

## Attributed Relational Graph Based Feature Extraction of Body Poses In Indian Classical Dance Bharathanatyam

Athira. Sugathan<sup>\*</sup>, Suganya. R<sup>\*\*</sup>

<sup>\*</sup>(Department of Computer Science, Amrita Vishwa Vidhyapeetham, Coimbatore -641 112)

<sup>\*\*</sup>(Department of Computer Science, Amrita Vishwa Vidhyapeetham, Coimbatore -641 112)

### ABSTRACT

Articulated body pose estimation in computer vision is an important problem because of convolution of the models. It is useful in real time applications such as surveillance camera, computer games, human computer interaction etc. Feature extraction is the main part in pose estimation which helps for a successful classification. In this paper, we propose a system for extracting the features from the relational graph of articulated upper body poses of basic Bharatanatyam steps, each performed by different persons of different experiences and size. Our method has the ability to extract features from an attributed relational graph from challenging images with background clutters, clothing diversity, illumination etc. The system starts with skeletonization process which determines the human pose and increases the smoothness using B-Spline approach. Attributed relational graph is generated and the geometrical features are extracted for the correct discrimination between shapes that can be useful for classification and annotation of dance poses. We evaluate our approach experimentally on 2D images of basic Bharatanatyam poses.

**Keywords** – Attributed relational graph, feature extraction, skeletonization

### I. Introduction

The main goal of the work is to extract geometrical features from the attributed relational graph of the 2D dance pose in images that are under uncontrolled imaging conditions. Features like orientation, length of branches, strength, and vector position of each node are extracting from the graph for classification. The uncontrolled images will have background clutter, diversity in clothing, illumination and the object may appear at any orientation and scale. In Bharatanatyam, each person's appearance is unconstrained, as he or she can wear any kind of bharathanatyam dresses, with high complex designs and colours/textures.

Bharatanatyam is the most popular classical dance which has 3 main aspects namely Nritta, Nritya, and Natya ie; poses, shorthand sign languages and facial expressions. This work involves only superior body poses ie; upper body poses of basic bharathanatyam poses of unique persons from 2D images to evaluate the similarity. The basic step of Bharathanatyam is called ADAVU. An adavu is the combination of standing posture, hand symbols and leg positions. Here, we are concentrating only on poses and short hand signs of basic dance steps. We built skeletonization and attributed relational graph prior to the feature extraction of dance poses from 2D images. Skeleton of a human structure is the powerful tool for efficient shape matching and it helps to understand both the shape and topology of object. Thinning and pruning methods included in skeletonization where thinning method makes the

skeleton into a single pixel structure and pruning method removes the unwanted branches presented in the thinned skeleton. B-spline approach is a set of continuous cubic spline curves which is used to get smoothed skeleton. The attributed relational graph is generated to find the geometrical features by setting the nodes in each endpoint, joint points and vertex points. The vectors of each nodes in the graph ie; the (x, y) position of each nodes, length of each branch, strength and orientation of the object are taken as the features for extraction. This allows us to leads to more correct discrimination between shapes by matching the geometrical features between the training data and testing data using a classifier. The experiments performed using 110 images of different bharathanatyam poses of different persons taken by HTC camera of 8 megapixel and downloaded 83 images of hand mudhras and poses of bharathanatyam from <http://www.dreamstime.com/photosimages/exponent/bharatanatyam-dance.html>. The work of recognizing dance action has a lot of practical applications that includes the software for the study and understanding of Indian classical dance Bharathanatyam.



Fig.1.Basic pose

The next sections include literature survey, proposed method and obtained results. In Section II we describe competitive approaches related to our methods. Section III presents details of our method, while Section IV presents the experimental results using input images. Also, we discuss some limitations and contributions of our work atlast.

## II. Literature Survey

Apratim Sharma et al. [1] proposed a method to find the group of poses and classify the action sequences of Bharathanatyam steps in real time using kinect. Skeletonization of each pose is obtained and joint angles are computed based on the orientation of every joint in the form of rotation matrices based on its orientation and scale. Cluster all the poses and histogram of poses is used as a feature vector for classification. The methods used here are good in real-time kinect videos but not good in images.

Marcin Eichner et al. [2] introduced Human Pose Co-estimation where many people in the image are in a common pose and estimate their poses jointly. This method demonstrated a weakly supervised learning of poses that is from images but not from manual annotations. Dictionary of poses can be generated from the annotated colored stickmen in the human body parts and each pose class is represented by its prototypes. Direct model is used in this method where it finds a single prototype and all local poses are equal to it.

Bangpeng Yao et al. [3], proposed a method of object detection that provides better human pose estimation and human pose estimation improves the accuracy of detecting the objects by considering the mutual context. Poses are obtained by clustering the configurations of human body parts. First denote the annotation of human body parts in an image and then align the annotations. Use hierarchical clustering with the maximum linkage measure to obtain a set of clusters. This method describes the human object interaction and needs to annotate the human body parts and objects in each training image. In this work, weakly supervised or unsupervised approach to

understand human-object interaction activities is not used.

Ling Shao et al. [4] proposed a method for human action recognition from silhouettes that combines the advantages of both local and global representations. First, bounding box is normalized to reduce the dimension of each frame and remove the variations of translation and scale. The normalized silhouettes are used as the features in each frame by extending the set of features model. The 2D silhouette mask is converted to 1D mask from each feature vector by scanning it from top to bottom. So, each frame is represented as the binary element vector and the length is taken as the multiplication of both row and column. This is not an effective method to encode correlations of action descriptors.

M. Andriluka et al. [5], proposed a method to develop a generic model for human detection and pose estimation that allows to detect highly articulated human body parts and to estimate their poses. A pictorial structure model is created and the parts are obtained using the part detector. The mean relative joint position is learned using maximum likelihood estimation. A fully connected graphical model for representing articulations which uses discriminative part detectors is proposed.

C. Di Ruberto et al. [6], proposed a method to use the skeleton of objects in the images in computer vision and pattern recognition where the object features are needed for classification. Skeletonization method is used here to get a model of the graph that leads to more correct representation of shapes by an attributed graph matching algorithm. The features like joint positions, edge positions, length are taken as the features in this method. This work fails to get more accurate graph model and fails to get the better determination between shapes while attributed graph matching process.

## III. Proposed method

The architecture of the system is shown in the figure 2.

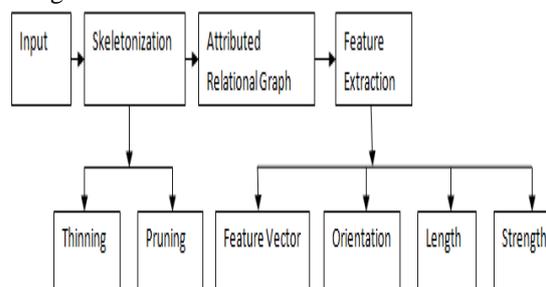


Fig.2.Proposed system architecture

### 3.1. Skeletonization

Skeleton of a human structure is a good representation of human pose. The reason for obtaining the skeleton of an object is that it is easier

to analyze than the original image and also maintaining the essential properties of the original image. Given an input binary image of poses and short hand signs (mudhras), skeletonization changes non-skeletal object pixels into background pixels. Different skeletonization techniques are used to get a skeleton. Some of them preserve topology while others preserve geometry of the original object. To accurately preserve both topology and geometry from 2-D images, thinning algorithm is used.

### 3.1.1 Thinning Algorithm

Thinning algorithm preserves both topological and geometrical properties of object from 2D images. It retains the topology of the original object and forces the skeleton to be in the middle of the object and also preserves the end points of the original image. A morphological thinning operation is used here, which is used to remove the foreground pixels from binary images. It results in a single pixel line thick and connected skeleton of the input image which is useful for shape description. The input image is thinned with a series of structuring elements and the object is reduced to a set of one pixel width connected lines. The skeleton is considered as a connected graph therefore each vertex is considered as an endpoint or junction points and each edge is considered as curve points. The end points, junction points and curve points of skeleton are detected which is important for the structural description.

Skeleton is obtained by translating the origin of the structuring element to each possible pixel position in the image and comparing it with the underlying image pixels. If foreground and background pixels in the structuring element exactly match the pixels in the image, pixel underneath the origin of the structuring element is set to the background. Otherwise, there is no change further.

Image  $A$  is thinned by a structuring element  $B$  and it is defined in terms of the hit-or-miss transform:

$$A \ominus B = A - (A \otimes B) = A \cap (A \otimes B)^c \quad (1)$$

Thinning of image  $A$  by a sequence of structuring elements:

$$A \circledast \{B\} = (\dots ((A \ominus B_1) \ominus B_2) \dots) \ominus B_n \quad (2)$$

The process is to thin  $A$  by structuring element  $B_1$ , then thin the result with structuring element  $B_2$  and repeated until  $A$  is thinned with one pass of  $B_n$ . The entire process is repeated until no further changes occur.

### 3.1.2 Pruning Algorithm

Pruning algorithm is an essential component for skeletonization after thinning. The skeleton of an object often contains both spurious and rough branches due to the boundary irregularities. To eliminate spurs on a skeleton a morphological pruning transformation is applied. It starts at the end

points and recursively removes a given number of points from each branch proceeds until stability is reached. Assume that the length of the spur component is within a specific number of pixels. Proposed algorithm has a size  $E$  for the pruning is equal to 4% of the skeleton length. First partition the skeleton into branch parts by subtracting the junction points from it to eliminate only the branches with distance  $E$  from an end point. By using a morphological reconstruction method, remove the branches that containing end points only. Then remove all the branches containing lesser pixels than  $E$ . The remaining branches with junction points and the branches that were not reconstructed from end points are united and obtained a pruned skeleton.

### 3.1.3 Smoothened Skeleton

In skeletal representation, to improve the smoothness and to reduce the amount of unwanted data, a set of continuous spline curves is used. It approximates the unnecessary branches of the original skeleton. Such a continuous representation allows us to compute the graph more easily and accurately. B-spline curves are piecewise polynomials that are defined by knots and points  $(t_i, y_i)$ . In this work we used cubic spline curves with degree 3. Given the nodes  $t_i$  and control points  $V_i$  the piecewise cubic B-spline curve is given by:

$$S(t) = \sum_i B_i^3(t) V_i \quad (3)$$

Here,  $B_i^3$  is the piecewise cubic B-spline. The control points  $V_i$  have both  $x$  and  $y$  components, and the curve is defined as

$$S(t) = (S_x^{(t)}, S_y^{(t)}) = \sum_i B_i^3(t) V_i = \left( \sum_i B_i^3(t) x_i, \sum_i B_i^3(t) y_i \right) \quad (4)$$

The  $x$  and  $y$  components of the curve are separately multiplied by B-splines, and the resulting set of  $(x, y)$  points gives a curve. A B-spline curve actually needs more nodes than control points and it is not defined over the entire interval  $[t_1, t_m]$  where  $m$  is the number of knots. Instead, for a cubic B-spline curve, the number of control points is  $m - 4$ , and the curve is defined over  $[t_4, t_m - 3]$ .

## 3.2 Attributed Graph

Skeleton can be represented as graph with end points and junction points as vertices and branches as edges. An attributed relational graph is built and used as a structural object for classification by means of graph matching. Attributed graph has set of nodes which are union of end points and junction points and set of edges which are represented by skeleton branches. It is partitioned into number of skeletal branches  $S_i(x), i=1,2,\dots,N$ . The graph is represented by adjacency matrices and for each relation type it have different adjacency matrix.

Weights are chosen to associate with the graph that links both geometrical and topological features.

The arrangements of skeleton branches can be obtained by skeletal branch orientation. The angle between the horizontal axis and the axis by the least second moment is the angle of object.

$$\theta = \frac{1}{2} \tan^{-1} \left[ \frac{2\mu_{11}}{\mu_{20} - \mu_{02}} \right] \quad (5)$$

Where,  $\mu_{ij}$  is the second moments that are computed over the nodes of the spline curves and forming approximated skeleton. The rate of change of the tangent vector in terms of arc length along with the curve is defined as the curvature of a curve. The planar curve  $c(t) = (x(t), y(t))$  is not parameterized with respect to arc length, therefore its curvature is:

$$k(t) = \frac{|x' y'' - x'' y'|}{(x'^2 + y'^2)^{3/2}} \quad (6)$$

With  $x' = dx/dt$  and  $y' = dy/dt$ .  $s_i(t)$  is the spline which we used to represent  $S_i(x)$  that is differentiable twice and can evaluate  $k(t)$ .

### 3.3 Feature Extraction

The main part of pose estimation is the feature extraction which helps for the correct discrimination between shapes of the objects. In this work the weights like angle, feature vector, length of the branches, strength etc are taken as features and extracted. Feature vector is taken as a feature for extraction. Each node position is obtained as  $(x,y)$  coordinates and the nodes for every object of same shape will be in the same  $(x,y)$  position in the graph. The graph window is normalized into a fixed size for the finding the node position. Angle of an object is calculated by the least second moment of inertia and the horizontal axis. This gives the correct orientation of all the branches from the junction points. Angle is a good feature which gives the exact position of each branches and it is easy for classification. Each of the curves  $s_i(t)$  has a length  $\lambda_i$  has been computed by the classical formula for the arc length and the integral has been numerically calculated.

$$\lambda_i = \int_{t_0}^{t_{ni}} \sqrt{\left( \frac{ds_i^{(1)}}{dt} \right)^2 + \left( \frac{ds_i^{(2)}}{dt} \right)^2} dt \quad (7)$$

The ratio between the length  $\lambda_i$  of the branch and the euclidean distance between the extreme points gives the strength of the skeleton branch.

$$\sigma_i = \frac{\lambda_i}{\sqrt{(x_{mi}^{(i)} - x_0^{(i)})^2 + (y_{mi}^{(i)} - y_0^{(i)})^2}} \quad (8)$$

Where  $a_0^{(i)} = (x_0^{(i)}, y_0^{(i)})$  and  $a_{mi}^{(i)} = (x_{mi}^{(i)}, y_{mi}^{(i)})$  are the extreme points of  $S_i(x)$ .

A graph is modeled whose set of links is represented through the set of vector of weights with

an object  $O$  with a skeleton  $X$  partitioned in  $N$  parts, is modeled by a graph:

$$E = \{(m_i, \theta_i, \lambda_i, \sigma_i)\} \quad i=1, 2 \dots N \quad (9)$$

## IV. Experimental result

The experiments are performed using the dataset of 2-D images of different basic steps of Indian classical dance Bharathanatyam. It includes 110 RGB images of basic bharathanatyam poses of different people of unique experiences and size that are taken by normal HTC camera of 8 megapixels and downloaded 83 images of hand mudhras and poses of bharathanatyam from <http://www.dreamstime.com/photosimages/exponent/bharathanatyam-dance.html>. The images used in this project are of plain background, so there is no background clutter present. Every image has only one person present in it.



Fig.3.Input Image



Fig.4. Binary Image

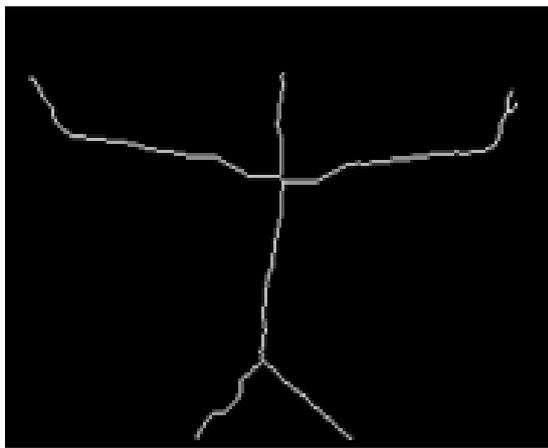


Fig.5. Thinned Image

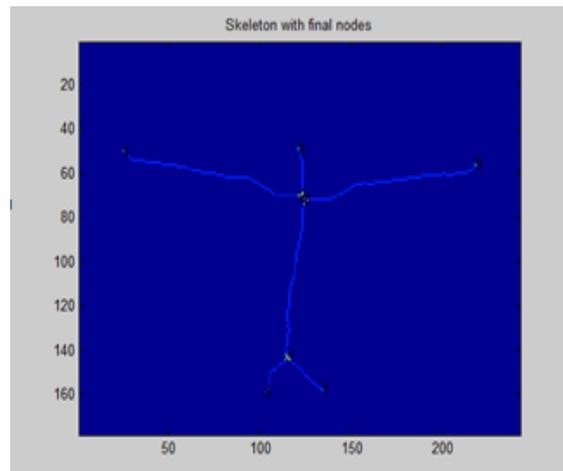


Fig.8. Skeleton with Nodes

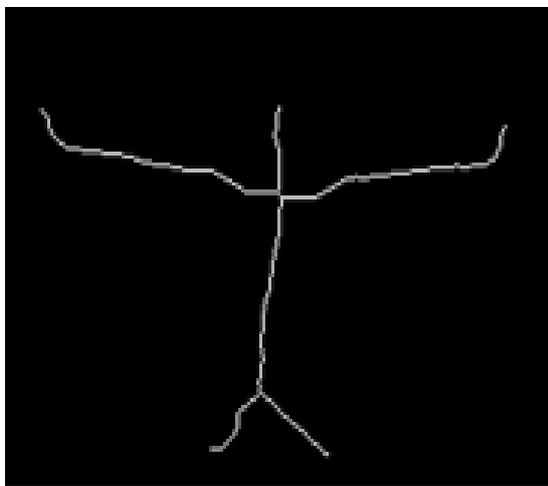


Fig.6. Pruned Image

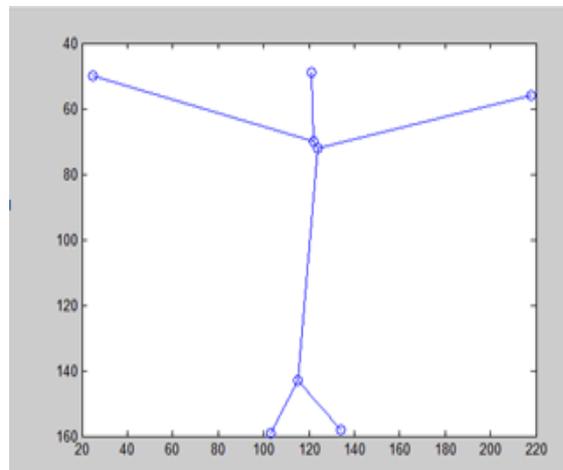


Fig.9. Graphical Representation

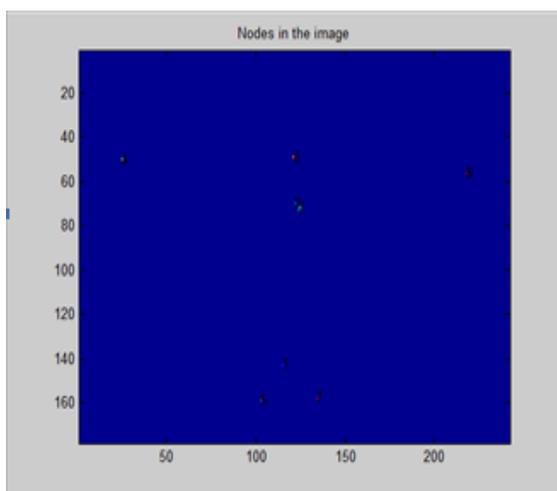


Fig.7. Nodes in the Image



Fig.10. Feature Vector

1	2	3	4
1	1	0	0
2	1	0	0
3	1	0	0
4	0	0	1
5	0	0	1
6	0	0	0
7	1	0	0
8	0	0	0
9	0	0	0
10	0	0	0
11	0	0	0
12	0	0	0

Fig.11. Angle Feature Extraction

1	2
1	16.7929 11.3578
2	189.3172 128.1015
3	16.7929 11.3578
4	189.3172 128.1015
5	16.7929 11.3578
6	189.3172 128.1015
7	16.7929 11.3578
8	189.3172 128.1015
9	16.7929 11.3578
10	189.3172 128.1015
11	16.7929 11.3578
12	189.3172 128.1015

Fig.12. Length

1	2
1	10.3923 14.7648
2	151.6674 216.2475
3	10.3923 14.7648
4	151.6674 216.2475
5	10.3923 14.7648
6	151.6674 216.2475
7	10.3923 14.7648
8	151.6674 216.2475
9	10.3923 14.7648
10	151.6674 216.2475
11	10.3923 14.7648
12	151.6674 216.2475

Fig.13. Strength

### V. Conclusion

In this work a method is proposed to increase the quality of skeleton of human object in 2-D images of Indian classical dance- Bharathanatyam.

A morphological skeleton of a binary image is created to enhance the skeleton quality in order to find more efficient features for classification. This allows finding a graph model with more attributes. In this method the skeleton characteristic points is represented as an attributed relational graph to model the skeleton. The future research will include finding a more accurate graph model, allowing the determination of more efficient attributes for the nodes and the edges. Next work includes classification and annotation of the poses and hand mudhras where it can leads to an automatic application for studying Bharathanatyam. In this work the basic steps of unique person is considered and evaluated.

### References

- [1] Apratim Sharma under the guidance of Dr. Amitabha Mukerjee, "Recognising Bharatanatyam Dance Sequences using RGB-D Data", A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Technology from Indian Institute of Technology, Kanpur, 2013.
- [2] Marcin Eichner and Vittorio Ferrari, "Human Pose Co-Estimation and Applications", *Proceedings of the IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 34, No. 11, November 2012 pp. 2282 – 2288.
- [3] Bangpeng Yao and Li Fei-Fei, "Recognizing Human-Object Interactions in Still Images by Modeling the Mutual Context of Objects and Human Poses", *Proceedings of the IEEE Transaction on Pattern Analysis and machine intelligence*, Vol.34, No.9, 2012, pp.1691-1703.
- [4] Di Wu and Ling Shao, "Silhouette Analysis-Based Action Recognition Via Exploiting Human Poses," *Proceedings of the IEEE transactions on circuits and systems for video technology*, vol. 23, no. 2, February 2013.
- [5] M. Andriluka, S. Roth, and B. Schiele, "Pictorial Structures Revisited, People Detection and Articulated Pose Estimation," *Proceedings of the IEEE Conference of Computer Vision and Pattern Recognition, 2009*, Vol. pp.1014 - 1021.
- [6] C. Di Ruberto, G. Rodriguez, "Recognition of shapes by morphological attributed relational graphs," *Proceedings of the IEEE Conference of Computer Vision and Pattern Recognition, 2004*, 37, 1, Vol. pp.21-31.
- [7] C. Di Ruberto and A.G. Dempster, "Attributed skeleton graphs using mathematical

- morphology”, *Electronics Letters*, vol.37 num.27 (2001) 1325–1327.
- [8] C. Di Ruberto, “Matching and Recognition of Shapes by Morphological Attributed Relational Graphs”, submitted 2002.
- [9] S. Gold and A. Rangarajan, “A graduated assignment algorithm for graph matching”, *Proceedings of the IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 18 num. 4 (1996) 377–388.
- [10] S. Gold and A. Rangarajan, “Graph matching by graduated assignment”, *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 1996, IEEE Computer Society (1996)*, 239–244.
- [11] Yanshu Zhu, Feng Sun, Yi-King Choi, Bert Juetler, Wenping Wang, “Spline Approximation to Medial Axis”, *arXiv:1307.0118v1[cs.GR]29, June 2013*.
- [12] K.J Maccallum and J.M Zhang, “Curve-Smoothing Techniques Using B-Splines”, *The Computer Journal*, Vol.29, No.6, 1986.
- [13] B. Jang and R.T. Chen, “Analysis of thinning algorithms using mathematical morphology”, *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 12 num. 6 (1990) 541–551.
- [14] Salim Jouili and Salvatore Tabbone, “Graph Matching based on Node Signatures”, published in "7th IAPR-TC-15 Workshop on Graph-based Representations in Pattern Recognition-GbRPR 2009 5534 (2009) 154-163", pp154-163, SpringerVerlag Berlin, Heidelberg ©2009.