Sp. Change[Val Acc.]	F-F	M-M	F-M	%SC[Train data]
200 msec	MFCC Filter Bank Gammatone	Features not good					
400 msec	MFCC Filter Bank Gammatone	Features not good					
600 msec	MFCC Filter Bank	Features not good					
	Gammatone	85%	82%	83%	76%	84%	48%
	Gammatone-Pitch	73%	91.3%	88.7%	89.29%	93.38%	54%
800 msec	Gammatone	89%	70%	71%	58%	73%	63.5%
	Gammatone-Pitch	72.68%	88.84%	88.2%	84.79%	91.56%	55.33%


input_1: InputLayer
dense_1: Dense
dense_2: Dense
dropout_1: Dropout
dense_3: Dense
dropout_2: Dropout
dense_4: Dense
input_2: InputLayer
concatenate_1: Concatenate
dense_5: Dense

Some key findings

- As expected, female-male speaker changes have accuracy's higher than female-female and male-male.
- On including pitch estimates, the accuracy of Male-Male speaker change detection increased.
- The models which use pitch estimates[deviations] generalize better than those models which don't include pitch estimates.

Future work

- Assigning a confidence measure to frames, so as to account for number of samples from speaker 1 and for speaker 2, for the given decision window.
- Using Siamese network to compare between different features

Thank You.

The scripts used, and other codes used can be found at:
`https://github.com/smittal6/leap-scd`