EMG Based Emotion Recognition in Indian Classical Dance

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ABSTRACT

In Indian classical dance, expressing nine emotions (Navras) through facial expression plays a significant role. However, scientifically measuring the correct emotion is the major challenge. This research work introduces the recognition of "Navras" in "Kathak" using an Electromyogram (EMG) signal. In this research, for emotion recognition, a unique combination of EMG signal acquired from facial expression and head movement is used. From EMG signals, three time-domain features, namely Root Mean Square (RMS) mean, RMS maximum, and RMS variance features are calculated. The Least Square Support Vector Machine (LSSVM) classifier is applied for the classification of nine emotions. LSSVM classifier achieved 69.63% and 80.3% classification accuracy without and with head motion condition, respectively, considering nine emotions for three subjects.

KEY WORDS: EMOTION RECOGNITION, EMG, LEAST-SQUARE SUPPORT VECTOR MACHINE CLASSIFIER, KATHAK.

INTRODUCTION

In Indian classical dance like Kathak and Bharatanatyam, expressing nine emotion (Navras), namely Shringar (loving smile), Hasya (humorous), Karuna (tragic), Raudra (fierce), Veer (heroic), Bhayanaka (fearful), Bibhatsa (disgusted), Adbhut (amazed), and Shant (peaceful) through facial expression plays a significant role. In dance examination, currently, the teacher does the evaluation. To provide automation in the evaluation process, the measurement of accurate emotion in a scientific way is the major challenge. Many researchers contribute their work in the recognition of Navras in Indian classical dance. Srimani et al. took images of dancers posing

Navras in Bharatanatyam and use image processing to analyze Navras concerning kurtosis with makeup and without makeup condition. The authors observed 85% similarity in variation with makeup condition and 95% similarity in variation without makeup. However, emotion identification is not made. Kishore et al. classified Indian classical dance action with 93% accuracy using the video processing method without emotion recognition.

Srimani et al. and Kishore et al. used the image processing and video processing method, which also has a restriction of the proper light condition and camera alignment. Mohanty et al. collected data using a Microsoft Kinect camera in different body postures of a dancer in a controlled and uncontrolled background environment. The author used a Support Vector Machine (SVM) and Convolution Neural Network (CNN) to find the classification accuracy of eight emotions and succeed 95.2% accuracy in real-world conditions. Microsoft Kinect camera can be used for major motion and posture by considering the skeletal structure of a person, but small variation in facial expression could not be detected. Hence, emotion recognition needs to be done without restricting the movement of the dancer.

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In an emotional state, the brain signal tightens a muscle, which developed voltage on it. Electromyogram (EMG) signals detected muscle movement. Hence, EMG based Navras recognition needs to be explored. In EMG based emotion recognition, signals are acquired from facial muscles. This research introduces Navras recognition through facial expression and head motion using the EMG signal. The basic process flow of the system is shown in Figure 1. EMG signals collected from facial and neck muscles are applied to a signal preprocessor. The Signal preprocessor amplifies, filters, and converts a signal in digital form. This signal is applied to the feature extractor to collect features. This feature is applied to classifiers for the recognition of the emotion.

Figure 1: Basic process flow of EMG based Navras recognition

In the case of EMG-based emotion recognition, Picard et al. classified eight emotions, namely reverence, joy, grief, anger, hate, romantic love, platonic love, and no emotion of a single subject. The author achieved 46% classification accuracy using K Nearest Neighbor (KNN) classifier with mean, standard deviation, mean absolute value features. Cheng et al. used a single-subject EMG signal from the Augsburg Bio-Signal Toolbox dataset (AUBT) of four emotions, namely anger, pleasure, sadness, and joy using the Back Propagation Neural Network (BPNN) improved by the Levenberg-Marquardt (LM) algorithm. The author achieved 75% classification accuracy. Yang et al. used a single-subject EMG signal from the AUBT dataset and recognized emotion with 91.66% using the Least Squares Support Vector Machine (LSSVM). Yang et al. and Cheng et al. recognized only four emotions, namely anger, pleasure, sadness, and joy. Jerritta et al. detected six emotions: afraid, disgusted, happy, sad, neutral, and surprised using a single-channel EMG acquisition unit.

The author achieved 69.50% classification accuracy using the KNN classifier and skewness and kurtosis features. Kehri et al. used a wavelet packet transform and SVM and achieved 91.66% classification accuracy of three emotions. From all the above literature, it is recapitulated that EMG based emotion recognition achieved overall accuracy in the range 46% to 91.66%. 46% classification accuracy was achieved for eight emotions, and 91.66% classification accuracy was achieved for three emotions with a single subject. Hence, there is a scope of improvement in classification accuracy concerning more emotions and subjects. All the above research used facial EMG signals for classification, but the head movement was not considered in this process. Current research uses face and neck muscles to identify emotion through head movement and facial expression.

2. Research Methodology: This research includes data collection, feature extraction, classification process.

a. Data Collection: EMG signals were collected from three Kathak students. All participants are qualified Kathak training level 4th and above. Before the data acquisition process, participants gave consent by filling up the form. Also, a detailed procedure of signal acquisition was explained to them before capturing emotion. To reduce the impedance level of the skin, the participant applied alcohol on the forehead, chick, and neck. Open BCI Cyton 8 channel bio-sensing board with a Wi-Fi shield is used to acquire an EMG signal. Out of eight channels, four channels are used to collect the EMG signal. The unit acquired an EMG signal with a 1000Hz sampling frequency. Ag-AgCl dry electrodes are used to sense EMG signals. The placement of the channel on the face and neck muscles of the subject is shown in Figure 2. Negative emotions, like anger, sadness, surprise, and disgust, activate the corrugators' supercilii muscle and the frontalis muscle. Positive emotions, like happiness and smile, activate the zygomaticus major. Hence, three channels are placed on corrugators' supercilii muscle, frontalis muscle, and zygomaticus major.

Figure 2: Placement of channels on the face and neck muscles of the subject

Figure 3: Images of nine emotions, namely Shringar (a), Hasya (b), Karuna (c), Raudra (d), Veer (e), Bhayanaka (f), Bibhatsa (g), Adbhut (h), and Shant (i) shown by Mrs. Pallavi Mhaiskar (Kathak Expert).

Tan et al. correlated the sternocleidomastoid (SCM) electromyography signal with head rotation angle. SCM muscle showed a significant role in neck movements. Hence, the fourth channel is placed on the SCM muscle. Two electrodes are placed at a 20mm distance. Participants performed 5 seconds dance step to show emotion. As shown in Figure 3, participants expressed nine emotions, namely Shringar (loving smile), Hasya (humorous), Karuna (tragic), Raudra (fierce), Veer (Heroic), Bhayanaka (fearful), Bibhatsa (disgust), Adbhut (amazed), and Shant (peaceful). EMG signals were acquired twenty times for nine emotions.

b. Feature Extraction: In this research, EMG signal preprocessing is done using MATLAB. Applied framing to a signal with 256 ms frame size. Hamed et al. mentioned in their research work, facial EMG signals give the best and steady information in the 256 ms segment; so, 19 frames are formed for each EMG signal. RMS was calculated for each frame. Then found RMS mean, RMS maximum, and RMS variance from 19 frames. Chen et al. mentioned in their research work that RMS contains the middling power of a signal, and it is simple for quick training and operating of the classifier. RMS maximum shows the maximum value, RMS mean shows the average value, and RMS variance shows a variation in the RMS level of each signal. It helps determine a minute change in emotions. The mathematical definition of features: RMS mean, RMS variance, and RMS maximum are given in Table 1. In this equation, x_j is the present point, j is the index of the present point x_j , L is the length of the frame, and k is the current frame of signal.

Table 1. The mathematical definition of features RMS mean, RMS variance, and RMS maximum

$RMS_k \text{ mean}$	$RMS_k \text{ variance}$	$RMS_k \text{ maximum}$
$= \text{mean} \left(\sqrt{\frac{1}{L} \sum_{j=1}^L x_j^2} \right)$	$= \text{variance} \left(\sqrt{\frac{1}{L} \sum_{j=1}^L x_j^2} \right)$	$= \text{maximum} \left(\sqrt{\frac{1}{L} \sum_{j=1}^L x_j^2} \right)$

c. Classification: This research uses the LSSVM for classification. The LSSVM is an improved version of the SVM. Equality constraint is used in classification. Quadratic programming changes into linear equation form. Hence, convergence accuracy is improved. Classification is done with a one vs. one coding scheme and RBF kernel.

RESULTS AND DISCUSSION

After extracting features from 540 EMG signals per channel, the complete dataset is separated into five divisions. One division is considered for testing, and the other divisions are considered for training. This process is repeated five times by considering different testing division and found the middling classification accuracy. Classification accuracy was calculated with and without head condition for individual participants and all three participants together. Table 2 and Table 3 show the average performance of the LSSVM for a different participant without and with head motion. In case of without head motion, consider only channel 1 to channel 3 EMG signals. These channels are connected to corrugators' supercilii muscle, frontalis muscle, and zygomaticus major.

In the case of with head motion condition, four channels are connected. The fourth channel is connected to the SCM. Classification accuracy of individual emotions and overall classification accuracy is found.

Figure 4 shows the performance bar graph of the LSSVM classifier of individual emotions for all participants' conditions. All emotions improved their classification accuracies by incorporating head motion. Adbhut and Hasya emotions improved classification accuracy by 8% and 8.3%, respectively, by incorporating head motion. Shringar emotion shows only 1.03% improvement in classification accuracy by incorporating head motions.

Table 2. Performance of LS SVM Classifier for a Different Participant without Head Motion

Participant number	Classification accuracies of nine emotions									Overall Accuracy
	Adbhut	Bhayanaka	Hasya	Karuna	Raudra	Shringar	Shant	Veer	Bibhatsa	
1	92.7	97.4	97.5	100	94.4	97.4	98.7	98.6	93.8	84.98%
2	89.7	99.3	96.78	98.7	97.3	98.7	93.14	94.7	97.3	83.3%
3	97.58	99.4	99.4	97.62	98.2	100	99.4	99.4	99.4	95.55%
All Participant	87.58	91.14	89.88	90.48	90.88	97.8	93.94	93.38	89.3	69.63%

Table 4 shows that without head motion condition and with head motion condition, classification accuracy achieved is 69.63% and 80.3%, respectively. Hence, it is observed that head movement improves 15.3% classification accuracy compared to accuracy observed without head movement. It signifies that head movement plays a vital role in emotion recognition. It is observed

that individual participant classification accuracy is significantly more than classification accuracy for all participants. In previous research work, Jerri et al. recognized a maximum of six emotions in an emotional environment with an accuracy of 69.5%. Current research achieved 80.3% classification with nine emotions, which are 15.53% more than previous research.

Table 3. Performance of LSSVM Classifier for a Different Participant with Head Motion

Participant number	Classification accuracies of nine emotions									Overall Accuracy
	Adbhut	Bhayanaka	Hasya	Karuna	Raudra	Shringar	Shant	Veer	Bibhatsa	
1	97.24	97.3	98.8	100	98.6	97.4	97.8	99.2	95	91.08%
2	99.34	98.9	97.58	98.9	100	99.3	95.9	97	97.64	91.66%
3	98.88	98.88	98.88	99.4	99.4	100	99.4	99.4	99.4	96.66%
All Participant	94.78	94.36	97.42	93.82	93.02	98.88	96.22	97.26	95.26	80.3%

Figure 4: Performance bar graph of LSSVM classifier of individual emotions for all participants' conditions

Table 4. Improvement in Emotion Classification with Head Motion

Sr. No	Participant number	Classification accuracy Without head motion (%)	Classification accuracy With head motion (%)	Improvement in classification accuracy(%)
1	1	84.98	91.08	6.69%
2	2	83.3	91.66	9.12%
3	3	95.55	96.66	1.16%
4	All Participant (1,2,3)	69.63	80.3	15.3%

CONCLUSION

In Indian classical dance, to automate the evaluation process of dance examination, it is needed to acquire and process Navras scientifically. This research work introduced the recognition of Navras in Kathak using the EMG signal. This research used a unique combination of EMG based facial expression and head movement for emotion recognition. LSSVM classifier trained with RMS mean, RMS maximum and RMS variance features classified Navras with 69.63% classification accuracy considering without head movement and 80.3% classification accuracy considering head movement. Hence, it is observed that head movement significantly improves classification accuracy compared to accuracy observed without head movement.

Future Scope: In this research work, signals are collected from only three participants. The plan is to collect EMG signals from ten participants during the Kathak dance step and classify nine emotions. In the current research, the classification accuracy of individual participants is comparatively more, and the classification accuracy of all participants is less. Future research planning explores the deep neural network to improve the classification accuracy of all participants together.

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