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Review of Shape Retrieval Approach with Geometric Distortion

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ABSTRACT: In this paper we proposed efficient method for shape retrieval using Feature point extraction. It provides detail analysis of how system works for shape retrieval from the databases of countable number of shapes. The human visual system retrieves shapes from incomplete information in the real world, and it has inspired a lot of computational methods of retrieving shapes. In order to retrieve shapes, the observed shapes are decided to be alike or unlike remembered shapes in memory after the comparison of these shapes. To compare the observed and remembered shapes, they must be appropriately represented so that the points on each shape can be mapped and compared. For this reason, the shape retrieval process needs a appropriate shape representation and shape mapping methods. Moreover, the shape representations should be normalized before the mapping process. However, a normalization process for representations under unpredictable conditions has not yet been established. In this paper, we describe a shape retrieval method that enables us to retrieve shapes under unpredictable conditions with a suitable normalization process. Using curvature partition and angle-length profile, our shape retrieval method normalizes the shape representation before it does the mapping. As a result, unlike the previously proposed methods, it can be used under unpredictable conditions such as when occlusion, geometric distortion, and differences in image resolution occur simultaneously.

KEYWORDS: Shape matching, Feature Point, scaling factor, geometric distortion, shape recognition etc.

I. INTRODUCTION

The real world is an unpredictably and dynamically changing environment. We, as living things, create certainty from uncertainty in order to adapt to such uncertainties. The human visual system always encounters uncertainty, since most visual shapes are incomplete. This incompleteness concerning visual shapes derives from (1) geometric distortion, and (2) differences in the resolution of images. However, even if occlusions and distortions such as expansion or rotation occur in shapes with low resolution, humans can still predict the original shapes by using their knowledge and memory. With the ability to predict complete shapes with the incomplete information, we detect and classify objects such as animals, plants, and landmarks [1]–[3]. Complete shapes must be retrieved from incompletely described shapes affected by occlusion, geometric distortion, and differences in image resolution. Such a retrieval will be successful if the shape representations appropriately describe the incompletely observed shapes and if the observed shapes are appropriately mapped to shapes in memory (the point correspondences are appropriately solved). Thereby, the incompletely observed shapes can be appropriately matched to shapes in memory and it can be decided if they are alike or unlike. For this reason, the task of shape retrieval will require appropriate shape-representation and shape-mapping methods. We assume that the shape retrieval methods should appropriately normalize the shape representations in the easily be normalized when the representations are based on completely described whole shapes. In such situations, there are easy normalizations using geometric transformations based on the centroid [4]–[8] or the whole contour of the shape [9]–[10]. Here, completely observed shapes are described with closed contours, whereas shapes affected by occlusion, geometric distortion, and differences in image resolution are shown as roughly described open contours. The previous approaches have tried to reconstruct whole shapes from incompletely described ones. For example, some methods use T-shaped intersections, simplicity of the hidden figure, symmetry, or good continuations as ‘‘cues’’ for reconstructing shapes . Although these completion mechanisms are innate in our human visual system, they are still sometimes inadequate for representations of incompletely described shapes since incompletely observed shapes do not always have enough ‘‘cues’’ for our visual system to reconstruct complete shapes. Moreover, a normalization for representations of incomplete shapes observed under unpredictable conditions such as when occlusion, geometric distortion, and differences in resolution of images occur simultaneously has not yet been established. Hierarchical processing models

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for shape retrieval have been proposed based on hierarchical neural network models [15]–[24]. These models rely on the fact that the shape representation is formed through a visual ventral pathway that hierarchically integrates the stimuli caught by the retinal cells by using cortical cells which have receptive fields of different sizes . These neural network models, however, do not accomplish suitable normalizations for the constructed shape representations. Fukushima's model and Poggio's model, for example, reconstruct the neuron's hierarchical receptive fields [1], [2], [3], [4]. Using these neurons, they hierarchically integrate the pixels of input images, and they recognize the pattern of the images with the neurons of the deepest layer. Although these models reconstruct the hierarchical pattern of the neural network well, they do not include any normalization process for the shape representations. Besides these methods, Grossberg's model exploits both global and local structures of images

Global and local structures are keys to the normalization since locally described structures can be normalized with local information. In these neural network models, however, the geometric relationships of the integrated features are fixed, and they do not have normalizations for the shape representations as the result of a geometric transformation. On the other hand, there are many computational shape retrieval methods [36]–[45]. These can roughly be classified into two streams, one of which uses ''shortest path searches'' for finding the correspondences between a series of points on the contours of partial shapes and those of the whole shape [1], [46]–[52], the other of which uses ''geometric consistency checks'' for finding the correspondences between feature points on the partial shapes and those of the whole shape Using the order of the points or the geometric relationship among the feature points, these methods excel in finding the point correspondences (the point-to-pointmapping) between two shapes. However, the previous studies only focused on solving the point correspondences; they did not deal with the normalization for the shape representation. Unless the features of the shapes are well normalized, the similarity of the corresponding points cannot be determined even if the shortest path is found. Moreover, unless the features of the shapes are well extracted, the geometric relationship between two shapes would be vague even if they are geometrically consistent. For example, the curvature representation is widely used to describe a series of contours on shapes [9] Curvature itself, however, varies when expansion occurs, since it is defined as the rate of change of angle per unit length. It is true that the curvature representation can be normalized if the whole body is completely observed.

II.FEATURE POINT EXTRACTION

We will introduce our feature point extraction method in this subsection. Based on the real-valued boundary point representation, the algorithm is very simple and straightforward, using only an angle calculation formula. Now, we define a so-called "feature point". The feature points have two forms in this paper. The first form is defined as any point with a sharp vertex angle < 150° (found experimentally to be a good value) called a corner point [4, 5, 6, 10, 11, 13, 14, 15, 18, 19], found by the angle calculation formula shown in Fig. 3.1. The second kind of feature points are those points whose distances to curve L are local maxima or local minima, where L is the curve with the two adjacent sharp vertex angle points (corner points) as end points. First of all, our algorithm takes the boundary points generated in Section 2 as input. Suppose these points are pi = (xi, yi), 1≦i≦n. For any pi we choose pi-2. pi and pi+2 to compute the angle between the two segments (pi, pi-2) and (pI, pi+2). If the angle is less than 150o, the point pi is a possible corner point. We consider the neighborhood of pi which has a series of possible corner points, and choose the point with the smallest angle as the corner point (the first form). This point is absolutely a true feature point because of its small angle. We illustrate this in Fig. 3.1. The boundary point pi with angle θ1 is selected as the feature point because it has the smallest angle among its neighborhood {p1.p2.p3}.

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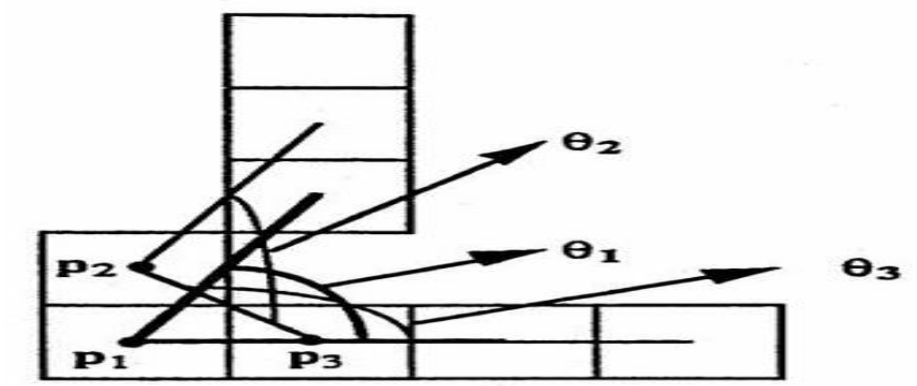

Fig.1 An example of selecting the feature point of the first form (corner point).

We will illustrate the algorithm in detail .First of all, when should our so-called curve should be separated? The two end points of a curve are both corner points. We connect these two points with a straight line and calculate the maximum distance from the curve to the line. If the length of the curve is larger than a given tolerance Tol1 and the maximum distance over the length is also larger than another given tolerance Tol2 then the curve needs to be separated. Secondly, our separating technique is a so-called **"incremental and decremental distance evaluation".** If the curve is to be separated, we then apply the technique. The incremental and decremental distance evaluation technique calculates the vertical distances from all the points in the curve to the line. We sequentially compare the differences of adjacent pairs of these distances and record the number of increases and decreases. A boundary point p is said to be at a "local maximum or minimum" if there is a sufficient number of increases (decreases) before p and enough decreases (increases) after p. These local minima and maxima are the second kind of feature points. After performing the separating process, all possible feature points will be found. In Fig. 3.2, point a and point b are the starting point and ending point of the curve (a, b) respectively. We will find the possible feature points c and d sequentially by using the separating technique

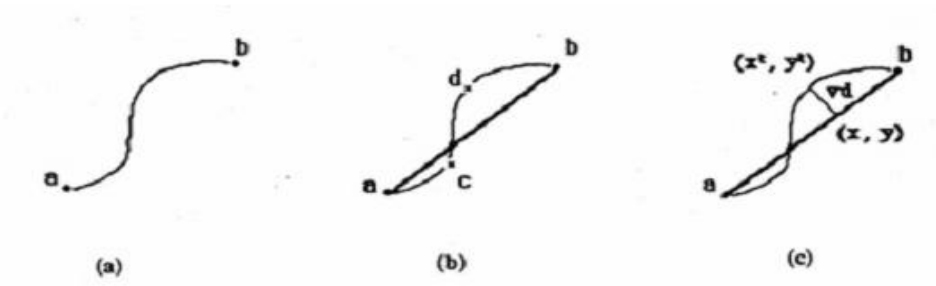

Fig. 2. An example of finding the feature points of the second form.

(a) Points a and b are feature points and two end points in curve (a, b).
(b) Points c and d are the feature points we want to find.
(c) The vertical distance between the point in the curve and the straight line is vd.
Suppose (x_1, y_a) and (X_b, y_b) are the coordinates of a and b respectively. The slope of the line is (ya-yb)/(xa-xb). Now we want to show how to calculate the vertical distance from the point in the curve to the line. Let (xt, yt) be the coordinate of the point on the curve and (x, y) be the point on the straight line such that the distance between (xt, yt) and (x, y) is the minimal distance from (xt, yt) to the line. Coordinate (x, y) and the vertical distance vd from (xt, yt) to (x, y) are computed as follows :

$y = (ya + slope * (x^t + y^t \times slope - xa)) / (1 + slope * slope)$
$x = x^t + y^t \times slope - y \times slope$
$vd = \sqrt{(X - xt)^2 + (Y - Yt)^2}$

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The above formula has been simplified and it is very easy, so we won't discuss it here. 253.2 Shape representation From the discussion in Subsection 3.1, we obtain the feature points stored sequentially in an array. The centroid (Xc, Yc) [8] .

III.PROPOSED SYSTEM PROPOSED SYSTEM FOR SHAPE RETRIEVAL

Our shape based image retrieval system consists of database construction part and image retrieval. The database construction part is intended to ensure high retrieval efficiency by extracting a feature set for each of the images and storing the feature set along with its corresponding image in the database. To access the database, the user initiates the image retrieval process by providing a query image as input, and then the system starts with extracting the features from the query image as shown in Fig.2. Afterwards, the system measures the similarity between the feature set of the query image a d those of the images stored in the database through BiSimilarity measure process. Finally, the system ranks the relevance based on the similarity and returns the results to the user.

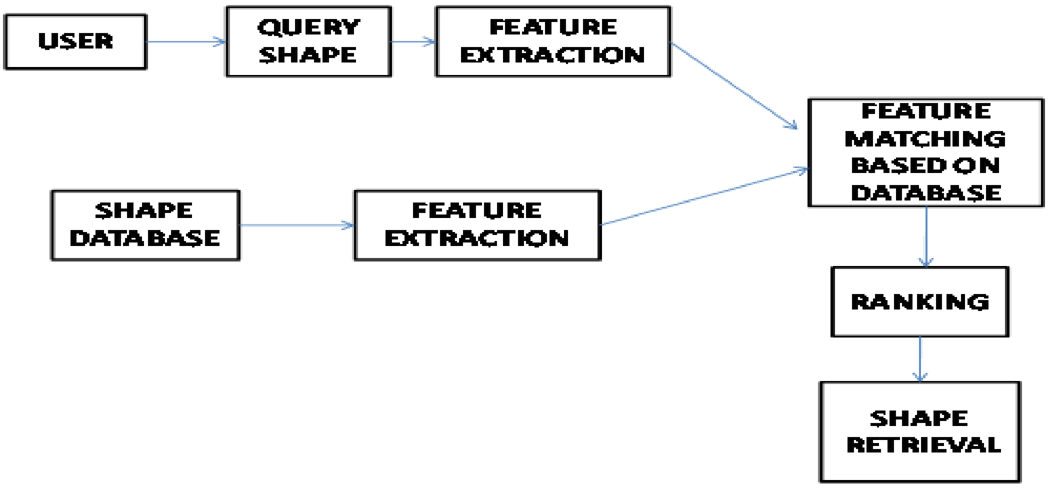

Fig 3. Basic Block Diagram of Shape Retreival

A.CANNY EDGE DETECTION ALGORITHM

The canny edge detection algorithm was developed to detect edge lines and gradients for the purpose of image processing. This algorithm provides good detection and localization of real edges while providing minimal response in low noise environments. The main stages of the Canny Algorithm are as follows:

1. Smoothing: Blurring of the image to remove noise.
2. Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.
3. Non-maximum suppression: Only local maxima should be marked as edges.
4. Double thresholding: Potential edges are determined by thresholding.
5. Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

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The main stages are explained below:

B. SMOOTHING

It is inevitable that all images taken from a camera will contain some amount of noise. To prevent that noise is mistaken for edges, noise must be reduced. Therefore the image is first smoothed by applying a Gaussian filter. The kernel of a Gaussian filter with a slandered deviation of σ =1.4 is shown in equation (1)

$$B = \frac{1}{159} \cdot \begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} \qquad (1)$$

C. FINDING GRADIENTS

The Canny algorithm basically finds edges where the greyscale intensity of the image changes the most. These areas are found by determining gradients of the image. Gradients at each pixel in the smoothed image are determined by applying what is known as the Sobel-operator. First step is to approximate the gradient in the x- and y-direction respectively by applying the kernels shown in Equation (2)

$$K_{GX} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$K_{GY} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \qquad (2)$$

The gradient magnitudes (also known as the edge strengths) can then be determined as an Euclidean distance measure by applying the law of Pythagoras as shown in Equation (3). It is sometimes simplified by applying Manhattan distance measure as shown in Equation (4) to reduce the computational complexity. The Euclidean distance measure has been applied to the test image. The computed edge strengths are compared to the smoothed image in Figure 3.

$$|G| = \sqrt{G_x^2 + G_y^2} \qquad (3)$$

$$|G| = |G_x| + |G_y| \qquad (4)$$

Where Gx and Gy are the gradients in the x and y directions respectively.

IV. SHAPE MATCHING

Pattern matching involves matching two shapes. Pattern shapes are called the standard shapes, and the input shapes are obtained from pattern shapes by means of from one to three mixed actions. These three types of actions are rotation, scaling and translation. In our shape matching, there is also one thing that we must pay special attention to. The size of the input shape relative to the pattern shape will be changed during these actions. The size of an object is defined as the number of boundary points. Knowing the relationship between the size of a pattern shape and the size of the input shape is necessary for the matching work. We define this relationship, called the Scaling Factor (SF), as follows:

$$SF = \frac{\text{the numberof boundar ypoints of the input shape}}{\text{the numberof boundarypoints of the pattern shape}}$$

$$\text{i.e.} SF = \frac{\text{the contour length of the input shape}}{\text{the contour length of the pattern shape}}$$

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V. SEGMENT AND POINT MATCHING

A.SEGMENT MATCHING

Compute the context descriptors h_{E1} and h_{E2} Compute cost of ending matching
C(E1, E2) = min $\sum_{E1}\sum_{E2}$ C (ex, ey)
Compute corresponding segments: $\Gamma_k \rightarrow \Gamma_{\varpi_k}$

B.POINT MATCHING

For each pair of segments
$\Gamma_1 = \{t_{1,1}, \{\mathbf{s}_{1,m}\}, t_{1,2}\}$ and $\Gamma_2 = \{t_{2,1}, \{\mathbf{s}_{2,n}\}, t_{2,2}\}$
Compute the context descriptors h_{T1} and h_{T2}
Revise set s into s ˆ by removing (n − m) outliers found via Maximizing

H $=\sum_{j}^{n-m} \sum_{i=1}^{m} c\ (s1, i, s2, j)$

Return point matches π : $\{s_1$,m} → {sˆ$_2$,m}.

V. CONCLUSION

In this project we proposed different methodologies of shape retrieval on the basis of feature point extraction, angle length profile & curvature partition. Shape with geometric distortion, differences in image resolution is here extracted with above proposed methodologies in different manner with database of countable number of shapes already stored for matching.

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