Recognition of 2D Shapes through Contour Metamorphosis

R. Singh   I. Pavlidis   N. P. Papanikolopoulos

Artificial Intelligence, Robotics, and Vision Laboratory
Department of Computer Science
University of Minnesota
Minneapolis, MN 55455

Abstract

A novel method for 2D shape recognition is proposed. The method employs as a dissimilarity measure the **degree of morphing** *between a test shape and a reference shape. A physics-based approach substantiates the* **degree of morphing** *as a deformation energy and casts the problem as an energy minimization problem. The method operates upon key segmentation points that are provided by an appropriate segmentation algorithm. The recognition paradigm is invariant to translation, rotation, and scaling. It can handle both convex and non-convex shapes. The proposed system exhibits robust recognition behavior and real-time performance in a series of experiments. The experiments also highlight the ability of the method to recognize deformable shapes.*

1 Introduction

2D shape recognition is one of the central issues of machine vision. The problem arises in a variety of contexts. For example, the sorting and handling of industrial parts in manufacturing environments often include the 2D shape recognition problem. The same problem emerges in the context of an Intelligent Transportation System (ITS) or a security system for monitoring pedestrian traffic. In addition, Automatic Target Recognition (ATR) systems for classifying images of military planes involve shape recognition tasks. Finally, the Optical Character Recognition (OCR) area for recognizing characters, words, and signatures is based on the classification of shapes. The common goal in all these applications is to reliably recognize the outline of a 2D object (silhouette of an industrial part or a pedestrian or an airplane) or a contour (letters, numerals).

This paper introduces a framework for handling comprehensively the recognition of rigid and deformable 2D shapes. It proposes the use of physics-based contour metamorphosis for shape recognition. Contour metamorphosis is a well established graphics technique that refers to the problem of computing a continuous contour transformation from an initial contour to a target contour. It has widespread applications in computer animation. Contour metamorphosis was first used for recognition purposes in [9]. There, a system for on-line handwriting recognition was reported that achieved very high correct classification rates. The same method has now been sufficiently modified and improved to deal with the more generic task of 2D shape recognition. The proposed system uses to its advantage the intuitive fact that two contours that are similar don't have to go through an extensive metamorphosis in order for one to assume the shape of the other. Thus, the *degree of morphing* between a test contour and a reference contour can be used as a shape matching criterion. The *degree of morphing* is an abstract quality that in our system is substantiated through a physics-based approach to contour metamorphosis first proposed by T. W. Sederberg *et al.* [12]. Sederberg's approach was developed for animation purposes and has been modified first in [9], and even further now, to deal with the pattern recognition tasks at hand.

Each contour is considered to be made of a piece of wire. Contour metamorphosis takes place through appropriate stretching and bending of the artificial wire out of which the initial shape is made of. That allows for the problem to be formulated as an energy minimization problem. The energy consumed for stretching and bending a wire contour to some other wire contour is the entity that quantifies the *degree of morphing* concept. The metamorphosis is guided not by every point but only by a few key points which are the result of a segmentation process. This reduces the computational complexity and abstracts away part of the variable nature of real world shapes. The proposed

formulation allows comparison of two shapes independent of their relative orientation and position. Scale invariance is achieved by mapping the shapes to a unit square.

In this paper we first present some previous work conducted in the area of 2D shape recognition and we compare it with the proposed method (Section 2). Then, in Section 3 we describe the method in some detail. The experimental performance of the system is reported in Section 4. Finally, conclusions are drawn and the future work is outlined in Section 5.

2 Previous Work

2D shape recognition is one of the most heavily researched areas in machine vision. (See for example [6] for a review of the literature). Shape recognition systems can be characterized by the shape representation method they adopt and by the dissimilarity measure they use. Regarding the shape representational aspect, recognition systems can fall loosely into five classes: representation by global features, local features, boundary description , skeleton, and 2D parts. Boundary representation is the most common representation for 2D objects [4, 7, 13]. In this context, polygonal approximation and dominant point detection are considered powerful representational techniques [8, 10, 15]. They can represent any shape to an arbitrary degree of accuracy. In fact, they can deliver an adequate representation of the shape, while at the same time reduce its data volume by as much as $70\% - 80\%$. Such algorithms have also low computational cost ($O(n)$ to $O(n^2)$) and thus, they are suitable for real-time machine vision applications. Our method is within this powerful representational framework and uses a segmentation algorithm [8] with special properties.

Shape recognition systems can also be classified according to the dissimilarity measure they use. For an extensive treatment of the subject one may look at [14]. Within the boundary description representational framework, some of the measures that have been used are the L_2 distance between the turning functions of two polygons [1], the Hausdorff distance, and the sum of squares of the Euclidean distances from each vertex of each polygon to the convex hull of the other polygon [5]. Generally speaking, a dissimilarity measure should satisfy the following properties proposed by Arkin et al. [1] in order to be effective:

1. The measure should be a metric.

2. It should be invariant under translation, rotation, and scale change.

3. It should be easy to compute.

4. It should match intuitive notions of shape resemblance.

The novel dissimilarity measure we propose (*degree of morphing*), as will be shown, satisfies all the above requirements.

Recently, a new generation of shape recognition systems has emerged that perform robustly in difficult machine vision tasks [2, 11]. These newer systems feature sophisticated representational mechanisms, dissimilarity measures that satisfy the properties suggested by Arkin et al. [1] and are resilient to noisy data and shape deformations. This is quite an improvement over the older machine vision systems that performed well for limited classes of rigid objects only and were sensitive to noise. The price, however, has been increased computational complexity which cannot be afforded in real-time applications. Most of the newer systems employ a deformation measure, the computation of which, involves nontrivial variational calculus [2] or finite element analysis [11]. In comparison, the system we propose computes its deformation measure (*degree of morphing*) by employing a very fast dynamic programming technique. At the same time, the system performs well in difficult recognition tasks, like the recognition of deformable objects. Thus, the proposed method not only features high quality recognition performance but also remains efficient and suitable for real-time applications in reasonably priced hardware.

3 The Proposed Method

Contour metamorphosis is defined as the transformation of one contour (initial) to another (target) [12]. Metamorphosis takes place at the point level. Points from the initial contour should be morphed to the corresponding points in the target contour. It would be computationally inefficient for all the shape points to participate in the metamorphosis process. It would also prove harmful to the recognition process due to the ever present noise at the point level. The necessary level of abstraction can be provided by a good segmentation algorithm.

Several well-known segmentation algorithms [3, 10] have been tried but none has produced satisfactory results for the needs of the proposed system. One major problem with most segmentation algorithms is that their performance even on similar shapes may vary both in the number and arrangement of segmentation points. This is caused by noise and local shape variability. Furthermore, most segmentation algorithms

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are parameter dependent. This precludes the automation of the recognition task and does not serve the purpose of the proposed system. As it will be shown later in this section, for the metamorphosis to work properly, the segmentation points between the initial contour and the target contour should correspond in meaningful ways. One way to do this is to have a high curvature point correspond to a high curvature point and a low curvature point correspond to a low curvature point if possible. This necessity determines the philosophy of the segmentation algorithm we propose. The basic idea is that the contour is considered as a succession of high curvature points (corners) and relatively low curvature regions that obey the pattern *... corner - low curvature region - corner ...* Segmentation reduces low curvature regions to a single point (key low curvature point) that is usually placed somewhere in the middle of the low curvature region. A full account of the segmentation algorithm we use and a comparative study that highlights its special qualities can be found in [8]. In short, the algorithm uses the method suggested by Brault *et al.* [3], slightly modified, to find the corners. The modifications introduced render the algorithm parameterless and thus fully automated. Then, innovatively, a method conjugate to that of locating corners, is used to find key low curvature points. The algorithm gives similar segmentations for similar shapes even in the presence of certain levels of noise. This facilitates the metamorphosis based matching process. Fig. 1 gives a characteristic example of the algorithm's performance. The points indicated by small squares are the corner points and the points indicated by small discs are the key low curvature points.
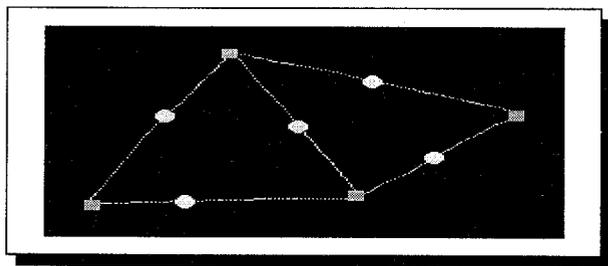

Figure 1: Segmentation of a pyramidal shape by the algorithm reported in [8].

In our approach, a shape is represented by the segmentation points of its outline contour only. If C_i $(i = 0, 1, \ldots, n)$ denote the segmentation points of the contour $\mathbf{C}$, then the contour $\mathbf{C}$ could be represented

in vector form as

$$\mathbf{C} = [C_0, C_1, \ldots, C_n]. \tag{1}$$

Metamorphosis from an initial contour $\mathbf{C}^I$ to a target contour $\mathbf{C}^T$ is accomplished by performing a linear interpolation between the corresponding segmentation points of the two contours,

$$
\begin{aligned}
\mathbf{C}(t) &= u\mathbf{C}^I + t\mathbf{C}^T \\
&= [uC_0^I + tC_0^T, uC_1^I + tC_1^T, \ldots, uC_n^I + tC_n^T] \\
&= [C_0(t), C_1(t), \ldots, C_n(t)]
\end{aligned}
\tag{2}
$$

where t is the time variable normalized to the interval $[0, 1]$ and $u = 1 - t$.

In general, the initial contour $\mathbf{C}^I$ has a different number of segmentation points (n points) than the target contour $\mathbf{C}^T$ (m points). Thus, point correspondence becomes the central issue in contour metamorphosis. Sederberg *et al.* in [12] addressed the point correspondence problem in the following manner: All the possible point correspondences between an initial contour of n points and a target contour of m points were represented by an $m \times n$ matrix. The determination of the preferred point correspondence is considered as an optimization problem and is solved by employing a dynamic programming technique. For this to happen, each candidate point correspondence is associated with a value (point correspondence cost). The computation of the point correspondence cost is based on the following physics paradigm. The contours are considered to be made of virtual wires, metamorphosis takes place through bending and stretching of the initial wire (contour) to the target wire (contour). Such a formulation allows each point correspondence to be associated with a deformation measure that represents the stretching and bending energy that is consumed during the metamorphosis. The optimal point correspondence is the point correspondence that consumes the least metamorphosis energy. A visualization of the method in action can be seen in Fig. 2. The first and the final frames in the action sequence have the output of the segmentation algorithm superimposed with the corner points represented by small squares and the key low curvature points represented by small discs.

Despite its merits, Sederberg's approach cannot be applied effectively to quantify 2D shape differences. It does not elaborate on how to automatically select points for representing a shape, nor does the metamorphosis energy satisfy the properties of a metric. This is not surprising in that the goal of Sederberg *et al.* in [12] was to obtain visually pleasing metamorphoses. We, however, are primarily concerned with using the
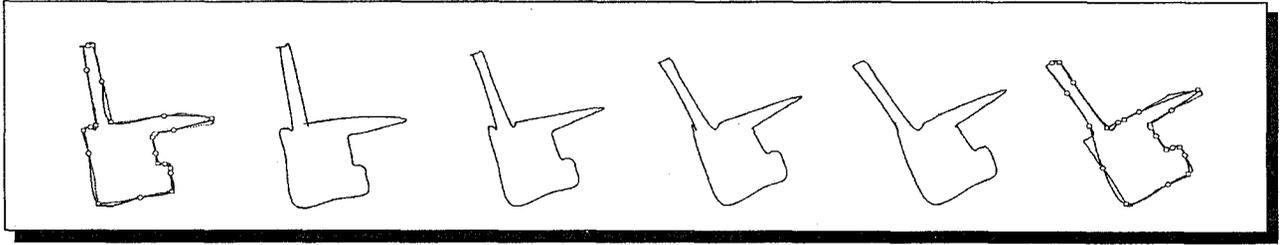
Figure 2: An industrial part is metamorphosed to the same industrial part that differs from the initial up to a noise level and a geometric transformation only. Because the initial and the target contours are very similar, the metamorphosis is least pronounced and the deformation energy spent is very small.

energy spent in metamorphosis as a dissimilarity measure for 2D shape recognition.

From [12], we have maintained the formula for the stretching energy (E_s):

$$E_s = k_s \frac{\mid L_T - L_I \mid^2}{(1 - c_s)min(L_I, L_T) + c_s max(L_I, L_T)}, \quad (3)$$

where L_I is the initial length of the wire and L_T is its length after the deformation. The term c_s is a user-definable parameter which controls the penalty for segments of the wire that collapse to points during the metamorphosis. Finally, k_s is the user-definable stretching stiffness parameter.
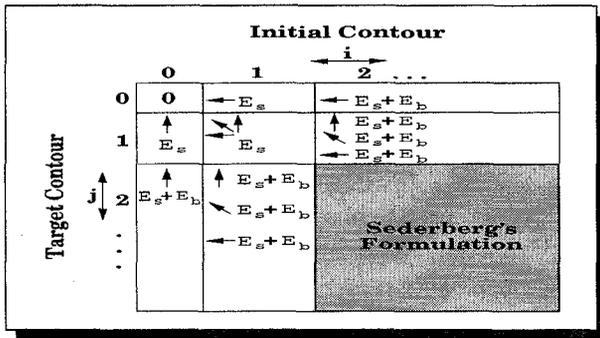

Figure 3: Computation of the optimal point correspondence.

We have introduced the following two important modifications in the original method [12]:

(A) The bending energy (E_b) is now computed as:

$$E_b = k_b(\Delta\theta)^2 \quad (4)$$

where k_b indicates the bending stiffness and $\Delta\theta$ represents the absolute bending angle change due to the metamorphosis of a particular triplet of segmentation points. The formulation in Eq. (4) takes into account only the difference in the corresponding angles between the input and the target

contour and nothing else. Contrary to the formulation in [12], the current formulation is symmetric with respect to the direction of metamorphosis.

(B) The matrix in Fig. 3 shows how to compute the cost of a point correspondence. The modifications introduced in the first two rows and columns ensure that the cost of point correspondences is always finite. This is achieved through the appropriate combination of stretching E_s and bending energies E_b. The cost of corresponding the point C_i^I of the input contour to the point C_j^T of the target contour is defined as the minimum cost of the previous point correspondence (C_{i-1}^I, C_j^T) or (C_i^I, C_{j-1}^T) or (C_{i-1}^I, C_{j-1}^T) and the incremental cost in connecting that to (C_i^I, C_j^T). The arrows at each cell in the table indicate the possible previous correspondences. By following the outgoing arrows from a cell to its immediate neighbors, we get the points participating in the computation of the corresponding stretching energy (E_s). By following two consecutive outgoing arrows (triplet of points), we get the points for the bending energy (E_b) computation. The symmetric structure of the matrix ensures that the deformation energy for each point correspondence is invariant to the direction of metamorphosis.
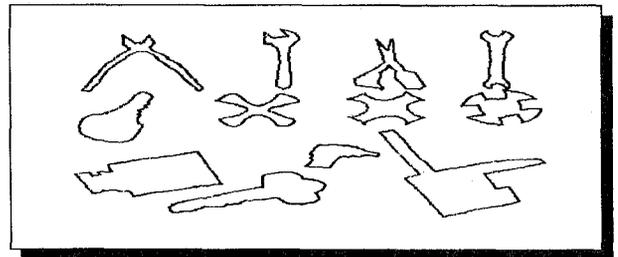

Figure 4: Representative shapes from the database.

Ref. Shapes	Test Shapes	Correct Classifications	Misclassifications	Success Rate
21	84	82	2	97.62%

Table 1: Experimental results.

We informally argue that with the above modifications, the energy deformation measure E (*degree of morphing*) fully satisfies the properties of a metric, namely:

(1) $E(\cdot, \cdot) \geq 0$

(2) $E(\mathbf{C1}, \mathbf{C2}) = 0$ iff $\mathbf{C1} = \mathbf{C2}$

(3) $E(\mathbf{C1}, \mathbf{C2}) = E(\mathbf{C2}, \mathbf{C1})$

(4) $E(\mathbf{C1}, \mathbf{C2}) + E(\mathbf{C2}, \mathbf{C3}) \geq E(\mathbf{C1}, \mathbf{C3})$

where $\mathbf{C1}$, $\mathbf{C2}$, and $\mathbf{C3}$ are arbitrary shape contours. The justification for the first two properties follows trivially from the definitions of the stretching and the bending energy. The third property, is satisfied after the introduction of the proposed modifications. For the fourth property, we observe that the bending and stretching energies are always positive. For the bending energy specifically, the angle changes between contour $\mathbf{C1}$, contour $\mathbf{C2}$, and contour $\mathbf{C3}$ may be either monotonic (for example, $\theta^{C1} > \theta^{C2} > \theta^{C3}$) or non-monotonic (for example, $\theta^{C2} > \theta^{C1} > \theta^{C3}$). Thanks to modification (B), in the monotonic case, the equal option of property (4) holds, while in the non-monotonic case, the inequality option of the property holds. With similar arguments, we can show that property 4 holds also for the stretching energy, and hence for the total energy (stretching and bending). The initial point correspondence for metamorphosis to occur can be chosen between two arbitrary segmentation points from the input and target shapes respectively. The *degree of morphing* is defined as the minimum energy over all possible initial point correspondences.

4 Experimental Results

The shape recognition ability of the proposed system was tested on a database of 21 object outlines (contours). The database contained among others, the outlines of a variety of industrial parts and tools (see Fig. 4). Some of the object contours included in the database have been taken from [7, 10, 12, 13]. For each reference contour four test samples were captured in random positions and orientations. During experimentation, each test contour was segmented and morphed to every reference contour. The metamorphosis that yielded the smallest energy indicated a match. The results of the experimentation are shown in Table 1. The misclassifications were the result of a poor segmentation performance. Interestingly, the system gives real-time responses in a moderate piece of hardware (SGI Indigo^{TM} R4000 that runs at 100 MHz).

Present experimental studies indicate that the method shows promise in the recognition of deformable shapes. An example of deformable shapes is a set of consecutive frames of a pedestrian. Recognition/classification of deformable shapes can play a fundamental role in areas like pedestrian detection (an interesting ITS application). Fig. 5 shows the first and the last frames of two action sequences that were stored as reference contours in the database. Fig. 6 shows three intermediate frames that were used as test contours in a classification experiment. Table 2 shows the recognition results for this experiment in terms of the *degree of morphing* values. All the shapes were correctly classified. Interestingly, the *degree of morphing* reflected the position of the intermediate test frames in their respective action sequences.

5 Conclusions and Future Work

A novel 2D object recognition method has been proposed that is based on shape metamorphosis. The method uses the *degree of morphing* as a powerful dissimilarity measure. The proposed measure satisfies all the properties of a metric. The method also employs a representational technique, first proposed in [8], that is well suited to the way metamorphosis works. The low computational complexity, the ability to handle arbitrary shapes, and the promise it has shown in the classification of deformable shapes, render the method suitable for a variety of real world, real-time applications.

The two misclassifications unearthed during the experimentation stage are due to the inadequate descriptional behavior of the segmentation algorithm. The segmentation algorithm used, allows a consistent description of shapes ... *corner – low curvature point – corner* ... which facilitates the metamorphosis. Nevertheless, the experimental results indicate the need to extend the system so that segmentation algorithms with better approximating capabilities can be used.

	Reference Contours			
Test Contours	Initial Dance Frame	Final Dance Frame	Initial Exercise Frame	Final Exercise Frame
Test Frame 1	145.88	204.85	409.26	483.38
Test Frame 2	181.21	172.47	370.30	429.66
Test Frame 3	314.85	303.02	255.01	168.28

Table 2: Classification table for the deformable shapes.
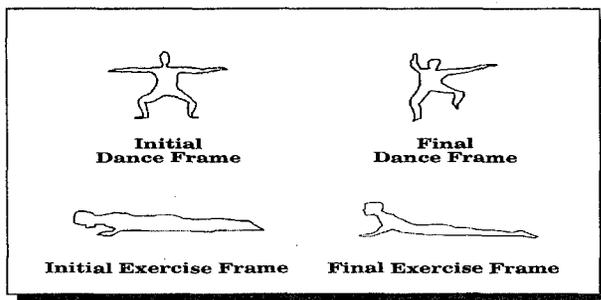
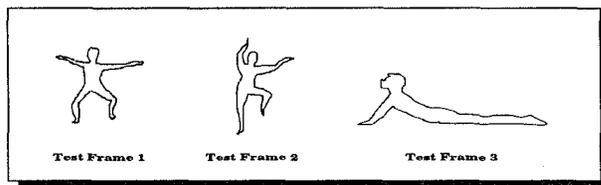**Figure 5**: Initial and final frames of two action sequences.

Figure 6: Intermediate frames from the action sequences of Fig. 5 that serve as test contours.

Acknowledgements

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