A Support Vector Machine Classifier of Emotion from Voice and Facial Expression Data

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Abstract- **The paper provides a novel approach to emotion recognition from facial expression and voice of subjects. The subjects are asked to manifest their emotional exposure in both facial expression and voice, while uttering a given sentence. Facial features including mouth-opening, eye-opening, eyebrow-constriction, and voice features including, first three formants: F_1, F_2, and F_3, and respective powers at those formants, and pitch are extracted for 7 different emotional expressions of each subject. A linear Support Vector Machine classifier is used to classify the extracted feature vectors into different emotion classes. Sensitivity of the classifier to Gaussian noise is studied, and experimental results confirm that the recognition accuracy of emotion up to a level of 95% is maintained, even when the mean and standard deviation of noise are as high as 5% and 20% respectively over the individual features. A further analysis to identify the importance of individual features reveals that mouth-opening and eye-opening are primary features, in absence of which classification accuracy falls off by a large margin of more than 22%.**

Keywords- **Linear Support Vector Machine, Facial expression, Speech, Linear Classification.**

I. INTRODUCTION

Emotion plays a vital role in non-verbal communication, and thus has immemnse applications in the next generation human-machine interactive system [28], [34]. If computers can recognize our emotion from our facial expression and voice, the scope of interactions between humans and machines can be improved significantly [3]. In [22], Picard proposed a new discipline of computing, called *affective computing*, that monitors the affective states of people, and provides them necessary support in critical/accident-prone environment. One interesting work in this regard is due to Li and Ji [20], where the authors proposed a probabilistic framework to dynamically model and recognize the users' affective states for timely and efficient services to those people. Picard et al. [24] also stressed the importance of emotions on our respective affective psychological states. Among others, the works of Scheirer et al. [28], Conati [6], Kramer et al. [18], and Rani et al. [25], [26] also deserve special applause in the fields of affective computing.

Besides affective computing, the study of emotions and emotional intelligence has important applications in psychological counseling, detection of anti-socials, digital movie making with artificial agents, and many others. Details of this are available in [7].

Among interesting works on emotion recognition, the work by Ekman and Friesen [7] needs special mention. They forwarded a scheme for recognition of facial expression from different regions of face, e.g. cheek, chin, and wrinkles. It reports a direct correlation of facial expression with the eyes, the eye-brows, and the mouth. Kobayashi and Hara [14], [15], [16] came forward with a neural net based [13], [31], [32], [33] solution to facial expression based emotion recognition problem. Researchers are also keen to employ Fourier descriptor [32], template matching [2], neural network models [8], [27], [32], and fuzzy integral [12] techniques for detection of emotion.

Cohen et al. considered variations in facial expressions, displayed in a live video to recognize emotions [4], [5]. She came up with a new architecture of hidden Markov models. It automatically segments and recognizes facial expressions, thus helping in emotion recognition. Gao et al. [9] attempted to interpret facial expression from a single facial image using line-based caricatures. Lanitis *et al.* [19] proposed a novel technique for automatic recognition and coding of face images using flexible models.

Sinéad McGilloway [21] proposed a method for recognition of emotion from voice of the subjects with the help of discriminant analysis that uses linear combinations of variables to separate samples that belong to different categories using neural net classifiers. Valery A. Petrushin [23] proposed an approach of emotion recognition from voice data. He used a part of a corpus for extracting the features and for training computer-based emotion recognizers. He then took some of the features and fed them as inputs to different types of recognizers, ultimately concluding that the neural network based recognizers work best.

In this paper, we intend to classify the emotions from the data obtained on different parameters of facial expression and voice. We also check the level of noise-acceptance of these data. Further, an analysis on the importance of individual facial and voice features on emotion classification is also studied using Support Vector Machines.

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This paper includes six sections. In section II and III, experimental set-ups and the processes for extraction of features have been discussed. Section IV introduces a brief theory of Support Vector Machine and its application in recognition of emotion on the basis of facial expression and voice and also the corresponding results are shown. The conclusions are drawn in section V.

II. EXPERIMENTAL SET-UP

A small research team at Artificial Intelligence Laboratory of Jadavpur University started working on multi-modal emotion recognition from voice and facial expression of the subjects [10]. The experiment was conducted with 7 subjects, where each subject was asked to utter the sentence "what are you doing here?" with emotions in both his/her voice and facial expression. The voice and facial expressions were recorded for subsequent feature extraction and classification of emotions. The features extracted from the voice samples include: i) pitch, ii) first three formants, and iii) powers at the three formants. During the period of his/her utterance, 6 snapshots were taken to determine the significant changes in the facial expression conveying emotion. For each facial expression, the features needed include mouth-opening, eye-opening, and the length of eyebrow-constriction. Thus, for 6 frames, altogether $3\times6=18$ features were obtained. Further, during the same period of time, 7 voice features, as stated above, were obtained, thus yielding a composite feature vector of (1×25) dimension. Now, the experiment was undertaken for 7 different emotions: anger, disgust, fear, surprise, happiness, sadness, and neutral, over 7 different individuals. Consequently, $7\times7=49$ distinct feature vectors of 7 emotions for 7 different individuals were obtained. Fig. 1 and 2 are sample facial expression and voice waveform for 7 distinct emotions of a subject.

III. FEATURE EXTRACTION

A. Extraction of facial expression data

Extraction of feature plays an important role in recognizing a particular emotion. In order to extract features for facial expression, we restricted our attention to mouth region, eye region and eyebrow region in order to obtain the required data for mouth-opening, eye-opening and eyebrow constriction [17]. Next, we fuzzified these features in three fuzzy sets as HIGH, MODERATE, LOW in the following way:

$$\mu_{HIGH}(x) = 1- \exp(- a\, x),\ a>0, \quad (1.a)$$
$$\mu_{LOW}(x) = \exp(- b\, x),\ b>0, \quad (1.b)$$
$$\mu_{MODERATE}(x) = \exp[- (x - x_{mean})^2 / 2\sigma^2] \quad (1.c)$$

where $x \in \{mo, eo, ebc\}$ and a, b, c, x_{mean} and σ were fixed experimentally. These fuzzified features were used to represent facial expressions in the subsequent part of this work.

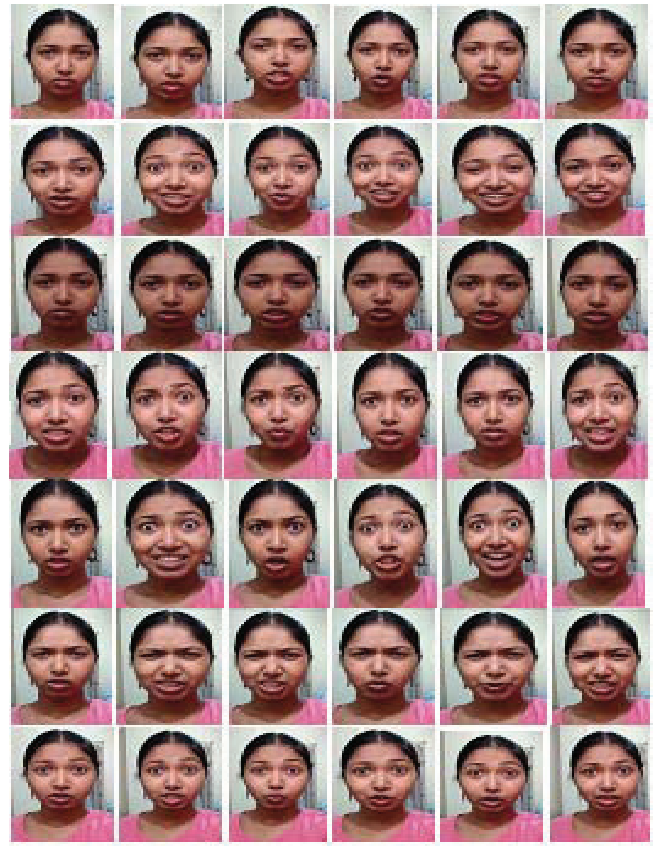

Fig. 1: Facial Expression pictures of emotions (row-wise) Relax, Happy, Sad, Fear, Anger, Disgust and Surprise respectively.

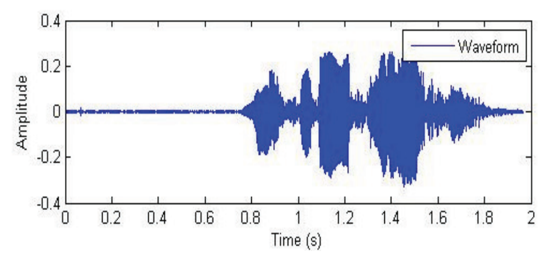

Fig 2.a: Voice waveform for emotion Relax

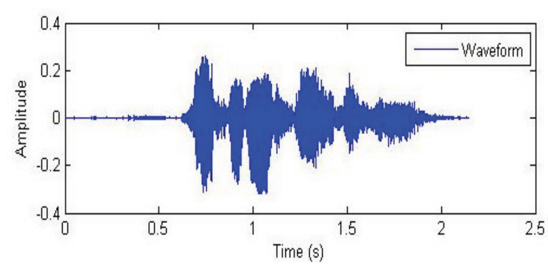

Fig 2.b: Voice waveform for emotion Happy

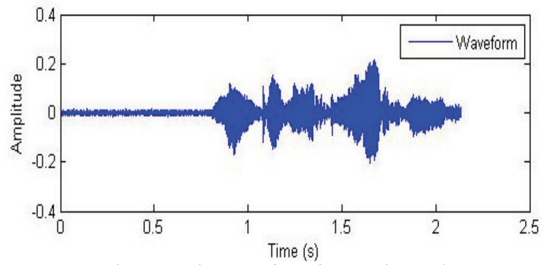

Fig 2.c: Voice waveform for emotion Sad

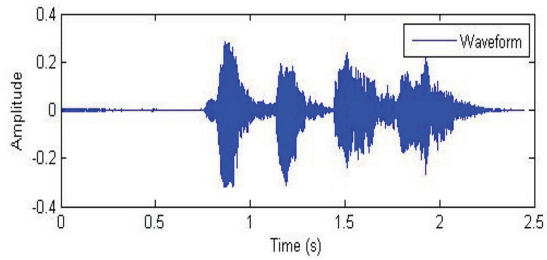

Fig 2.d: Voice waveform for emotion Fear

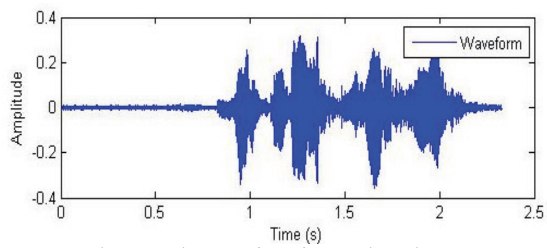

Fig 2.e: Voice waveform for emotion Disgust

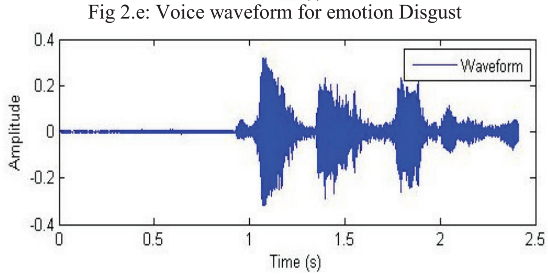

Fig 2.f: Voice waveform for emotion Anger

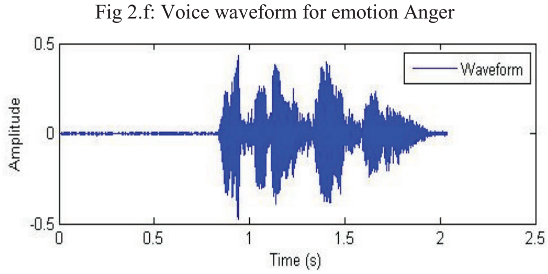

Fig 2.g: Voice waveform for emotion Surprise

B. Extraction of Voice data

To obtain data for voice, the audio-visual clip was first read by using the MATLAB command "wavread" that reads WAVE (.wav) file. Then subsequent calculations were done in order to obtain the pitch, formants 1, 2 and 3 along with the powers at respective formants. Pitch was calculated using the MATLAB code "xcorr" that gave the auto-correlation between the sequences, one obtained using command "wavread" and the other, with the minimum speech at 50 Hz with the sequence being normalized so that the autocorrelations at zero lag are identically 1.0. [10]

IV. Support Vector Machine And Its Application

A. Support Vector Machine (SVM)

A Support Vector Machine (SVM) has been successfully used for both linear and non-linear classification. However, as non-linear operation yields results with lesser accuracy, in this paper, we focus on the linear operation only. To understand the basic operation of SVM, let us consider Fig. 3 where X is the input vector and y is the desired scalar output that can take +1 or -1 values, indicating linear separation of the pattern vector X.

The function f (X, W, b) can be represented as follows:

$$f(X, W, b) = \text{sign}(WX + b) \tag{2}$$

where $W=[w_1 \ w_2 \ldots\ldots w_n]$ is the weight vector
$X=[x_1 \ x_2 \ldots\ldots\ldots x_n]^T$ represents the input vector
$b=[b_1 \ b_2 \ldots\ldots\ldots\ldots b_n]$ represents the bias vector

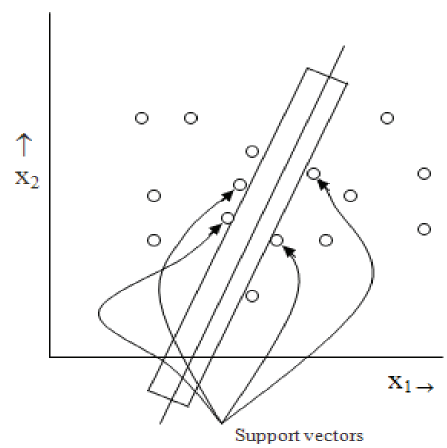

Fig 3: Defining support vector for a linear SVM system.

The function f classifies the input vector X into two classes denoted by +1 or -1. The straight line that segregates the two pattern classes is usually called a hyperplane. Further, the data points that are situated at the margins of the two boundaries of the linear classifier are called support vectors. Fig. 3 describes a support vector for a linear SVM.

Let us now select two points X^+ and X^- as two support vectors. Thus by definition

$$WX^+ + b = +1 \tag{3.a}$$

and

$$WX^- + b = -1 \tag{3.b}$$

which jointly yields

$$W(X^+ - X^-) = 2. \tag{3.c}$$

Now, the separation between the two support vectors lying in the class +1 and class -1, called *marginal width* is given by

$$M = \{(WX^{+} + b) - (WX^{-} + b)\}/\|W\| = 2/\|W\| \quad (4)$$

The main objective in a linear Support Vector Machine is to maximize M, i.e., to minimize $\|W\|$, which is same as minimizing $\frac{1}{2}W^TW$. Thus, the linear SVM can be mathematically described by:

Minimize $\varnothing(W) = \frac{1}{2} W^TW$ *subject to* $y_i (WX_i + b) \geq 1$ for all i, where y_i is either 1 or -1 depending on the class which X_i belongs to. (5)

Here, the objective is to solve W and b that satisfies the above equation. In this paper, we are not presenting the solution to the optimization problem, referred to above. This is available in standard text in neural network [11]. One important aspect of SVM is the kernel function selection. For linear SVM, the kernel K for two data points X_i and X_j is defined by

$$K(X_i, X_j) = X_i^T X_j \quad (6)$$

B. Application of SVM

After the feature extraction is complete, we constructed training instances using both facial and voice features, and used **svmtrain** code of MATLAB to train the support vector machine with the training instances. The classification of features into one of 7 classes is then studied with MATLAB code **svmclassify**. The trained instances were correctly classified with 100 % accuracy.

Next we studied the effect of Gaussian noise on emotion classification. We added Gaussian noise of specific mean and standard deviation over the mean and variance of individual components of the feature vector, and the classification was performed using MATLAB code **svmclassify**. The percentage classification noisy feature vector into emotion classes is then studied with varied ratio of noise mean to data mean and noise variance to data variance as in Table 1.

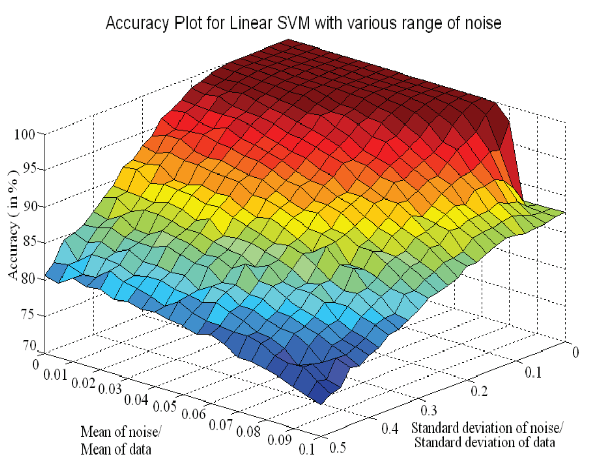

FIG. 4: CLASSIFICATION ACCURACY OF NOISY FEATURE VECTORS OVER EMOTION CLASSES

TABLE I: ACCURACY OF LINEAR CLASSIFICATION OF FACIAL EXPRESSION AND SPEECH DATA

		Mean of Noise/ Mean of Data					
		0	0.02	0.04	0.06	0.08	0.1
Standard deviation of noise/ Standard deviation of data	0	100.0	100.0	100.0	100.0	97.95	87.75
	0.02	100.0	100.0	100.0	100.0	94.57	87.73
	0.04	100.0	100.0	100.0	99.91	94.85	87.24
	0.06	100.0	100.0	99.97	99.59	93.93	87.24
	0.08	100.0	100.0	99.89	98.97	93.08	86.97
	0.1	100.0	99.95	99.73	97.85	93.00	87.26
	0.12	99.97	99.77	98.89	96.75	92.34	87.40
	0.14	99.81	99.63	98.32	96.42	91.69	86.79
	0.16	99.53	99.02	98.36	94.89	90.59	86.28
	0.18	98.97	98.65	96.97	94.30	89.53	85.53
	0.2	98.57	97.63	96.12	92.95	90.22	85.55
	0.22	97.51	97.22	95.02	91.61	89.10	84.48
	0.24	96.53	96.46	94.22	91.53	88.53	84.00
	0.26	95.91	94.83	93.40	90.95	86.87	83.57
	0.28	94.04	93.42	92.65	90.40	87.48	83.30
	0.3	93.18	92.91	91.04	88.75	85.44	82.18
	0.32	91.83	90.73	89.89	87.85	86.10	81.26
	0.34	91.34	90.44	89.02	87.40	83.59	80.63
	0.36	89.32	89.32	87.04	86.06	82.46	80.36
	0.38	88.22	88.12	86.73	85.77	83.00	79.06
	0.4	86.77	85.95	85.57	84.22	81.55	78.59
	0.42	85.55	85.36	84.77	82.85	80.73	77.55
	0.44	84.91	84.95	83.69	81.87	80.26	77.91
	0.46	84.44	83.34	82.32	81.42	78.71	75.75
	0.48	81.89	83.08	80.55	80.14	78.32	75.26
	0.5	80.61	81.04	80.16	79.48	76.97	74.48

The classification accuracy obtained in Table-I is plotted in Fig. 4 for the sake of convenience. It is clear from Fig. 4 that larger is the ratio of mean noise to mean data, and standard deviation of noise to standard deviation of data, the larger is the fall-off in percentage classification accuracy. It is clear from Fig. 4 that for a 10% ratio of mean noise to data noise and 1% ratio of standard deviation of noise to standard deviation of data the percentage accuracy in emotion classification is as high as 90.14%. This proves the robustness of the SVM classification.

C. Classification with Only Facial and Only Voice Features

To study the significance of both voice and facial features, we study the classification with only facial and only voice features, and plot the classification accuracy with varied ratio of mean noise to mean data, and standard deviation of noise to standard deviation of data. The results are prepared like Table I, but not included here for lack of space. Fig. 5 and 6, obtained form the prepared table, present the classification accuracy surfaces for only facial and only voice feature sets.

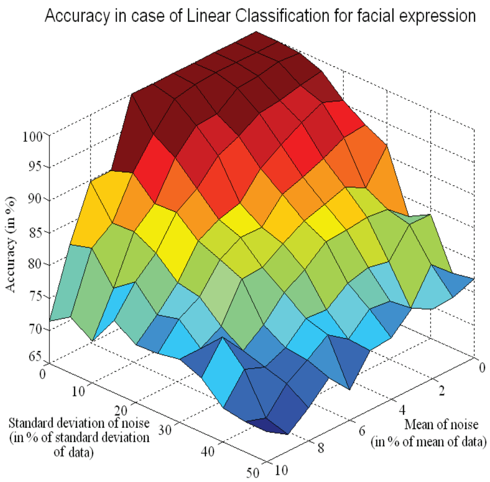

Fig 5: Accuracy plot for linear SVM of all the features of Facial expression data

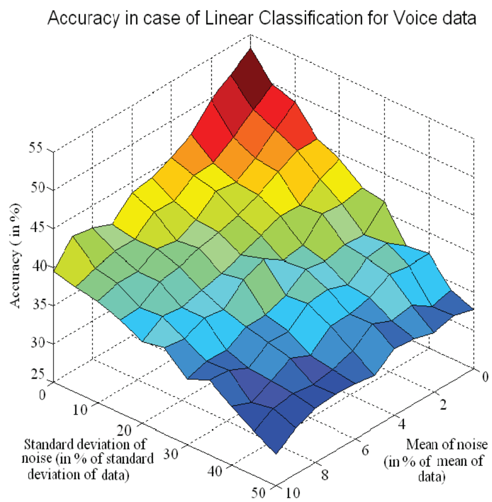

Fig 6: Accuracy plot for linear SVM of all the features of voice data

It is apparent from Fig. 5 and 6 that the fall-off in percentage classification in only voice is much steeper than only facial expression based classification. Further, in either case the classification is poorer than both facial expression and voice based classification.

It is clear from Table II and III that for a 10% ratio of mean noise to data noise and 1% ratio of standard deviation of noise to standard deviation of data, the percentage accuracy in emotion classification by only facial features and only voice features are as low as 88% and 37% respectively. This justifies the significance of composite facial and voice features. It is also noted that facial features are more important than the voice features from the emotion classification point of views.

D. Study of Importance of Features

The experiment started with several facial and voice features to recognize emotion of the subject. It is, however, questionable whether the entire facial and voice features are equally useful. One way to determine this is to drop one feature from the application instance, and measure the % accuracy in classification. In case there is a significant (say 5% or more) fall-off in percentage classification of emotions, then that particular feature is regarded as an essential feature. If the fall-off is less than 5%, we can ignore the specific feature, as dropping it out of the list does not make significant changes in decision-making from the classifier point of views. The process of dropping one feature from the application (measurement) instance and continuing classification in absence of the selected feature is thus repeated for each feature one by one, and the significant changes in the result are tabulated in Table IV below. A cross under a column in Table IV means that the particular feature is dropped from the application instance to recognize emotion class.

TABLE IV: CLASSIFICATION OF EMOTIONS AFTER REMOVAL OF FEATURES

eye-opening	mouth-opening	eyebrow-constriction	pitch	formants			accuracy (in %)
				1	2	3	
							95.08
	×						87.61
×	×						73.63
×	×	×					40.82
×	×	×		×			30.86
×	×	×		×		×	22.39
×	×	×		×	×	×	15.96

It is apparent from Table IV that mouth-opening and eye-opening are fundamental facial features, and first formant is also a very important voice feature, in absence of which percentage classification falls off by a large margin.

An experiment with limited 7 features, as indicated in Table IV, was used to test the % misclassification of emotion for unknown application instances (i.e. those instances not used for training). The experimental results are tabulated in Table V.

It is clear from Table V that anger and disgust are correctly classified even with unknown application instance. Fear is misclassified rarely as anger. Sadness is misclassified as neutral or happy. Neutral is sometimes misclassified as happy, and happy is misclassified as neutral or sad. On a whole, sadness is not correctly recognized by more than 20%.

TABLE V: TABLE FOR MISCLASSIFICATION OF EMOTIONS (IN %)

		Determined Class						
		Neutral	Happy	Sad	Anger	Disgust	Fear	Surprise
Original Class	Neutral	89.72	10.14	0	0	0	0.14	0
	Happy	0.29	99.43	0.14	0.14	0	0	0
	Sad	18.43	3.86	77.71	0	0	0	0
	Anger	0	0	0	100	0	0	0
	Disgust	0	0	0	0	100	0	0
	Fear	0	0	0	0.71	0	98.71	0.58
	Surprise	0	0	0	0	0	0	100

V. Conclusion

The paper proposed a new approach to emotion classification from facial expression and voice using linear support vector machine. Facial and voice features are extracted from the subjects, having arousal of emotions in both their voice and facial expression while uttering a given sentence.

Significance of the paper lies in studying the effect of noisy features on the classification of emotion. Gaussian noise is added to the features with varying mean and standard deviation, and the percentage fall-off in classification is recorded with increased noise variance. It follows from the experiment that 95% classification accuracy can be maintained even when the mean and variance of noise is as high as 5% and 20% respectively over their individual features.

One more interesting study undertaken in the paper is to study the importance of individual feature. This was studied by dropping one feature one at a time, and by measuring the drop-up in percentage classification accuracy. Those features giving rise to high drop-up are considered as essential features. By this approach, we identified eye-opening, mouth-opening and the first formant as essential features for emotion classification from facial expression and voice.

The significance of composite voice and facial expression over the individual expressions is also studied, and the results show that the composite feature is more robust for classification, when noise is picked up in measurements. The percentage fall-off surfaces with increased mean and variance of noise reveal that the fall-off is much sharper when only voice features is used , is nominal when facial features only is used, and slow when composite features of face and voice is used.

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