Phoneme Modeling for Speech Recognition in Kannada using Multivariate Bayesian Classifier

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ABSTRACT: *We build an automatic phoneme recognition system based on Bayesian Multivariate Modeling which is a static scheme. Phoneme models were built by using stochastic pattern recognition and acoustic phonetic schemes to recognise phonemes. Since our native language is Kannada, a rich South Indian Language, we have used 15 Kannada phonemes to train and test these models. As Mel – Frequency Cepstral Coefficients (MFCC) are well known acoustic features of speech, we have used the same in speech feature extraction. Finally performance analysis of models in terms of Phoneme Error Rate (PER) justifies the fact that though static modeling yields good results, improvization is necessary in order to use it in developing Automatic Speech Recognition systems.*

Keywords- *Bayesian Classification, Kannada, MFCC, Pattern Recognition; PER, Phoneme Modeling*

I. INTRODUCTION

The Automatic Speech Recognition (ASR) System of any language must be able to recognize spoken sentenses, words, syllables and phonemes of that particular language [1][2]. Here sentenses consist of many utterances of different words, words are made up of many syllables and each syllable is a meaningful utterance of phonemes. Hence it is very clear that phoneme is the smallest part of speech and it is absolutely necessary to build a phoneme recognition system which can be later used for syllable or word recognition which in term can be used for recognizing sentenses leading to a language model basically which works in controlled environments. Keeping this in mind, in order to build a language model for Kannada, this work is our first approach to build a phoneme recognition system.

For phoneme recognition there are several signal processing techniques that have been proposed [3][4][5], which evidently proves that we get the PER in the range 30% to 60%. The most successful results are for HMM which have used MFCC as speech features[3]. Since speech is a pseudo-random signal having quasi-periodic nature, we can also use stochastic analysis for its features' pattern recognition. Hence we have used Bayesian multivariate modeling which uses Bayesian decision rule, also known as Maximum a Posteriori (MAP).

To demonstrate these concepts, we have built a database of 15 Kannada phonemes. Each phoneme is recorded 500 times for training and 200 times for testing with a sampling rate of 8kHz. While recording the phonemes, we have recorded the same phoneme under different background noise but using the same microphone and software tool. Hence we have 7500 phonemes in the training database and 3000 phonemes in testing database. The training phase of phonemes include the mean and covariance of their MFCC to generate a prodability density function using multivariate modeling. Given this model in testing phase, we can estimate the likelihood of any testing sample belonging to all 15 classes and that class which gives higher likelihood is the recognized phoneme.

II. WORKING OF BAYESIAN CLASSIFIER

The basic idea here is to develop a model that aims at the production of the most probable phoneme Q* when we give an acoustic observation sequence S as an input. If Q_i is the i-th possible phoneme sequence and the conditional probability is evaluated over all the possible phonemes and ψ represents the parameters that are used to estimate the probability distribution, then the Bayesian or MAP decision rule can be given by[10]

$$Q^* = {}^{argmax}{}_{Q_i} P(Q_i \,/\, S, \Psi) \qquad (1)$$

Since each phoneme Q* has to be realized in infinite number of possible acoustic ways, it can be represented by its model M_i which yields

$$M^* = {}^{argmax}{}_{M_i} P(M_i \,/\, S, \Psi) \qquad (2)$$

Here M* is the model of the sequence of phoneme data which represents the linguistic message in the speech input S, $M_i$is the possible phoneme data sequence Q_i, $P(M_i\ /\ S, \Psi)$ is the posterior probability model of phoneme data sequence given the acoustic input S and the maximum is evaluated over all the possible models. Now we can apply Bayes' ruleas follows

$$P(M_i\ /\ S, \Psi)\ = \frac{P(S\ /\ M_i, \Psi) P(M_i / \Psi)}{P(S / \Psi)} \qquad (3)$$

III. METHODOLOGY

There are two phases in our work, training and testing.

3.1 Construction of Database

Though the ultimate goal is to develop a speaker independent system, to start with, we have decided to build a speaker dependent system. So all the samples were recorded for the same native Kannada speakerboth for training and testing.Details of the database are shown in Table1.

TABLE1: DETAILS OF PHONEME DATABASE

Unicode	Kannada Character	Number of Training samples	Number of Testing Samples
0C85	ಅ	500	200
0C87	ಇ	500	200
0C89	ಉ	500	200
0C8E	ಎ	500	200
0C92	ಒ	500	200
0C950CBD	ಕ್	500	200
0C950CBF	ಕಿ	500	200
0C950CC1	ಕು	500	200
0C950CC6	ಕೆ	500	200
0C950CCA	ಕೊ	500	200
0C970CBD	ಗ್	500	200
0C970CBF	ಗಿ	500	200
0C970CC1	ಗು	500	200
0C970CC6	ಗೆ	500	200
0C970CCA	ಗೊ	500	200

3.2 Pre-processing

Since the recordings of speech samples were made in normal conditions with different background noise, it becomes absolutely necessary to isolate speech from noise including end point detection of speech. We have used the method proposed in [6] for noise removal. Our database has different folders arranged by phoneme Unicode inside which, all corresponding phonemes are saved after pre-processing in .wav format.

3.3 Feature Extraction

Mel-Frequency Cepstral Coefficients were used as the acoustic phonetic features. The MFCC extraction includes Pre-emphasis, Framing, Windowing, computation of Fast Fourier Transform(FFT), Mel Frequency Warping, its logarithm and finally computation of Discrete Cosine Transform(DCT) as explained in [7]. The output of DCT is of 12 dimensions. For pictorial representation of phonemes, we have used first two dimensions of MFCC data. Such a plot for four phonemes is as shown in Fig.1 and it can be observed that phonemes have serious overlap in 2D vector space.

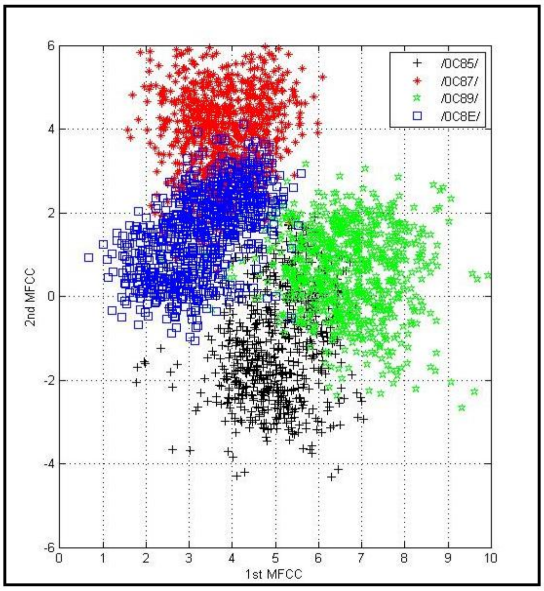

Fig.1: 2D scatter plot for four phonemes

3.4 Phoneme recognition using Bayesian classifier

To recognize an unknown phoneme from our testing database given its MFCC, we perform multivariate model for each class by calculating the mean and covariance matrices of corresponding phoneme sequences. The mean and standard deviation ellipse of the multivariate processes shown in Fig.1 is plotted in Fig.2.

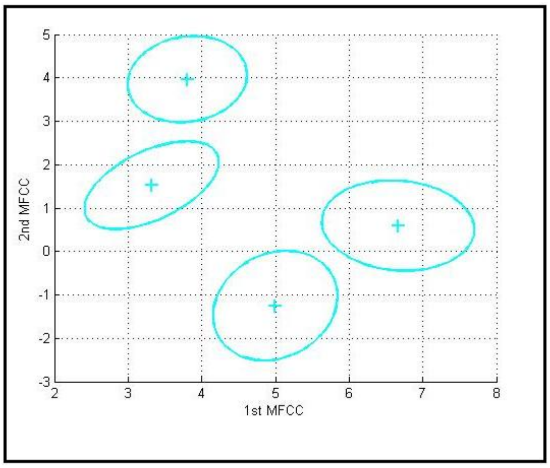

Fig.2: Mean and Standard deviation ellipse for the multivariate process in Fig.1.

Later we estimate the likelihood of the given test feature vector using the multivariate model for each class[8][9]. The likelihood will be higher for only one class than any other class and we declare that the test vector of the phoneme belongs to that class. Since the phonemes do not have the same prior probabilities, we must calculate the posterior probabilities by multiplying the likelihood of the sample with priors of each class and dividing by the marginal likelihood of the sample obtained by adding its likelihood for all classes.

IV. RESULTS AND DISCUSSIONS

The result analysis was done by using Phoneme Error Rate(PER), which can be defined as the ratio of the number of phonemes misclassified to the total number of phonemes used for testing. The PER calculation is as shown in Table2.

TABLE 2: PER CALCULATIONS

Unicode	PER for Likelihood (%)	PER for Posterior (%)
0C85	22.5	23.5
0C87	18.5	19.5
0C89	16.5	18.0
0C8E	20.0	22.0
0C92	17.0	18.5
0C950CBD	29.0	31.50
0C950CBF	33.5	37.0
0C950CC1	31.5	34.0
0C950CC6	28.5	30.0
0C950CCA	26.0	29.5
0C970CBD	28.5	30.5
0C970CBF	33.5	35.5
0C970CC1	34.0	37.5
0C970CC6	28.5	28.5
0C970CCA	26.5	28.5

The result analysis was done by using Phoneme Error Rate(PER), which can be defined as the ratio of the number of phonemes misclassified to the total number of phonemes used for testing. The PER calculation with Posterior probabilities is higher compared to the PER calculation with likelihood. It is because of the fact that likelihood calculation considers phoneme priors as equiprobable whereas the Posterior calculations do not. Above results are consistant with the results obtained from traditional methods[3].

V. CONCLUSION

In this work, we presented Bayesian Multivariate Modeling for phoneme recognition. This is a novel approach, different from traditional methods. Results reveal that, this method is useful for building phoneme recognition systems. This work can be further extended by including various acoustic phonetic features and by using Gaussian Mixture Modeling as a different approach in automatic phoneme recognition for Kannada language.

VI. ACKNOWLEDGEMENTS

We thank everyone who supported us with valuable suggestions during this work.

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