A Revisit to Speech Processing and Analysis

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ABSTRACT
Speech recognition is an active area in signal processing. Various researchers have been invested different concepts in speech recognition system as part of feature extraction techniques, speech classifiers, statistical analysis, encompassing mathematical models, signal processing and transformations, database and performance evaluation. In the current era, multi-speecher analysis is the newly focused area in speech processing and analysis. It includes audio segmentation, extraction of relevant features, classification of features, template generation and training. Also, other techniques like Bank-of-filters, Linear Predictive Coding Model, Vector Quantization, Hidden Markov Model and Gaussian Mixture Model to get better result. In this paper, various approaches have been analyzed based on acoustic and articular features focusing on Human Auditory System (HAS). Even focusing on the cross-functional approach by using machine learning, artificial intelligence-based techniques and neural networks.

General Terms
Automatic speech recognition, modelling and matching techniques

Keywords
Automatic speech recognition, feature extraction, dimension reduction, modeling and matching techniques

1. INTRODUCTION
Communication is a powerful mechanism for sharing the information. In human-machine interaction helps to identify the design, evaluation and implementation of interactive computing systems for human. The aim of the speech recognition task is to address the speaker by dividing the speech sample into small segments. There are so many languages like regional, national and international languages that have been spoken around the globe. It is needed to recognize someone by listening the speech if the language is understood. This recognition system has been implemented in different areas such as personal computers, mobile phones, security systems, healthcare, robotics, military, education, dictation and many more.

Currently, the Automatic Speech Recognition (ASR) system uses acoustic and articulatory features from speakers in noisy environments like car environment, reverberant environment and other vehicular environment. Before implementing the model to recognize the speech, samples need to be preprocessed to desire scales and overlapped with each other to get the smooth results.

2. CLASSIFICATION OF SPEECH RECOGNITION SYSTEM
The speech recognition system is based on utterance, vocabulary size and speaker.

2.1 Classification Based on Utterances
Speech recognition system can be segregated into different classes by describing what types of utterances in the speech. These are classified as follows. Isolated word recognizers usually require each utterance to have quiet (lack of an audio signal) on both sides of the sample window. It accepts single word or single utterance at a time. The systems having “Listen/Not-Listen” states, where they require the speaker to wait between utterances. Connected word systems are similar to isolated words, but allows separate utterances to be run-together with a minimal pause between them. Continuous speech is the speech having words are connected (words are not separated by breathing space). It is difficult to find the start and end points of the words. Spontaneous Speech is generated by disrupted air flow generated in the vocal tract, nonlinear neuromuscular processes may take place at the larynx and the level of vocal cords.

2.2 Classification Based on Vocabulary Size
The computational complexity, processing requirement and the accuracy of the speech recognition system depends on the vocabulary size of the speech. As the vocabulary size increases, the task of recognition system become quite tedious. ASR system is classified based on the vocabulary as follows.

i. Small Vocabulary - 10 Words
ii. Medium Vocabulary - 100 Words
iii. Large Vocabulary - 1000 Words
iv. Very-Large Vocabulary - 10000 Words
v. Out-of-Vocabulary - Mapping a word from the vocabulary into the unknown words.

Speaker Independent Systems do not require a user to train the system i.e. they are developed to operate for any speaker. Speaker Dependent Systems need user to train the system according to users voice. Train data and the test data are from the same set of speakers.
3. SPEECH ANALYSIS

Speech analysis are often evaluated in various conditions including environment, microphone, data simulation mismatch. Generally, four steps should be followed in order to design the speech recognition system.

i. Analysis
ii. Feature Extraction
iii. Modelling
iv. Testing

3.1 Analysis

Speech is used as a tool for manipulating electronic devices. In Human-machine interaction, a lot of desktop and web based services are used to provide the functionality of automatic dictation, voice search etc.[9].

3.1.1 Sampling and Quantization.

Most speech signals are nonstationary processes with multiple components that may vary in time and frequency [10]. So, speech signal should be digitized the continuous-time signal by the help of sampling and quantization. The continuous signal \( x(t) \) is sampled to give \( x(n) \), which yields \( x_Q(n) \) after quantization [11].

\[
W(x) = 0.54 - 0.46 \cos \left( \frac{2\pi n}{N-1} \right), \quad 0 \leq X \leq N - 1
\]  

Normlization is applied to the speech samples which is used to reduce speaker and recording variability without losing the strength of the features [15]. If mean \( \mu \) and standard deviation \( \sigma \) of the data, standardization is expressed as

\[
X_s = \frac{x - \mu}{\sigma}
\]

To get high speech recognition rate, Noise Reduction techniques must be used to reduce the environmental or background noises [16]. Minimum mean square error (MMSE) and log-spectral amplitude MMSE (LogMMSE) estimators are mostly used for noise reduction [13] [17]. Even filtering techniques like spectral subtraction, spectrum reconstruction and regression model are also used for noise Reduction [18].

3.2 Feature Extraction

In Speech analysis, Feature extraction helps the feature extractor to keep relevant information and discard the irrelevant information which helps the formulation of the Speaker Identification and verification system [1]. Speech is a continuous signal of varying length. Below global or local features can be extracted to analyze the ASR system [13].

i. Prosodic Features
ii. Spectral Features
iii. Voice Quality Features
iv. Teager Energy Operator (TEO) Based Features

3.2.1 Prosodic Features.

There are several prosodic features that influence speech e.g. Pitch, Formant and Energy or Loudness etc. [19]. Based on segmentation, continuous speech is divided into syllable-like units, sentences/phrases or even fixed-interval segments [20]. Prosodic features are divided into

i. Inflections or start/end voicing
ii. Information from F0 and energy contour
iii. Detection of voice region

Pitch is a feature defined as the number of periods of vocal folds vibration per second. The pitch is calculated frame by frame based on the robust algorithm for pitch tracking [21]. Formant is basically referred as the acoustic resonance of human vocal tract. The concentration of acoustic energy is also detected within a particular range of frequency. This can also be measured by Hamming, Hann, Blackman are used to design the ASR system [14]. The window function for window size \( N \) and frame \( w(x) \) is expressed as

\[
W(x) = 0.54 - 0.46 \cos \left( \frac{2\pi n}{N-1} \right), \quad 0 \leq X \leq N - 1
\]
frequency peak in the spectrum \([22]\). The amplitude of unvoiced segments is generally much lower than the amplitude of voiced segments. The signal does not contain unvoiced segments, its Short Time Energy (STE) is usually bigger. For a discrete signal \(S(n)\), the energy is given by

\[
E_s = \sum_{n=-\infty}^{\infty} |S(n)|^2 \tag{3}
\]

The power of discrete-time signal \(S(n)\) is given by \([23]\).

\[
P_s = \lim_{N \to \infty} \frac{1}{2N+1} \sum_{n=-N}^{N} |S(n)|^2 \tag{4}
\]

In general, signals can be classified into three types: an energy signal, which has a non-zero and finite energy, a power signal and the third type is neither. Zero-crossing rate is one parameter which is used to find the voiced and unvoiced portion of the speech. At first the speech sample is divided into frames, then zero-crossing is calculated for each frame to detect the voiced and unvoiced portion of the speech \([24]\). Auto-correlation is a measure of self-similarity of a signal in time domain also the similarity between the signal and its delayed version. The auto-correlation value of positive 1 (+1) represents strong positive association, negative 1 (-1) represents a negative association and 0 shows no association. Auto-correlation function is used to determine the periodicity present in a signal and used to estimate the pitch (fundamental frequency) of a signal \([25]\). This also used for Noise-Robust Speaker Recognition \([26]\). The Wavelet Transform gives a similarity with how human ear processes sound. Therefore, it is suitable for speech processing. It is of two types Discrete Wavelet Transform (DWT) and Wavelet Packet Decomposition (WPD) \([27]\). DWT operates in discrete steps over signal and provides sufficient information with varying window size, being wide of low frequency and narrow for high frequency \([28]\). WPD to obtain high frequency and low frequency set of coefficients which allows better time-frequency localization of signals \([29]\).

3.2.2 Spectral Features. Speech signals having segmental spectral features contain enough information, which helps for speech recognition. The features such as Linear Predictive Cepstral coefficients (LPCC) and Mel-Frequency Cepstral Coefficients (MFCC) \([30] [31]\) are used frequently. Spectral features are obtained by transforming the time domain signal into the frequency domain signal by using the Fourier transform by segmenting the speech samples to 20 to 30 milliseconds \([13]\). Mel Frequency Cepstral Coefficients (MFCC) represents short-time power spectrum of an audio clip based on the discrete cosine transform of log power spectrum on a nonlinear equally spaced mel scale which mimics the human auditory system \([24]\). Linear Predictive Coding (LPC) draws out parameters of speech like spectra and pitch formants. It also equivalents to the resonance structure of human vocal which reduce the square difference between original and estimated speech signal at a finite time. Gammatone Frequency Cepstral Coefficients (GFCC) is obtained by windowing and Fourier transforms similar to MFCC then filtered using the Gammatone filters. This also gives the Time-Frequency representation \([32]\). A spectrogram represents the strength or loudness of a signal over time at different frequencies in a particular waveform. These are used to verify the frequencies in continuous signals and represented by a graph with two geometric dimensions in which time is viewed on the horizontal axis, while the vertical axis identified by frequency and the intensity or color of each point in the image corresponds to amplitude of particular frequency at particular time. Short Term Fourier Transform (STFT) is usually applied to the speech sample to generate spectrogram from the time signal. Using Fast Fourier Transform (FFT) for generating the spectrogram is a digital process \([33]\).

3.2.3 Voice Quality Features. Voice quality is determined by the physical properties of the vocal tract. Spontaneous changes may produce a speech signal that might differentiate speech by using properties such as jitter, shimmer, and Harmonics to Noise Ratio (HNR) \([13]\). Jitter is the variability of fundamental frequency between successive vibratory cycles, while shimmer is the variable of the amplitude. Jitter is a measure of frequency instability, whereas shimmer is the amplitude instability.

The voice qualities are grouped into the following categories \([34]\).

i. Voice Level: Signal amplitude, energy and duration.  
ii. Voice pitch  
iii. Phase, phenome, word and feature boundaries

3.2.4 Teager energy operator-based features. According to Teager, speech is formed by a non-linear vortex-airflow interaction in the human vocal system. An exciting situation affects the muscle tension of the speaker that results in an alteration of the airflow during the production of the sound. The operator developed by Teager to measure the energy from a speech by this non-linear process was documented by Kaiser as follows where \(\psi[]\) is Teager Energy Operator and \(x(n)\) is the sampled speech signal or discrete signal \([13]\).

\[
\psi[x(n)] = x^2(n) - x(n+1)x(n-1) \tag{5}
\]

The TEO for a continuous time signal is defined as \([35]\).

\[
\psi(x(t)) = \frac{\partial x(t)^2}{\partial t} - x(t)(\frac{\partial^2 x(t)}{\partial t^2}) \tag{6}
\]

3.2.5 Entropy. Entropy measures the amount of information content in a signal. By the help of Boltzmann’s formula is determined how much a signal could be compressed, the more information content in a signal the less it could be compressed.

\[
H(n) = -\sum_{i=1}^{M} P[X = x_i]\log([P(X = x_i)]) \tag{7}
\]

where \(M\) is the number of possible values of discrete random variable \(X\) (i.e. the signal), \(x_i\) is the \(i^{th}\) of these values. Spectral entropy has been determined for each frame but not decomposed in frequency bands \([36]\).

4. FEATURE SELECTION AND DIMENSION REDUCTION

Feature selection methods aim to select a subset of the original high-dimensional features based on some performance criterion. Therefore, it can be preserved the semantics of the original features and produce dimensionally reduced results that are more interpretable for domain experts \([17]\). Mostly the feature selection algorithms are grouped into following categories.

i. Feature Transform based feature selection  
ii. Information theoretical based feature selection  
iii. Statistical based feature selection
In similarity based feature selection category, data similarity has been preserved. By Laplacian Score method constructs a nearest neighbor graph for dataset samples and use the Laplacian matrix to calculate a score for each feature which shows the importance of the feature in preserving the similarity and locality of dataset samples [38]. Information theoretical based feature selection method uses the label data to consider the relevance and redundancy of features by maximal statistical dependency criterion based on mutual information [59]. Statistical based feature selection, this category based on various types of statistical procedures which evaluates individually. Variance-score, t-score and chi-score are well-known representatives of this family [39]. Dimension Reduction is to transform of data from a high-dimensional space into a low-dimensional space by which some meaningful properties of the original data can be retained and also reduce the amount of overtraining. Commonly used techniques are Principal Component Analysis (PCA) [40] and even Linear Discriminant Analysis (LDA). PCA is an unsupervised learning dimensionality reduction method by mapping high dimensionality feature set to low dimensionality space, in which feature set is decomposed by the covariance matrix to obtain the principal components and weights of feature set. It utilizes the variance of data projection to assess the amount of feature representation information. PCA is intended to select first k-dimension features with the largest variance to ensure the data after projection satisfies the variance maximization [41] [42]. LDA is a supervised dimensionality reduction method used as a dimensionality reduction and feature extraction tool in pattern recognition. This measures the information with the difference of labels and categories. LDA can be class-dependent or class-independent, based upon maximization of the ratio between class variance to within class variance or maximization of the ratio of overall variance to within class variance respectively [43] [44]. The Joint principal component and discriminant analysis, is used to transform the initial feature set into a new subspace and also extract the discriminant information classification task [45].

5. MODELLING
The main purpose of modelling technique is to generate speaker models using speaker specific feature vector. The modeling techniques are used for speaker recognition and speaker identification. The Acoustic-Phonetic approach is based on acoustic phonetics and postulates particularly the acoustic phonetic search. Using International Phonetic Alphabet (IPA) methods, Similarities for probabilities of content dependant acoustic model for new language can be found out. Pattern Recognition approach involves two steps, pattern training and pattern comparison. This approach used to decide whether the given speech segment belongs to voiced, unvoiced or silence and also can be applied to a sound, a word, a phrase [46]. Dynamic time warping (DTW) is the simplest way to recognize Variations of word structure (VoWS), Normalized Phoneme Distances Thresholding (NPDT), Furthest Segment Search (FSS) and Normalized Furthest Segment Search (NFSS) [47]. The artificial intelligence approach is a hybrid of the acoustic phonetic approach and pattern recognition approach, is used to mechanize the recognition procedure according to the way a human being applies its intelligence. Support Vector Machine (SVMs) is the binary classifier consists of linear and nonlinear separating hyperplanes for information categorization. This model consists of classification of static information vectors only. But this technique cannot be classifying the dynamic data. Also operates the complexity of the model by controlling the vector quantization dimensions of the model [38].

5.1 MATCHING TECHNIQUES
In the next step, it needs to match a detected word from a known word. This can achieve by whole word matching and sub word matching [19]. Whole Word Matching framework compares the incoming digital-audio signal against a prerecorded template of the words having connected word string spoken frequently [50]. Sub Word Matching framework looks for sub-words usually phonemes and then performs further pattern recognition on those [51].

5.2 PERFORMANCE OF SYSTEMS
A speech recognition engine recognizes all words uttered by a human but, practically the performance of a speech recognition engine depends on a number of factors. Vocabularies, multiple users and noisy environments [52]. Word Error Rate (WER) is the common metric of the accuracy of a speech recognition system. WER is derived from the Levenshtein distance, working at the word level instead of the phoneme level [53]. In Command Success Rate, system stores data vocabularies and the vocabulary contain the ten digits from 0 to 9 mapped with ten command words like enter, erase, go, help, no, rubout, repeat, stop, start, and yes. Based on the commands, the training and the testing data set can be identified [54].

6. CHALLENGES
Although there are many amendments in speech recognition system, still several impediments that need to be removed to make a successful recognition system. First problem is getting or creation of the proper data set as per the required task. Most of the data is embedded with noise and other environmental distractions. Some lacunae are there to identify the speech recognition system in unsupervised manner so that the performance of the computer assistants can be improved. Again, the design of model for speech recognition system should focus on individuals own way of speaking, which depends upon various factors that may include the dialect and accent of the speaker as well as the socioeconomic background of the speaker. Among various speech processing problems, Automatic Speech Recognition (ASR) for converting recorded speech automatically to text is one of the most challenging tasks.

7. CONCLUSIONS
In this survey paper, multiple research work in speech recognition with feature extraction. Speech recognition model design have been described. Basically, preprocessing is required to remove the noise from the speech sample and make the sample processable. Then features are needed to analyse the speech signal differently as part of the various domains. After that the features are processed in a designed speech system to get an intended performance. The focus should be on the previous studies and the used techniques to know the benefits of the designed system and their performances. This also covers accent, speaking style, speaker physiology, age, emotions. General methods for diagnosing weaknesses in speech recognition approaches are also highlighted. Finally, the paper proposed an overview of general and specific techniques for better handling of variation sources in Automatic Speech Recognition.
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