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Speech Emotion Recognition using Different Centred GMM

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Abstract—In human machine interaction automatic speech emotion recognition is so far challenging but important task which paid close attention in current research area. As the role of speech is an increase in human computer interface. Speech is attractive and effective medium due to its several features expressing attitude and emotions trough speech is possible. In this paper we have analysed emotion recognition performance on eight different speakers. IITKGP-SEHSC emotional speech corpora used for emotions recognition. The emotions used in this study are anger, fear, happy, neutral, sarcastic, and surprise. The classifications were carried out using Gaussian Mixture Model (GMM). Mel Frequency Cepstral Coefficients (MFCCs) features are used for identifying the emotions. It can be observed that, when we increase the number of centres then recognition performance increases.

Keywords— Emotion Recognition, Gaussian Mixture Model (GMM), Male-scale Frequency Cepstral Coefficient (MFCC), IITKGP-SEHSC (Indian Institute of Technology Kharagpur Simulated Hindi Emotional Speech Corpus).

I. INTRODUCTION

Human being express there feelings through emotions, and the way of expression may be through face, gesture and speech. Emotions are essential for conveying crucial information. Presence of emotion makes speech more natural. Human being use emotion extensively for expressing their intention through speech. It is observed that same message can be conveyed in different way by using appropriate emotion. Speech signal contain information like intended message, speaker identity, emotion state of speaker. The speech signal is the fastest and the most natural method of communication between humans. Hence speech can use for fast and efficient way of interaction between human and machine. However, this requires that the machine should have the sufficient intelligence to recognize human voices. We are still far from having a natural interaction between man and machine because the machine unable to understand the emotional state of the speaker. Therefore the identification of emotion present in the speech is necessary to understand the emotional state of human interpret the message properly. So there is needed to develop speech system that recognizes emotion efficiently.

An important issue in speech emotion recognition is the need to determine a set of the important emotions to be classified by an automatic emotion recognizer. There are different types of emotions present it's very difficult to classify all these emotions. Many researchers agree with the 'palette theory'., which states that any emotion can be decomposed into primary emotions similar to the way that any colour is a combination of some basic colours. Primary emotions are Anger, Disgust, Fear, Joy, Sadness, and Surprise. The task of speech emotion recognition is very challenging for the following reasons. First, it is not clear which speech features are most powerful in distinguishing between emotions. The acoustic variability introduced by the existence of different sentences, speakers, speaking styles, and speaking rates adds another obstacle because these properties directly affect most of the common extracted speech features such as pitch, and energy contours. Moreover, there may be more than one perceived emotion in the same utterance; each emotion corresponds to a different portion of the spoken utterance.[1][2][5]

II. WORKING PROCESS

In this work we are recognizing the emotion present in speech using Gaussian Mixture Model (GMM). GMM on the other hand consider a signal to contain different component that are independent of each other. These components represent the broad acoustic classes. IITKGP-SEHSC database is used for the recognition. We are using Mel Frequency Cepstral Coefficients (MFCCs) feature of speech sample for classifying speech sample into different emotions. Our developed emotion recognition system basically has two phases training phase and testing phase. In training phase using training data we create the model for each emotion. And in testing phase new speech sample is tested with all emotion models which we got in training phase and speech sample can classified in particular emotion according to probability values of each model.In this work we are focuses on the seven types of emotions Anger, Fear, Happy, Neutral, Sarcastic, and Surprise. GMM classification model used for recognition. [6][10]

The structure of the paper is as follows. Next section describes the emotional speech corpus used in this work. Section IV presents the feature extracted from speech for recognition. Section V provides the details of classification model used for recognition. Section VI describes the Architecture of Emotion recognition system. Section VII presents the experiment study, results got in experiment and observations on those results. And finally section VIII gives conclusion and at the end references.

III. MOTIONAL SPEECH CORPUS

For characterizing the emotions, either for synthesis or for recognition, a suitable emotional speech database is a necessary prerequisite. The design and collection of emotional speech corpora mainly depends on the research goals. For example a single speaker emotional speech corpus would be enough for the purpose of emotional speech synthesis, whereas recognizing emotions needs a database with multiple speakers and various styles of expressing the emotions.

The survey presented in this section critically analyzes the emotional speech databases based on the language, number of emotions and the method of collection. This approach has been verified using IITKGP-SEHSC database to carry out the emotion classification. This database is particularly designed and developed at the Indian Institute of Technology, Kharagpur, to support the study on speech emotion recognition. The proposed speech database is the first one developed for analysing the common emotions present in day-to-day conversations. This corpus is sufficiently large to analyse the emotions in view of speaker.IITKGP-SEHSC (Indian Institute of Technology Kharagpur Simulated Hindi Emotional Speech Corpus) is a Hindi speech database recorded using 10 (5 males and 5 females) professional artists from All India Radio (AIR) Varanasi, India. The eight emotions considered for recording this database are anger, disgust, fear, happy, neutral, sadness, sarcastic and surprise. Each of the artists has to speak 15 sentences in 8 given emotions in one session. The number of sessions recorded for preparing the database is 10. The total number of utterances in the database is 12000 (15textprompts*8emotions*10speakers*10sessions). Each emotion has 1500 utterances. The total duration of the database is around 7 hours.

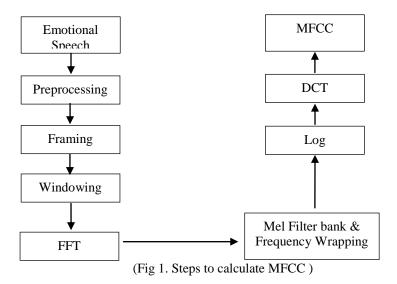
The proposed approach is using six emotion states such as Anger, Fear, Happy, Neutral, Sarcastic and Surprise of eight different speaker from this database. The data samples of speech are separated into two groups. One group for training and other group for testing. The first group is used for training the data samples and the second group is used for testing purpose. The GMM classifier is used to classify different emotions from these testing data samples. The data samples which were used for testing purpose is to be compared with the data samples which is already trained. This comparison gives the detection of emotion from these data samples .[1][3][4]

IV. MALE-FREQUENCY CEPSTRAL COEFFICIENT

Mel-frequency cepstral coefficients (MFCCs) are based on the known variation of the human ear's critical bandwidth with frequency filter spaced linearly at low frequencies and logarithmically at high frequencies have been used to capture the phonetically important characteristics of speech. This is expressed in the Mel frequency scale, which is linear frequency spacing below 1000 Hz and a logarithmic spacing above the 1000 Hz. This frequency warping can allow for better representation of sound.

Steps to calculate MFCCs are as follows:

- 1. Pre-emphasize the speech signal.
- 2. Signal divided into sequence of frames with frame size 20 ms and frame shift 10 ms. Apply hamming window for each frame.
- 3. Compute magnitude spectrum for each windowed frame by applying Fourier transform.
- 4. Mel spectrum is computed by passing the Fourier transform signal through Mel filter bank.
- 5. Discrete cosine transform is applied to the log Mel frequency coefficients (log Mel spectrum) to derive the desired MFCCs.[8][9]



V. GAUSSIAN MIXTURE MODEL

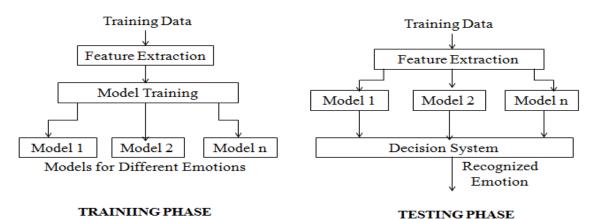
Gaussian mixture model is a probabilistic model for density clustering and estimation.GMMs are very efficient in modelling multi-modal distributions and their training and testing requirements are much less.GMMs cannot model temporal structure of the training data since all the training and testing equations are based on the assumption that all vectors are independent. Determining the optimum number of Gaussian components is an important but difficult problem.

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In this study GMMs are used as classification tools to develop emotion recognition models. They model the probability density function of observed variables using a multivariate Gaussian mixture density. Given a series of inputs, GMM refines the weights of each distribution through expectation-maximization algorithm. Mixture models are a type of density model which comprise a number of component functions, usually Gausses. These component functions are combined to provide a multimodal density. In this work for experimental purpose we used 3 different variations of GMM 8 centred, 16 centred and 32 centred GMM. For each test case we can create the 3 model for each emotion using GMM.[6][7][10]

VI. EMOTION RECOGNITION SYSTEM ARCHITECTURE

System architecture used for recognition is as shown in figure. Basically this architecture has two phases. (1)Training phase. (2)Testing phase. In training phase the models are trained for different emotion. In this first we classify the training data according to the class / emotion it belongs. During feature extraction features of speech utterance are extracted. The emotion recognition model (GMM) is trained using MFCC features vectors. After completion of training phase we have the model for each emotion. In testing phase passes testing feature vectors to all models which gives the probability value .Whichever model having highest probability value the speech utterance can classified according to that model. For example suppose for particular speech sample Anger emotion model gives highest probability value compare to other models hence we can conclude that emotion present in speech sample is Anger emotion.[7][10]



(Fig 2. Emotion recognition architecture for both training and testing phase)

VII. RESULTS AND OBSERVATION

In this emotion recognition, single speaker data for 6 emotions is used for both training and testing. Here, for each speaker, 1 to 8 sessions of each emotion were used to train the model (15sentences *8sessions*6emotions= 720 utterances) and for remaining 9 and 10 sessions (15sentences *2sessions*6emotions = 180 utterances) were used for testing purpose. Therefore, in this case, training and testing data were 80% and 20% respectively. Table-1 shows the emotion recognition performance of speaker 7 from IITKGP-SEHSC (Indian Institute of Technology KharaGPur-Simulated Emotion Hindi Speech Corpus), Hindi language database.

In this experiment, we have explored different number of components 8, 16 and 32. First, we build the GMM model in basic way. Table-2 shows the emotion recognition performance using 32 centered GMM model, for speaker 7 from Hindi language. Average recognition accuracy is observed to be 87.22 % for 32 centered GMM Model,81.67% for 16 centered GMM model and 81.67% for 8 centered GMM Model. Diagonal values of table show the correctly recognized samples. Table-2 shows the Confusion Matrix for data using 32 centered GMM model on Hindi database. Table-3 shows the Confusion Matrix for data using 16 centered GMM model. Table-2 shows the Confusion Matrix for data using 8 centered GMM model.

	8 Centered GMM		16 Centered GMM		32 Cer	32 Centered GMM	
y	81.67 %		81.67 % 87.22 %		7.22 %		
(Table 1: Average emotion recognition performance of speaker 7)							
Anger	Fear	На	арру	Netural	Sarcastic	Surprise	
76.67	0		10	6.67	6.67	0	
0	96.67	3	.33	0	0	0	
0	0	90	6.67	3.33	0	0	
10	0	6	.67	60	0	0	
0	0		0	0	100	0	
3.33	0	3	.33	0	0	93.33	
Average performance:87.22%							
	Anger 76.67 0 0 10 0	y 81.67 % (Table 1: Average emotion) Anger Fear 76.67 0 0 96.67 0 0 0 0 10 0 0 0 0 0	St.67 %	St.67 %	S1.67 % S1.67 % S1.67 %	y 81.67 % 8 (Table 1: Average emotion recognition performance of speaker 7) Anger Fear Happy Netural Sarcastic 76.67 0 10 6.67 6.67 0 96.67 3.33 0 0 0 0 96.67 3.33 0 10 0 6.67 60 0 0 0 0 100 3.33 0 100 0 3.33 0 0 0	

(Table 2: Confusion Matrix for Text Dependent data using 32 centered GMM)							
	Anger	Fear	Нарру	Netural	Sarcastic	Surprise	
Anger	73.33	0	13.33	13.33	0	0	

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Fear	0	86.67	3.33	6.67	0	3.33
Нарру	0	0	93.33	3.33	3.33	0
Natural	43.33	0	3.33	53.33	0	0
Sarcastic	0	0	0	0	100	0
Surprise	10	0	3.33	3.33	0	83.33
	Average performance :81.67%					

(Table 3: Confusion Matrix for Text Dependent data using 16 centered GMM)

	Anger	Fear	Нарру	Netural	Sarcastic	Surprise
Anger	56.67	0	13.33	20	10	0
Fear	0	93.33	0	6.67	0	0
Нарру	0	0	100	0	0	0
Natural	43.33	0	3.33	53.33	0	0
Sarcastic	0	0	0	0	96.67	3.33
Surprise	3.33	0	0	6.67	0	90
	Average performance:81.67%					

(Table 4: Confusion Matrix for Text Dependent data using 8 centered GMM)

Table-5 shows the average emotion recognition performance using 8 centered, 16 centered and 32 centered GMM model. Average performance was calculated by taking the average of eight different speaker's results obtained in different test cases of emotion recognition.

	8 Centered GMM	16 Centered GMM	32 Centered GMM
Accuracy	66.81 %	71.46 %	75.01 %

(Table 5: Average emotion recognition performance of all the speaker)

VIII. CONCLUSIONS

Although it is difficult to get a accurate result, but we can show the variations that occur when emotion changes.MFCC features of speech sample used for the recognition. Emotional speech database of Hindi language were used for experiment. Performance of the emotion recognition is depending on the speaker, emotion and language used for recognition. We use GMM to classify six different emotions as: Anger, Fear, Happy, Neutral, Sarcastic and Surprise of eight different speaker from database. Three type of GMM model used namely 8 centred GMM, 16 centred GMM, and 32 centred GMM. It is observed that, the average recognition accuracy is observed to be 75.01% for 32 centered GMM, 71.46% for 16 centered GMM and 66.81% for 8 centered GMM, when the training and testing data were 80% and 20% respectively.GMM model when we increase the number of centres then recognition performance increases.

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