

Shape Similarity Measure For k Nearest-Neighbor Queries

Irina G. Mocanu¹

Abstract – One of the content based image retrieval techniques is the shape based technique which allows users to ask for objects similar in shape to a query object. In this paper, a region-based approach to shape representation and similarity measure is presented. The proposed algorithm is based on the grid descriptor method. Its performance is compared with the grid descriptor method in case of the k nearest-neighbor queries. The performance is tested using a database of synthetic shapes. Experimental results show that the proposed method performs favorably compared with the grid based method in case of the k-nearest neighbor queries.

Keywords: shape representation, shape similarity measure, image retrieval, grid descriptor

1. INTRODUCTION

With the explosive growth of multimedia applications, the ability to index or retrieve multimedia objects in an efficient way became an increasingly active area. A major data type stored and managed by these applications is represented by two dimensional objects. Objects contain many features, like color, texture, shape. Shape is an important low-level image feature. The shape representation of objects can be used for indexing, retrieval and as a similarity measure.

A good shape representation and similarity measurement for recognition and retrieval purposes should have the following two important properties [1]: (i)each shape should have a unique representation, invariant to translation, rotation, and scale; (ii)similar shapes should have similar representations so that retrieval can be based on distances among shape representations.

There are generally two types of shape descriptors [2]: contour-based shape descriptors and region-based shape descriptors. Contour-based shape descriptors exploit only boundary information, they cannot capture shape interior content and these methods cannot deal with disjoint shapes. In contrast, in region-based techniques all the pixels within a shape region are taken into account to obtain the shape representation. These techniques can describe disjoint shapes.

The paper presents a new method for shape similarity measure based on the grid descriptor method. The grid method is a region based method [1]. The proposed algorithm outperforms the grid descriptor method in case of k nearest-neighbor queries.

The rest of the paper is organized as following: section II presents the grid descriptor method; section III describes the new technique for shape representation and similarity based on the grid descriptor method; section IV shows the results of the retrieval experiments; section V concludes the paper.

II. THE GRID DESCRIPTOR METHOD

The grid-based method attracts interest for its simplicity in representation. In this method, a grid space is overlaid over the shape [1], [3]. The grid space consists of fixed size square cells. In Fig. 1 the shape is mapped on to a grid of fixed cell size in a manner that the shape is justified to the top left corner. The grid is then scanned from left to right and top to bottom. 1 is assigned to the cells of the grid partially or wholly covered by the shape and 0 to the cells outside of the shape boundary, which gives us a sequence of numbers which can be used for shape representation.

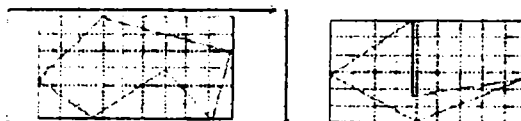


Fig 1 Mapping a shape to a grid.

The sequence of 1's and 0's for the shape boundary is defined the binary number for the shape boundary. The binary numbers obtained for the shape boundaries in Fig. 1(a) and Fig. 1(b) are 001111000 01111111 11111111 11111111 11110011 00110011 and 00110000 01110000 11110000 11110000 01111100 000111000 respectively. The difference between the two shapes can be calculated as the number of cells in the grids that are covered by one shape and not the other and hence the sum of 1's in the result of the exclusive-or of the two binary

¹Universitatea Politehnica București - Facultatea de Automatică și Calculatoare, Secția Calculatoare
Spl. Independenței Nr. 313, 060032, București, e-mail irinam@cs.pub.ro

numbers [1]. In the above case the difference between the shapes is 27 by XOR operation on the two sets. Hence, in grid method two objects are similar in shape, if and only if the difference between their binary representations is less than a prespecified threshold, and they have similar eccentricities. However, it must be noted that the binary number obtained for the same shape with a different orientation in space or with a different scale will be different. However, it must be noted that the binary number obtained for the same shape with a different orientation in space or with a different scale will be different. The criteria for invariance of indices is not met and hence it is required to normalize the shape to achieve scale, rotation and translation invariance. The normalization process involves three steps: (i) shape boundaries are normalized for rotation, (ii) they are normalized for scale, (iii) they are normalized for translation. The principals steps of computing grid descriptor are: (i) binary image, (ii) major axis, (iii) rotation normalization, (iv) scale normalization, (v) translation normalization, (vi) scan grid cells.

The following definitions are needed to perform the normalization process [3]:

- Major axis: is the straight line segment joining the two points on the boundary farthest away from each other (in case of more than one, select any one);
- Minor axis: is perpendicular to the major axis and of such length that a rectangle with sides parallel to major and minor axes that just encloses the boundary can be formed using the lengths of the major and minor axis;
- Basic rectangle: the above rectangle formed with major and minor axis as its two sides.

A shape after rotation will have a different binary number. This is because rotation changes the spatial relationships between the grids and the shape. This problem can be solved by normalizing the shape for rotation. The purpose of rotation normalization is to place shape regions in a unique common orientation. Hence the shape region is rotated such that its major axis is parallel to the x-axis. There are still two possibilities as shown in Fig. 2 b) and d), caused by 180° rotation.

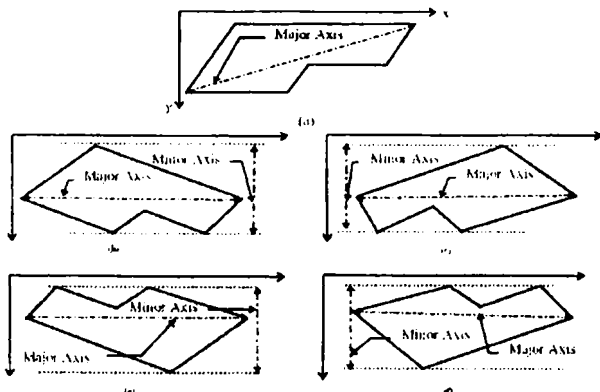


Fig. 2. a) a shape before rotation normalization b), c), d), e) the shape after rotation normalization

Further, two more orientation are possible due to the vertical and horizontal flips of the original region, like in Fig. 2 c) and e).

Both the shape size and the grid size affect the binary number derived for a boundary. This problem is handled by choosing a fixed length of the major axis (the "standardized major axis") and then scaling the shape in a manner that the major axis of the shape equals the standardized major axis. Scaling normalization is thus achieved by scaling along the major-axis so that the major axis of the shape becomes equal to the length of the standardized major axis. The shape is scaled along the minor axis proportionally in order to maintain the perceptual similarity of the shape, like in Fig. 3 a), b) and respectively in Fig. 3 c).

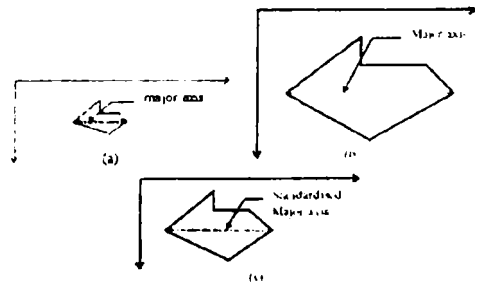


Fig. 3. a) and b) two similar shapes before scale normalization. c) the shapes after scale normalization

To improve the efficiency of this method, another shape feature, eccentricity was used [1]. Eccentricity of shape is the ratio of the major axis to the minor axis. Therefore, for two objects to be similar, their sequences of numbers and their eccentricity values should be similar [1]:

- If two normalized shapes have the same basic rectangle, the distance between them is equal to the number of positions having different values in their corresponding binary sequences;
- If two normalized shapes have very different basic rectangles (i.e., they have very different minor axis lengths), there is no need to calculate their similarity, because the shapes are very different. The difference threshold between minor axes depends on applications and cell size. Normally, if the lengths of the minor axes of two shapes differ by more than 3 cells, these two shapes are considered quite different;

If two normalized shapes have very different basic rectangles, it is still possible these two shapes to be perceptually similar. It is added 0s at the end of the index of the shape with shorter minor axis, so that the extended index is of the same length as that of the other shape. The distance between these two shapes is calculated as in the first case a).

The grid descriptor algorithm is applicable for contour-based shape and it assumes shape boundary coordinates have been known. This algorithm is

extended into describing region-based shape. The main extension to the grid method is the method of finding the major axis and region interpolation after scale rotation.

In the case of region shape, boundary information is not known. That is not practical to find the major axis of a region shape by traversing all the points in the shape region, the computation would be $O(N^2)$, where N is the number of pixels in the shape region. Therefore, the major axis for a region shape is found by searching the outer border point pairs on the shape boundary in a number of directions (e.g. 360 directions). The algorithm for calculating the major axis involves three major steps: (i) find the bounding box of the shape; (ii) find the pair of boundary points in a number of directions; (iii) find the two points at the furthest distance in the found boundary points. The algorithm is described below:

1. Find the bounding box of the shape;
2. Start from a line segment d_0 which passes through the shape center, trace from the two end points towards the center along the line segment. If a shape point is found, it is a boundary point. For every tracing, two boundary points are found;
3. Increase the angle of d_0 by an increment of $2\pi/n$ (n is the number of directions to trace), repeat step 2;
4. Repeat step 3 until boundary points at all orientations are found;
5. Find the two points p_1, p_2 with the furthest distance in the above boundary points, then p_1p_2 is the major axis.

III. A NEW SHAPE SIMILARITY MEASURE

Consider the following five shapes A, B, C, D, E, F with similar eccentricities (7/4, 7/4, 7/6, 7/4, 7/4) from Fig. 4. If we notate with $d(x, y)$, the distance between shapes x and y conform with the grid method, then $d(A, B) = 4$, $d(A, C) = 4$, $d(A, D) = 3$, $d(A, E) = 3$. Hence, shapes D and E will be more similar with shape A than shapes B and C, which is not conforming to human intuition.

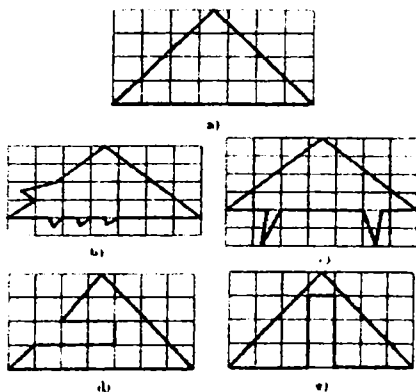


Fig 4 Five shapes with their eccentricity values a) shape A, b)shape B, c)shape C, d)shape D, e)shape E

If we want to extract all the images which are similarly with the shape from a query, this method of calculating distances between shapes doesn't influence the result. In the knearest-neighbor query [4], the user's query is specified by a vector and an integer k . The k objects whose distances from the query vector are the smallest are retrieved. Using the grid method for evaluating the k nearest-neighbor query, the results will not be conforming to human intuition. For example, if we want to perform a k nearest-neighbor query to extract shapes similar with shape A from shapes of Fig. 4, for $k=2$, the result will be shapes D and E. Shape B is the most similar with shape A, conform with human intuition. To obtain this, a new method to calculate shape differences was proposed.

Instead of calculating the difference between two shapes like in grid method, we associated a weight to each cell in the grid that are covered by one shape and not the other. At a first stage, this weight is chosen to be inverse proportionally with the number of cell's neighbors which are covered by the two shapes. The difference between two shapes will be the sum of these associated weights. For example $d(A, B) = 5 - 2 + 5 - 2 + 5 - 2 + 5 - 2 = 8$. $d(A, C) = 8 - 3 + 8 - 3 + 5 - 0 + 5 - 0 = 20$, $d(A, D) = 8 - 4 + 8 - 5 + 8 - 7 = 8$ and $d(A, E) = 8 - 4 + 8 - 6 + 8 - 7 = 7$. In this case the shapes D and E are more similar to shape A than shape C, too. But this is not sufficient. We must differentiate between a shape's peek produced by noise (shapes B and C) and a hole in a shape (shapes D and E). The cell's neighbors considered for determining the associated weight of the respective cell may form a continuous sequence (like in case of shape B and C) or not (like in case of shapes D and E). At a second stage, the weight associated with a cell will be multiply with a predefined factor α in case that the considered cell's neighbors will not form a continuous sequence. For example if $\alpha = 2$, $d(A, D) = (8-4) * \alpha + (8-5) * \alpha + 8 - 7 = 15$ și $d(A, E) = (8-4) * \alpha + (8-6) * \alpha + 8 - 7 = 13$ and $d(A, B) = 8$, $d(A, C) = 20$. Therefore, using this method for calculating distances between shapes, for a k nearest-neighbor queries with $k=2$, the result consist of shape B and E, which is more similar with human intuition than grid descriptor method.

IV. RETRIEVAL EXPERIMENTS

To test the proposed method, a retrieval framework, on a database with synthetic shapes was implemented. The performance has been evaluated using precision and recall [1]. Precision is defined as the ratio of the number of similar shapes retrieved to the total number of shapes retrieved. Recall is defined as the ratio of the number of similar shapes retrieved to the total number of similar shapes in the whole database. Precision indicates accuracy of the retrieval and recall indicates the robustness of the retrieval performance. For each query object the relevant items in the database are the object shapes which are perceptually similar to the query object shape. The database used consists of approximate 3,000

polygons. The average precision and recall of the shapes used as k nearest-neighbor queries is given in Fig. 5.

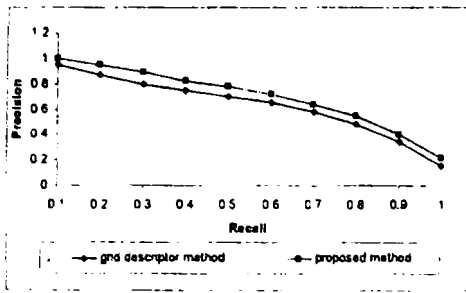


Fig. 5. Average retrieval performance of the two methods for k nearest-neighbor queries

For k nearest-neighbor queries, the precision and recall of the proposed method is similar with the grid method, but the shapes retrieved using this method will be conform to human intuition more than in the case of the grid method.

V. CONCLUSIONS

This paper presents a new shape similarity method based on the grid descriptor representation. and retrieval method based on the shapes' contour which has a better retrieval performance compared to the distance histogram method. The method is invariant to translation, scale and rotation. The distance histogram method discards spatial information to obtain rotation invariant. In the proposed method, the radii together with the edges' directions associated with them are used for shape representation.

REFERENCES

- [1] Guojun Lu - *Multimedia Database Management Systems*, Artech House, 1999
- [2] Mayatham H. Safar, Cyrus Shahabi - *Shape Analysis and Retrieval of Multimedia Objects*, Kluwer Academic Publishers, 2003
- [3] Atul Sajjanhar, Guojun Lu - *A Grid Based Shape Indexing and Retrieval Method*, *Australian Computer Journal*, Vol. 29, nr. 4, pag. 131-140, 1997
- [4] V. S. Subrahmanian - *Principles of Multimedia Database System*, Morgan Kaufmann Publishers, 1997