International Journal of Electrical and Computer Engineering (IJECE)
Vol. 7, No. 5, October 2017, pp. 2537~2546
ISSN: 2088-8708, DOI: 10.11591/ijece.v7i1.pp2537-2546

Indian Classical Dance Mudra Classification Using HOG Features and SVM Classifier

K.V.V. Kumar[1], P.V.V. Kishore[2]
Department of Electronics and Communications Engineering, K.L. University, India

Article Info

Article history:

Received Dec 9, 2016
Revised Jun 17, 2017
Accepted Sep 17, 2017

Keyword:

Indian classical dance mudras
HOG features
Mudra recognition frequency
Scale invariant features
SVM classifier

ABSTRACT

Digital understanding of Indian classical dance is least studied work, though it has been a part of Indian Culture from around 200BC. This work explores the possibilities of recognizing classical dance mudras in various dance forms in India. The images of hand mudras of various classical dances are collected form the internet and a database is created for this job. Histogram of oriented (HOG) features of hand mudras input the classifier. Support vector machine (SVM) classifies the HOG features into mudras as text messages. The mudra recognition frequency (MRF) is calculated for each mudra using graphical user interface (GUI) developed from the model. Popular feature vectors such as SIFT, SURF, LBP and HAAR are tested against HOG for precision and swiftness. This work helps new learners and dance enthusiastic people to learn and understand dance forms and related information on their mobile devices.

Corresponding Author:

Dr. P.V.V. Kishore,
Department of Electronics and Communications Engineering,
Multimedia and Vision Computing Research Center, K L University,
Green Fields, Vaddeswaram, Guntur DT, Andhra Pradesh, India - 522502.
Email: pvvkishore@kluniversity.in

1. INTRODUCTION

Indian dance forms are a mirror to rich cultural heritage that existed from the past 5000 years. The name for these classical dance forms is called ‘Natya Rasa’ as portrayed in the bible of Indian dance ‘Natya Shastra’. According to Natya Shastra there are 108 karanas [1] meaning action of hands, feet and body. These poses symbolize various physical meaning related to nature, god and actions. A few hasta mudras are shown in Figure 1 for reference [2].

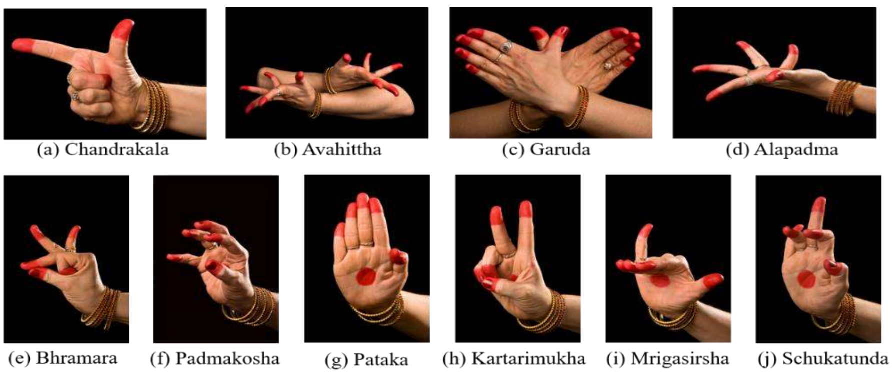

Figure.1. Hasta mudras of indian classical dances

In this work we seek to classify hasta mudras used in various Indian classical dance forms. Creation of dataset for this task is a complex process. For the initial phase of testing, we work on images available on internet dance sites. A careful section of precisely captured images are grouped together to form our training and testing datasets for the classifier. Our dataset is having 5 different sets of 24 hasta mudras from various dance forms.

Bailey, H. et.al considers the role and impact of new and emerging e-Science tools on practice-led research in dance. Specifically, it draws on findings from the e-Dance project. This two-year project brings together an interdisciplinary team combining research aspects of choreography, next generation of video conferencing, and Human-computer interaction analysis incorporating hypermedia and non-linear annotations for recording and documentation [3], [4].

The key feature of the e-Dance project is the creative and critical engagement with e-Science and specifically AG. It focuses on the Grid in terms of its visual communicational capacity, and from an arts perspective it is particularly concerned with meaning production in this visual, tele-communicational context. This focus on meaning bridges the disciplinary divide through user interface design and 'sense making' [5] on the e-Science side, and spectator/participant engagement and interpretation from the perspective of the arts [6].

The regular image segmentation algorithms such as thresholding [7], edge [8] and color clustering [9] fail to extract full features of the mudras. This is due to occlusions of fingers during capture and colouring used for fingers during performances. General feature extraction models in literature are used to represent the dance mudras. These features are histogram of oriented gradients (HOG), speed up robust features (SURF), scale invariant feature transform (SIFT), local binary patterns (LBP) and haar wavelet features (HAAR).

A comparison of these features on images of dance mudras from web and self-captured data is performed. Support vector machines (SVM) are used as classifier of these features to identify a mudra class in kuchipudi dance mudras. We found that these 24 mudras are the basis for all 8 classical dance forms in India. Hence, classification in Kuchipudi can be extended to other dance forms as well.

The idea is to represent Indian classical dance on a digital platform. Indian cultural dance forms are most complex human gestures to be represented in digital format. Feature extraction is most complicated task as the images are full of color, occlusions and finger closeness. This can be observed in images in Figure 1. The regular image processing segmentation models such as thresholding and edge detection fail to represent the correct shapes as found in the original images. This can be observed in Figure 2 for a mudra from kuchipudi dance form.

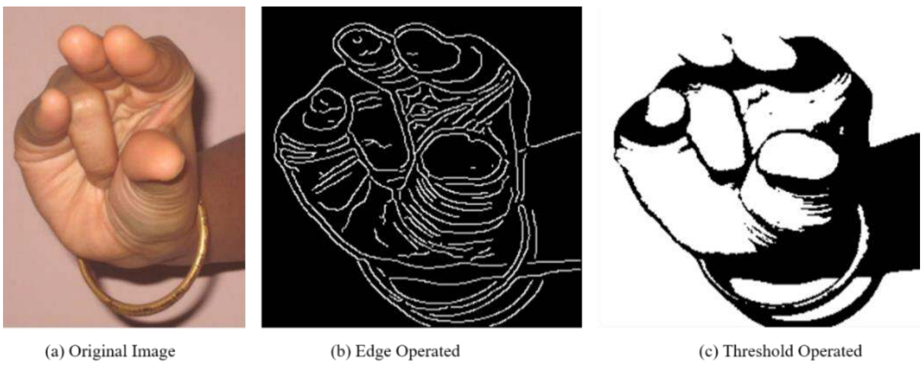

Figure 2. (a) Original mudra named 'kangula' in kuchipudi (b) Edge segmented and (c) thresholded image

The most vibrant and highly used models of segmentation in recent times are active contours. Many models have been proposed in literature [10, 11]. But the basic model sufferers from many drawbacks such as illumination, position of the mask and number of iterations. We believe focused active contour models with more spatial information using color, texture and shape have profound effect on extracting the correct segments [12]. Figure 3 shows the result of active contour model on hand mudra in Figure 2(a).

A number of methods in literature help in determine shape features. This paper tests 5 such features and provide an indicator telling the dance mudra classification algorithm for best matching score. A two-decade long challenge for producing an imaging feature that is immune to illumination, noise, scale, orientation, partial occlusions giving accuracy and speed is coming good.

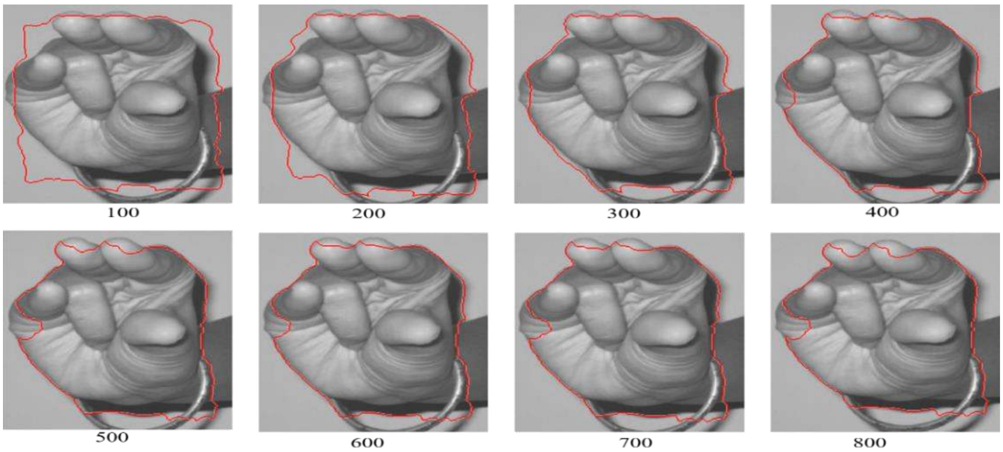

Figure 3. Active contour based image segmentation model for 800 iterations on hand mudra.

The literature has SIFT [13], HAAR [14], Features from accelerated segment test (FAST) [15], SURF [16], HOG [17] and many more. A formal comparison of these methods indicate that each one has got their pros and cons. Table 1 characterizes these features based on the parameters required for good feature descriptor.

Table 1. Feature Descriptor Characterization for Dance Mudra Classification

Methods	Timing	Transformation	Scaling	Rotation	Blurring	Illumination
FAST	Common	Common	Common	Bad	Bad	Bad
SIFT	Bad	Good	Good	Best	Best	Best
SURF	Good	Best	Best	Good	Good	Good
HOG	Good	Best	Best	Best	Best	Best
LBP	good	Good	Good	Good	Common	Good

From Table 1, it can be understood that the best feature descriptor is HOG. There are many variations for HOG such as HOG-LBP, HOG-LSS (local self similarity), local gradient (LG)-HOG and so on. In this paper we tried all of them and results match to that indicated in Table 1. Please refer the corresponding literature for additional information regarding low level image feature descriptors in the references provided adjacent to them above.

Chung-wei [18] is proposed moving object classification likes: cars, motorcycles, pedestrians and bicycle by using local shape and wavelet transform HOG features with hierarchical SVM classification. The proposed method used to test in six video sequences for classification. The computer processing times of the object segmentation in 79ms, object tracking in 211ms, feature extraction and classification in 0.01ms respectively.

In recent years, SVM classifier with HOG features are the most popular techniques for vehicle detection [19]. In real time implementation which is important for advanced driver assistance systems applications. To reduce the complexity of the SVM is to reduce the dimensions of HOG features. The proposed method SVM classification for vehicle detection is three times speed-up in other detection performance. The rest of the paper is organized as: section 2 describes the followed methodology for mudra classification. Results and discussion is presented in section 3 with conclusions in section 4.

2. METHODOLOGY

The experiment involves only dance mudras from kuchipudi dance form as they are the basic structures for formation of any dance. Methodology involves two phases: training phase and testing phase. During training phase 24 dance mudras are used to the train the SVM classifier. The capabilities of SVM classifier are mapped to multiple classes to form a multi-class SVM.

2.1. Dataset for kuchipudi dance form

The dataset is made from a combination of lab dance mudras and dance mudras images on the websites of Indian art and culture. For each mudra, we have made a set of 5 images from 5 different artists. Figure 4 shows the set used for capturing the dataset at university multimedia centr. A mixture of 5×24 images is used for training and testing. We have 2 sets of images from our dancers, 2 sets from dance websites and 1 set from Youtube video frames.

Figure 4. Setup used for capturing dance images of kuchipudi mudras

2.2. Banalization of images and feature extraction

Processing easiness for feature extraction calls for this step. The dimensionality is reduced to red plane and local maxima are computed. The local maxima in a 16×16 block is used as a threshold for that particular block making the process invariant to brightness and contrast. A set of binary sign images are coupled in Figure 4 in the training side. Shape features are modelled from these binary images. Five feature vectors and their combination are used to extract features from the mudras.

2.3. Support vector machines

SVM's analyze data and produces binary responses for classification come under a class of supervised learning. The basic SVM classifies only two class problems by projecting a hyper plane between data during training phase. The hyper plane is characterized by a subset of data points acting as support vectors. During training the SVM is presented with example vectors $\boldsymbol{x_i} \in \Re^n$, $\boldsymbol{i} = 1.....\boldsymbol{l};\boldsymbol{l}$ training sample, to label each data sample as either as class label +1 or −1 which forms the indicator vector $\boldsymbol{y_i} \in \{+1, -1\}$. SVM formulates the optimization problem as a decision boundary $\boldsymbol{D}(\boldsymbol{x})$ such that

$$\boldsymbol{D}(\boldsymbol{x}) = \min_{\boldsymbol{w},\boldsymbol{b},\lambda} \left(\frac{1}{2} \boldsymbol{w}^T \boldsymbol{w} + \boldsymbol{C} \sum_{\boldsymbol{i}=1}^{\boldsymbol{l}} \lambda_i \right)$$

$$\text{Subject to } \boldsymbol{y_i} \left\{ \boldsymbol{w}^T \phi(\boldsymbol{x_i}) + \boldsymbol{b} \right\} \geq 1 - \lambda_i \text{ with } \lambda_i \geq 0, \boldsymbol{i} = 1, 2, ..., \boldsymbol{l}; \qquad (1)$$

Where $\boldsymbol{C}$ is a positive constant defining regularization. The terms $\boldsymbol{w}$ and $\boldsymbol{b}$ are weight and bias. λ is the misclassification handler. The function $\boldsymbol{m}(\boldsymbol{x}) : \boldsymbol{x} \rightarrow \phi(\boldsymbol{x})$ maps feature vector $\boldsymbol{x}$ to a higher dimensional space. The mapping function $\boldsymbol{m}(\boldsymbol{x})$ maps $\boldsymbol{x}$ into a dot product of feature space that satisfies $\boldsymbol{m}(\boldsymbol{x}_{i-1}, \boldsymbol{x}_i) = \phi^T(\boldsymbol{x}_{i-1})\, \phi(\boldsymbol{x}_i)$.

2.4. Multi class SVM

The most widely used multi class SVM models are One Vs All (OVA), One Vs One (OVO) [20], Directed Acyclic Graph (DAG) [21] and Error Correcting Output Codes (ECOC) [22]. OVA creates N binary SVM's for all categories where N is class number. For a nth SVM, only examples in that class are positive and reaming are negative. The computation time is less but at a compromised efficiency. OVO creates a pairwise 0.5N(N-1) SVM's and pairwise voting to accommodate new samples for solving multi class problems. DAG training is from OVO model and testing is from binary acyclic graph model. ECOC disambiguates output binary codes to construct a code word matrix which is compared with generated bit vectors by selecting row as a class having minimum hamming distance. This method gives good classification rates compared to other four at the cost of speed of execution. The slower speed is due to the increased length of code words to disambiguates N classes. The minimum code words in ECOC is $\log_2 \boldsymbol{N}$ to a maximum of $2^{N-1} - 1$ bits. Comparing the multi class SVM methods from MALAB implementation, we found

ECOC is performs better at optimum speeds. The similarity measure for 24 different kuchipudi dance mudras using computer vision model and machine learning algorithm is executed.

3. RESULTS AND DISCUSSION

The dataset consists of 24×5 images of Indian dance form kuchipudi are collected from various sources. These 120 images are contrast enhanced by 20% to smooth pixel values. Feature extraction module is initiated to extract features for the 120 mudras. Each mudra feature is labelled to identify them with a particular class. The class labels are the names of the mudras in kuchipudi dance form. We came to understand that these basic mudras are common to all Indian dance forms listed in [1].

Figure 5 shows the five features used on some mudras. Visual observations of the Figure 5 provide a better performing feature vector in the set {HOG, SURF, SIFT, LBP and HAAR}. This particular application of computer vision on human hands indicate HOG as the better performer compared to other 4 feature extraction models.

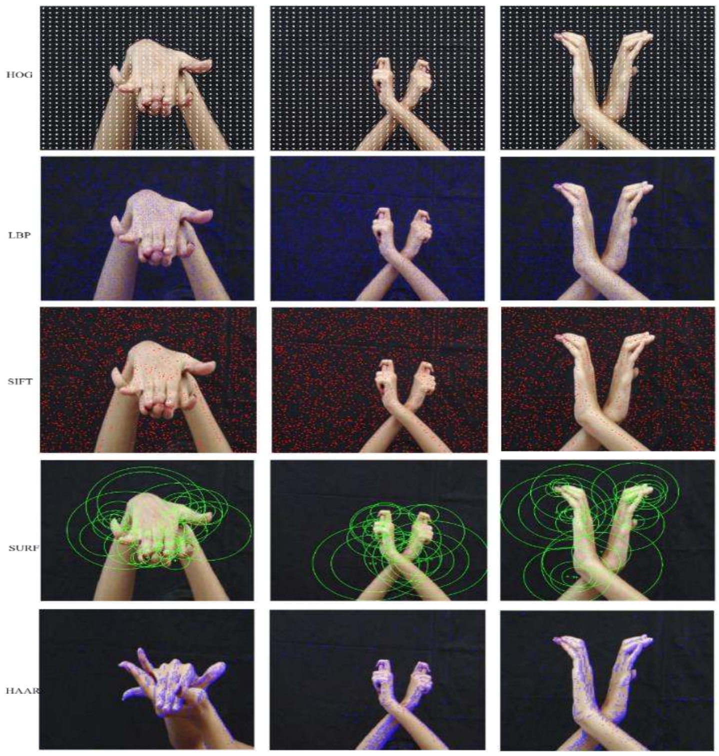

Figure 5. Feature Vector generations from 5 feature extraction models

The other problem encountered is in the number of feature vectors produced per image mudra. Depending on the hand density in the image frame, the number of features in each feature vector are of different size. To tackle this problem, we modified the feature vectors of all images to a normalized feature size. The normalization process involved selection of important features based on magnitude of feature vectors.

The max pooling algorithm is used to extract useful features from a set of features. The support vector machine is supplied with the normalized feature vectors from a set of mudras. Training on these set of mudras is given to the SVM. A set of 24 multiple classes of kuchipudi dance mudras is the target vector. Training vector consists of only one mudra set, that was perfectly captured during lab trials.

Testing SVM by using the same set of mudras resulted in a 100% match to the class. The class labels are [Pataka, Tripataka, Ardhapataka, Kartarimukha, Mayura, Ardhachandra, Arala, Shukatunda, Mushthi, Shikhara, Chandrakala, Sarpashirsha, Simhamukha, Trishula, Swastikam, Matsya, Kurma, Varaha, Garuda, Shivalingam, Pushpaputam, Karkatam, Kapotam, Bherunda]. For HOG features the confusion matrix is shown in Figure 6.

	Pat	Trip	Ardp	Kar	May	Ardc	Ara	Shu	Mus	Shi	Cha	Sar	Sim	Tris	Swa	Mat	Kur	Var	Gar	Shi	Push	Kark	Kap	Bher
Pataka	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Tripataka	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ardhapataka	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kartarimukha	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mayura	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ardhachandra	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arala	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Shukatunda	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mushthi	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Shikhara	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chandrakala	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sarpashirsha	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Simhamukha	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Trishula	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Swastikam	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Matsya	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Kurma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Varaha	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Garuda	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Shivalingam	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Pushpaputam	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Karkatam	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Kapotam	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bherunda	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Figure 6. Confusion matrix between lab dataset and youtube frame dataset for HOG features

The confusion matrix gives the matching metrics between the trained samples and the testing samples. The training samples for SVM and the testing samples were different in Figure 6. Training was given only once using the lab captured dance images. Testing is done with lab images, web images and YouTube images. The confusion matrix indicates a 75% match between the mudras of unseen by the SVM.

The mudra recognition frequency (MRF) is defined as number of correctly recognized mudras to total number of mudras used for classification. MRF is improved by increasing the training vector from one mudra set to two mudra sets. For a 2 mudra set training involving both lab captured and web images the classification of unseen mudras in improved by 14%. The MRF in this case is around 89%.

The reason for misclassification between similar mudras can be attributed to the hand shapes, hand colors, hand orientations and hand textures. The next best feature vector that has shown maximum MRF is SIFT. For same training and testing vectors, SIFT has a MRF of 96%. However, the MRF is down to 71% for different training and testing samples. In case of multiple training vectors, SIFT showed an increase in MRF by 9%.

The overall MRF's for all 5 feature vectors used is plotted in Figure 7. Plot shows MRF values for single same set training and testing (1STTV), single different set training and testing (1DTTV), two same set training and testing (2STTV) and two different set training and testing (2DTTV). Along with the proposed feature extraction models, we also tested SVM with multi-feature extraction models with HOG combination. The plots show an increase in the MRF value for HOG combined features. Other combinations of feature vectors are also tested but the results were not encouraging and were discarded from reporting in the plot of Figure 7.

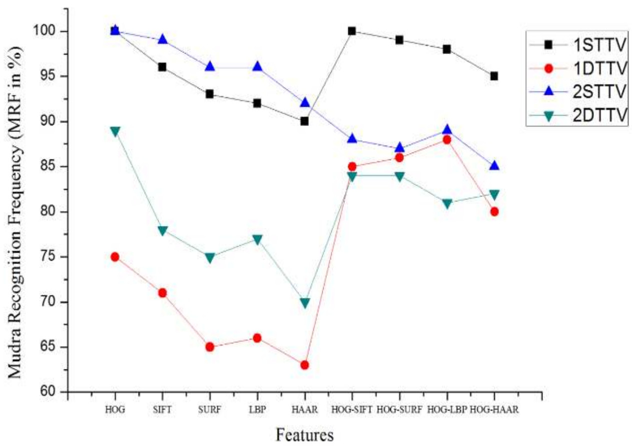

Figure 7. Plot comparing various feature vectors with respect to MRF

The results are validated by measuring a parameter called structural similarity index (SSIM) between the mudras using a graphical user interface (GUI). The GUI has on one side a query mudra and the other side in a mudra of different image along with their names. Figures 8 and 9 shows the operation of GUI for same mudra images and different mudra images for the same class.

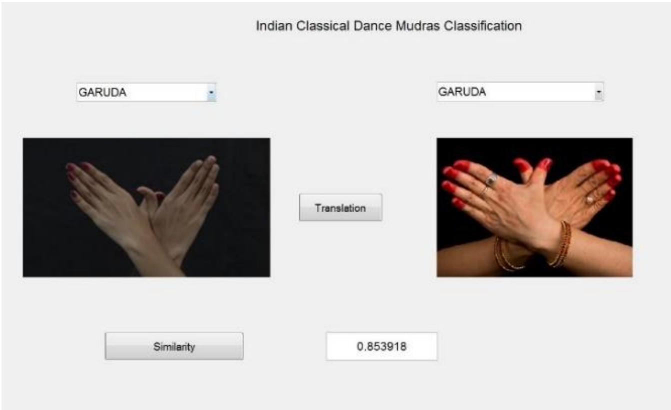

Figure 8. GUI showing SSIM for same mudra image of a class for training and testing

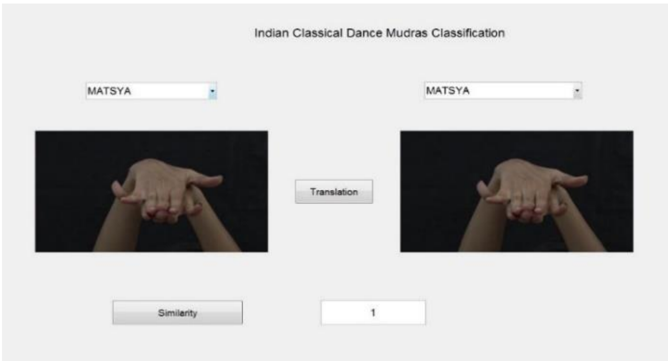

Figure 9. GUI showing SSIM for different mudra image of a class for training and testing

HOG features is providing good feature extraction compared to other types of features commonly used in computer vision for dace mudra classification. In this work, we also used two more segmentaion methods popular with computer vision namely marker controlled watershed (MCW) [23] and simple linear iterative clustering (SLIC) [24] for dance mudra segmentation. The shape or edge features are extracted from the mudra images and are classified using SVM classifier.

The similarity estimate between the HOG, MCW and SLIC are compared using Structural similarity index measure (SSIM) [25] on the extracted features from a hand segmented image. The similarity index measures are shown in Table 2. We find that HOG features are closely related in structural connectivity compared to other two methods of feature extraction. Hence when classified using Multi class SVM, HOG features registered a higher MRF of 98%. For MCW and SLIC MRF is around 66%, which is way below the HOG.

Table 2. SSIM based Comparison

Mudra Names	Watershed Based Pose Estimation	Slic Basesd Dance Pose Estimation	Our Proposed Method
Pataka	0.668	0.771	0.871
Tripataka	0.681	0.782	0.882
Ardhapataka	0.656	0.748	0.848
Kartarimukha	0.649	0.757	0.857
Mayura	0.652	0.787	0.887
Ardhachandra	0.659	0.762	0.862
Arala	0.661	0.751	0.851
Shukatunda	0.674	0.779	0.879
Mushthi	0.678	0.773	0.873
Shikhara	0.661	0.771	0.871
Chandrakala	0.501	0.681	0.781

Sarpashirsha	0.524	0.696	0.796
Simhamukha	0.598	0.671	0.771
Trishula	0.581	0.654	0.754
Swastikam	0.527	0.707	0.707
Matsya	0.511	0.694	0.794
Kurma	0.594	0.669	0.769
Varaha	0.617	0.699	0.799
Garuda	0.624	0.698	0.824
Shivalingam	0.687	0.719	0.814
Pushpaputam	0.648	0.751	0.801
Karkatam	0.624	0.764	0.799
Kapotam	0.621	0.741	0.806
Bherunda	0.629	0.724	0.794

Table 3. PSNR based Comparison

Mudra Names	Watershed Based Pose Estimation	Slic Basesd Dance Pose Estimation	Our Proposed Method
Pataka	8.35	9.15	12.74
Tripataka	8.17	9.27	12.59
Ardhapataka	8.01	8.81	12.46
Kartarimukha	8.34	9.26	12.57
Mayura	8.81	9.38	12.49
Ardhachandra	8.52	9.29	12.65
Arala	8.45	8.92	12.38
Shukatunda	8.57	9.09	12.29
Mushthi	8.15	9.21	12.56
Shikhara	8.47	9.51	12.93
Chandrakala	7.92	7.91	10.12
Sarpashirsha	7.85	8.01	10.26
Simhamukha	8.05	8.96	10.04
Trishula	7.95	8.89	9.98
Swastikam	7.99	8.12	10.46
Matsya	8.04	8.99	10.01
Kurma	8.11	8.14	10.17
Varaha	7.65	8.07	10.31
Garuda	7.24	7.94	10.56
Shivalingam	8.01	7.99	11.65
Pushpaputam	7.91	8.21	10.91
Karkatam	7.76	8.19	10.56
Kapotam	7.92	8.11	10.84
Bherunda	8.09	8.26	10.99

Table 4. IQI based comparison

Mudra Names	Watershed Based Pose Estimation	Slic Basesd Dance Pose Estimation	Our Proposed Method
Pataka	0.723	0.762	0.896
Tripataka	0.736	0.773	0.907
Ardhapataka	0.698	0.739	0.873
Kartarimukha	0.691	0.748	0.882
Mayura	0.694	0.778	0.912
Ardhachandra	0.701	0.753	0.887
Arala	0.703	0.742	0.876
Shukatunda	0.716	0.770	0.904
Mushthi	0.720	0.764	0.898
Shikhara	0.703	0.762	0.896
Chandrakala	0.543	0.672	0.806
Sarpashirsha	0.566	0.687	0.821
Simhamukha	0.640	0.662	0.796
Trishula	0.623	0.645	0.779
Swastikam	0.569	0.698	0.732
Matsya	0.553	0.685	0.819
Kurma	0.636	0.660	0.794
Varaha	0.659	0.690	0.824
Garuda	0.666	0.689	0.849
Shivalingam	0.729	0.710	0.839
Pushpaputam	0.690	0.742	0.826
Karkatam	0.666	0.755	0.824
Kapotam	0.663	0.732	0.831
Bherunda	0.671	0.715	0.819

Peak signal to noise ratio (PSNR) [26] in db is a measure of differentiating the amount of unwnatedness in the image features. When PSNR is computed on extracted features and the ground truth features, HOG features for dance mudra images registered highest value. This results are shown in Table 3. PSNR shows that there is a high relativity between HOG features of original mudras and the Hand segmented ground truth mudras, compared to MCW and SLIC features.

Image quality index (IQI) [27] measures the quality of features from all three algorithms compared to ground truth image. Table 4 gives the measures of comparison on different dance mudra images. The values show that HOG matins good feature quality compared to the other two algorithms MCW and SLIC. For video dance classification and analysis, SLIC and Active Contours can extract better segmentation outputs when more information in the form of color, shape and texture information is provided as an input to the convex optimization function. In future works, we propose to use features described in [28] with Artificial neural network models in [29] related to big data applications modules discussed in [30] on Indian classical dance videos available in our database and the internet.

4. CONCLUSION

An attempt is made to find similarity between dance mudras of Indian classical dance form kuchipudi based on image processing models and pattern classifiers. Five feature extraction techniques are compared for this work. Multi class Support vector machine classified these features and the performance of the classifier with respect to a particular feature is measured. Visual verification and structural verification using SSIM are preformed to check the classifiers performance. The SVM classifier registered an average MRF of 90% with HOG feature vector and the remaining feature vectors produced less than 80% matching. A GUI is built to validate the results produced by feature vectors using SSIM indicator. The SSIM indicator has closely related the feature models of HOG and SIFT for same and different data sets. Most of the mudras with two hands produced occlusions that induced bottleneck's during feature extraction stage. This model of mudra classification will help enhance the learning capacity of a first time learner.

REFERENCES

[1] A Karana in dance is defined as "The coordination of the movements of the hands and feet" , Naidu, N. Naidu, B.V. Pantulu, P.R. Tandava Lakshanam :The Fundamentals of Ancient Hindu Dancing. New Delhi,: Munshiram Manoharlal, 1971, 1980, p.19.

[2] http://natyanjali.blogspot.in/

[3] Okada, A., Buckingham Shum, S. & Sherborne, T. 2008 Knowledge Cartography: Software Tools and Mapping Techniques. (eds.) London: Springer.

[4] Bailey, H, Buckingham Shum, S, LeBlanc, A, Popat, S, Rowley, A and Turner, M (2009) Dancing on the Grid: Using e-Science tools to extend choreographic research. *Philosophical Transactions of the Royal Society A*, 1898; 367: 2793 – 2806.

[5] Weick, Karl E. Sensemaking in organizations. Vol. 3. Sage, 1995.

[6] Kozel, Susan. Closer: performance, technologies, phenomenology. MIT Press, 2007.

[7] Chatterjee, S., Matrix estimation by universal singular value thresholding. *The Annals of Statistics*, 2015; 43(1):177-214.

[8] IKGD Putra, E Erdiawan, "High performance palmprint identification system based on two dimensional gabor," *TELKOMNIKA Telecommunication Computing Electronics and Control.,* vol. 8, no. 3, pp. 309-318, 2010.

[9] Celenk, M., A color clustering technique for image segmentation. *Computer Vision, Graphics, and Image Processing*, 1990; 52(2), 145-170.

[10] Kishore, P. V. V., D. Anil Kumar, E. N. D. Goutham, and M. Manikanta. *Continuous sign language recognition from tracking and shape features using Fuzzy Inference Engine.* In Wireless Communications, Signal Processing and Networking (WiSPNET), International Conference on, 2016; 2165-2170. IEEE.

[11] Kishore, P. V. V., S. R. C. Kishore, and M. V. D. Prasad. Conglomeration of hand shapes and texture information for recognizing gestures of Indian sign language using feed forward neural networks. *International Journal of engineering and Technology (IJET)*, ISSN (2013): 0975-4024.

[12] Anandh, A., K. Mala, and S. Suganya. *Content based image retrieval system based on semantic information using color, texture and shape features.* In Computing Technologies and Intelligent Data Engineering (ICCTIDE), International Conference on, 2016; 1-8. IEEE.

[13] Lowe, D.G., Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 2004; 60(2): 91-110.

[14] Viola, P. and M. Jones. *Rapid object detection using a boosted cascade of simple features*. in Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on. 2001. IEEE.

[15] Rosten, E. and T. Drummond. *Machine learning for high-speed corner detection*. in European conference on computer vision. 2006. Springer.

[16] Bay, H., et al., Speeded-up robust features (SURF). *Computer vision and image understanding*, 2008; 110(3): 346-359.

[17] Hamed, A., N.A. Belal, and K.M. Mahar. *Arabic Sign Language Alphabet Recognition Based on HOG-PCA Using Microsoft Kinect in Complex Backgrounds*. in 2016 IEEE 6th International Conference on Advanced Computing (IACC). 2016. IEEE.

[18] Liang, C.-W. and C.-F. Juang, Moving object classification using local shape and HOG features in wavelet-transformed space with hierarchical SVM classifiers. *Applied Soft Computing*, 2015; 28: 483-497.

[19] Lee, S.-H., et al. *An efficient selection of HOG feature for SVM classification of vehicle*. in 2015 International Symposium on Consumer Electronics (ISCE). 2015. IEEE.

[20] Galar, M., et al., An overview of ensemble methods for binary classifiers in multi-class problems: Experimental study on one-vs-one and one-vs-all schemes. *Pattern Recognition*, 2011; 44(8): 1761-1776.

[21] Zhang, X., S. Ding, and T. Sun, Multi-class LSTMSVM based on optimal directed acyclic graph and shuffled frog leaping algorithm. *International Journal of Machine Learning and Cybernetics*, 2016; 7(2): 241-251.

[22] Bai, X., et al., Learning ECOC code matrix for multiclass classification with application to glaucoma diagnosis. *Journal of medical systems*, 2016; 40(4): 1-10.

[23] Lu, Siyuan, Shuihua Wang, and Yudong Zhang. A note on the marker-based watershed method for X-ray image segmentation. *Computer Methods and Programs in Biomedicine*, 2017; 141: 1-2.

[24] Rantalankila, Pekka, Juho Kannala, and Esa Rahtu. *Generating object segmentation proposals using global and local search.* In Proceedings of the IEEE conference on computer vision and pattern recognition, 2014; 2417-2424.

[25] Wang, Zhou, Alan C. Bovik, Hamid R. Sheikh, and Eero P. Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing,* 2004;13(4): 600-612.

[26] Tanchenko, Alexander. Visual-PSNR measure of image quality. *Journal of Visual Communication and Image Representation, 2014;* 25(5): 874-878.

[27] Prashanth, H. S., H. L. Shashidhara, and Balasubramanya Murthy KN. *Image scaling comparison using universal image quality index*. In Advances in Computing, Control, & Telecommunication Technologies, 2009. ACT'09. International Conference on, 2009;859-863. IEEE.

[28] Rao, G. Ananth, and P. V. V. Kishore. "Sign Language Recognition System Simulated for Video Captured with Smart Phone Front Camera." International Journal of Electrical and Computer Engineering (IJECE) 6, no. 5 (2016): 2176-2187.

[29] Rao, D. Narasimha, T. Surendra, and S. Tara Kalyani. "DPFC Performance with the Comparison of PI and ANN Controller." International Journal of Electrical and Computer Engineering (IJECE) 6, no. 5 (2016): 2080-2087.

[30] Thanekar, Sachin Arun, K. Subrahmanyam, and A. B. Bagwan. "Big Data and MapReduce Challenges, Opportunities and Trends." International Journal of Electrical and Computer Engineering 6, no. 6 (2016): 2911.

BIOGRAPHIES OF AUTHORS

K. V. V. Kumar born in India 1987. Obtained his B.Tech, from VRS&YRN College of Engineering and Technology Chirala. During 2007-2010. & M.Tech from K.L University in the Specialization of Communication and Radar systems during 2010-2012.He is having More than 5 years teaching experience and having 8 international and national journals / Conference papers Like IEEE and SPRINGER He is Associate member of I.E.T.E and ISSE other bodies Like I.S.T.E. His research interested areas includes Image processing and Signal Processing. and Video Processing.

P.V.V.Kishore is having Ph.D degree in Electronics and Communications Engineering from Andhra University College of engineering in 2013. He received M.Tech degree from Cochin University of science and technology in the year 2003.He received B.Tech degree in electronics and communications engineering from JNTU, Hyd. in 2000. He is currently full professor and Image,signal and speech processing Research Head at K.L.University, ECE Department. He is currently engaged in a project sponsered by Department of Science and Technology,SEED, Government of India, under the Technology for Disabled and Elderly scheme, related to sign language 3D invarient models for Indian sign language. His research interests are digital signal and image processing, Artificial Intelligence and human object interactions. He is currently a member of IEEE. He has published 70 research papers in Various National and International journals and conferences including IEEE, Springer and Elsevier.