# Automatic Speech Recognition of Urdu words using Linear Discriminant Analysis

Hazrat Ali[a,*], Nasir Ahmad[b] and Xianwei Zhou[a]

[a]*School of Computer and Communication Engineering, University of Science and Technology Beijing, 10083, Beijing, P.R. China.*
[b]*Department of Computer Systems Engineering, University of Engineering and Technology Peshawar, 25120, Peshawar, Pakistan.*

**Abstract**. Urdu is amongst the five largest languages of the world and possess a very important role as it shares its vocabulary with languages as Arabic, Persian, Hindi and several other languages of the Indo-Pak. The Automatic Speech Recognition task of Urdu has not been addressed significantly. This paper presents the statistical based classification technique to achieve the task of Automatic Speech Recognition of isolated words in Urdu. The proposed approach is based on calculation of 52 Mel Frequency Cepstral Coefficients for each isolated word. The classification has been achieved with Linear Discriminant Analysis. The successful or incorrect matches have been presented in the Confusion Matrix. As a prototype, the framework has been trained with audio samples of seven speakers including male/female, native/non-native and speakers with different ages. The test set comprises of audio data of three speaker. For each isolated, percentage error has been calculated. It was found that majority of the words are recognized with percentage error less than 33 %. Some words suffer 100 % error and were referred to be the bad words. This work may provide a baseline for further research on Urdu Automatic Speech Recognition.

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[*]Corresponding author. E-mail: engr.hazratali@yahoo.com

## 1. Introduction

User friendly and natural interaction between man and machine has always been a complementary part of technological development. Speech is the most effective medium of communication between human and same is envisaged to be applicable for human-machine interaction. Therefore, Automatic Speech Recognition (ASR) has significantly attracted researchers for the last five decades and has attained considerable success in noise-free environments. Successful ASR enables the computers to exhibit human-like behavior by understanding the voice input to them. Such hearing systems have been developed in various languages such as English, French, Japanese, Chinese and Arabic [1-5], and have widespread application ranging from data entry to security and surveillance. The research on ASR has enabled the communities with lower level of literacy to interact with machines, and similarly facilitated the interaction of blind and disabled people with the computers [6].

Despite the development of ASR systems in these languages, there has been no significant contribution to ASR of Urdu language, which is one of the largest languages of the world, with approximately 70 million across the globe[1]. Wiqas [7] has summarized the research work conducted on the ASR of the languages of the Indo-Pak, including the research work on Urdu ASR. A continuous speech ASR system for Urdu language has been presented in [8], however, no information about the corpus has been provided. The recognition rate for the continuous speech ASR is reported to be 54%. Furthermore, it lacks the information about the use of number of words/sentences and the training/test data. Azam [9] has proposed an Artificial Neural Networks (ANN) based Urdu speech recognition system however; this work is limited to digits recognition only. Moreover, the application of the system is limited to single speaker only. Ahad et al [10] has used a different class of ANN called multilayer perceptrons (MLP) however; they have achieved recognition of Urdu digits from 0 to 9 for mono-speaker database only. Hasnain et al [11] has made yet another effort to achieve the task of digits recognition for 0 to 9, based on the use of feed-forward neural network models developed in Matlab. A more recent contribution to isolated words recognition has been made by [12], developing a Hidden Markov Model (HMM) [13] based speaker-independent speech recognition sys-

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[1] [Online] http://www.ethnologue.com/language/urd

tem for Urdu. In this work the open source framework Sphinx-4 has been used for the classification. A "wordlist" grammar language model was adopted where each word was represented as a single phoneme instead of dividing into sub-units. An apparent limitation of this approach is that this may be applicable to shorter words but for longer words, the performance may degrade drastically. Huda [14] has used a relatively larger data set for the training purpose, however, the system developed is for continuous speech recognition task and thus different than the work reported in our paper. Besides, the recognition results are yet modest and are limited to one particular accent only.

Research on ASR can be targeted at small, medium or large vocabulary applications; it may be for digits only, isolated words only or continuous speech applications. The applications of isolated words recognition are well known including the automated banking applications, automatic data and PIN codes entry applications, e-health monitoring and voice dialing phone applications etc. In this paper the ASR task for medium vocabulary isolated words has been undertaken containing 100 isolated words of Urdu.

The three important components of an ASR system are the corpus i.e. the database of speech data, the features extraction and the classification. In Section 2 of this paper, the corpus used for this work has been discussed briefly. The features extraction approach and the major steps involved in the extraction of these features have been presented in Section 3. The classification of the different words based upon the features obtained for each word, has been discussed in Section 4. Finally, the results have been summarized in Section 5.

## 2. Corpus Selection

The use of a standard corpus forms the most important component of an ASR framework. A standard corpus should cover a range of acoustic variations and different aspects of a language. These include session and speaker variations. In this work, the corpus developed by Ali et al [15], has been used. This corpus contains 250 isolated words selected from the list of most frequently used words, developed by the Center for Language Engineering [16]. Audio files for one hundred isolated words have been selected from the corpus and used in the training and testing of the system. The one hundred words used contain the digits from 0 to 9, names of seasons, days of the week and the names of months. Few of the words

are also accompanied by their corresponding antonyms. The words are available in separate audio files with an average length of 500 milliseconds and stored in mono format with *.wav* extension. Based upon the attributes such as age, gender and origin, this corpus provides a balanced distribution. The files include the words uttered by both male and female speakers of different ages. Similarly, a variety of accents has been covered by including the audio recordings by both native and non-native speakers originating from different areas. For example, Pashto speakers who origin from different locations in Pakistan have variations in their pronunciations of the same Urdu words. Thus, data from these speakers provide a variety of samples for training and testing purpose. A sample representation of the attributes of the speakers has been shown in Table 1.

Table 1(a)

Sample of Representation of the Speech Data (as in [15]).

Note: G1 represents age group of 20-25 years, G2 represents age group of 26-30 years.

| Speaker Identification | Age Group | Gender | Native Non-Native |
|---|---|---|---|
| AAMNG1 | G1 | Male | Non-Native |
| ABMNG1 | G1 | Male | Non-Native |
| ACMNG2 | G2 | Male | Non-Native |
| AEFYG1 | G1 | Female | Native |
| AFFYG1 | G1 | Female | Native |
| AGMNG1 | G1 | Male | Non-Native |
| AHMNG1 | G1 | Male | Non-Native |

Table 1(b)

Sample of Representation of the Speech Data for Test set.

| Speaker Identification | Age Group | Gender | Native Non-Native |
|---|---|---|---|
| AIMYG2 | G2 | Male | Native |
| AJMNG2 | G2 | Male | Non-Native |
| AKFNG1 | G1 | Female | Non-Native |

## 3. Features Selection

Feature Extraction is one of the most important modules of an Automatic Speech Recognition System. For continuous speech recognition, the feature extraction is typically aimed to capture the distinguishing characteristics of the phonemes i.e. the smallest unit of sound. However, for isolated words recognition, each word is usually split into equal number of segments and features are extracted from each of the segments. In this work, each word is split into four segments and the Mel Frequency Cepstral Coefficients (MFCC) based features have been obtained for each segment. This also ensures that the feature vectors for both the training and test sets data have same dimensions.

### 3.1. Mel Frequency Cepstral Coefficients

The MFCC features are the most commonly used features for ASR applications. The MFCCs closely resembles the mechanism of human hearing. The Mel scale is based on the fact that the frequency response of the human's ear to the audio signal is not a linear function of frequency. This response can be best modeled on a Mel scale where the spacing between frequencies above *1000 Hz* is logarithmic [17]. The relation between the Mel scale frequencies and the Hertz frequencies can be represented by the following equation:

$$f_{mel} = 2595 \log(1 + \frac{f}{700 Hz}) \qquad (1)$$

The Mel Frequency Cepstrum is the power spectrum of a speech signal for short term and is based upon a linear cosine transform of a log power spectrum on the Mel scale. The Mel Frequency Cepstrum comprises of the MFC coefficients. Several methods for MFCC extraction have been proposed by [17-19]. The major steps in the extraction of MFCC are shown in Figure 1.
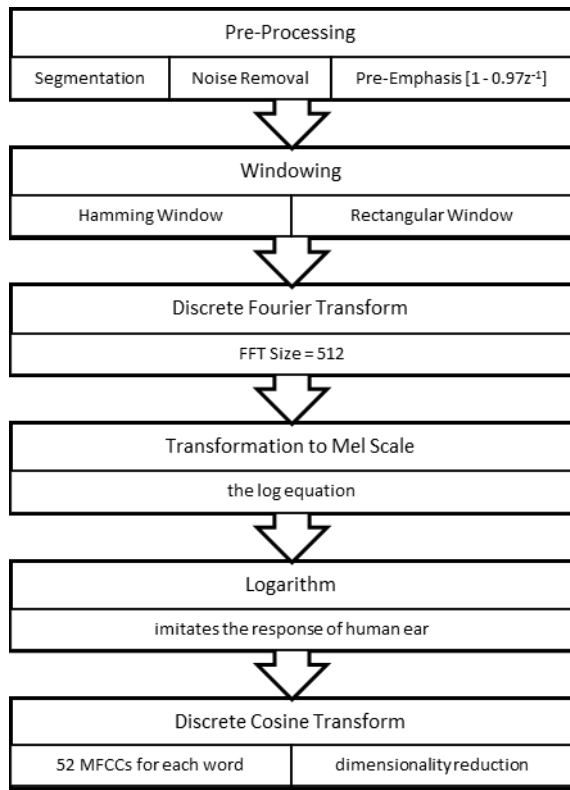
Figure 1 Extraction of Mel Frequency Cepstral Coefficients

In the pre-processing step, the segmentation of the words and noise removal have been achieved by using Adobe Audition Software. The sampling rate was set to *16000* Hz and the audio samples were saved as .wav files in mono format before being input to the algorithm. The Adobe Audition software has also been utilized for amplification or attenuation of the audio signal, as necessary, to obtain a uniform *db* level for all the samples. The pre-processing stage also includes the Pre-emphasis of the signal to increase the energy of the higher frequency contents. The pre-emphasis is achieved using filter of the form, *H(z)*:

$$H(z) = 1 - 0.97z^{-1} \qquad (2)$$

The pre-processing is followed by the windowing of the speech signal. A rectangular window as defined by equation for *w(n)* in Eq. (3) has been used. For speech processing applications, hamming window is more commonly used to avoid information loss, however for isolated words processing, rectangular window is equally beneficial.

$$w(n) = \begin{cases} 1 & 0 \leq n \leq M-1 \\ 0 & otherwise \end{cases} \qquad (3)$$

where $M = 128$. Fast Fourier Transform [20-21] is applied to the windowed frame of the signal. The size of FFT is $N = 512$. The spectrum, thus obtained, is transformed to the Mel scale, as defined by the equation for $f_{mel}$. To imitate the logarithmic response of human ear, the output of the mel scale filters bank is subjected to *base 10 Logarithmic* function. Finally, the application of Discrete Cosine Transform (DCT) [22] generates the MFCCs, i.e. *52* MFCCs for each isolated word.

## 4. Classification

The recognition on the basis of MFCCs requires a supervised classification technique for which Linear Discriminant Analysis is a strong candidate [23-24]. The classification includes; 1) Training of the system and 2) Testing of the system. *70* % percent of the data has been used for training the ASR system and the remaining *30* % data has been used for testing of the system.

### 4.1. Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a classification as well as dimensionality reduction technique. LDA can be class-dependent or class-independent, based upon maximization of the ratio of between class variance to within class variance or maximization of the ratio of overall variance to within class variance, respectively [23-26].

### 4.2. Training and Testing Data

To evaluate the performance of the ASR system, the MFCCs of a total of hundred words have been used for training and testing of the system. As a simple case, the training and testing has been done with the speech data of first ten speakers. The training set contains data from both native and non-native speakers of Urdu. Similarly, it also contains male as well as female speakers, as shown in Table 1.

### 4.3. Confusion Matrix

The number of correct matches from the testing data with the training data has been summarized in a Confusion Matrix. The confusion matrix is of size $N \times N$ for N number of words. It can be represented as shown by $M_c$.

$$M_c = \begin{matrix} m_{11} & m_{12} & m_{13}\cdots & m_{1N} \\ m_{21} & m_{22} & m_{23}\cdots & m_{2N} \\ m_{31} & m_{32} & m_{33}\cdots & m_{3N} \\ \cdot & \cdot & \cdot\;\cdots & \cdot \\ \cdot & \cdot & \cdot\;\cdots & \cdot \\ m_{N1} & m_{N2} & m_{N3}\cdots & m_{NN} \end{matrix} \qquad (4)$$

The number of correct matches for a word $i$ has been shown by the diagonal entries of the confusion matrix, i.e. $m_{ij}$ for $i=j$. Number of confusions of word $i$ with word $j$ has been shown by non-diagonal entries, i.e. $m_{ij}$ for $i \neq j$.

## 5. RESULTS

The error in the recognition of any isolated word is calculated from the confusion matrix. For an isolated word $i$, the diagonal entry $m_{ii}$, divided by the sum of all the entries in row $i$, gives the fraction of test data correctly matched. The sum of all the entries in a row is always equal to the number of test signals. This ratio can be defined mathematically as;

$$Correct\ Match, C \overset{\text{def}}{=} \frac{m_{ij}}{m_{i1} + m_{i2} + \ldots m_{iN}}, \qquad (5)$$

$$for\ i = j, j = 1, 2, 3 \ldots N$$

Thus, the error is measured by using the following equation;

$$\%\ error = (1 - C) \times 100 \qquad (6)$$

### 5.1. Results for first ten words

Figure *2* shows the confusion matrix graph for the first ten words. The x-axis and y-axis represent the indexes for the words i.e. *001* to *010*. The number of successful or incorrect matches is represented by the height of the bars. As already mentioned, the maximum possible height is *3* as the number of test signals used here is *3*. The percentage error and number of fraction of test signals correctly recognized has been summarized for the first ten words in Table 2. As shown in this table, the first word gives 66 % correct match, also depicted by the confusion matrix graph, by the first bar having a height of *2*. The test signals for word *004* has undergone a *0* % error and the bar for this word has a height of *3*. Similarly, the results for other words are obvious from the confusion matrix graph and the corresponding table.
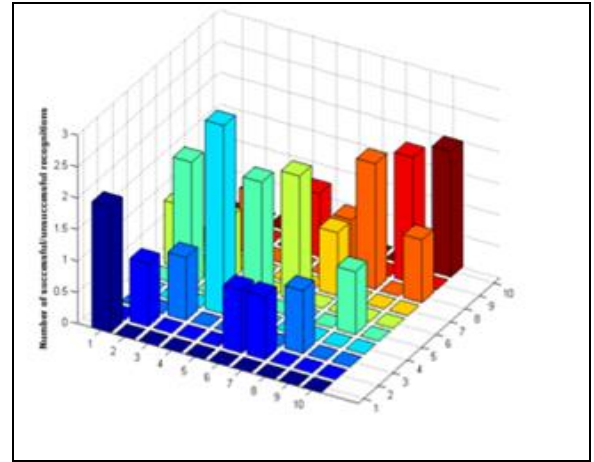


Figure 2 Confusion Matrix Graph for First Ten Words.
Note: The horizontal axes can be read as values from 1 through 10. The vertical axes shows the number of successful/unsuccessful recognition.

Table 2

Percentage Error for words 001 to 010

| S. No | Word Number | Value of C | % Error |
|---|---|---|---|
| 1 | 001 | 0.6667 | 33.33 % |
| 2 | 002 | 0.3333 | 66.67% |
| 3 | 003 | 0.3333 | 66.67% |
| 4 | 004 | 1.0 | 0 % |
| 5 | 005 | 0.6667 | 33.33 % |
| 6 | 006 | 0.6667 | 33.33 % |
| 7 | 007 | 0.3333 | 66.67% |
| 8 | 008 | 0.6667 | 33.33 % |
| 9 | 009 | 0.6667 | 33.33 % |
| 10 | 010 | 0.6667 | 33.33 % |

### 5.2. Results for words 031 to 040

As a second sample of the result, confusion matrix graph for word *031* to *040* has been shown in Figure 3. The corresponding fractional values for correct matches and percentage error have been summarized in Table 3. The results shown in Table 3 are very important and needs to be discussed. As shown in Table 3, it is obvious that there is a zero percent error for words *032* through word *034*. On the other hand, a complete mismatch exists for word *031*, resulting in a *100* % error.
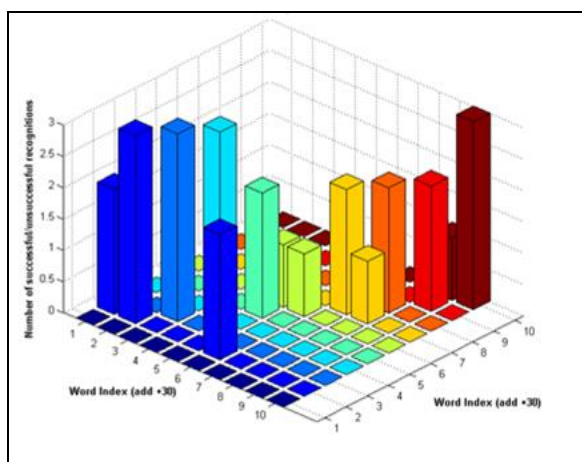
Figure 3 Confusion Matrix Graph for words 031 to 040.
Note: The horizontal axes can be read as values from 31 through 40. The vertical axes shows the number of successful/unsuccessful recognition.

Table 3

Percentage Error for words 031 to 040

| S. No | Word Number | Value of C | % Error |
|-------|-------------|------------|---------|
| 1 | 031 | 0 | 100% |
| 2 | 032 | 1.0 | 0% |
| 3 | 033 | 1.0 | 0% |
| 4 | 034 | 1.0 | 0 % |
| 5 | 035 | 0.6667 | 33.33 % |
| 6 | 036 | 0.3333 | 66.67% |
| 7 | 037 | 0.6667 | 33.33 % |
| 8 | 038 | 0.6667 | 33.33 % |
| 9 | 039 | 0.6667 | 33.33 % |
| 10 | 040 | 1.0 | 0% |

*5.3. Overall Percentage Error*

Figure 4 shows the proportion of the words with *100%, 66.67%, 33.33%* and *0%* error, respectively. The analysis shows that the percentage error is either zero or *33.33 %* for majority of the words. However, for few of the words, the value is larger approaching the maximum possible value i.e. *100%.* The overall error, $E$, can be measured as;

$$\frac{100\% \ of \ (10 \ \times 3) + 66.67\% \ of \ (13 \ \times 3) + 33.33\% \ of \ (32 \ \times 3) + 0\% \ of \ (45 \ \times 3)}{(100 \ \times 3)}$$

From this calculation, $E = 29.33\%$. These results have been previously reported in [27]. This is comparable with so many existing ASR systems as developed for other languages with audio-only based features. This value, however, can be reduced further by increasing the amount of training data.
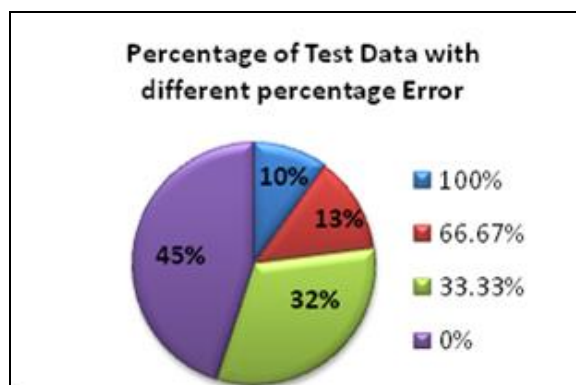


Figure 4 Percentage of Test Data having different percentage error

*5.4. Bad Words*

The words having a *100%* error rate are referred to be the Bad Words. The primary reason for such a poor performance of the ASR system for these words, is the poor quality of recording which was determined through manual analysis of the audio files. Besides this, as each word has been divided into four segment, there is a possibility that more than one segment are matching exactly with segments of other words and the ASR framework is confused.

## 6. FUTURE WORK

This ASR system has been developed for speech recognition of isolated words only. This is a medium vocabulary application limited to a hundred words and can be extended to several thousand words. However, in that case, an even larger data for the training of the system will be required. Thus, there is need to increase the corpus size. This paper can serve as a baseline for future research on ASR of Urdu language and can be extended to Continuous Speech Recognition of Urdu. This is an audio-only based feature extraction for ASR. The system can be evaluated by using audio-visual features which should result in the enhancement of the performance. Furthermore, a more promising development recently made in ASR is based on deep learning models. These deep learning models can be explored and investigated further for Urdu ASR.

## 7. ACKNOWLEDGEMENT

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