Shape Matching and Object Recognition Using Shape Contexts

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Abstract—This paper presents my work on computing shape models that are computationally fast and invariant basic transformations like translation, scaling and rotation. In this paper, I propose shape detection using a feature called shape context. Shape context describes all boundary points of a shape with respect to any single boundary point. Thus it is descriptive of the shape of the object. Object recognition can be achieved by matching this feature with a priori knowledge of the shape context of the boundary points of the object. Experimental results are promising on handwritten digits, trademark images.

Keywords-component; Shape descriptor, shape context, polar plot, shape recognition, object recognition

I. INTRODUCTION

Object recognition is one of the common problems featured in most computer vision applications. An object recognition system finds objects in the real world from an image of the world, using object models which are known a priori. Multiple visual cues like shape, color, texture are used to describe shapes. My motivation was to develop a shape detection scheme that can be very fast to assist vision systems on robot excavators to detect objects of interest based on its shape. My work aims to develop a simple and fast method of object recognition.

This paper looks into developing a shape descriptor for a sampled boundary point of any shape. Quite different and novel, my idea of shape context is derived from shape context work done in Berkeley by Serge Belongie, Jitendra Malik and Jan Puzicha.[1] The main idea is to develop a computationally inexpensive and transformation invariant measure of a shape boundary that can be used in shape recognition. Shape is an important cue as it captures a prominent element of an object. However, the description of a shape is difficult to specify since humans may perceive two shapes to be similar despite variation in size, orientation and boundary. As an example, bananas come in different shapes and sizes. Often the silhouette of a banana obtained after preprocessing has same visual form but different boundary structure. Shape contexts describe a distribution of all boundary points with respect to one point on the boundary. Belongie et al. [1] have introduced the shape context descriptor, which characterizes a particular point location on the shape. The descriptor computes the histogram of relative polar co-ordinates of any single boundary point. Shape contexts as defined by Belongie et al. [1] are only invariant to translation as all measures are with respect to a point on the boundary. This paper looks into a modified shape context that is invariant to scaling and rotation. Since it is a very rich descriptor, results have shown it to be robust against partially occlusion. Later, the paper also gives an insight into the existing graph matching technique and how shape contexts can be applied in an object based image retrieval scheme.

1.1 PREVIOUS WORK

Most approaches to shape matching, find a transformation that gives a factor of dissimilarity between two shapes. The extent of this dissimilarity decides whether we have a match. People have used various properties like curvature, contour to describe shape boundaries. Shape matching has also been implemented using various feature-based and brightness based methods. Feature based methods are often used for silhouette images. The feature being Characteristic of the object is used in content based matching approaches. In eigenvector or modal matching based approaches, sample points are transformed into a mass-spring damper equation and the vibrations are used to estimate matching. PCA was successfully used for faces to create a dimensionally reduced mean shape that was used for matching shapes. Another approach to shape matching was computing skeletal framework of the object that is used as a descriptor for matching. Shape context is a novel approach in shape descriptor. They are simple to compute yet are rich descriptors of the shape boundary.

1.2 SHAPE CONTEXTS

Belongie et al. [1] introduced the idea of shape contexts. In their seminal work, they have defined a descriptor for a boundary as a function of other boundary points. He proposes a log-polar plot of the boundary of the shape as viewed from any arbitrary boundary value. Histogram of a log polar plot of the shape boundary gives the shape context for that particular boundary point. Corresponding points on two similar shapes are supposed to have same shape context that facilities shape recognition. Belongie et al. reduce it to a problem of bipartite graph matching.

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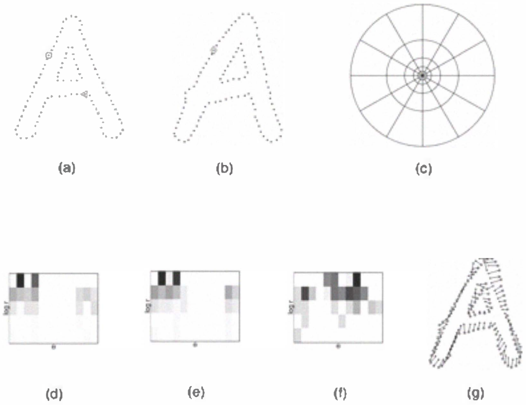

Fig.1 Shape context computation and matching. (a) and (b) Sampled edge points of two shapes. (c) Diagram of log- polar histogram bins used in computing the shape contexts. We use five bins for log r and 12 bins for θ. (d), (e), and (f) Example shape contexts for reference samples marked by ◦,◊, in (a) and (b). Each shape context is a log-polar histogram of the coordinates of the rest of the point set measured using the reference point as the origin. (Dark=large value.) Note the visual similarity of the shape contexts for ◊ and ◊, which were computed for relatively similar points on the two shapes. By contrast, the shape context for is quite different. (g) Correspondences found using bipartite matching, with costs defined by the $\chi 2$ distance between histograms.

II. Modified Shape Contexts

Shape contexts defined by Belongie are applied to images after aligning transforms. The shape descriptor presented in this paper computes the histograms such that they are invariant to simple transforms like scaling, rotation and translation. My further work will try to normalize the histograms for all affine transforms and extend shape contexts to 3D shapes. Modified shape context is based on the idea of computing rich descriptors for fewer boundary points. Present implementation of shape matching using Hungarian method of weighted bipartite graph matching works with a complexity of O(n3) Modified Shape Context aims to use computationally faster methods of matching. Simple correlation based matching yields satisfactory results on silhouette images. Besides, it also gives an indication of where occlusion has occurred when matching shape with occlusion. Shape contexts are computed along all boundary points of a shape model. Later during matching any boundary point on the candidate image is chosen at random. The shape context of that boundary value is matched with the database of shape contexts. It gives a measure of dissimilarity that decides whether the candidate object is same as that in the database.

III. Computing Modified Shape Contexts.

Any image is preprocessed to remove noise. Edge Detection and segmentation are used specific to the image to obtain a clear silhouette boundary of the object. The boundary points are sampled to n points. A shape is represented by discrete set of sampled boundary points. Let B be the set of sampled boundary points. Select any point b1. Compute distance of each boundary point in set B from point b1. Normalize this distance by a factor λ. λ being the maximum of distance between any two points in set B. Compute polar co-ordinates r and θ for all the boundary points as shown. The center of mass of any shape is invariant to scaling, rotation or translation. Hence we compute the angle with respect to line joining the point b1 and the center as the reference 0o.

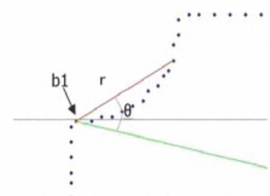

Fig.2

These r and θ form the polar co- ordinates of the boundary point. Log polar histograms as shown in fig (3) are overlaid on the shape to calculate the shape context.

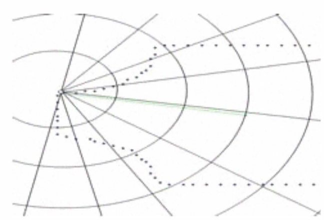

Fig.3

Now, to compute the histogram we count the number of boundary points within each sector or bin to form the shape context. Thus the shape context is a matrix of m×n elements where m and n are the radial and angular divisions of the histogram.

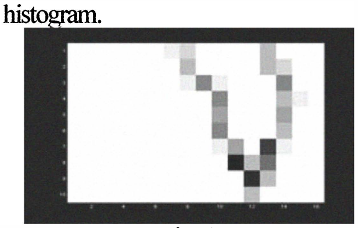

Fig. 4

The figure shows shape context histogram for 10 radial divisions and 16 angular divisions. The darker cells indicate greater intensity of boundary points with that bin. For example, in the above context most boundary points are distributed between radial belt of 5 to 9 divisions and angular belt of 9 to 14 divisions (i.e. approx 200 o to 310 o).

IV. Invariance and Occlusion

During applications of shape recognition often the descriptor has to be invariant to scaling, rotation, translation of the object to facilitate accurate and fast matching. The idea of this shape descriptor itself is translation invariant as we compute values relative to a point on the boundary itself. It is invariant to rotation as the angle is computed with respect to an axis defined by the point and the center of mass of the shape. Since the center of mass is invariant to rotation, the shape context is also rotation invariant. The radial distance for the polar histogram bins are normalized by λ, which is the maximum distance between any two sample points on the boundary. Shape contexts also take into consideration occlusion or partial view of the shape. Since occluded shapes will have shape context with difference only in certain bins, it can be accounted during matching

V. Object recognition using Shape Contexts

Object recognition involves assigning correct labels to regions or a set of regions, in the image given an image containing one or more objects of interest and a set of labels corresponding to a set of models known to the system. Object recognition using Shape Contexts can be categorized in three steps as follows.

1. Building an offline database of shape contexts of all boundary points.
2. Obtain boundary points of the candidate object and compute shape context of any one point.
3. Match the shape context with the database to calculate a measure of dissimilarity.

My implementation has approached the matching problem as a simple correlation of two histograms. Calculate Δ as the number of bins in the histograms than have dissimilarity more than an error threshold ε. The shape recognition has a match at permitted minima of Δ.

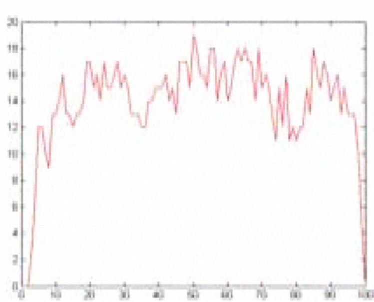

Fig 5

While searching for the similar shape context, it is not necessary to search all values sequential. A faster approach to implement a variation to the binary search as the measure of dissimilarity can be used to predict the boundary value with a greater chance of success. As in the following image.

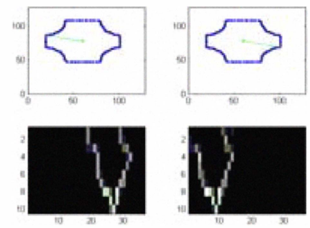

Fig. 6

Shape contexts calculated for two diagonally opposite boundary points. Since the object is symmetric similar pattern on the other side of the histogram. Shape contexts of two diagonally opposite points are similar patterns but in opposite positions on the axis. The dissimilarity here is high; indicating the chance of a match is far away from the current boundary point. This helps to skip number of boundary points during context matching.

VI. Test results

Present test results are based on a small sample

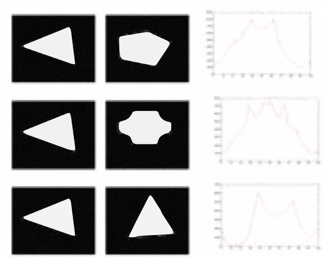

Fig. 7

Column 1 shows the database object. Column 2 shows the candidate object. Column 3 shows the dissimilarity plot. Observe that for first two cases the min dissimilarity is of the order of 1000, whereas the third case shows a min dissimilarity of 50 at about the 30th boundary point.

VII. Conclusion

Shape context can be improved to a really efficient shape descriptor that can be effectively used with graph matching for object recognition. Present implementation gives a dissimilarity map. Further I propose to work on implementing effective graph matching algorithms and develop a query based approach to test robustness of shape contexts.

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