Graph-based Shape Representation for Object Retrieval

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Abstract: Shape analysis has been an area of interest and research in image processing for a long time. Developing a discriminant shape representation and description method is a concern in many applications like image retrieval systems. This paper presents a new shape representation model which is based on graphs. We also present developed similarity measure technique to find correspondences between shapes. In our approach, features extracted from boundary of the shape are used to build up a graph. By means of a novel solution for attributed graph matching a new method for shape similarity measure is built up.

1 INTRODUCTION

There is little doubt that researches related to main human sense or vision are among the most recent stimulating research fields. Effective computer vision systems are essential whenever necessary to automate or to improve. Within recent years object recognition has become a fundamental and challenging problem in computer vision.

There are different properties like shape, texture, colour, etc. used in object recognition. Among those features, shape is most effective in semantically characterizing the object and one can be perceived and used for recognition and classification tasks (Daliri and Torre, 2010). Shape representation is a very important issue in computer vision and pattern recognition. Using the shape of an object for object recognition and image understanding are expanding topics in computer vision and multimedia processing. Hence, finding powerful shape descriptors and matching measures are the central issues in these applications (Xu et al., 2009).

This paper discribes the result of investigating a new model for shape representation based on graphs and new similarity measure technique to find correspondences between different shapes in the proposed methodology. Discrete curve evolution (DCE) algorithm (Bai et al., 2007) is employed to find important points of the shape's boundary, which has been simplified by polygonal approximation. Features extracted from these points are stored in a graph representing the shape. To find the similarity between shapes, a new attributed graph matching algorithm exploiting dynamic programming has been developed. Our approach is invariant to affine transformation and can handle partial occlusion. Moreover, it is low computationally complex that is very important in retrieval systems.

The paper is organized as follows: in Section 2 related works are discussed. Section 3 introduces a novel graph-based shape representation and shape similarity measure technique. Section 4 is dedicated for evaluation of our approach and discussion about the result. Finally, in Section 5 this work is summarized by conclusion as well as discussion concerning the future work.

2 RELATED WORKS

Several authors have already proposed methods for shape representation. Some early works tried to use a polygonal approximation for shape representation. Maes (1991) represented a shape by polygon and proposed a cyclic string matching technique for polygonal shape recognition. However, the proposed cost function to measure similarity is not robust enough. Tan et al., (2008) used equilateral polygonal approximation for shape representation. However, they did not propose a solution to find similarity measure based on their technique.

Probably the most relevant work to this paper has been proposed by Bai and Latecki (2008). They represent a shape by skeleton pruned using DCE (Bai et al., 2007) to remove useless branches. DCE algorithm selects important points of the skeleton

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lying on the contour. The detained points are in fact vertices of the polygon in our approach. To compare the shapes, instead of geometric features, they use geodesic paths between skeleton endpoints. The result of applying their algorithm on Kimia 216 dataset demonstrates its robustness. However, skeleton matching involves high degree of computation (Bai and Latecki, 2008) and their approach is not suitable for fast recognition.

Another approach which is comparable to our approach is work of Berretti et al., (2000). In this method the curvature zero-crossing points from a Gaussian smoothed boundary are used to obtain some primitives, called tokens. The feature for each token is its maxi-mum curvature and its orientation. Similarity between two tokens is measured by the weighted Euclidean distance. Since the feature includes curve orientation, it is not rotation invariant. Matching of tokens also involves thresholding which is chosen empirically.

3 SHAPE REPRESENTATION AND MATCHING

In this Section we explain our approach for graph-based shape representation and matching. First, the graph-based model which stores extracted shape's features will be discussed. Then we introduce the technique developed to measure shape similarity, based on the proposed model

3.1 Graph-based Shape Representation

Many of presented techniques in literature for contour based shape representation are either complex (Bai and Latecki, 2008) or not invariant to rotation, scale and translation. Moreover, none of them are suitable to describe and represent complex shapes which include more than one contour.

We exploit the graphs ability to describe structured data and relation of information to represent the shape. Our approach to model a shape by a graph consists of extracting important information of the shape's contour and storing them in a graph. Nodes of this graph correspond to selected points of the boundary. To assure that extracted features carry all spatial information of the shape, in this work we consider some simple shapes, uniformly filled areas enclosed by contours.

In our approach two attributes of a vertex of polygon are selected so that they are invariant to rotation, scale and translation, and are able to completely characterize such kind of shapes. These two attributes are interior angle α of each corner and ratio r of the longer side to the shorter side of it. These two attributes are depicted in Figure 1. These two parameters are stored as attributes for each vertex in an attributed graph.

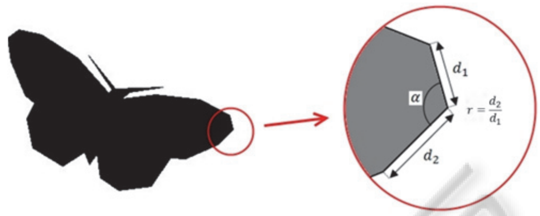

Figure 1: Internal angle and ratio of longer side to shorter side are two attributes of each vertex.

3.2 Shape Similarity Measure

Developing a shape similarity measure technique based on the presented graph-based model constitures the main part of our research.

Consider the similarity measure between two nodes N_i and M_j from two different shapes (Figure 2), measuring distance between two feature vectors N_i and M_j is insufficient. The problem is that after polygonal approximation, possibility of finding similar corners among two shapes having similar values for angle and ratio is high. Therefore some other parameters increasing the robustness of the error function to discriminate between similar areas of two contours are needed.

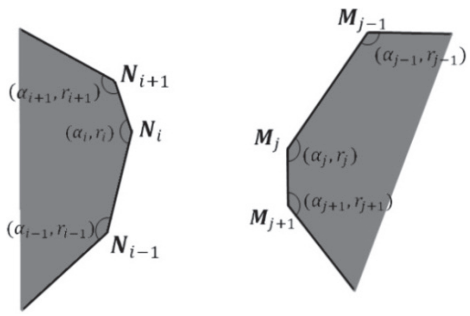

Figure 2: Indexed vertices in two parts of different shapes with attributes of each vertex. Neighbours are involved in measuring similarity between N_i and M_j.

To find the new similarity measure and error function, some experiments have been carried out. Therefore, a range of different vertices has been generated (Figure 3). The slight changes between vertices in the prepared database have been analysed. Then the required function and parameters have been found. Carried out experiments revealed that attributes of the neighbours are also important to measure similarity between two areas.

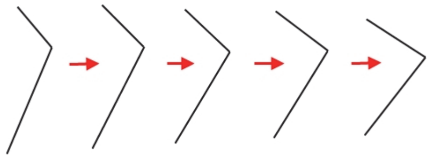

Figure 3: Increasing dissimilarity by gradual changes of the interior angle and side's ratio.

To measure the distance between two feature vectors, Euclidean norm is used. The difference between two feature vectors is then formulated as:

$$\|\boldsymbol{N}_i - \boldsymbol{M}_j\| = \sqrt{k_\alpha(\alpha_i - \alpha_j)^2 + (r_i - r_j)^2} \quad (1)$$

Where, k_α is a constant factor balancing the unknown influence of interior angel and side's ratio. The error function that includes measure of difference between feature vectors of the two target corners N_i and M_j as well as parts to involve their neighbors in similarity measure is formulated as follows:

$$F_{ij} = \sqrt{\begin{array}{c} w_c\|\boldsymbol{N}_i - \boldsymbol{M}_j\|^2 \\ +w_n(\Delta\alpha_{i-1,j-1}^2 + \Delta\alpha_{i+1,j+1}^2) \end{array}} \quad (2)$$

Equation 2 consists of two main parts. First part is a weighted difference between feature vectors of the two target corners N_i and M_j. The second part is a weighted sum of difference between two angels adjacent to the target nodes ($\Delta\alpha_{i-1,j-1}^2$, $\Delta\alpha_{i+1,j+1}^2$). Experiments showed that using attributes of more than two neighbours does not improve the result significantly and just increase the computational complexity.

The problem of finding correspondences between two attributed graphs is a typical assignment problem and it can be solved using Hungarian algorithm. Unfortunately this algorithm cannot be used to find the correspondences between two shapes described by proposed error function because it does not preserve the order of the match. This is not acceptable in finding correspondences between two shapes because the contour of each shape is an ordered sequence of points. It means that, assuming that two similar shapes, their correspondences also have the same order. Therefore, we need to develop another solution to this problem.

To explain our approach to solve the assignment problem, consider we have two graphs $G1$ and $G2$ with n and m nodes respectively and we want to find correspondences between their nodes. The computational complexity of the algorithm is $O(n^m)$. Usually this problem is NP hard. However, the solution can be found exploiting dynamic programming as well as applying additional criteria:

1. For each node N_i of graph $G1$, a node M_j of graph $G2$ is acceptable as a correspondence, when the value of error function is lower than a specific threshold. This threshold indicates minimum similarity between two nodes and is determined experimentally.
2. Node M_j can be selected as a correspondence to N_i if it preserves the order of nodes of $G2$ which are selected as acceptable matches for nodes of $G1$.

Based on these two rules and exploiting dynamic programming we solved the problem searching for longest sequence among candidate nodes for matching. In the case that longest sequence is not unique, we use path error: which can helps us to select best solution among all valid ones.

$$e_{path} = \sum_{i=1}^{n} F_{ij} \quad (3)$$

This equation helps us to select the best solution among all valid answers.

4 EXPERIMENTS AND RESULTS

Among various applications of shape representation and matching, retrieval systems became very important and popular during last decade (Desai et al., 2007). One of the most popular methods to evaluate the discrimination power of shape representation models and similarity measure techniques is to use them within a retrieval system.

To have an accurate evaluation of our method we used Kimia 216 dataset (Sebastian et al., 2004). The dataset consists of 216 shapes from 18 different categories and for each category there are 12 images.

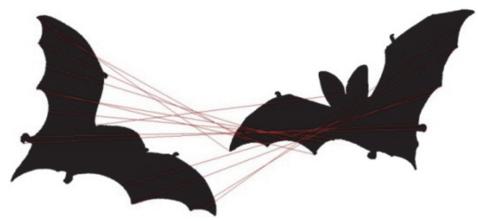

Figure 4: Result of finding correspondences between two similar shapes.

To the discriminant performance of our

algorithm, all images in the dataset were used as query and system searched for similar shapes among other shapes of the dataset. Considering the fact that each class consists of 12 images, 11 closest matches to the query image were considered to see if they belong to the same class as the query image. The results of this investigation are illustrated in Table 1.

Table 1: Result of retrieval system using our model on Kimia 216 dataset.

	1st	2nd	3rd	4th	5th
Result	179	161	148	137	128

6th	7th	8th	9th	10th	11th
118	108	103	87	71	74

In this table, from left to right, correct positive matches to all queries are sorted. First column represents the best matches for all the queries. It indicates that by selecting all 216 shapes as query, for 179 of them, the best match was correct and for 37 of them the best match was false positive. The positive feature of our approach which is comparable to other methods is low computational complexity. Unfortunately there is no feedback about computational complexity of the other methods and therefore comparison of computational performance between them and our method is not possible. However, by considering that average time to find similar shapes of a query in our method is less than 7 seconds (in a system with Intel Core Due 2 cpu and 4 GB ram), it seems that none of existing approaches is comparable to it.

5 CONCLUSIONS AND FUTURE WORKS

In this work three main issues are investigated. First, the novel graph-based model for shape representation is discussed. Then, the new technique for measuring shape similarity is introduced and finally the robustness of the model and similarity measure technique is explained and verified using a retrieval system.

In conclusion, evaluation of this method for shape representation and results obtained by testing shape similarity measure technique reveal the potential power of this method for shape recognition applications. A promising characteristic of our method is good recognition speed which shows that developing this method can lead to establish a fast and robust technique for online applications.

Probably the main development possibility of this work is applying this method for complex and 3D shape analysis. As mentioned, this type of shape representation can be very helpful to describe complex shapes which are composed of more than one contour. The possibility to use this technique for 3D shape analysis can be also investigated. Acknowledgment

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