Multiple Features Indexing and Object Retrieval using Shape

S.Rubiya,
M.E. Department of CSE,
GCE, Tirunelveli.

K.Thulasimani,
Assistant Professor,
Department of CSE,
GCE,Tirunelveli.

ABSTRACT
This Paper presents a very simple and efficient approach that not only performs almost as good as many state-of-the-art techniques but also scales up to large databases. Each shape is indexed based on a variety of simple and easily computable features which are invariant to articulations, rigid transformations, etc. The features characterize pairwise geometric relationships between interest points on the shape. The fact that each shape is represented using multiple features instead of a single global feature that captures the shape and provides robustness to the approach. Shapes in the database are ordered according to their similarity with the query shape and similar shapes are retrieved using an efficient scheme.

Keywords
Fast retrieval, indexing, shape matching.

1. INTRODUCTION:
Image retrieval techniques are useful in many image-processing applications.The technique for image retrieval from a digital collection by using feature-element values that are extracted automatically from the optical contents of the images is called content-based image retrieval. Feature extraction and analysis is performed from the images so that resulting values are comparable by the use of a computing machine for examining the similarity between images. Useful features for content-based image retrieval are considered those that mimic the features seen by humans, those that are perceived by the human vision. The use of such optical features, that reflect a view of image similarity as this is perceived by a man, even if he has difficulty in describing these features, increases the probability that the system recalls images that are similar according to the human perception.

The features that are used for content-based image retrieval are characterized as global when they refer to the whole image. The basic characteristics that are used for content-based image retrieval are: the color, the shape, the texture the location. Using a single feature for image retrieval cannot be a good solution for the accuracy and efficiency. High dimensional feature will reduce the query efficiency, low dimensional feature will reduce query accuracy, so it may be a better way using multi features for image retrieval.

Each point is characterized by the spatial Distribution[2] of the other points relative to it. Similarity computation involves establishing correspondences using bipartite graph matching and thin plate spline (TPS)-based alignment.Each contour [15] is transformed into a string of symbols which is then matched using a modified edit distance. Geometric similarity and matching algorithm[29] uses similarity criterion based on the average of minimum point distances.Applications of shape matching and recognition have made it a very important area of research in the field of computer vision Character recognition, trademark logo retrieval, activity recognition, object recognition, and human pose estimation are a few of the challenging applications that can benefit from accurate and efficient shape matching techniques.

2. RELATED WORKS:
Shape[3] has been classified using inner distance. The inner-distance is defined as the length of the shortest path between landmark points within the shape silhouette. An unsupervised learning approach[5], attempting to discover the set of action classes present in a large collection of training images. These action classes were then be used to label test images.Champer matching method[12], point correspondences on the two shapes have been established. After aligning the shapes using the correspondence given by shape, [15] transform each contour into a string of symbols which is then matched using a modified edit distance.

The hierarchical Procrustes matching algorithm [16]was proposed for finding a point-to-point correspondence between two shapes to that of finding a segment-to-segment correspondence. There is another body of work for capturing part structures in which shapes are represented using shock graphs [19]. The shock graph grammar helps to reduce the shock graph representation to a
unique rooted shock tree which is then matched using a tree matching algorithm. Geodesic shape distribution[34] that measures the global geodesic distance between two arbitrary points on the surface to be able to better capture the intrinsic geometric structure of the data. Given a test shape, the matching bins in the index table are determined.

A single parse through the matching bins returns the most similar shapes. The top matches returned by the single parse retrieval algorithm may directly be used as the similar shapes or there may be a need to further compare the query against the top few matches using a more rigorous algorithm to refine their ordering.

Existing shape matching methods can also be classified based on the kind of input they require. Some methods require the shape to be represented as a closed contour [3], [24] while some others are more flexible in the kind of input they can work with and just require a set of points as their input [2],

[18]. Our approach falls in the first category, but has the advantage of being efficient while being able to handle complex deformations like articulations of part structures.

3. SHAPE REPRESENTATION

Many techniques, including chain code, polygonal approximations, curvature, fourier descriptors and moment descriptors have been proposed and used in various applications Pairwise Geometrical Features.Here we use features that depend only on a few points on the shape and also take the global shape into account. The features in addition to being indexable, should be invariant to different rigid and nonrigid transformations as required by the application. Each shape is characterized by a set of feature vectors. Each vector consists of the following features that are robust to different deformations.

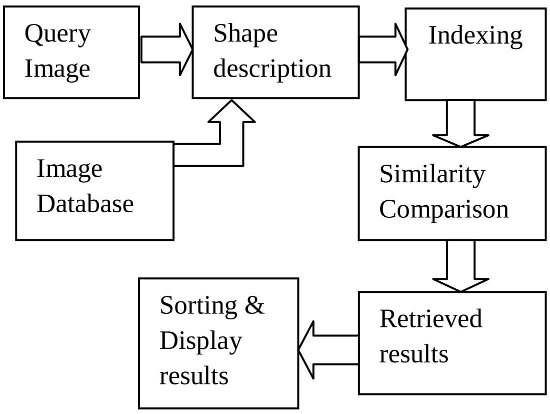

Figure.1.Overview of the shape similarity search system

3.1. Inner Distance Between Two Points

The inner distance(ID) between two points is the length of the shortest path within the silhouette of the shape. Computation of inner distance[3] involves forming a graph with landmark points on the shape forming the nodes. Two nodes in this graph are connected if there is a straight line path between the corresponding points which is completely inside the shape contour. The corresponding edge weight is the Euclidean distance between the two. From this graph, any standard shortest path algorithm can be used to compute the inner-distance for all the unconnected nodes.

3.2. Relative Angles

Relative angles encode the angular relationship between a pair of points. Since absolute orientation of the line segment connecting the points is not invariant to rotations, we use the relative orientation of the connecting line segment with respect to the incident tangents at each end point. If the inner distance is used, this is the relative orientation of the first segment of the path corresponding to the inner distance.

3.3. Contour Distance

The contour distance (CD) is analogous to geodesic distance for 3-D shapes and captures the relative positions of the two points with respect to the entire shape contour. The contour distance between two points for 2-D silhouettes is simply the length of the contour between the two points. The distance is robust to both articulations and contour length preserving deformations and complements inner distance in characterizing the relative location of the point pair with respect to the entire shape.

3.4. Articulation-Invariant Center of Mass

For matching across rigid transformations, the distance of the points and the line segment joining them from the center of mass can be used as additional features to encode their relative placement. Clearly, since the center of mass can change appreciably with articulations, these features are not invariant to articulations. The proposed approach first transforms a given shape to an articulation-invariant space. All objects related by articulations of their part structures get transformed to the same shape in the new space. This essentially means that the distances between the transformed points are invariant to articulations.

The transformation is done using multidimensional scaling. MDS[42] essentially places the points in a new Euclidean space such that the inter-point distances are as close as possible to the given inner distances in a collective manner. The transformation computation involves spectral decomposition of inner product matrix, which is related to the (squared) inner-distance matrix as follows:

$$B = -1/2\ JDJ \qquad (3.1)$$

D- Inner distance matrix

$$J = I - 1/n 1 1^T, \text{ where } 1_{1xn} = [1,1,...,1]^T \qquad (3.2)$$

Where B is symmetric, positive matrix and can be expressed as

$$B = V \Lambda V^T \quad \text{where } \Lambda = \mathrm{diag}(\lambda_1, \lambda_2, \ldots, \lambda_n) \quad (3.3)$$

4. INDEXING AND RETRIEVAL

A shape is represented using a set of indexable feature vectors which are appropriately mapped to a hash table.Query image feature vector is compared with each image feature vector in database.

4.1. Indexing Framework

Hashing the feature vectors of each shape to the index table requires discretization of the space of feature vectors. The steps in the indexing are described below in detail.

1) For each shape in the database, landmark points are extracted from the shape contour.

2) For each pair of landmark points, features are computed. This results in a collection of feature vectors for each shape.

3) Each feature vector is quantized using the proposed quantization scheme.

4) The quantized feature vectors are mapped on to the appropriate bins in the hash table.

4.2. Shape Retrieval

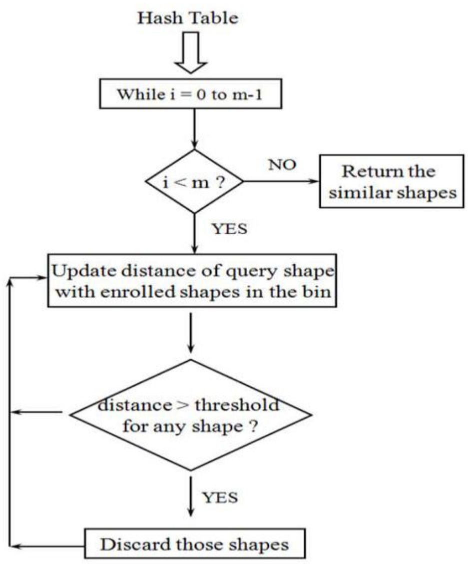

Figure. 2. Schematic Representation Of Shape Retrieval Algorithm

The different steps involved in the retrieval phase are enumerated below.

1)Feature vectors for the query shape are extracted in a manner similar to the one used for indexing.

2) Each vector is quantized using the same quantization steps as used for the shapes enrolled in the database.

3) Hashing each feature vector to the index table results in a list of matching bins.In general, the number of matching bins is much less than the total number of bins in the hash table.

4) The distance of the query with each shape in the database is initialized to zero.

5) Now we parse through the list M and update the distance of the query with each enrolled shape at every step.

6) If during parsing, the distance for any particular shape in the database exceeds a pre-specified threshold, then that shape is discarded from further computation.

7) At the end of the parse, we get a list of shapes from the database which are most similar to the query shape.

5. APPLICATIONS

Efficient Shape matching and retrival is useful for many practical applications.

5.1. Human Pose Estimation

Human activities in videos can often be described by the body pose in still frames. Human pose estimation implies matching corresponding human silhouettes in the 2-D images based on their body posture.

5.2. Activity Classification

The goal of activity classification is to classify the content of human activity sequences in an unsupervised manner without any prior knowledge of the type of actions being performed.

6. RESULTS

In this section we demonstrate experimental results based on input image of .jpg format with width 111 and height 166, which is compared with each shape in the database and top most similar shapes are retrieved and sorted.

Figure.3.Image retrieval based on Human pose.

First column shows query image. Second to sixth columns show the top 5 matches**.**

7. CONCLUSION AND FUTURE WORK

This paper provides an efficient and robust approach for fast matching and retrieval of shapes by computing inner distance for all shapes. As dissimilar shapes are eliminated very early during our retrieval process, little effort is wasted in comparing a query to the database shapes which are very different, making the system scalable. We also proposed a refinement stage to further highlight the usefulness of the proposed shape representation and indexing framework. Future work includes the retrieval of video sequences from database and comparison of color, texture and shape based retrieval.

8. REFERENCES

[1] H. Ling and D. W. Jacobs, "Shape classification using the inner-distance," IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 2, pp.286–299, Feb. 2007.

[2] Y.Wang, H. Jiang, M. Drew, L. Ze-Nian, and G. Mori, "Unsupervised discovery of action classes," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2006, pp. 1654–1661.

[3] A. Thayananthan, B. Stenger, P. H. S. Torr, and R. Cipolla, "Shape context and chamfer matching in cluttered scenes," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2003, pp. 127–133.

[4] M. Daliri and V. Torre, "Robust symbolic representation for shape recognition and retrieval," Pattern Recognit., vol. 41, no. 5, pp.1799–1815, 2008.

[5] G. McNeill and S. Vijayakumar, "Hierarchical procrustes matching for shape retrieval," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2006, pp. 885–894.

[6] A. Peter, A. Rangarajan, and J. Ho, "Shape lne rouge: Sliding wavelets for indexing and retrieval," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2008, pp. 1–8.

[7] T. Adamek and N. OConnor, "A multiscale representation method for nonrigid shapes with a single closed contour," IEEE Trans. Circuits Syst. Video Technol., vol. 14, no. 5, pp. 742–753, May 2004.

[8] A. B. Hamza and H. Krim, “Geodesic object representation and recognition,” in DGCI, LNCS 2886, 2003, pp. 378–387.

[9] S. Belongie, J. Malik, and J. Puzicha, “Shape matching and object recognition using shape contexts,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 4, pp. 509–522, Apr. 2002.

[10] Y. Liu, H. Zha, and H. Qin, “The generalized shape distributions for shape matching and analysis,” in Proc. Int. Conf. Shape Modeling and Applications, 2002.

[11] P. Tresadern and I. Reid, “An evaluation of shape descriptors for image retrieval in human pose estimation,” in Proc. British Machine Vision Conf., 2007.

[12] D. Rafiei and A. Mendelzon, “Efficient retrieval of similar shapes,” Int. J. Very Large Data Bases, vol. 11, no. 1, pp. 17–27, 2002.