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Speech Emotion Recognition by using SVM-Classifier

Vaishali M. Chavan, V.V. Gohokar

Abstract*— Automatic emotion recognition in speech is a current research area with a wide range of applications in human-machine interactions. This paper uses the support vector machine (SVM), to classify five emotional states: anger, happiness, sadness, surprise and a neutral state. The classification performance of the selected feature subset was done with that of the Mel frequency cepstrum coefficients (MFCC), Periodicity Histogram and Fluctuation Pattern. Within the method based on SVM, a new method by using Multi-class SVM is used as a classifier. Experiments were conducted on the Danish Emotion Speech (DES) Database. The recognition rates by using SVM classifier were 68 %, 60 %, 55.40 % and 60 % for Linear, Polynomial, RBF, and Sigmoid Kernel Function respectively. The recognition rates by Multiclass SVM using Linear, Polynomial, RBF and Sigmoid kernel function for Danish database for Periodicity Histogram are 64.77 %, 78.41 %, 79.55 % and 78.41% respectively.

Keywords*— Emotion recognition, Mel frequency cepstrum coefficients (MFCC), Support Vector Machine.

I. INTRODUCTION

Speech emotion recognition is an important part in emotion recognition. Accurate detection of emotion from speech has clear benefits for the design of more natural human- machine speech interfaces or for the extraction of useful information from large quantities of speech data. It is also becoming more and more important in computer application fields as health care, children education, etc. In speech-based communications, emotion plays an important role. Sometimes, playing an even bigger role than the logical information included in the speech. Research has long been done on emotion in the fields of psychology and physiology. More recently it is the subject of attention by engineers. Its most important application is in intelligent human-machine interaction. In today's human-machine interaction systems, machines can recognize "what is said" and "who said it" using speech recognition and speaker identification techniques. If it is equipped with emotion recognition techniques, machines can also know "how it is said" to react more appropriately, and make the interaction more natural. Other applications of automatic emotion recognition include psychiatric diagnosis, intelligent toys, and lie detection. [1] Today there are many different algorithms which were used for various signal processing applications. In this paper the emotions from the speech signal are recognized by considering the features of the speech signal by using SVM classifier. While classifying different emotions, several features like Periodicity Histogram, Fluctuation Pattern and MFCC (Mel Frequency Cepstral Coefficient) is used. [17] The data samples of speech are separated into two groups. The first group is used for training the data samples and the second group is used for testing purpose. The SVM 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. In this project, Danish Emotional Database is used which gives the satisfactory detection of emotions. [26, 30]

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II. SPEECH EMOTION RECOGNITION SYSTEM

The structure of the speech emotion recognition system studied in this paper is depicted in Figure 1. Like the typical pattern recognition system, it contains five main modules: emotional speech input, feature extraction, feature labelling, SVM training and classification and recognized emotion output. A feature selection module is part of the SVM classifier.

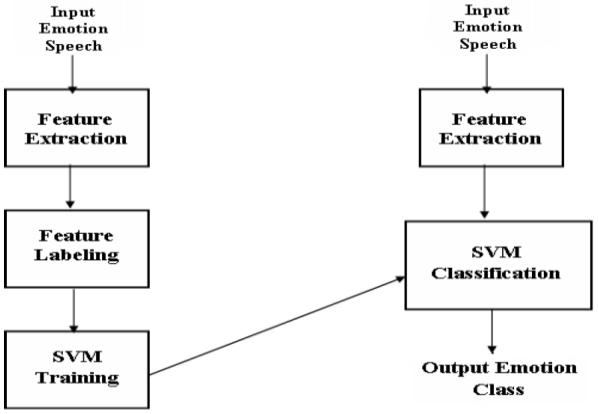

Fig.1: Structure of Speech Emotion Recognition System

A. Feature Extraction

In feature extraction process three features are extracted MFCC, fluctuation pattern and periodicity histogram. The continuous time signal (speech) is sampled at sampling frequency. At the first stage in MFCC feature extraction is to boost the amount of energy in the high frequencies. This pre-emphasis is done by using a filter. Then framing or segmenting of the speech samples are obtained from analog to digital conversion (ADC), into the small frames with the time length within the range of 20-40 msec.

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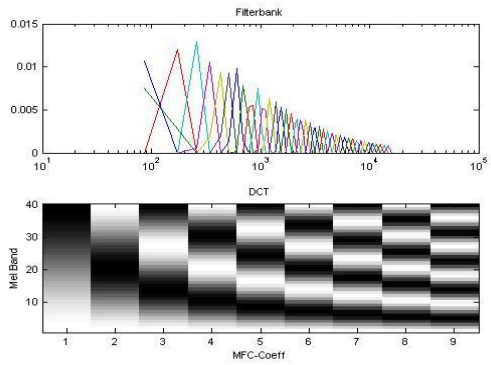
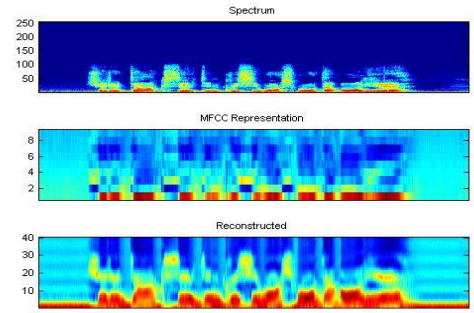
Framing enables the non-stationary speech signal to be segmented into quasi-stationary frames, and enables Fourier Transformation of the speech signal. It is because, speech signal is known to exhibit quasi-stationary behaviour within the short time period of 20-40 msec. Windowing is the another step which is meant to window each individual frame, in order to minimize the signal discontinuities at the beginning and at the end of each frame. Then Fast Fourier Transform (FFT) [11] algorithm is used for evaluating the frequency spectrum of speech. FFT converts each frame of N samples from the time domain into the frequency domain. The mel filter bank consists of overlapping triangular filters with the cut-off frequencies determined by the centre frequencies of the two adjacent filters. The filters have linearly spaced centre frequencies and fixed bandwidth on the mel scale. The logarithm has the effect of changing multiplication into addition. Therefore, this step simply converts the multiplication of the magnitude in the Fourier transform into addition. Take Discrete Cosine Transform to orthogonalise the filter energy vectors. Because of this orthogonalisation step, the information of the filter energy vector is compacted into the first number of components and shortens the vector to number of components.

First of all, take one input audio sample. Then convert its frequency scale to bark scale (as it is more close to human frequency interpretation). As a spreading function we can use ‘terhardt’ or ‘modified terhardt’. Using this bark scale representation, the frames of the input is converted into 'sone' units. (So it will be easy to differentiate between the actual speech and noise). Using this sone values, we can plot a histogram (it can be work as a feature, but we don't use this as it does not differentiate the emotions properly).

Again using this sone values and its distribution we can design a fluctuation pattern (it can work as a feature which gives good results). Again using this sone values and its distribution we can design a periodicity histogram (it can also work as a feature).



(a)



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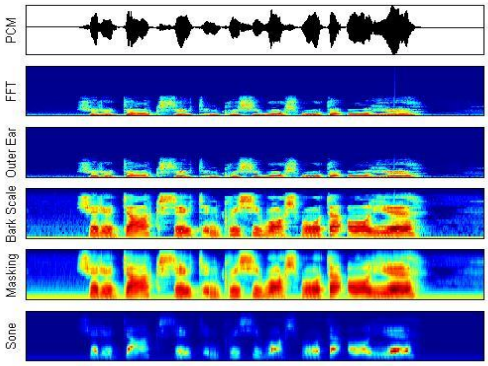

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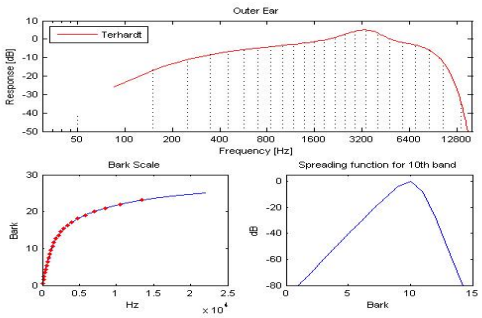

(d)

Fig. 2: Waveforms of extracted features (a: Filtered signal; b: MFCC & Spectrum of speech signal, c: Converted Sone signal, & d: Frequency Response of signal)

B. SVM training and classification

Now once we have a set of features available with us we can take use of the classifiers to distinguish between the different emotional states. Now we take use of the multiclass SVM classifier for classification purpose. First we train the classifier with some inputs of different emotional states. After training the classifier, we can use it for recognizing the new given input. The process of SVM training contains labelling of extracted features and training SVM. In the training process, every extracted feature has to assign an associated class label. The SVM is trained according to this labelled feature. The SVM kernel functions are used in the training process of SVM. The result can be improved if we use all the above features properly.

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III. EXPERIMENTAL STUDY

A. Emotional Speech Database

The emotional speech database used in this study is the Danish Emotional Speech (DES) Database which includes expressions by four actors familiar with radio theatre, two male and two female. The speech is expressed in five emotional states: anger, happiness, neutral, sadness and surprise. In this study, the speech signal was re-sampled to 16 kHz, and the silence segments at the beginning and the end of the speech were cut out artificially. Total 88 samples were used for the conduction of emotion recognition process.

B. Experimental Results

The MFCC, Fluctuation Pattern and Periodicity Histogram features are extracted. Every feature value must have corresponding label of belonging class. As SVM is binary classifier the class labels are $\{+1, -1\}$. In this work SVM using linear kernel function is implemented for non separable data. The test results are calculated by using implemented SVM as well as Multiclass SVM. In Multiclass SVM [28] results are taken by using Fluctuation Pattern, Periodicity Histogram and MFCC feature for all the Kernel Functions. The overall percentage accuracy is obtained by using Multiclass SVM. Whereas for SVM classifier the particular emotion from the selected test file is to be obtained.

Table 1: Confusion Matrix for SVM Classifier (Linear Kernel Function)

Emotion	*Anger*	*Fear*	*Happy*	*Normal*	*Sad*
Anger	*61.53*	*6.67*	*17.78*	*2.22*	*2.22*
Fear	*15.38*	*66.67*	*20*	*6.67*	*8.89*
Happy	*15.38*	*15.56*	*57.78*	*1.11*	*2.22*
Normal	*2.56*	*4.44*	*2.22*	*74.44*	*8.89*
Sad	*5.12*	*6.67*	*2.22*	*15.56*	*77.78*

Table 1 shows confusion matrix of implemented SVM for Danish emotion speech utterance using one-to-one multiclass method. The Sad emotion gives maximum 77.78% and Happy gives minimum 57.78% recognition rate. The overall recognition accuracy for Danish emotion is 68% by using Linear Kernel Function.

Table 2: Confusion Matrix for SVM Classifier (Polynomial Kernel Function)

Emotion	Anger	Fear	Happy	Normal	Sad
Anger	51.28	8.89	15.56	7.78	2.22
Fear	30.77	75.56	44.44	7.78	11.11
Happy	10.26	8.89	35.56	3.33	2.22
Normal	2.56	2.22	2.22	63.33	8.89
Sad	5.13	4.44	2.22	17.78	75.56

Table 2 shows confusion matrix of implemented SVM for Danish emotion speech utterance using one-to-one multiclass method. The Sad and Fear emotion gives maximum 75.56% and Happy gives minimum 35.56% recognition rate. The overall recognition accuracy for Danish emotion is 60% by using Polynomial Kernel Function.

Table 3: Confusion Matrix for SVM Classifier (RBF Kernel Function)

Emotion	Anger	Fear	Happy	Normal	Sad
Anger	46.15	4.44	13.33	0	0
Fear	2.56	48.89	0	0	0
Happy	10.26	2.22	42.22	0	0
Normal	0	0	0	42.22	2.22
Sad	41.02	44.44	44.44	57.78	97.78

Table 3 shows confusion matrix of implemented SVM for Danish emotion speech utterance using one-to-one multiclass method. The Sad emotion gives maximum 97.78% and Happy and Normal gives minimum 42.22% recognition rate. The overall recognition accuracy for Danish emotion is 55.40% by using RBF Kernel Function.

Emotion	Anger	Fear	Happy	Normal	Sad
Anger	97.45	71.11	80.00	33.33	66.67
Fear	2.56	24.44	0	0	0
Happy	10.26	4.44	20.00	0	0
Normal	0	0	0	30.00	2.22
Sad	0	0	0	3.33	31.11

Table 4: Confusion Matrix for SVM Classifier (Sigmoid Kernel Function)

Table 4 shows confusion matrix of implemented SVM for Danish emotion speech utterance using one-to-one multiclass method. The Angry emotion gives maximum 97.45% and Happy gives minimum 20% recognition rate. The overall recognition accuracy for Danish emotion is 60% by using Sigmoid Kernel Function.

Table 5: For Multiple Class SVM Test Method

Sr. No.	Kernel Function	Fluctuation Pattern	Periodicity Histogram	MFCC
1.	Linear	62.5%	64.77%	54.55%
2.	Polynomial	34.09%	78.41%	61.36%
3.	Radial Basis Function	39.77%	79.55%	39.77%
4.	Sigmoid	14.77%	78.41%	14.77%

Figure 6: Graph for Multiple Class SVM Test Method

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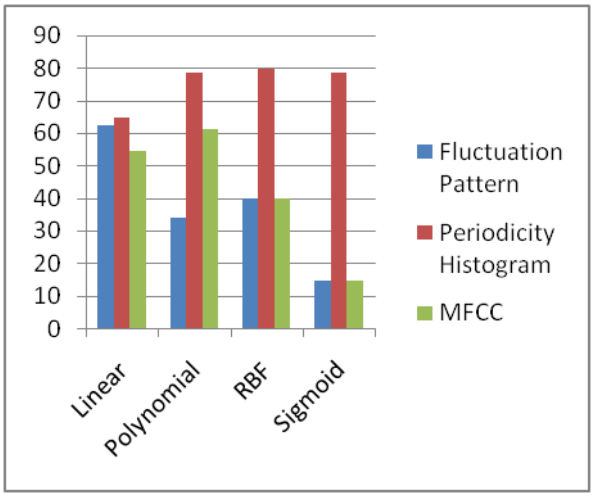
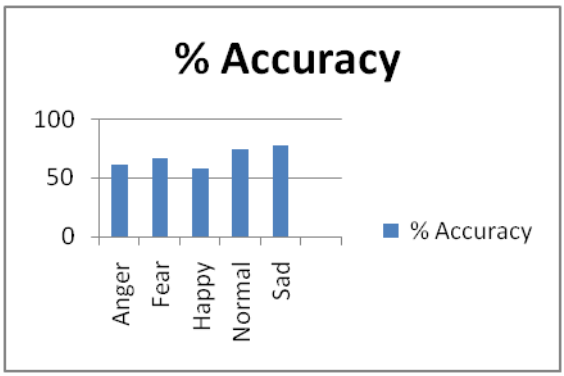


Figure 5 & 6 shows the table & graph of Multiclass SVM Test Method. The graph shows Kernel functions on X-axis and Percentage accuracy on Y- axis. It gives the Percentage accuracy on the basis of four kernel functions by using three features i.e. Fluctuation Pattern, Periodicity Histogram and MFCC.

Figure 7: Graph for Linear Kernel function



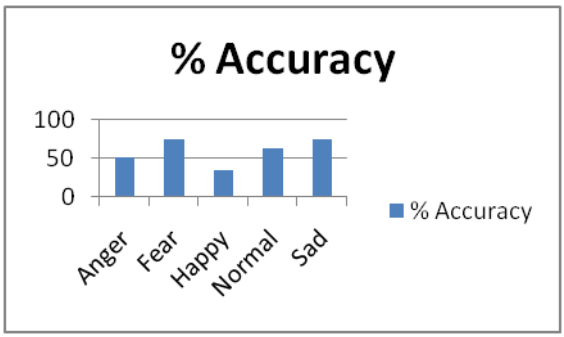


Figure 8: Graph for Polynomial Kernel function

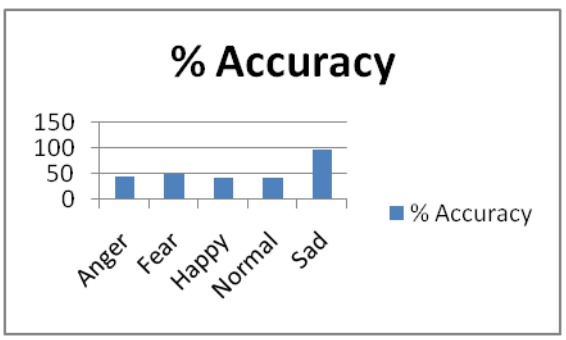


Figure 9: Graph for RBF Kernel function

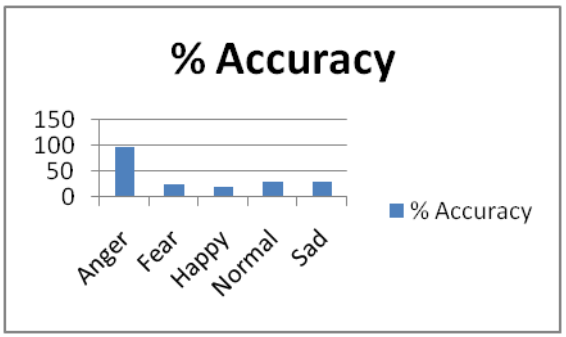


Figure 10: Graph for Sigmoid Kernel function

IV. CONCLUSION

From experimentation and results, it is proved that system is speaker and text independent. It is also observed that results from SVM and Multiclass SVM are much better. The recognition rates by implemented SVM classifier are 68 %, 60 %, 55.40 % and 60 % for Linear, Polynomial, RBF, and Sigmoid Kernel Function respectively. The recognition rates by Multiclass SVM using Linear, Polynomial, RBF and Sigmoid kernel function for Danish database for Periodicity Histogram are 64.77 %, 78.41 %, 79.55 % and 78.41% respectively. From results it is observed that maximum confusion occurs while recognizing happy and anger emotions for Danish emotion utterances. Total time required is 15 seconds for training data set of 25 values and 1 second for testing each value for SVM implementation, whereas total time required for testing 88 values by using Multiclass SVM is 43 sec. In future, this time period required for the testing purpose can be reduced and hence the efficiency can be improved.

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