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TO STUDY VARIOUS TECHNIQUES FOR FEATURE EXTRACTION IN SPEECH RECOGNITION SYSTEM

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ABSTRACT
The time domain waveform of a speech signal carries all of the auditory information. From the phonological point of view, very little can be said on the basis of the waveform itself. However, past research in mathematics, acoustics, and speech technology have provided many methods for converting data that can be considered as information if interpreted correctly. In order to find some statistically relevant information from incoming data, it is important to have mechanisms for reducing the information of each segment in the audio signal into a relatively small number of parameters, or features. These features should describe each segment in such a characteristic way that other similar segments can be grouped together by comparing their features. There are enormous interesting and exceptional ways to describe the speech signal in terms of parameters. Though, they all have their strengths and weaknesses, we have presented some of the most used methods with their importance.
KEYWORDS: Speech Recognition System, Signal Processing, Hybrid Feature Extraction Methods

INTRODUCTION
Speech is one of the ancient ways to express ourselves. Today these speech signals are also used in biometric recognition technologies and communicating with machine.

These speech signals are slowly timed varying signals (quasi-stationary). When examined over a sufficiently short period of time (5-100 msec), its characteristics are fairly stationary. But, if for a period of time the signal characteristics changes, it reflects to the different speech sounds being spoken. The information in speech signal is actually represented by short term amplitude spectrum of the speech wave form. This allows us to extract features based on the short term amplitude spectrum from speech (phonemes). The fundamental difficulty of speech recognition is that the speech signal is highly variable due to different speakers, nt speaking rates, contents and acoustic conditions.

The feature analysis component of an ASR system plays a crucial role in the overall performance of the system. Many feature extraction techniques are available, these include

- Linear predictive analysis (LPC)
- Linear predictive cepstral coefficients (LPCC),
- perceptual linear predictive coefficients (PLP)
- Mel-frequency cepstral coefficients (MFCC)
- Power spectral analysis (FFT)
- Mel scale cepstral analysis (MEL)
- Relative spectra filtering of log domain coefficients (RASTA)
- First order derivative (DELTA) Etc.

BASIC IDEA OF ACOUSTIC FEATURE EXTRACTION
The task of the acoustic front-end is to extract characteristic features out of the spoken utterance. Usually it takes in a frame of the speech signal every 16-32 msec and updated every 8-16 msec [2], [9] and performs certain spectral analysis. The regular front-end includes among others, the following algorithmic blocks: Fast Fourier Transformation (FFT), calculation of logarithm (LOG), the Discrete Cosine Transformation (DCT)

and sometimes Linear Discriminate Analysis (LDA). Widely used speech features for auditory modeling are cepstral coefficients obtained through Linear Predictive Coding (LPC). Another well-known speech extraction is based on Mel-frequency Cepstral Coefficients (MFCC). Methods based on Perceptual Prediction which is good under noisy conditions are PLP and RASTA-PLP (Relative Spectra Filtering of log domain coefficients). There are some other methods like RFCC, LSP etc. to extract features from speech. MFCC, PLP and LPC are the most widely used parameters in area of speech processing.

FEATURE EXTRACTION METHODS

Features extraction in ASR is the computation of a sequence of feature vectors which provides a compact representation of the given speech signal. It is usually performed in three main stages. The first stage is called the speech analysis or the acoustic front-end, which performs spectra-temporal analysis of the speech signal and generates raw features describing the envelope of the power spectrum of short speech intervals. The second stage compiles an extended feature vector composed of static and dynamic features. Finally, the last stage transforms these extended feature vectors into more compact and robust vectors that are then supplied to the recognizer.

a. Title Mel Frequency Cepstrum Coefficients (MFCC)

The most prevalent and dominant method used to extract spectral features is calculating Mel-Frequency Cepstral Coefficients (MFCC). MFCCs are one of the most popular feature extraction techniques used in speech recognition based on frequency domain using the Mel scale which is based on the human ear scale. FCCs being considered as frequency domain features are much more accurate than time domain features [9], [10].

Mel-Frequency Cepstral Coefficients (MFCC) is a representation of the real cepstral of a windowed short-time signal derived from the Fast Fourier Transform (FFT) of that signal. The difference from the real cepstral is that a nonlinear frequency scale is used, which approximates the behaviour of the auditory system. Additionally, these coefficients are robust and reliable to variations according to speakers and recording conditions. MFCC is an audio feature extraction technique which extracts parameters from the speech similar to ones that are used by humans for hearing speech, while at the same time, deemphasizes all other information. The speech signal is first divided into time frames consisting of an arbitrary number of samples. In most systems overlapping of the frames is used to smooth transition from frame to frame. Each time frame is then windowed with Hamming window to eliminate discontinuities at the edges [6], [11].
The filter coefficients w (n) of a Hamming window of length n are computed according to the formula:

$$W(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right), 0 \le n \le N-1$$
$$= 0, \text{otherwise}$$

Where N is total number of sample and n is current sample. After the windowing, Fast Fourier Transformation (FFT) is calculated for each frame to extract frequency components of a signal in the time-domain. FFT is used to speed up the processing. The logarithmic Mel-Scaled filter bank is applied to the Fourier transformed frame. This scale is approximately linear up to 1 kHz, and logarithmic at greater frequencies [12]. The relation between frequency of speech and Mel scale can be established as:
Frequency (Mel Scaled) = [2595log (1+f (Hz)/700]

MFCCs use Mel-scale filter bank where the higher frequency filters have greater bandwidth than the lower frequency filters, but their temporal resolutions are the same.

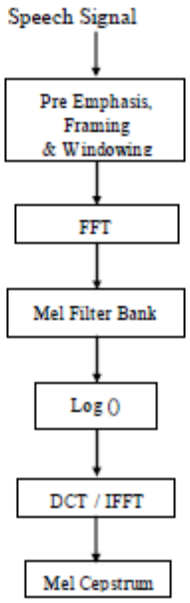

Figure 1: MFCC Derivation

The last step is to calculate Discrete Cosine Transformation (DCT) of the outputs from the filter bank. DCT ranges coefficients according to significance, whereby the 0th coefficient is excluded since it is unreliable.

The overall procedure of MFCC extraction is shown on Figure 1.
For each speech frame, a set of MFCC is computed. This set of coefficients is called an acoustic vector which represents the phonetically important characteristics of speech and is very useful for further analysis and processing in Speech Recognition. We can take audio of 2 Second which gives approximate 128 frames each contain 128 samples (window size = 16 ms). We can use first 20 to 40 frames that give good estimation of speech. Total of forty Two MFCC parameters include twelve original, twelve delta (First order derivative), twelve delta-delta (Second order derivative), three log energy and three 0th parameter.

b. Body Linear Predictive Codes (LPC)
It is desirable to compress signal for efficient transmission and storage. Digital signal is compressed before transmission for efficient utilization of channels on wireless media. For medium or low bit rate coder, LPC is most widely used [13]. The LPC calculates a power spectrum of the signal. It is used for formant analysis [14]. LPC is one of the most powerful speech analysis techniques and it has gained popularity as a formant estimation technique [15].

While we pass the speech signal from speech analysis filter to remove the redundancy in signal, residual error is generated as an output. It can be quantized by smaller number of bits compare to original signal. So now, instead of transferring entire signal we can transfer this residual error and speech parameters to generate the original signal. A parametric model is computed based on least mean squared error theory, this technique being known as linear prediction (LP). By this method, the speech signal is approximated as a linear combination of its p previous samples. In this technique, the obtained LPC coefficients describe the formants. The frequencies at which the resonant peaks occur are called the formant frequencies [16]. Thus, with this method, the locations of the formants in a speech signal are estimated by computing the linear predictive coefficients over a sliding window and finding the peaks in the spectrum of the resulting LP filter. We have excluded 0th coefficient and used next ten LPC Coefficients In speech generation, during vowel sound vocal cords vibrate harmonically and so quasi periodic signals are produced. While in case of consonant, excitation source can be considered as random noise [17]. Vocal tract works as a filter, which is responsible for speech response. Biological phenomenon of speech generation can be easily converted in to

equivalent mechanical model. Periodic impulse train and random noise can be considered as excitation source and digital filter as vocal tract.

c. Perceptual Linear prediction (PLP)

The Perceptual Linear Prediction PLP model developed by Herman sky. PLP models the human speech based on the concept of psychophysics of hearing [2, 9]. PLP discards irrelevant information of the speech and thus improves speech recognition rate. PLP is identical to LPC except that its spectral characteristics have been transformed to match characteristics of human auditory system.

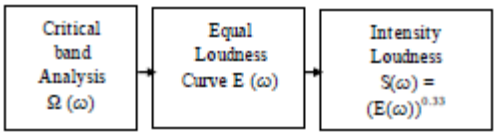

Figure 2: Block Diagram of PLP Processing

Figure 2 shows steps of PLP computation. PLP approximates three main perceptual aspects namely: the critical-band resolution curves, the equal-loudness curve, and the intensity-loudness power-law relation, which are known as the cubic-root.

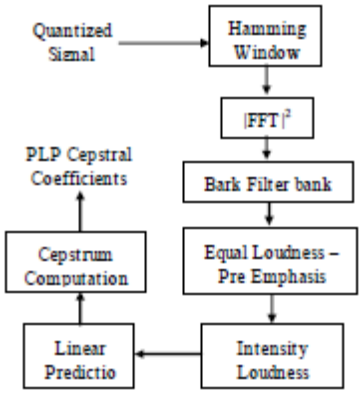

Figure 3: PLP Parameter Computation

Detailed steps of PLP computation is shown in figure 3. The power spectrum of windowed signal is calculated as,

$P(\omega) = Re(S(\omega))\ 2 + Im(S(\omega))\ 2$

A frequency warping into the Bark scale is applied. The first step is a conversion from frequency to bark, which is a better representation of the human hearing resolution in frequency. The bark frequency corresponding to an audio frequency is,

The auditory warped spectrum is convoluted with the power spectrum of the simulated critical-band masking curve to simulate the critical-band integration of human hearing. The smoothed spectrum is down-sampled at intervals of ≈ 1 Bark. The three steps frequency warping, smoothing and sampling are integrated into a single filter-bank called Bark filter bank. An equal-loudness pre-emphasis weight the filter-bank outputs to simulate the sensitivity of hearing. The equalized values are transformed according to the power law of Stevens by raising each to the power of 0.33. The resulting auditory warped line spectrum is further processed by linear prediction (LP). Applying LP to the auditory warped line spectrum means that we compute the predictor coefficients of a (hypothetical) signal that has this warped spectrum as a power spectrum. Finally, Cepstral coefficients are obtained from the predictor coefficients by a recursion that is equivalent to the logarithm of the model spectrum followed by an inverse Fourier transform.

The PLP speech analysis method is more adapted to human hearing, in comparison to the classic Linear Prediction Coding (LPC). The main difference between PLP and LPC analysis techniques is that the LP model assumes the all-pole transfer function of the vocal tract with a specified number of resonances within the analysis band. The LP all-pole model approximates power distribution equally well at all frequencies of the analysis band. This assumption is inconsistent with human hearing, because beyond 800 Hz, the spectral resolution of hearing decreases with frequency and hearing is also more sensitive in the middle frequency range of the audible spectrum [9].

NEURAL NETWORK

The Generalization is the beauty of artificial neural network. It provides fantastic simulation of information processing analogues to human nervous system. Multilayer feed forward network with back propagation algorithm is the common choice in classification and pattern recognition. Hidden Markov Model, Gaussian Mixture Model, Vector Quantization are the some of the techniques for acoustic features to visual speech movement. Neural network is one of the good choices among all. Genetic Algorithm can be used with neural network for performance improvement by optimizing parameter combination.

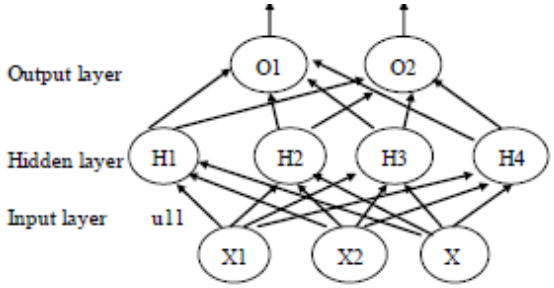

Figure 4: Structure of neural network

We can use multi-layer feed forward back propagation neural network as shown in Figure 4 with total number of features as number of input neurons in input layer for LPC, PLP and MFCC parameters respectively. As shown in Figure 4 Neural Network consists of input layer, hidden layer and output layer. Variable number of hidden layer neurons can be tested for best results. We can train network for different combinations of epochs with goal as minimum error rate.

CONCLUSIONS

We have discussed some feature extraction methods and their pros and cons. LPC parameter is not so acceptable because of its linear computation nature. It was seen that LPC, PLP and MFCC are the most frequently used features extraction techniques in the fields of speech recognition and speaker verification applications. HMM and Neural Network are considered as the most dominant pattern recognition techniques used in the field of speech recognition.

As human voice is nonlinear in nature, Linear Predictive Codes are not a good choice for speech estimation. PLP and MFCC are derived on the concept of logarithmically spaced filter bank, clubbed with the concept of human auditory system and hence had the better response compare to LPC parameters.

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