Effects of Frequency-Based Inter-frame Dependencies on Automatic Speech Recognition

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Outline

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Automatic Speech Recognition

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Automatic speech recognition tries to solve problems like :

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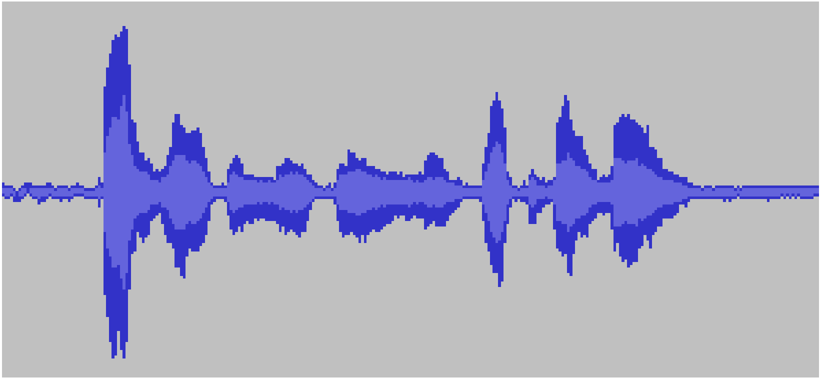
what is the person saying?



Answer :

Automatic Speech Recognition

Automatic speech recognition tries to solve problems like :

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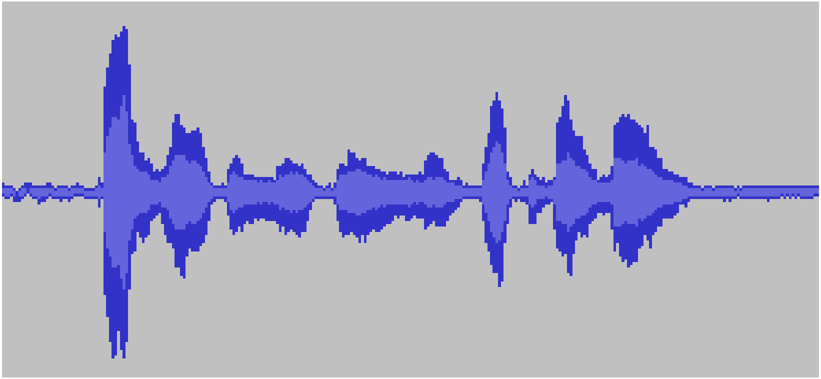

Answer : All work and no play makes Jack a dull boy

Features

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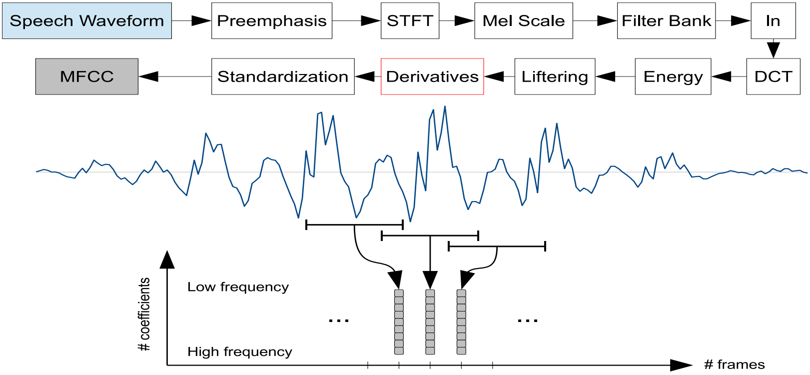
MFCC : Mel-frequency cepstral coefficients



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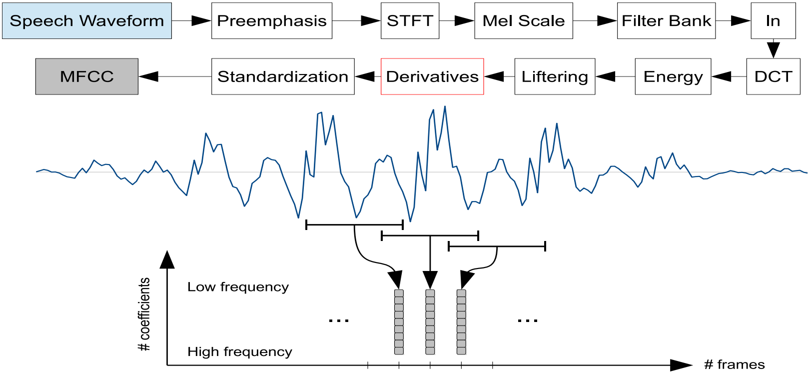

The differentiation of a noisy signal amplifies the noise. Can something else be used?

Contributions

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   Motivations
   High-dimensional features.

Triangular Window (Contribution 1)

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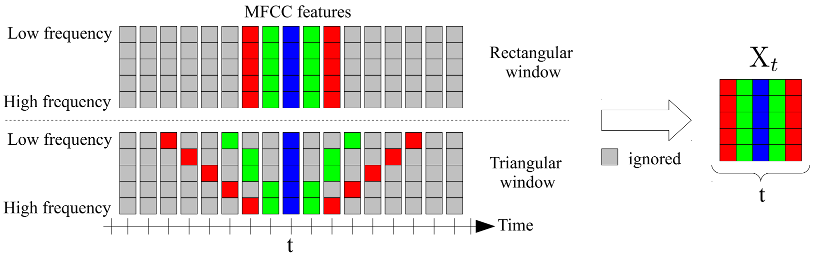
Original MFCC

Concatenation of derivatives

Our Features

Concatenation of coefficients on each side of a frame according to the shape of the window.



Motivations for Triangular Window

Motivations for Triangular Window

Variation of the intensity of different frequency components.

Long and continuous lines implies slow variation.

Short lines implies high variation.

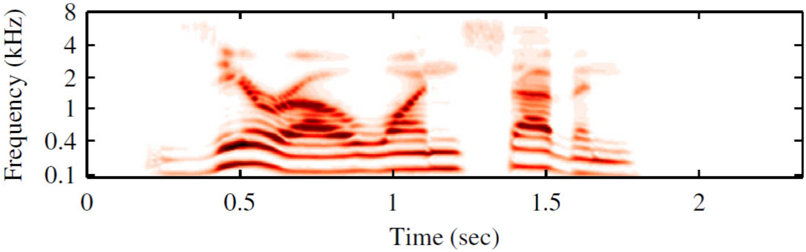


Figure taken from [Heckmann et al., 2011]

Outline

Phoneme Based Hidden Markov Model

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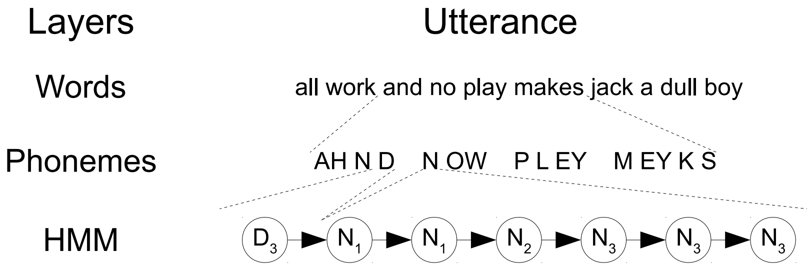
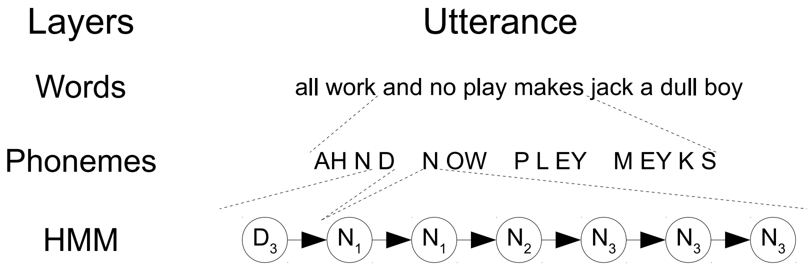


Phoneme Based Hidden Markov Model



Original Model

HMM with a mixture of Gaussian densities. (GMM-HMM)

Our Model

HMM with a mixture of Matrix Normal densities. (MNMM-HMM)

Learning MNMM-HMM (Contribution 2)

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Matrix Normal Distribution

Let X and M be $n \times p$ dimensional matrices, U be $n \times n$ and V be $p \times p$. If $X \sim \mathcal{MN}(M, U, V)$, then:

Learning MNMM-HMM (Contribution 2)

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$$p(X|M, U, V) = \frac{\exp\left(-\frac{1}{2}\,\mathrm{Tr}\left[V^{-1}(X - M)^{\top}U^{-1}(X - M)\right]\right)}{(2\pi)^{\frac{np}{2}}|V|^{\frac{n}{2}}|U|^{\frac{p}{2}}}\ , \quad (1)$$

where M is the mean, U is the among-row variance and V the among-column variance.

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where M is the mean, U is the among-row variance and V the among-column variance.

Learning

Using the posterior probability computed by the well-known Forward-Backward recursion, we can update the parameters M, U and V.

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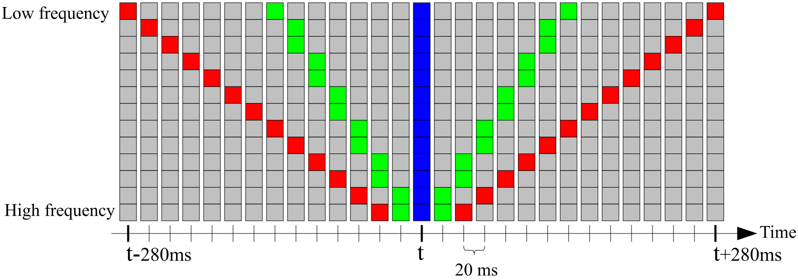
- Test A : 28,028 utterances
- Test B : 28,028 utterances
- Test C : 14,014 utterances

Triangular Window

Triangular Window

We tested multiple configurations for the triangular window.

This is the shape of the best triangular window we found.



Triangular Window (cont.)

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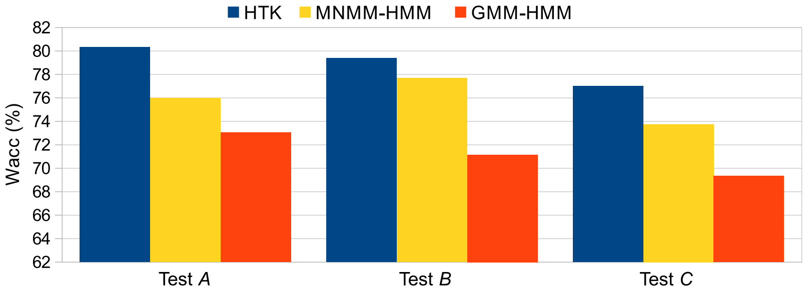

Our features, our model

Original features, original model

Reference only

Our implementation shows that its helps simpler speech recognizer.

Rectangular VS Triangular

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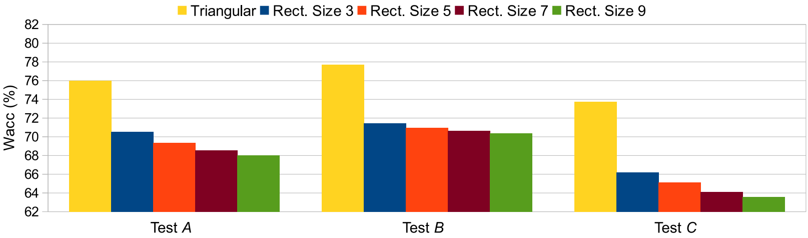

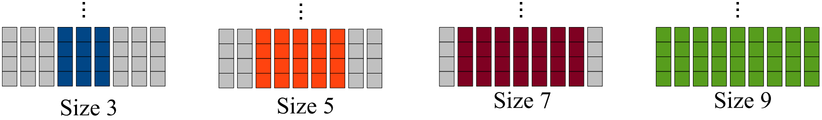

Taking into account the frequency of the coefficients, the triangular window outperformed mere concatenation.

Adding more information degrades the performances of rectangular.

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The concatenation of adjacent features might be a better idea than the concatenation of derivatives.

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Future Work

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1. Feature representation model to learn the shape of the window.

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Future Work

1. Feature representation model to learn the shape of the window.
2. Triangular window directly on the waveform.