Off-Line Recognition of Signatures Using Revolving Active Deformable Models

I. Pavlidis R. Mavuduru N. Papanikolopoulos

Artificial Intelligence, Robotics, and Vision Laboratory
Department of Computer Science
University of Minnesota
4-192 EE/CS Building
200 Union St. SE
Minneapolis, MN 55455

Abstract

This paper presents a novel approach to the problem of signature recognition. We introduce the use of revolving active deformable models as a powerful way of capturing the unique characteristics of a signature's silhouette. Experimental evidence shows that the silhouette of a signature uniquely determines the signature in the majority of cases [14, 16]. The objective of our method is to recognize signatures based on the spatial properties of the signature boundaries. Our active deformable models originate from the snakes introduced to computer vision by Kass et al. [9], but their implementation has been tailored to the task at hand. These computer-generated models interact with the virtual gravity field created by the image gradient. Ideally, the uniqueness of this interaction mirrors the uniqueness of the signature's silhouette. The proposed method obviates the use of a computationally expensive segmentation approach and yields satisfactory results regarding performance, without compromising the accuracy rate. Interestingly, the active deformable models have been implemented in such a way, that the method is potentially fully parallelizable. The experiments performed with a signature database show that the proposed method is promising.

1 Introduction

The recognition of handwritten characters, numerals, and signatures has been an active research topic for more than twenty years [1, 2, 3, 4, 5, 10, 11, 12, 14, 15, 16, 17]. Nowadays, we have reached the point where both graphics and text can be recognized in machine-generated documents. However, recognition of highly cursive script and signatures still remains a partially solved problem [10].

The automation of signature recognition and verification has been justified in a number of papers, for financial as well as security reasons [4, 10, 15]. Signature recognition searches for the identity of a given signature through a signature database. Signature verification verifies whether a given signature belongs to a specified individual. Apparently, the signature recognition problem is more complex than the signature verification problem and relatively little research effort has been focused on this area so far.

It is customary to distinguish *on-line* from *off-line* signature recognition and verification systems. In an on-line system the user has to sign on an electronic tablet which gives a signal $\mathbf{z}(t) = [x(t), y(t)]^T$ (i.e., coordinates as a function of time). This system enables dynamic information such as stroke sequence, pressure, and acceleration to be captured in real-time. In contrast, in an off-line system the user does not use a tablet but instead he/she signs on a paper and his/her signature is captured via a camera or a scanner. Obviously, valuable information that can be easily extracted in the on-line method, it is very difficult or impossible to be recovered in the off-line method. However, the use of special hardware by the on-line method restricts its applicability.

The handwritten signature is considered to be among the best means for an automated personal identification system. It can be produced nearly anywhere and unlike passwords or identity cards cannot be forgotten or lost [4]. It would be of great value an intelligent identification system, where the user does not have to go through the awkward procedure of laying an identity claim by punching an ID number (veri-

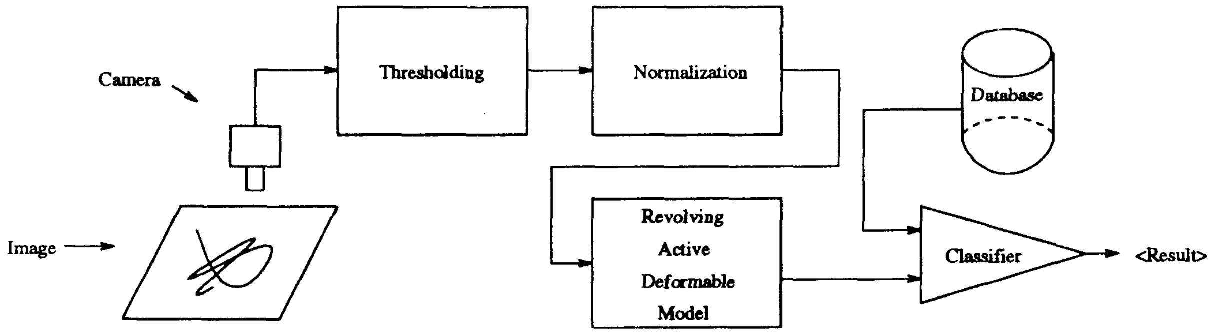

Figure 1: Block diagram of the signature recognition system.

fication). Instead, the system should be capable of arriving at an identification decision (recognition and verification) based solely upon the signature of the user. Such a system is the ultimate goal of the line of research we are pursuing. We consider the problem of signature recognition and verification as a two stage process. In the first stage, signature recognition should be achieved. The second stage should verify that indeed the signature has been written by the user whose identity has been recovered in the first stage and not by an impostor. In the recognition stage, the unique characteristics of the signature's silhouette are captured first. Then, if the system cannot arrive at a definite conclusion, it should resort to the internal structure of the signature. Experimental evidence shows that the silhouette of a signature uniquely identifies the signature in the majority of cases [14, 16]. Only for a relatively small percentage of problematic signatures, the system needs to resort to the internal structure module.

In this paper we address the problem of recognizing signatures off-line by capturing the unique characteristics of their boundaries. The organization of the paper is as follows: Section 2 presents some previous work conducted in the area. Section 3 outlines the proposed system. Sections 4, 5, and 6 describe in detail the various modules of our system. In Section 7 the experimental results are presented. Finally, in Section 8 the paper is summarized and conclusions are drawn.

2 Previous Work

Traditionally, the techniques used in the off-line case can be classified into one of the following three categories [10, 17]:

- *Global approach:* The extraction of global features is easy [12, 16], but the method deteriorates rapidly when significant distortion and style variations are present and satisfactory position alignment cannot be achieved.
- *Statistical approach:* The method is more tolerant than the global approach to distortion and style variations since it incorporates a certain amount of topological and dynamic information [2, 3].
- *Geometrical and topological approach:* Geometrical and topological features can tolerate a high degree of distortion and style variations, and they can even tolerate up to a certain degree of translation and rotation variations [1, 5, 10].

3 Outline of the Proposed System

The geometrical and topological approach has been proved the most effective so far. Geometrical and topological feature extraction in conventional methods is primarily based upon segmentation techniques. Segmentation usually leads to a heavily heuristic approach and places a considerable burden on the computational process. Our approach departs totally from this mode of tracing signatures off-line. Instead of segmenting the signature, we rather follow a *holistic* approach.

We address the problem of capturing the spatial properties of signatures' boundaries using a technique that is well established in the area of active vision for tracking objects [6, 18] but has never been tried before in the field of signature recognition and verification. We introduce the use of computer-generated *active deformable models* for approximating the external shape of a signature. Our active deformable models are similar, but not exactly the same with the *snakes* introduced by Kass *et al.* [9].

In more detail, the proposed method consists of three modules (see Fig. 1):

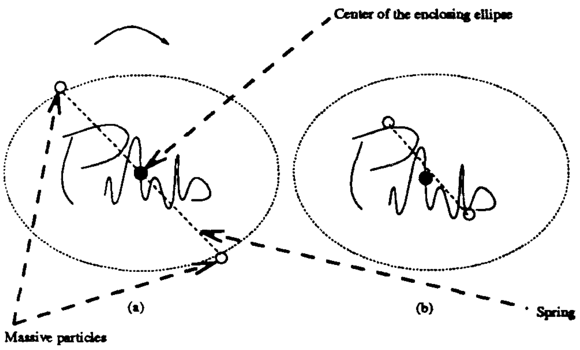

Figure 2: Instance of a revolving active deformable model (a) Initial position (b) Final position.

1. *Preprocessing:* Preprocessing includes a thresholding operation to clear up the image and an orientation normalization procedure that facilitates the recognition process.

2. *Revolving active deformable model:* This is the main part of the whole procedure. Two-particle active deformable models are applied to the signature (see Fig. 2). The particles are connected through an elastic spring that goes through the center of an enclosing ellipse. The particles lie initially on the enclosing ellipse 180^o apart. Each pair of particles gets attracted to the external signature edges, locally, under the influence of a virtual gravity field. The pairs of particles are applied in a revolving fashion at equally spaced angular intervals and at various resolutions. Each pair of particles reaches finally a stable condition. The dynamic information that pertains to the virtual field created around each signature, is used to establish the feature vector, based upon which, the final module matches the signature image with one of the signatures from the signature database.

3. *Classification:* A unique match between the signature image and a prototype signature stored in the signature database is established. The classification is based on the characteristics of the signature's virtual gravity field, which ideally mirrors the unique characteristics of the signature's silhouette. In the case of failure to come up with a clear-cut match, the system classifies the case as inconclusive.

4 PREPROCESSING

4.1 Thresholding

It is very important for the main processing module of a recognition system to be applied to a noise-free image. We actually need a binary signature image where the signature body will clearly stand out in a perfectly clean background. This is especially true for the case of active deformable models, because salt and pepper noise can totally alter the virtual gravity field of the image. We also need the thresholded signature image to represent the sampled signature as faithfully as possible, since the best recognition technique would be useless if applied to a heavily distorted image.

The thresholding technique chosen for that purpose is a method devised by Otsu [13]. It involves a nonparametric and unsupervised method of threshold selection. An optimal threshold is selected, so as to maximize the separability of the resultant classes in gray levels. The algorithm utilizes only the zeroth- and the first-order cumulative moments of the gray-level histogram and is extremely fast. Fig. 3 shows the original image of a sample signature and Fig. 4 shows the thresholded image.

4.2 Normalization

The normalization process involves only an orientation normalization and not a size normalization. The classifier later on classifies according to features that are size invariant. More specifically a signature is oriented in such a way that its elongation axis is horizontal. The alignment of the elongation axis with the horizontal axis is achieved through the use of second-order spatial moments [7].

Utilizing only second-order moments for orienting a 2-D shape leaves us with a *two-way ambiguity*. The elongation axis has been properly aligned to the horizontal axis of the coordinate system, but it is not known if the oriented shape should be rotated by 180^o or not (that is, which part should face east and which should face west). To resolve this matter we resort to the determination of the most distant point from the centroid [8].

The most distant point from the centroid is computed as the one of the eight extremal points of the signature image that has the maximum Euclidean distance from the centroid. The extremal points of a signature region R can be defined in terms of the topmost row ($xmin$) of R; the bottommost row ($xmax$) of R; the leftmost column ($ymin$) of R; and the rightmost column ($ymax$) of R. These extremal rows and columns are in fact determined during the computation of the bounding rectangle of the signature, that is absolutely essential during the next processing stage, and thus, they do not constitute an additional computational burden. Fig. 5 shows the signature image after the orientation normalization phase.

Figure 3: Signature image before thresholding.

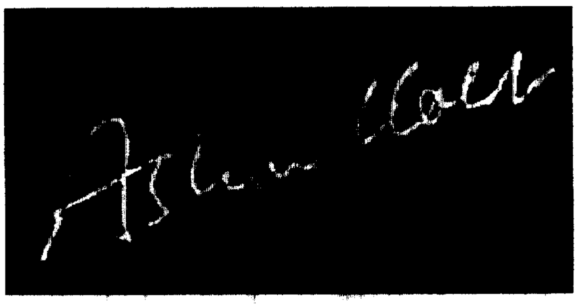

Figure 4: Signature image after thresholding.

Figure 5: Signature image after orientation normalization.

5 Revolving Active Deformable Model

An active deformable model is a mesh of artificial massive particles connected to each other by artificial elastic springs. Each particle interacts with the silhouette of the signature through attracting forces created by high values in the image-gradient map. The movement of the active deformable model on the image plane is governed by the laws of classical mechanics. Our active deformable models are modeled after the active deformable models used by Couvignou *et al.* [6] for visually tracking moving objects with two notable differences. First, our active deformable models are not used in tracking moving objects but rather in capturing the spatial properties of the silhouette of static signature images. Second, we don't arrange the mesh of particles in a rectangular fashion around the signature, but we rather apply pairs of particles in succession, along the enclosing ellipse of the signature, at equally spaced intervals and in a revolving fashion. This mode of active deformable model application not only yielded dramatic performance gains but entailed the method to be potentially fully parallelizable.

In more detail, the enclosing ellipse of the signature is defined as the ellipse whose foci are the middle points of the left and right edges of the bounding rectangle. The particles are connected through an elastic spring that goes through the center of the ellipse. The particles lie initially on the enclosing ellipse 180^o apart. We chose the starting positions of the particles to be on the enclosing ellipse, because it gives us a nice parametric model to achieve half a revolution around the signature, and in addition, it circumscribes the signature more closely than any other simple closed curve, facilitating a strong interaction with the signature's gravitational field. Each pair of particles gets attracted to the signature edges, locally, under the influence of a virtual gravity field. The particles are moving in the image plane, and the motion of each *ith* particle obeys the classical dynamic equation,

$$m_i \ddot{\mathbf{r}}_i = \mathbf{F}_i^{ext} + \sum_{j=1}^{n} \mathbf{F}_{ij}^{int} \quad (1)$$

where $\mathbf{r}_i = (x_i, y_i)^T$ is the position vector of the *ith* particle in the image plane, $\mathbf{F}_i^{ext}$ is the *external force*, exerted by objects external to the system, and $\mathbf{F}_{ij}^{int}$ is the *internal force* exerted on the *ith* particle by the *jth* particle. External forces are created by the image gradient magnitude of the signature's boundary pixels. Internal forces are spring forces that tend to oppose the deformation of the model. The pairs of particles are applied in a revolving fashion, at equally spaced angular intervals and at various resolutions. Each pair of particles finally reaches a stable condition, represented pictorially by small circular traces on the signature's boundary (see Fig. 6, 7, and 8).

6 Classification

The system is trained by presenting it one sample signature of every individual we consider as a user of the system. The feature extraction for the prototype samples is taken place by applying the revolving active deformable model at its maximum resolution. The maximum resolution in the current system is 36 pairs applied at 5^o apart from each other. Then, for each test case, the revolving active deformable model is applied at various resolutions. Currently, it is applied at 6, 9, 12, 18, and 36 pair resolution. These correspond to angular intervals of 30^o, 20^o, 15^o, 10^o, and 5^o.

Figure 6: Snapshot of a revolving active deformable model in action–towards the initial phase.

Figure 7: Snapshot of a revolving active deformable model in action–towards the middle phase.

Figure 8: Snapshot of a revolving active deformable model in action–towards the final phase.

The feature vector we are using is constructed as follows: each particle of every active deformable model follows a trajectory from its initial position to the border of the signature under the combined influence of the local virtual gravity field of the signature image and the internal spring forces. The trajectories of all the particles of the revolving active deformable model characterize the virtual field of the signature, and it makes strong intuitive sense to incorporate in some way this information into our feature vector. For each particle i $(1 \leq i \leq N)$ we keep the tangent of the angle α_i formed between the elongation axis and the *average trajectory* of the particle. We define as the average trajectory of each particle, the line segment that connects its initial position with its final position. We call these angles, ***approach angles***. Thus, for each prototype signature in the database, the feature vector is a point in the 36–dimensional space. For each test case, similar feature vectors are constructed in the 6–, 9–, 12–, 18–, and 36–dimensional space. These feature vectors are compared with the 36–dimensional reference vectors of the database. For the vectors of the test cases that have less than 36 dimensions a simple interpolation scheme is used to facilitate comparison. The Euclidean distance has been chosen as the discriminating measure. The winning reference vector at each resolution, is the vector that is closest to the test case vector, in terms of Euclidean distance. Matching occurs with that winning reference vector that stands the farthest apart from its contender. If the difference is too narrow then the system classifies the case as inconclusive.

The fact that various resolutions come into play during the recognition process compensates for the variability factor in the signatures of the same individual. For example, the gap usually encountered in some signatures between the first and the last name may vary at each try. In that case, a coarser resolution will alleviate the gap effect and help the matcher lock in the correct reference signature. This will be expressed as a clear-cut distance in the feature space from the immediate contender at the specific resolution.

7 Experimental Results

The user population of the system is currently forty individuals. The system has been trained with one sample signature from each individual user. The system has been tested with 120 test signatures, three from each user. The test signatures have been collected at different days and times and no restrictions have been applied. The test subjects were graduate and undergraduate students and various professionals. Out of 120 test signatures, 85 have been correctly recognized which amounts to 70.83% success rate, 16 test cases have been signaled as inconclusive (13.33%), and for the remaining 19 signatures (15.84%) the system gave false recognition. The system failed to recognize particular problematic signatures. The results are summarized in Table 1.

Table 1		
Correct	Inconclusive	False
85 *or* 70.83%	16 *or* 13.33%	19 *or* 15.84%

8 Conclusion

In this paper we addressed the question of whether elastic structures similar to snakes introduced by Kass *et al.* [9] can be of some value in a first stage classifier in the area of signature recognition and verification. The most important contribution of this work is the introduction of the revolving active deformable models as a powerful means for capturing the spatial properties of a signature's silhouette. The experiments confirmed that signatures are uniquely determined by their silhouette in the great majority of cases. Recognition rates are satisfactory for a first stage classifier, and the system responds reasonably fast. Speed, however, will increase dramatically once we exploit the parallelization potential of the model.

Future research efforts will focus on diminishing the false recognition rate. This is the most important hurdle before we move on to the verification part of our perspective system, since the verification process for these false recognized cases will be meaningless. We need to transfer as much as possible out of the false percentage to the inconclusive percentage. Then, the perspective internal structure module will be able to resolve the ambiguity. In case that the false percentage is not zeroed, the first best two or three matches might need to be considered in the subsequent stages. In the current system, the correct match is always among the top three best matches.

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