Application of Deformable Structures to Signature Identification

I. Pavlidis 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

Automatic signature verification is a well established and active research area [1, 8, 12, 13] with numerous applications. In contrast, automatic signature identification has been given little attention, although there is a vast array of potential applications that could use the signature as an identification tool. This paper presents a novel approach to the problem of signature identification. We introduce the use of the revolving active deformable model as a powerful way of capturing the unique characteristics of the overall structure of a signature. Experimental evidence [10] as well as intuition support the idea that the overall structure of a signature uniquely determines the signature in the majority of cases. Our revolving active deformable model originates from the snakes introduced in computer vision by Kass et al. [6], but its implementation has been tailored to the task at hand. This computer-generated model interacts with the virtual gravity field created by the image gradient. Ideally, the uniqueness of this interaction mirrors the uniqueness of the signature's overall structure. The proposed method obviates the use of a computationally expensive segmentation approach and is parallelizable. The experiments performed with a signature database show that the proposed method is promising.

1 Introduction

The automation of signature verification and identification has been justified in a number of papers for financial as well as security reasons [3, 7, 13]. Signature identification 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 identification problem is more complex than the signature verification problem and little research effort has been focused on this area.

It is customary to distinguish *on-line* from *off-line* signature identification and verification systems. In an on-line system the user has to sign on an electronic tablet which typically gives a signal $z(t) = [x(t), y(t)]^T$ (i.e., image coordinates as a function of time). On the other hand, 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 (static image). The dynamic information associated with the on-line method is of special value to verification systems since the forger might be able to copy the overall shape of the owner's signature but it would be almost impossible to copy the timing and the rhythm with which it is written.

It would be of great value an intelligent signature identification system, where the user does not have to go through the awkward procedure of laying an identity claim by punching an ID number (verification). Instead, the system should be capable of arriving at a foolproof identification decision (identification 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 foolproof signature identification as a two stage process. In the first stage, signature identification through static image analysis 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 a skillful impostor. In this second stage, the use of on-line information would be essential (hybrid system). In the identification stage, the unique characteristics of the signature's overall structure are captured first. Then, if the system cannot arrive at a definite conclusion, it should resort to a more detailed

- and more time consuming - investigation of the signature's structure. Experimental evidence [10] as well as intuition support the idea that the overall structure of a signature uniquely determines the signature in the majority of cases. Only for a relatively small percentage of problematic signatures, the system would need to resort to the detailed structure analysis module.

In this paper we address the problem of identifying signatures by capturing the unique characteristics of their overall structure. As will be explained in subsequent sections, by introducing the use of the revolving active deformable model, we manage to capture the signature's overall shape in such a way that at the same time it conveys information about the signature's internal structure. Thus, while we maintain the simplicity, the intuitiveness, and the speed of the global methods [8, 14], we achieve at the same time descriptional detail comparable to that obtained by localized methods [2, 7], without resorting to a computationally expensive and heavily heuristic segmentation approach. Interestingly, speed can be further increased by exploiting the parallelization potential of the algorithm. Specifically, the proposed method consists of three modules as it is shown in Fig. 1.

The organization of the paper is as follows: Sections 2, 3, and 4 describe in detail the various modules of our system. In Section 5 the experimental results are presented. Finally, in Section 6 the paper is summarized and conclusions are drawn.

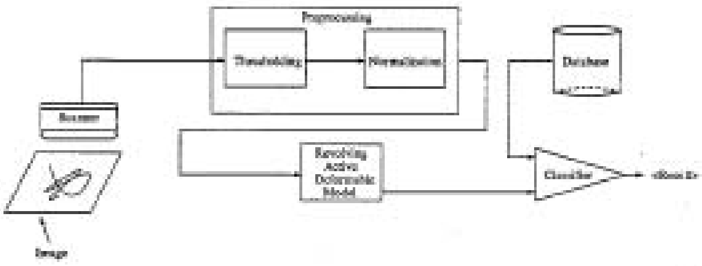

Figure 1: Block diagram of the signature identification system.

2 PREPROCESSING

Preprocessing consists of a thresholding operation to clear up the image and a normalization process. The thresholding technique chosen is a method devised by Otsu [9]. It involves a nonparametric and unsupervised method of threshold selection. The normalization process involves only an orientation normalization and not a size normalization. The classifier module later 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 [5]. 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° or not (that is, which part should face east and which should face west). The problem has been overcome by processing both the aligned image yielded by the above orientation algorithm and its flipped (rotated by 180°) version for each prototype signature image. The results of this processing are kept into two separate fields, one for the aligned reference image and one for its flipped version, and linked with the node of the corresponding prototype signature database entry. A test signature image is oriented by using the second-order spatial moments only, then is processed, and the result of processing is matched against both fields of every reference signature database entry.

3 Revolving Active Deformable Model

Active deformable modes originate from the *snakes* introduced by Kass *et al.* [6]. An active deformable model is a mesh of artificial massive particles connected to each other by artificial elastic springs. Each particle interacts with the signature image 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.* [4] 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 overall structure 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 (revolving active deformable model) not only yielded dramatic performance gains but entailed the method to be potentially fully parallelizable.

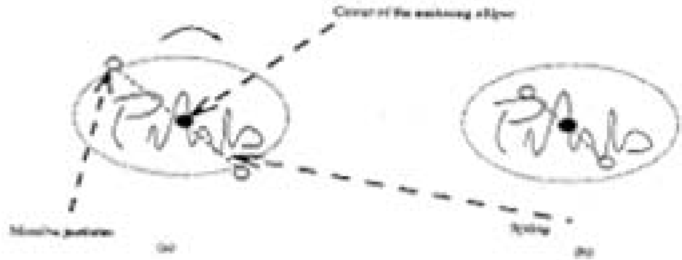

Figure 2: Instance of a revolving active deformable model (a) Initial position (b) Final position.

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° apart (see Fig. 2). We choose 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. The pairs of particles are applied in a revolving fashion at equally spaced angular intervals (5° apart). Each pair of particles gets attracted to the signature edges, locally, under the combined influence of the spring forces and of a virtual gravity field. The pair finally reaches a stable condition, represented pictorially by small circular traces on the signature's boundary (see Fig. 3).

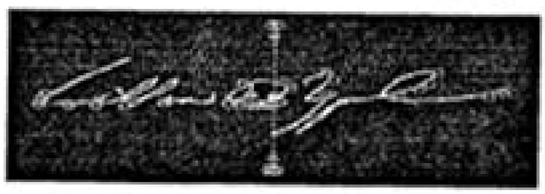

Figure 3: Snapshot of a revolving active deformable model in action.

The particles are moving in the image plane, and the motion of each *ith* particle obeys the classical dynamic equation,

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

where m_i is the mass of the *ith* particle, $\mathbf{r}_i = (x_i, y_i)^T$ is the position vector of the *ith* particle in the image plane, $\mathbf{F}_i^{ext}$ is the *external force*, exerted by sources external to the system of particles, 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 pixels. Internal forces are spring forces and their main function is to bring the pair of particles from its initial position on the enclosing ellipse where the gravitational field is non-existent or weak, closer to the signature image, where the gravitational field becomes stronger and can define the trajectories of the particles. In our case, the sum of internal forces is trivialized to F_{12}^{int} since our active deformable model consists of only two particles.

The window $W(i)$ centered at the particle i within which the virtual gravity field that affects the trajectory of particle i is computed, it reaches eventually image areas well beyond the outermost edges of the signature. Thus, the internal structure of the signature plays a role too in the definition of the particle trajectories. It is obvious now why the traces left by the revolving active deformable model do not merely constitute a polygonal approximation to the overall shape of the signature but in addition, they mirror the overall structure of the signature.

The points gathered from the application of the revolving active deformable model are filtered through a polygonal approximation algorithm [11], that has a smoothing effect.

4 Classification

4.1 Similarity Measure

The points produced by the polygonal approximation algorithm represent an approximation of the signature's overall shape. At the same time, these points, as it was explained in Section 3, convey information about the internal structure of the signature. All this information in order to be useful for matching purposes needs to be transformed into another more appropriate form. The internal angles of the polygonal shape have been chosen as its defining feature. The computation of each internal angle is achieved through the use of the dot and cross products of its sides.

Angles are coded into one of eighteen possible symbols $A, \ldots, R$, corresponding to 20° increments; that is, $A: 0^\circ < \theta \leq 20^\circ$; $B: 20^\circ < \theta \leq 40^\circ$; $\ldots$ $R: 340^\circ < \theta \leq 360^\circ$. The strings formed this way constitute the feature vectors of the signature images. Suppose that two polygonal fits, $\mathcal{D}$ and $\mathcal{E}$, of two signature images, are coded into strings following the above scheme and let us denote those strings as $d_1 d_2 \ldots d_n$ and $e_1 e_2 \ldots e_m$, respectively. There are two kinds of matches that may occur between the symbols of the two strings: a *full match* and a *half match*. A full match occurs if $d_k = e_j$, where k and j may be different in the general case. A half match occurs if $d_k - 1 = e_j$ *or* $d_k + 1 = e_j$, where again k and j might be different in the general case too. Let H represent the number of credit points accrued from the matches between the two strings according to the following scheme: a full match gathers two credit points and a half match gathers one credit point. Half matches account, basically, for the high variability factor found in some signatures of the same individual. A perfect match would accrue $2 * |\mathcal{D}| = 2 * |\mathcal{E}|$ credit points, where $|arg|$ is the length (number of symbols) in the string representation of the argument. Thus, a non-perfect match differs

$$J = 2 * \max(|\mathcal{D}|, |\mathcal{E}|) - \mathrm{H} \tag{2}$$

credit points from a perfect match. Of course, $J = 0$ if and only if $|\mathcal{D}|$ and $|\mathcal{E}|$ are identical. The similarity measure between $\mathcal{D}$ and $\mathcal{E}$ according to which classification is done is the ratio

$$Q = \frac{H}{J} = \frac{H}{2 * \max(|\mathcal{D}|, |\mathcal{E}|) - \mathrm{H}}. \tag{3}$$

Because matching is done symbol by symbol, the starting point on each boundary is important in terms of reducing the amount of computation. This is the reason that an orientation normalization stage preceded this module. The starting point, is always the right trace left from the very first application of the revolving active deformable model.

The system is trained by using one sample signature of every individual we consider as a user of the system. The feature vectors of both the aligned and the flipped version of each such reference signature are established and stored in the system database along with the corresponding id. Then, the system tries to match the feature vector of each test signature with one of the feature vectors of the reference signatures using the similarity measure Q. The largest value of Q signifies the best match.

4.2 String Matching

The usual string matching strategy followed in pattern recognition problems is a sequential one. Starting from the starting symbol, symbols are compared one by one until we run out of symbols for the shortest string. This technique does not work very well in signature identification and perhaps is not quite suitable for other pattern recognition problems of similar difficulty. The reason is that due to the variability factor typically present in the signatures of the same individual, the corresponding polygonal approximations may differ locally at some areas, although they maintain pretty much the same shape overall.

For a matching process that proceeds in a sequential manner once the first significant difference in the outline between the test signature and the corresponding reference signature is encountered, the process is derailed and is unable to catch subsequent parts of great similarity between the two polygonal shapes. A novel algorithm, the Synchronized String Matcher (SSM), inspired from error recovery techniques in compiler design, but tailored to the task at hand, has been developed to cope with the particular problem.

Essentially, the SSM algorithm tries to resynchronize the matching process between the reference signature string and the test signature string, after each derailment, always within a prespecified distance (number of lookahead symbols) L. In order to apply the algorithm we need to know which string has the minimum length between the test string and the reference string. Let *minlen* be the length of the shorter string and *maxlen* be the length of the longer string. In addition, *imin* and *imax* are two indices pointing initially at the first symbols of the corresponding strings. In case the strings have equal lengths, *minlen* is the length of the reference string and *imin* traces the reference string. Let also U be the number of consecutive unsuccessful matches since the last successful match took place. It is also important to note that H is the number of credit points accrued from the symbol matches of two strings. Then, the SSM algorithm in pseudocode form could be expressed as follows:

```
SSM(L)
U ← 0
H ← 0
while (imin < minlen) and (imax < maxlen)
        case: Successful match
            imin ← imin + 1
            imax ← imax + 1
            U ← 0
            if full match
                then H ← H + 2
                else H ← H + 1
        case: Unsuccessful match
            if (U < L)
                then if ((imax − imin) > L) or (imax = (maxlen − 1))
                            then imax ← imax − U
                                 imin ← imin + 1
                                 U ← 0
                            else imax ← imax + 1
                                 U ← U + 1
                else imin ← imin + 1
                     imax ← imax − L
                     U ← 0
                     if (imin − imax) > L
                         then imax ← imax + 1
return H
```

5 Experimental Results

The user population of the system is currently sixty individuals. The system has been trained with one sample signature from each individual user. The system has been tested with 180 test signatures, three from each user. The test signatures have been collected at different days and times and no restrictions have been applied. The individuals participated in the experiment were asked to sign on a plain piece of paper using a pen or a pencil. The test subjects were graduate and undergraduate students and various professionals. Out of 180 test signatures, 142 have been correctly identified which amounts to 78.89% success rate, 33 test cases have been signaled as inconclusive (18.33%), and for the remaining 5 signatures (2.78%) the system gave false recognition. The test results are summarized in Table 1.

Correct	Inconclusive	False
142 *or* 78.89%	33 *or* 18.33%	5 *or* 2.78%

Table 1: Test results.

The system uses two kinds of thresholds. One threshold has been set up to disallow signatures of individuals who are not registered users of the system to weakly match some random reference signature, thus allowing intrusion in to the system. The other threshold has been set up in order to direct very close - and thus, questionable - matches to the perspective detailed structure analysis system for further investigation.

The main reason for the failures (which is the true detrimental element of the current system) is that the signatures of certain individuals exhibit great variability and as a result their structure differs noticeably in certain areas.

It takes the system on the average 17.1 seconds to arrive at an identification decision on the current implementation platform (IRIS Indigo™ R4000). It is expected that the above time will be drastically reduced once the system migrates to parallel hardware and the revolving active deformable model algorithm is properly parallelized.

6 Conclusion

In this paper, we addressed the question of whether deformable structures can be of some value as a first stage classifier in the area of signature identification and verification. The most important contribution of this work is the introduction of the revolving active deformable model as a powerful tool for capturing the signature's overall structure. The experiments confirmed that signatures are uniquely determined by their overall structure in the great majority of cases. Identification 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 identification 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 identified cases will be meaningless. We need to transfer as much as possible out of the false percentage to the inconclusive percentage. Then, the perspective detailed structure analysis system will be able to resolve the ambiguity. Building the feature reference vector of each user entry as the average of multiple feature vectors corresponding to multiple signature samples of the same individual, would increase the robustness of the system. In the 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.

Acknowledgements

We thank the students of the Cs5561–day and Cs5116–extension classes during the academic year 1993-94 as well as the faculty members and the staff of the Computer Science Department at the University of Minnesota, who kindly provided us with their signatures. This work has been supported by the Graduate School of the University of Minnesota through contract #1546 – 521 – 5998, by the National Science Foundation through contract #IRI–9410003, and by the McKnight Land-Grant Professorship Program of the University of Minnesota.

References

[1] M. Ammar, Y. Yoshida, and T. Fukumura. "A New Effective Approach for Off-line Verification of Signatures by Using Pressure Features". In *Proceedings of the 8th International Conference on Pattern Recognition*, pages 566–569, 1986.

[2] M. Ammar, Y. Yoshida, and T. Fukumura. "Description of Signature Images and its Application to their Classification". In *Proceedings of the 9th International Conference on Pattern Recognition*, pages 23–26, 1988.

[3] J.J. Brault and R. Plamondon. "A Complexity Measure of Handwritten Curves: Modeling of Dynamic Signature Forgery". *IEEE Transactions on Systems, Man, and Cybernetics*, 23(4):400–413, 1993.

[4] P.A. Couvignou, N.P. Papanikolopoulos, and P.K. Khosla. "Hand-eye Robotic Visual Servoing Around Moving Objects Using Active Deformable Models". In *International Conference on Intelligent Robots and Systems*, pages 1855–1862, 1992.

[5] R.M. Haralick and L.G. Shapiro. *Computer and Robot Vision*, volume 1, chapter 3, pages 59–75. Addison–Wesley, Reading, Massachusetts, 1992.

[6] B. Kass, A. Witkin, and D. Terzopoulos. "Snakes: Active Contour Models". *International Journal of Computer Vision*, 1(4):321–331, 1987.

[7] S. Lee and J.C. Pan. "Off-Line Tracing and Representation of Signatures". *IEEE Transactions on Systems, Man, and Cybernetics*, 22(4):755–771, 1992.

[8] W.F. Nemcek and W.C. Lin. "Experimental Investigation of Automatic Signature Verification". *IEEE Transactions on Systems, Man, and Cybernetics*, 4(1):121–126, 1974.

[9] N. Otsu. "A Threshold Selection Method from Gray-Level Histograms". *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1):62–66, 1979.

[10] I. Pavlidis, R. Mavuduru, and N. Papanikolopoulos. "Off-Line Recognition of Signatures Using Revolving Active Deformable Models". In *1994 IEEE International Conference on Systems, Man, and Cybernetics*, pages 771–776, 1994.

[11] T. Pavlidis. *Structural Pattern Recognition*, pages 175–179. Springer-Verlag, Berlin, 1977.

[12] R.I. Phelps. "A Holistic Approach to Signature Verification". In *Proceedings of the 6th International Conference on Pattern Recognition*, page 1187, 1982.

[13] R. Plamondon and G. Lorette. "Automatic Signature Verification and Writer Identification – The State of the Art". *Pattern Recognition*, 22(2):107–131, 1989.

[14] R. Sabourin and R. Plamondon. "Preprocessing of Handwritten Signatures from Image Gradient Analysis". In *Proceedings of the 8th International Conference on Pattern Recognition*, pages 576–579, 1986.

[15] D. Terzopoulos and R. Szeliski. "Tracking with Kalman Snakes". In A. Blake and A. Yuille, editors, *Active Vision*, pages 3–20. The MIT Press, Cambridge Massachusetts, 1993.