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Recognition of Emotion in Indian Classical Dance Using EMG Signal

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Abstract— **Indian classical dance forms like Kathak are an enrichment of Indian culture and tradition. These dance forms glorify its beauty by expressing nine emotions (Navras) such as Adbhut (amazed), Bhayanaka (fearful), Hasya (humorous), Karuna (tragic), Raudra (fierce), Shringar (loving smile), Veer (heroic), Bibhatsa (disgusted), and Shant (peaceful). Identifying correct emotions is an important task. The objective of this research work is to recognize Navras in the Kathak dance. Proposed research work can assist dance teachers in an accurate and unbiased evaluation process of dance examination. This research work analyzed the Electromyogram (EMG) signals acquired from eleven subjects. The EMG signals collected from the various locations on the face and neck represent the emotions and head movement. The EMG signals are processed to extract integrated EMG (IEMG) features. This research introduced a new feature named 'difference in IEMG feature' for improving the accuracy of emotion recognition. For the classification of nine emotions, the Least Square Support Vector Machine (LSSVM), Nonlinear Autoregressive Exogenous Network (NARX), and Long- and Short-Term Memory (LSTM) classifiers were used. The classifiers' performance is judged with head motion and without head motion. The classification accuracies are calculated using a maximum, variance, and mean of the feature. LSSVM, NARX, and LSTM classifiers achieved 60.80%, 81.67%, and 92.28% classification accuracies, respectively, using the IEMG feature and head motion. Using the new feature, LSSVM, NARX, and LSTM classifiers achieved 64.29%, 81.27%, and 93.63% classification accuracies, respectively. The overall classification accuracy improved by 1.46% by using the new feature.**

Keywords—**Emotion recognition; EMG; classifier; Indian classical dance; Kathak; Navras.**

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I. INTRODUCTION

The performance of Indian classical dance becomes graceful with an expression of nine emotions (Navras). Navras include Adbhut (amazed), Bhayanaka (fearful), Hasya (humorous), Karuna (tragic), Raudra (fierce), Shringar (loving smile), Veer (heroic), Bibhatsa (disgusted), and Shant (peaceful) [1]. In the current status, the dance teacher assesses dance examination by observation and personal judgment. The accurate and unbiased evaluation of the examiner needs automation in the evaluation process. Some studies [2], [3] used a camera to capture images and videos of a dancer in a different dancing pose. Srimani *et al.* [2] used an image processing method to analyze Navras.

The Navras was analyzed with and without the makeup condition of a dancer and achieved 85% and 95% similarity in variation with and without makeup conditions. Kishore *et al.* used a video processing method and identified dancing poses with 93% accuracy without considering emotion [3]. Srimani et al. [2] and Kishore *et al.* [3] need camera alignment and proper light conditions. These conditions impose the dancer to present expression in front of the camera.

Mohanty *et al.* [4] captured the body posture of a dancer using the Microsoft Kinect camera. The author identified eight emotions through body posture with 95.2% classification accuracy. Microsoft Kinect camera only detects the skeletal structure of body posture. It cannot find a change in facial expression. Hence, it is necessary to develop a system to detect emotions without restricting the dancer.

Physiological signals like Electroencephalogram (EEG), Electrocardiogram (ECG), and Electromyogram (EMG) signals are also used for emotion detection [5]. It does not require proper light conditions. Out of these signals, this research used EMG signals for emotion recognition.

Cognize judgment of the brain controls activities of facial muscles. Emotional expression is coming from the brain. The brain connects twelve pairs of cranial nerves. The seventh pair of cranial nerves (CN VII) is known as the facial nerve. Branches of the facial nerve provide a signal to the muscles of the head and neck. The facial nerve ended by diverging into five motor branches. These motor branches stimulate the muscles for facial expression. Movement in muscles developed the voltage across it. This signal is known as the EMG signal [6]. EMG signals detect a change in muscle movements; hence, this research used EMG-based emotion recognition [7].

Partala *et al.* [8] collected EMG signals generated from Zygomaticus-major and Corrugator supercilii. The author used pictures and videos for emotional stimulation. The author used regression analysis for classification and achieved 70% accuracy by showing picture conditions and achieved 80% accuracy by showing video conditions. The author recognized only positive, negative, and neutral emotions.

Picard *et al.* [9] used K Nearest Neighbor (KNN) classifier with mean, standard deviation, mean absolute value features. The author classified anger, grief, romantic love, hate, platonic love, no emotion, reverence, and joy emotions of a single subject with 46% classification accuracy. This research achieved low classification accuracy due to more number of emotions [9].

Cheng *et al.* used EMG signal from Augsburg Bio-Signal Toolbox (AUBT) [10]. This data bank includes 25 EMG signals of four emotions, pleasure, sadness, anger, and joy, recorded from a single subject with a 32Hz sampling frequency. The authors have applied the minimum and maximum of the wavelet coefficients to the Back-Propagation Neural Network (BPNN). The author got 75% classification accuracy.

Yang *et al.* [11]used a single subject's EMG AUBT dataset and applied wavelet transform with the Db5 base function on it. The authors extracted the minimum and maximum wavelet coefficient features. The author achieved 83.3% accuracy using BPNN and 91.67% accuracy using Least Squares Support Vector Machine (LSSVM). High classification accuracy has been achieved only for four emotions of a single subject [10], [11].

Jerritta *et al.* [12] recognized surprise, disgust, neutral, sad, afraid, and happy emotions for fifteen subjects and achieved only 69.50% accuracy using the KNN classifier. Kehri *et al.* [13] collected EMG signals from twelve subjects for disgust, anger, and happiness emotions using SVM and wavelet packet transform and achieved 91.66% classification accuracy only for three emotions.

In all the above research work, high classification accuracy, above 90% is achieved either only for three emotions [13] or for a single subject [11]. Some researchers recognized eight emotions with 46% classification accuracy [9] and six emotions of fifteen subjects with 69.55% classification accuracy [12]. Hence, research is needed to improve the classification accuracy for more emotions and more subjects.

Our previous research work introduced EMG-based Navras recognition through facial expression and head motion [14]. LSSVM classifier with mean, maximum, and variance of Root Mean Square (RMS) features used for classification. This research achieved 96.66% classification accuracy for a single subject and 80.3% classification accuracy for three subjects. The degradation in classification accuracy for three subjects is a limitation of previous research work. The current research objective is to improve the classification accuracy for more emotions and subjects.

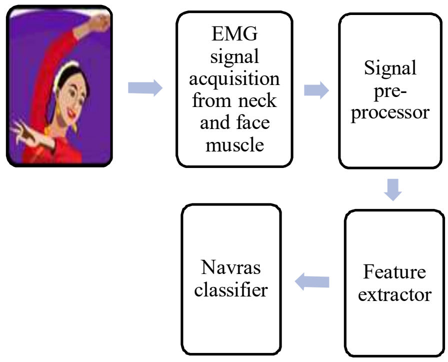

Fig. 1 The course of action flow of the research work [15]

Fig. 1 shows the course of action of the research work. In the data collection, acquired EMG signal from face and neck muscles during dance movement. In the preprocessor, the signal is first amplified, filtered, and converted into digital form. The feature extractor extracted statistical values of signals and applied these features to the classifier. Navras classifier classified nine emotions [15].

In this research paper, section II describes the material and method. This section includes preparation of research work, EMG signal acquisition process, feature selection method, and Navras classification methods. Section III covers the result and discussion. This section covers the classifiers' performance with an existing feature, an innovation of a new feature, and classifier evaluation with a new feature. Section IV concludes a research work.

II. Material and Method

A. Initial Preparation of Research Work

To understand the Kathak dance evaluation process, surveyed thirteen Kathak dance teachers. As per 84.6% of teachers, the weightage of marks for facial expression is more than 50%. Current research work will help Kathak dance teachers in assisting the evaluation process in the Kathak dance examination.

There was no online data bank available of EMG signals in which data collected from Kathak dance subjects. Hence, it was necessary to collect EMG signals from Kathak students. Two Kathak experts and dance teachers were ready to supervise the EMG acquisition process. They allowed their students to participate in it.

B. EMG Signal Acquisition

EMG signals were collected from eleven Kathak subjects, belonging to four different dance institutes. All subjects have achieved Kathak training level-4 and above from the University of 'Akhil Bhartiya Gandharva Mahavidyalaya Mandal, Mumbai.'

Before the data acquisition process, a detailed signal acquisition procedure was explained to subjects and took consent from them. Subjects cleaned their face and applied alcohol on the chick, forehead, and neck for diminishing skin impedance. Four channels of Open BCI Cyton bio-sensing board, with Wi-Fi shield, are used to collect EMG signal [16], [17]. It acquired EMG signals with 1000 samples per second. Ag-AgCl dry electrodes sensed EMG signals. Maintained a 20mm distance between electrodes to avoid any interference.

Fig. 2 shows the position of channels on the face and neck muscles of subjects. Wingenbach *et al.* [18] stated that chick movements express happiness and smile, and forehead movements express sad and angry emotions. Zygomaticus-major muscle cause chick movement. Corrugators' supercilii muscle and Frontalis muscles are responsible for forehead movement [19], [20], and Sternocleidomastoid (SCM) muscles cause head motion [21], [22]. Hence, the Zygomaticus major, Corrugators' supercilii, Frontalis, and SCM muscle used for the EMG signal acquisition [16].

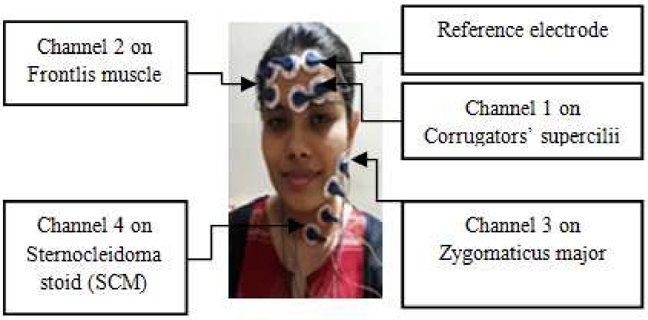

Fig. 2 Position of channels on the face and neck muscle of subjects

Fig. 3 Images of nine emotions, namely Adbhut (a), Bhayanaka (b), Hasya (c), Karuna (d), Raudra(e), Shant (f), Shringar (g), Veer (h), and Bibhatsa (i) shown by Mrs. Darshana Kamerkar (Kathak expert and dance teacher)

As shown in Fig. 3, the subject expressed nine emotions, namely, Adbhut (amazed), Bhayanaka (fearful), Hasya (humorous), Karuna (tragic), Raudra (fierce), Shringar (loving smile), Veer (heroic), Bibhatsa (disgusted), and Shant (peaceful) in the 5-second dance step. Eleven subjects expressed nine emotions twenty times, and the acquisition unit collected EMG signals during this time. Hence the data bank consists of 7920 EMG signals. Each EMG signal includes 5000 samples.

EMG signal first filtered using a high pass filter with a 50Hz corner frequency. Found rectified EMG signal and then signal smoothed using a 10Hz low pass filter [23]. Fig. 4 shows filtered EMG signals for Adbhut emotions for all channels. Channel 2 and Channel 3 muscles are more activated in Adbhut, as compared to other Channels. Similarly, visually inspected the EMG signal of each emotion. Then normalized the EMG signal with the min-max normalization method.

As mentioned in Hamedi in Hamedi [24] and Nazmi 2017 [25], EMG signals present the finest and stable information in the 256 ms slice. Hence, five thousand samples are divided into 256 ms slices. It resulted in 19.53 slices. Out of 19.53 slices, nineteen slices of each EMG signal considered for further processing.

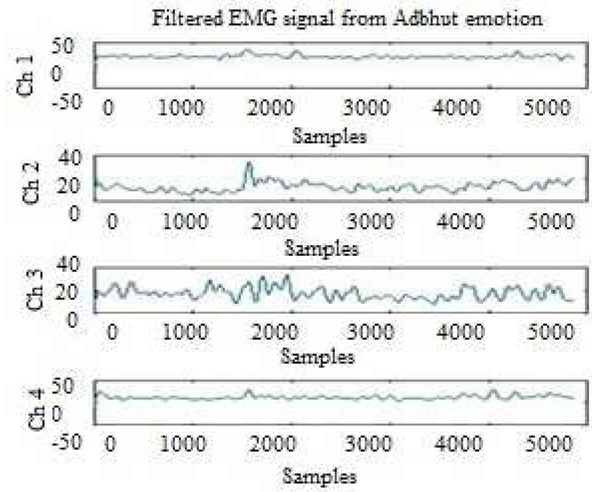

Fig. 4 Filtered EMG signal for Adbhut emotion

C. Feature Selection

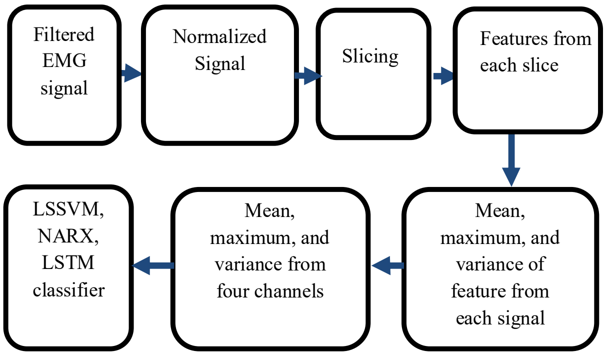

Fig. 5 Flow chart of research work

This research used MATLAB for feature selection and classification. As shown in Fig. 5, extracted the 'time-domain feature' and 'frequency and time-domain features' from each slice. Time-domain features included Mean Absolute Deviation (MAD), RMS, Variance (VAR), and Integrated EMG (IEMG) [26]. RMS contains the middling power of a signal. IEMG is used as an arrival exposure index in EMG non-pattern identification [23]. MAD gives the average distance between each data point to its mean value, and variance gives the dataset's spreading to its mean value.

Equations 1 to 4 represent formulas to find out each of these features. Here M is the slice range, g is the present slice, E_k is the current value of the signal, and k is the current index. Found mean, maximum, and variance value of these features from 19 slices of each EMG signal.

$$RMS_g = \sqrt{\frac{1}{M}\sum_{k=1}^{M} E_k^2} \tag{1}$$

$$IEMG_g = \sum_{k=1}^{M} |E_k| \tag{2}$$

$$MAD_g = \frac{1}{M}\sum_{k=1}^{M} |E_k - \bar{E}\,| \tag{3}$$

$$VAR_g = \frac{1}{M}\sum_{k=1}^{M} (E_k - \bar{E})^2 \tag{4}$$

Yang et al. [11] found the minimum and maximum value of the Db6 wavelet coefficient and achieved 91% classification accuracy for four emotions. Hamedi et al. [24] reconstructed the signal using the wavelet decomposition structure and found the IEMG feature from it. The author recognized ten facial gestures. Hence in frequency and time domain features, minimum, maximum, and IEMG features are calculated from the reconstructed wavelet decomposition structure.

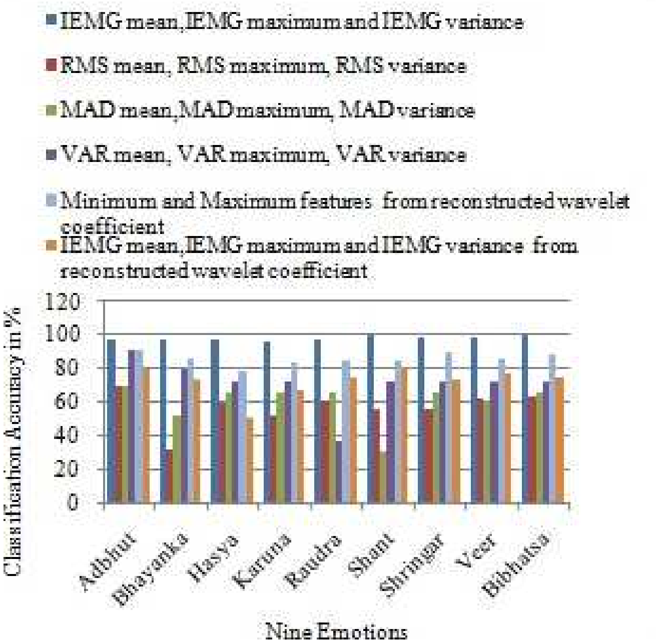

Fig. 6 Performance of features using LSTM classifier

Fig. 6 shows the features' performance using the Long- and Short-Term Memory (LSTM) classifier. Out of all features, mean, maximum, and variance of IEMG features give high classification accuracy as compared to others. Hence, further calculations consider these IEMG features.

D. Navras Classification

For Navras classification, this research used LSSVM, Nonlinear Autoregressive Exogenous Network (NARX), and LSTM classifiers. LSSVM is an enhanced edition of the SVM. LSSVM classifier used Radial Basis Function (RBF) kernel and one versus one coding scheme for training. NARX and LSTM classifiers are types of recursive neural networks. Both classifiers support nonlinear dynamic changes in feature input.

NARX classifier relates two events that are far away from each other. NARX classifier gets features from the input layer and displayed nine emotions from the output layer [27], [28]. The LM algorithm for training has been used [29]. Here, selected four hidden nodes for maximum classification accuracy.

The LSTM uses short-term memory to unravel the everlasting dependency problem. LSTM classifier gets features from the input layer and displayed nine emotions from the classification layer. LSTM consists of hidden nodes. This research selected 373 hidden nodes for maximum classification accuracy and the 'Adam' algorithm for training. Adam is an adaptive learning rate optimization algorithm [30]–[32].

In all previous research, work done so far has used only facial muscles for emotion recognition. This research work evaluated performance using facial and neck muscles. The classifiers' performance is judged with head and without head motion to show the importance of head movement in emotion recognition. In the case of without head motion, features collected from channel 1 to channel 3, and in the case of with head motion, features collected from all four channels.

III. Result and Discussion

A. Evaluation of Classifier Using Mean, Maximum, and Variance of IEMG Feature

The classifier's performance is analyzed by considering the accuracy, sensitivity, precision, and area under the curve (AUC). Accuracy shows correct emotion identifications to total observations. Sensitivity is a fraction of actual emotions that are correctly classified. Precision is a fraction of emotion identification that was correct. Receiver Operating Characteristics (ROC) is a curve between the sensitivity and false-positive rate of emotions, and AUC is the area under the curve of ROC. For perfect classification, the sensitivity must be high than the false-positive rate of emotion. Hence, AUC should be in the range of 0.9 to 1 [33], [34].

After extracting features from 7920 EMG signals, the entire dataset is divided into four sections. Three sections are considered for training, and one is considered for testing. Classifiers are first trained with the training section and found accuracies, sensitivity, precision, and AUC for the testing section. This process is repeated four times by considering a different combination of testing and training sections. Found the average of all classifier's performance parameters.

Table I and Table II show the performance of classifiers without and with head motion. Accuracies of LSSVM, NARX, and LSTM classifier, without head motion, are 50.40%, 68.15%, and 84.48%. The LSSVM, NARX, and LSTM classifiers achieved 60.80%, 81.67%, and 92.28%, respectively, with head motion.

Fig. 7 and 8 show the classifiers' performances considering accuracies, sensitivity, precision, and AUC. The performance parameters of NARX are better than LSSVM. However, LSTM has the best performance parameters of all classifiers. The Head movement improved the classification accuracy by 9.23% using the LSTM classifier. The head movement also improved sensitivity, precision, and AUC.

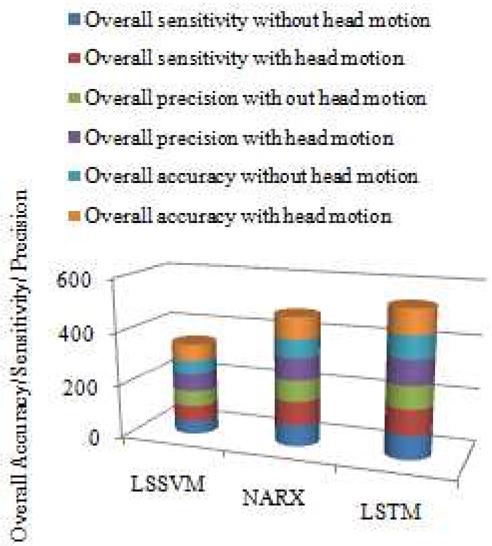

Fig. 7 Sensitivity, precision, and accuracy performance of classifiers with and without head motion

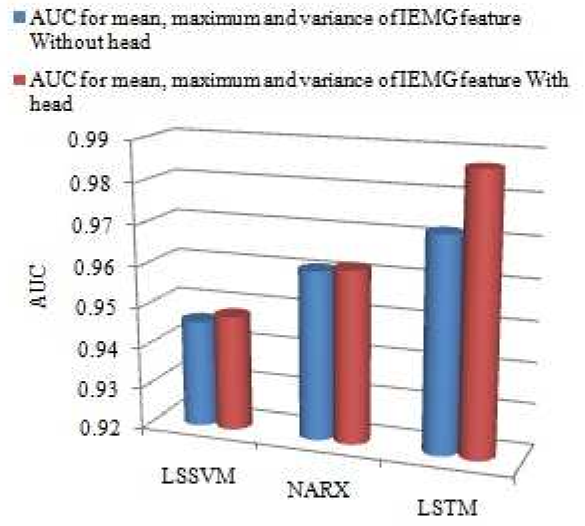

Fig. 8 AUC performance of classifiers with and without head motion

TABLE I
PERFORMANCE OF CLASSIFIER USING MEAN, MAXIMUM, AND VARIANCE OF IEMG FEATURE WITHOUT HEAD MOTION

Name of Classifier	**Performance Parameter**	**Adbhut**	**Bhayanaka**	**Hasya**	**Karuna**	**Raudra**	**Shant**	**Shringar**	**Veer**	**Bibhatsa**	**Overall Parameter %**
LSSVM	Sensitivity	40.25	40	48.5	41.5	40.5	78.25	38.87	70	55.75	50.40
	Precision	46.17	52.17	54	42.5	45.75	100	53.5	74.25	54.25	58.06
	Accuracy	82	81.5	81.5	77.7	79	94.5	80.75	86.25	81.5	50.40
	AUC	0.77	0.979	0.965	0.986	0.963	0.954	0.923	0.984	0.988	0.946
NARX	Sensitivity	72.5	60.67	72.1	NAN	98.1	73.35	82.3	98.8	75	79.10
	Precision	100	98.2	98.2	0	96.4	96.4	74.1	49.55	98.2	79.00
	Accuracy	92.6	88.17	91.75	85.5	92.5	88.25	88.5	92.15	92.75	68.15
	AUC	0.998	0.985	0.990	0.872	0.915	0.925	0.968	0.994	0.994	0.961
LSTM	Sensitivity	86.77	80.26	86.62	83.04	89.67	96.45	91.55	99.97	96.9	90.13
	Precision	91.36	71.95	79.09	80	70.45	95	86.8	88.63	90.45	83.75
	Accuracy	97.7	93.76	95.11	94.29	94.6	98.45	96.52	97.2	97.87	84.48
	AUC	0.94	0.92	0.97	0.97	0.98	0.99	0.99	0.99	1	0.972

TABLE II
PERFORMANCE OF CLASSIFIER USING MEAN, MAXIMUM, AND VARIANCE OF IEMG FEATURE WITH HEAD MOTION

Name of Classifier	**Performance Parameter**	**Adbhut**	**Bhayanaka**	**Hasya**	**Karuna**	**Raudra**	**Shant**	**Shringar**	**Veer**	**Bibhatsa**	**Overall Parameter %**
LSSVM	Sensitivity	54	44.02	59.5	47.6	67.75	78.75	41.5	70	69.25	59.15
	Precision	55	58.25	69.75	67	73	97.25	55.85	70.5	52.75	66.59
	Accuracy	84	85	88	87	84	95	86	91	88	60.8
	AUC	0.747	0.961	0.968	0.986	0.986	0.963	0.927	0.995	0.995	0.948
NARX	Sensitivity	91.72	96.17	48.47	97.83	80.3	100	96.4	95.17	97.85	89.32
	Precision	100	87.75	98.2	64.1	98.65	0.45	98.2	98.2	90.02	81.73
	Accuracy	98.42	97.85	87.25	94.75	95.25	87.75	96.25	98.75	98	81.67
	AUC	0.998	0.954	0.989	0.908	0.970	0.877	0.991	0.993	0.971	0.962
LSTM	Sensitivity	90.94	90.13	88.79	92.03	95.64	97.75	93.85	97.28	98.1	93.83
	Precision	92.72	90.45	91.81	89.09	84.09	96.36	96.36	92.72	96.81	92.26
	Accuracy	97.87	97.19	97.28	95.37	97.57	99.22	98.79	98.73	99.34	92.28
	AUC	0.94	0.96	0.993	0.997	0.995	1	1	1	1	0.987

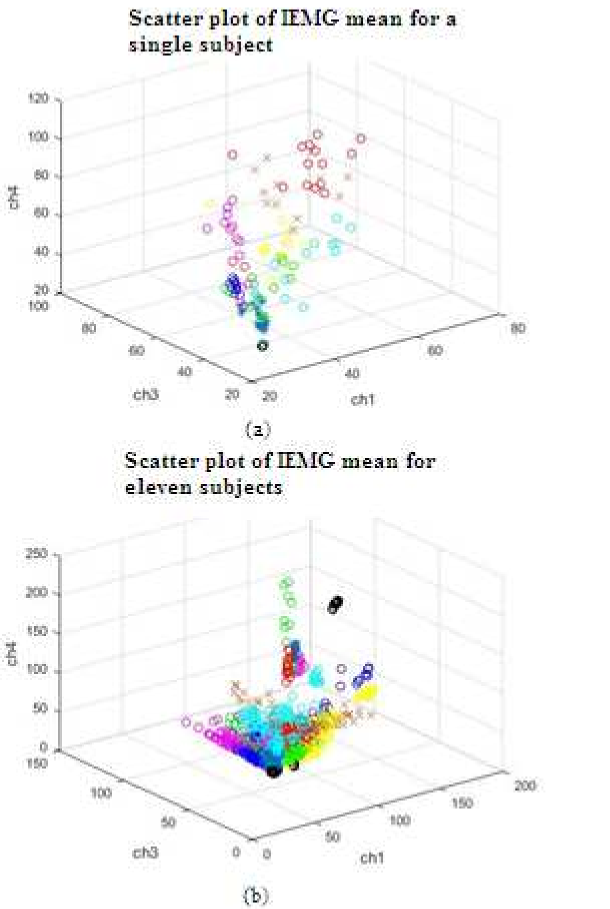

Fig. 9 Scatter plot of 'IEMG mean' for a single subject (a) and eleven subjects (b). Green used for Adbhut, red for Bhayanaka, magenta for Hasya, yellow for Karuna, cyan for Raudra, black for Shant, blue circle for Shringar, blue '*' for Veer, and brown 'X' for Bibhatsa

Fig. 9(a) and (b) show a scatter plot of IEMG mean for a single and eleven subjects, respectively. In the case of a single subject, the features for nine emotions are comparatively separable. However, in Fig. 9(b), many clusters of features overlap. Due to this, LSSVM showed poor performance for eleven subjects [35].

NARX and LSTM classifiers are types of recursive neural networks. Both classifiers support nonlinear dynamic changes in feature input. Due to these characteristics, NARX and LSTM classifiers judge the pattern of changes in magnitude level of features for nine emotions and predict test emotions. LSTM classifier consists of a forgetting layer that keeps the required information and ignores unwanted data. Hence, LSTM with head motion shows high sensitivity, precision, accuracies, and AUC than other classifiers.

This research develops a new feature named 'differences in IEMG feature for further improvement in classification.' The rest of this paper compares two feature extraction methods. Method1 considers the IEMG feature, and Method 2 considers a 'differences in IEMG feature.'

B. Introduction of 'Differences in IEMG Feature'

Fig. 10 (a) and (b) show four channels IEMG features for all nine emotions of subjects 2 and 3. Slices represent (0-18) for Adbhut (amazed), (19-37) for Bhayanaka (fearful), (38-56) for Hasya (humorous), (57-75) for Karuna (tragic), (76-94) for Raudra (fierce), (95-113) for Shant (peaceful), (114-132) for Shringar (loving smile), (133-151) for Veer (heroic), and (152-170) for Bibhatsa (disgusted). Each subject has its IEMG feature value.

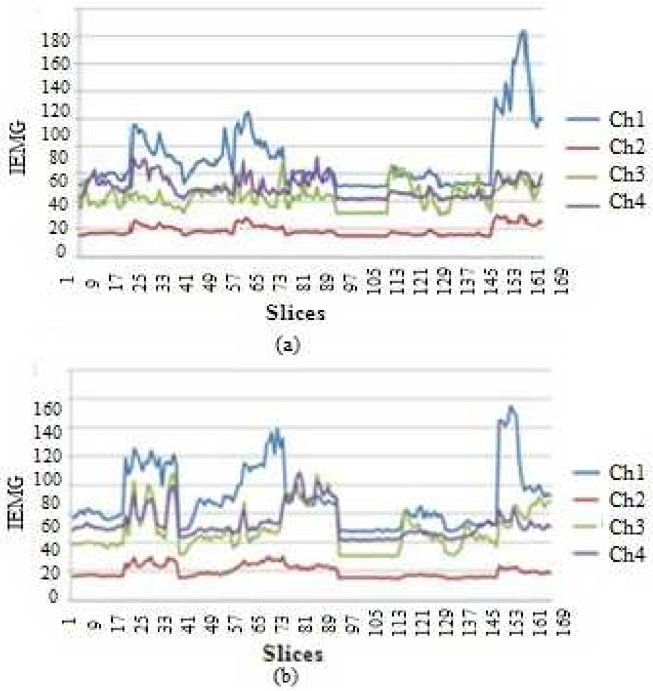

Fig. 10 IEMG features of subject 2 (a) subject 3 (b) for all nine emotions (Slices represent (0-18) for Adbhut (amazed), (19-37) for Bhayanaka (fearful), (38-56) for Hasya (humorous), (57-75) for Karuna (tragic), (76-94) for Raudra (fierce), (95-113) for Shant (peaceful), (114-132) for Shringar (loving smile), (133-151) for Veer (heroic), and (152-170) for Bibhatsa (disgusted))

In all emotions, the IEMG feature of the Ch2 shows less magnitude than other channels. Both subjects used the Kathak dance form, but the IEMG values of expressing emotion are slightly different. IEMG values differ significantly from subject to subject, based on individual muscle movement. There is a difference between feature values of the same emotion for various subjects. Hence, to reduce the difference in feature values, it is necessary to consider the relative difference between the channels.

Channel 2 (Ch2) having low IEMG values. Hence, 'Channel 2' values are considered for calculating the relative difference between channel values by subtracting the 'Channel 2' value from high IEMG channel values. IEMG1 is the 'Channel 1' value, IEMG2 is the 'Channel 2' value, and so on. In this case, IEMG1 - IEMG2, IEMG3 - IEMG2, and IEMG4 - IEMG2 are calculated and observed in a scatter plot to indicate emotion classification.

Fig. 11 (a) and (b) show a scatter plot of maximum, mean, and variance of the Method 1 feature and the Method 2 feature for a single subject, respectively. In a scatter plot for perfect classification, the intra-cluster elements should be closed to each other. Intra cluster elements of maximum, mean, and variance of Method 1 features more distantly located. However, in the Method 2 feature, the intra-cluster feature points appeared closer to each other. The subtraction of 'Channel 2' reduces the distance between the feature points of the same emotion. Due to this reason, feature points are located more closely to each other. This phenomenon improves classification accuracy.

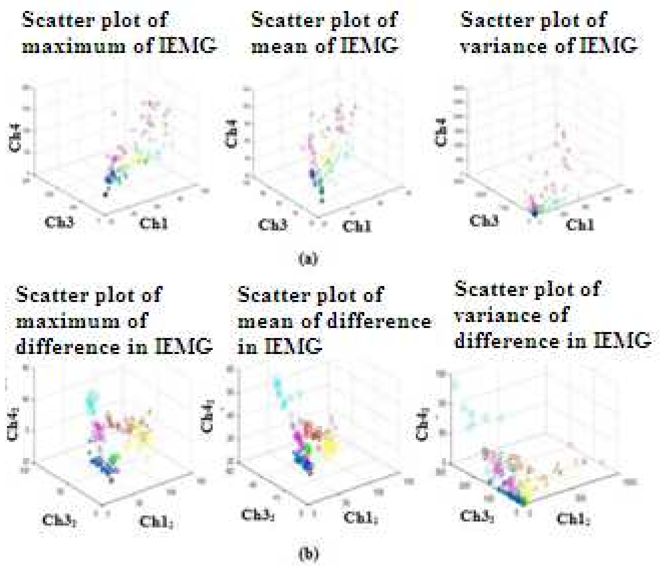

Fig. 11 Scatter plot of maximum, mean, and variance of the IEMG feature (a) and difference in IEMG features for a single subject (b). Green used for Adbhut, red for Bhayanaka, magenta for Hasya, yellow for Karuna, cyan for Raudra, black for Shant, blue circle for Shringar, blue '*' for Veer, and brown 'X' for Bibhatsa

In the NARX and LSTM classification, time-series data needs to be applied. So nearby emotions should be uncorrelated to improve classification accuracy. Hence, found a correlation coefficient of nearby emotional features and compared Method 1 and Method 2's performance with and without head motion. Without a head motion, 'IEMG1 - IEMG2' and 'IEMG3 - IEMG2' are used to classify emotions. In the case of with head motion, 'IEMG1 - IEMG2', 'IEMG3 - IEMG2', and 'IEMG4 - IEMG2' are used for classification of emotions.

As shown in Fig. 12, the average correlation coefficient of the IEMG feature (Method1) is comparatively higher than the average correlation coefficient of difference in the IEMG feature (Method 2). In the case of the Method 2 feature, nearby emotions are comparatively uncorrelated. Hence, Method 2 feature can improve the classification accuracy.

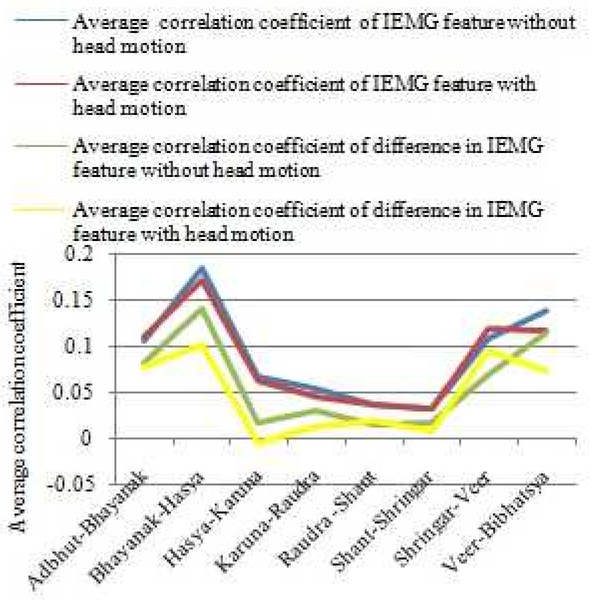

Fig. 12 Performance of features considering the correlation coefficient

C. *Evaluation of Classifier Using Mean, Maximum, and Variance of 'Differences in IEMG Feature'*

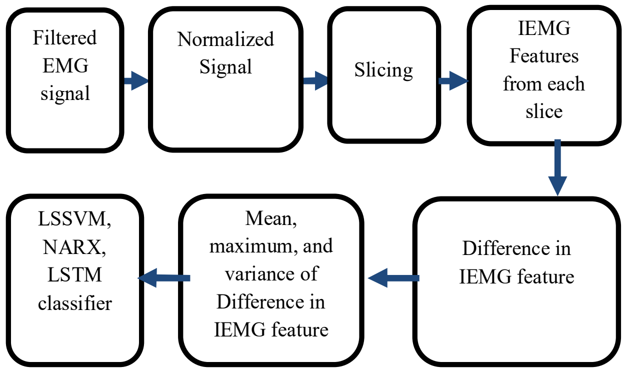

Fig. 13 Flow chart of Navras classification using the difference in IEMG feature

As shown in Fig. 13, the flow chart of Navras classification is similar to Fig. 5 flow chart, up to feature selection from each slice. Calculated 'difference in the IEMG feature' of each signal, then found mean, maximum, and variance of 'difference in IEMG feature.' These features applied to classifiers.

Table III and Table IV show the classifiers' performance using mean, maximum, and variance of 'difference in IEMG feature' without head motion and with head motion, respectively. Accuracies of LSSVM, NARX, and LSTM without head motion, are 53.58%, 73.8%, 88.68%, and with head motion 64.29%, 81.27%, and 93.63%, respectively. The performance of the LSTM is superior to NARX and LSSVM. The Head movement improved the classification accuracy by 5.58 % using the LSTM classifier and Method 2 feature.

Fig. 16 shows a performance plot of the accuracy of the LSTM classifier for nine emotions. The seven emotions other than Adbhut and Bibhatsa are higher using Method 2 feature than Method 1 feature.

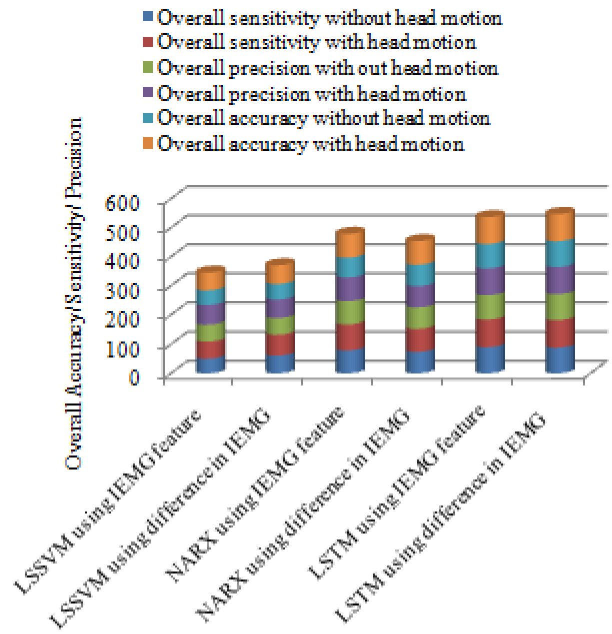

Fig. 14 Performance of classifier using Method 1 and Method 2 features by considering accuracy, sensitivity, and precision

TABLE III

PERFORMANCE OF CLASSIFIER USING MEAN, MAXIMUM, AND VARIANCE OF DIFFERENCE IN IEMG FEATURE WITHOUT HEAD MOTION

Name of Classifier	Performance Parameter	Adbhut	Bhayanaka	Hasya	Karuna	Raudra	Shant	Shringar	Veer	Bibhatsa	Overall Parameter %
LSSVM	Sensitivity	47.5	50.9	71.9	49.9	47.6	99.5	48.9	74.2	58.7	61.02
	Precision	70.8	46.2	44.3	51.3	37.5	77.9	42.6	73.0	57.1	55.64
	Accuracy	83.0	82.8	86.6	81.1	83.2	95.4	82.3	88.3	83.2	53.58
	AUC	0.747	0.968	0.981	0.988	0.940	0.959	0.943	0.961	0.988	0.942
NARX	Sensitivity	100	73.6	98.6	72.2	49.5	0	74.1	98.6	98.2	73.87
	Precision	98.1	73.6	72.4	70.1	66.2	NAN	95.8	73.4	100	72.18
	Accuracy	99.7	96.3	92.5	90.8	86.6	86.7	91.8	99.4	99.7	73.8
	AUC	0.998	0.957	0.995	0.986	0.957	0.780	0.963	0.993	0.992	0.958
LSTM	Sensitivity	88.6	82.2	89.0	90.0	80.4	94.0	86.3	91.8	91.7	88.27
	Precision	89.9	83.6	90.5	90.9	86	93.1	92.5	82.6	98.2	89.71
	Accuracy	96.7	95.4	96.8	96.7	94.3	98.0	97.5	97.5	99.0	88.68
	AUC	1	0.945	0.988	0.993	1	1	1	1	1	0.992

TABLE IV

PERFORMANCE OF CLASSIFIER USING MEAN, MAXIMUM, AND VARIANCE OF DIFFERENCE IN IEMG FEATURE WITH HEAD MOTION

Name of Classifier	Performance Parameter	Adbhut	Bhayanaka	Hasya	Karuna	Raudra	Shant	Shringar	Veer	Bibhatsa	Overall Parameter %
LSSVM	Sensitivity	60.22	67.3	77.2	65.92	75.25	99.1	59.4	79.2	65.57	72.13
	Precision	62.2	57.2	61.35	64.05	65.4	79.05	54	70.4	64..52	64.21
	Accuracy	89.7	88.8	90.5	89.1	90.75	96.3	86.3	91.6	85.3	64.29
	AUC	0.697	0.959	0.968	0.990	0.995	0.990	0.936	0.990	1	0.948
NARX	Sensitivity	100	96.4	98.2	79.5	24.1	24.1	98.65	98.2	98.2	79.71
	Precision	72.5	94.6	97.7	97.2	24.5	24.5	89.2	98.2	59.6	73.11
	Accuracy	93.15	98.62	99.3	98.8	90.1	90.1	97.5	99.4	89	81.27
	AUC	0.994	0.995	0.984	0.995	0.860	0.892	0.997	0.990	0.992	0.967
LSTM	Sensitivity	88.18	91.8	95.9	94	89	99	91.36	96.3	95	93.39
	Precision	92.56	83.07	92.9	94.47	96.15	96.8	95.18	93.7	98	93.65
	Accuracy	97.4	97.5	98.36	98.43	98.26	99.36	98.89	98.94	99.06	93.63
	AUC	1	0.979	0.995	0.993	0.993	1	1	0.997	0.997	0.995

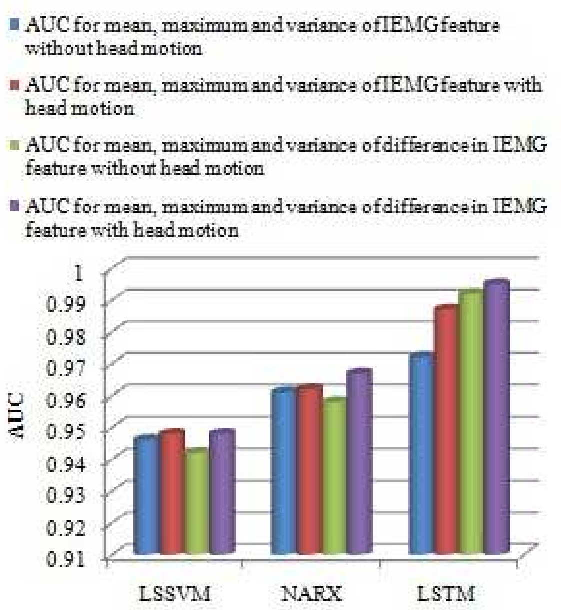

Fig. 15 Performance of classifier using Method 1 and Method2 features by AUC

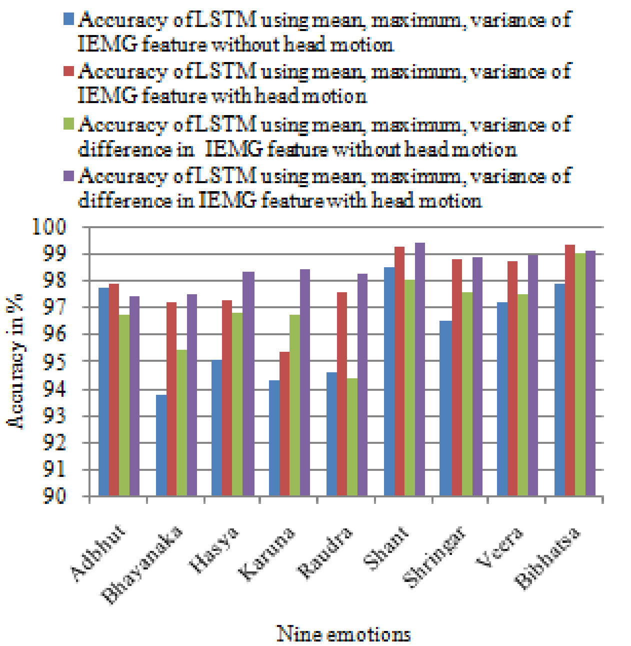

Fig. 16 Performance plot of the accuracy of LSTM classifier for nine emotions

Adbhut and Bibhatsa emotions activate Frontalis muscles, and Channel 2 captured the EMG signal of these muscles. In Method 2, Channel 2 subtracted from other channels, which results in lower accuracy for Adbhut and Bibhatsa emotions in Method 2.

Most improvement in accuracy is observed for Karuna and Hasya emotions by 3.21% and 1.11%, respectively, using Method 2 features. Shant emotion has high classification accuracy, which is 99.36%, and Adbhut has comparatively less accuracy, which is 97.4% using the Method 2 feature. Accuracies of nine emotions for Method 2 features are in the range of 97.4% to 99.36%. It is higher in comparison to the accuracies of nine emotions for the Method 1 feature. Method 1 accuracy is in the range of 95.37% to 99.34%.

TABLE V
PERFORMANCE OF METHOD 1 AND METHOD 2 FEATURES USING TESTING AND TRAINING DATASET

	Performance on The Testing Dataset				**Performance on The Training Dataset**			
	Method 1 Feature		**Method 2 Feature**		**Method 1 Feature**		**Method 2 Feature**	
	Overall Accuracy Without Head Motion	**Overall Accuracy With Head Motion**	**Overall Accuracy Without Head Motion**	**Overall Accuracy With Head Motion**	**Overall Accuracy Without Head Motion**	**Overall Accuracy With Head Motion**	**Overall Accuracy Without Head Motion**	**Overall Accuracy With Head Motion**
LSSVM	50.4	60.8	53.58	64.29	63.3	68.8	66.2	79.4
NARX	68.15	81.67	73.8	81.27	68.1	84.8	76.9	86.8
LSTM	84.48	92.28	88.68	93.63	89.2	95.1	92.5	98.8

Up till now, the performance of the classifiers is observed using a testing dataset. Now the performance of the classifiers for Method 1 and Method 2 features are shown in Table V, using testing and training datasets. In the case of a testing dataset, testing data is different from training data, and in the case of a training dataset, testing data is a part of the training data.

The accuracy of the testing dataset is lower than the training dataset. In the training dataset, the LSTM classifier's accuracy with head motion is higher than other classifiers. Hence, this research work achieved 93.63% classification accuracy in the testing dataset and 98.8% classification accuracy in the training dataset using the LSTM classifier with head motion and a 'difference in IEMG feature.'

Table VI shows a comparison of current research work with previous research work. Previous research work achieved above 90% classification accuracy only for three emotions [13] or for a single subject [11]. However, this research works achieved 93.63% classification accuracy for nine emotions of eleven subjects.

TABLE VI
COMPARISON CHART OF CURRENT RESEARCH WORK WITH PREVIOUS RESEARCH WORK

Research Work	**Number of Emotions**	**Number of Peoples**	**Classification Accuracy %**
[9]	8	01	46.00
[10]	4	01	75.00
[11]	4	01	91.67
[12]	6	15	69.50
[13]	3	12	91.66
[14]	9	03	80.30
Current Research	9	11	93.63

IV. CONCLUSION

This research work recognized Navras in Indian classical dance like Kathak using EMG signal for eleven subjects. This research introduced a new feature named 'difference in IEMG feature' and compared this feature with the IEMG feature. The new feature maintained a low average correlation coefficient of nearby emotions as compared to the IEMG feature. The mean, maximum, and variance of the IEMG feature and mean maximum and variance of 'difference in IEMG feature' with LSTM classifier achieved respectively 92.28% and 93.63% classification accuracy. The new feature has helped to enhance accuracy by 1.46%. LSTM classifier achieved high classification accuracy, precision, sensitivity, and AUC than NARX and LSSVM classifiers.

Classifier performance was observed by considering with head and without head movements. The Head movement improved the classification accuracy in both methods. As compared to research work done so far, this research work achieved high classification accuracy, 93.63%, for nine emotions and eleven subjects.

This research work recognized nine emotions in only Kathak classical dance. In the future, this research can use to analyze emotion recognition for other forms of Indian classical dance like Bharatnatyam, Kuchipudi, Odissi, and Manipuri.

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