

On-line Signature Verification Using 1-D Velocity-based Directional Analysis

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Abstract—In this paper, we propose a novel approach for identity verification based on the directional analysis of velocity-based partitions of an on-line signature. First, inter-feature dependencies in a signature are exploited by decomposing the shape (horizontal trajectory, vertical trajectory) into two partitions based on the velocity profile of the base-signature for each signer, which offers the flexibility of analyzing both low and high-curvature portions of the trajectory independently. Further, these velocity-based shape partitions are analyzed directionally on the basis of relative angles. Support Vector Machine (SVM) is then used to find the decision boundary between the genuine and forgery class. Experimental results demonstrate the superiority of our approach in on-line signature verification in comparison with other techniques.

Keywords—on-line signature; inter-feature dependencies; curvature; support vector machine;

I. INTRODUCTION

On-line Signature Verification is a process of verifying user's identity on the basis of signature's shape along with some dynamic features such as velocity, acceleration, curvature, pressure, total signature time, RMS speed, average writing speed etc [1], [2], [3]. In the past, it has been observed that the on-line signature verification based on a composite feature set containing both shape and dynamic features (velocity, pressure and angle) can outperform verification systems based on the shape alone [4], [5], [6].

This paper also proposes a composite feature set based upon the velocity-based directional analysis of an on-line signature. Recently, a 16-band Decimation-Free Directional Filter Bank (DDFB) was used for the same purpose [7]. But there are two major problems with the DDFB-based system. The first problem with the DDFB-based system, is that it takes the image as an input. In [7], spatial areas corresponding to velocity-based partitions were converted into gray-scale images, due to which, the information of each independent trajectory was lost. The second problem with DDFB or with any filter bank is the selection of the order of the filter. As we know, the more we increase the order of the filter, the more we will get artifacts in the output of the filter. In case of signature, these artifacts can lead to non-existing spatial areas which reduces the verification performance. So, there is a need for a directional analysis

tool which can perform the directional analysis in the same manner as DDFB does, but without converting the on-line signature into an image and without any constraint on the order of the filter. In this paper, we provide a novel approach for the directional analysis of a signature based on velocity partitions which first decompose the shape (*horizontal and vertical trajectories*) of the signature into two velocity-based partitions for analyzing the high-curvature and low-curvature portions of the trajectory independently. Following this, the low and high-curvature segments are split into two relative angle based partitions respectively. In this work, our proposed directional analysis tool does not need to convert the signature trajectories into an image. Also one can have ideal partitions of signature based on its relative angles - the details of which are deferred to Section III-A.

The remainder of this paper is organized as follows: the second section deals with the acquisition of signature data and preprocessing steps; the third section is dedicated to the design and structure of our proposed system; the experimental results and concluding remarks are presented in the final section of this paper.

II. DATA ACQUISITION AND PREPROCESSING

For the experimental results, we have used our own private database of 25 signers that contains 600 genuine and 250 highly skilled forgeries [5], [7] per signer. In order to reduce the intra-class variation, a number of preprocessing steps has been performed as suggested in [6], [5] with respect to a single signature called the base-signature b^i for each i th signer. Base-signature is one of the training signatures of each i th signer, that has minimum average Euclidean distance with all of its genuine training signatures. Fig. 1 shows the results of preprocessing steps applied in this paper.

III. PROPOSED SYSTEM

Our proposed system comprises of two main stages namely: Training and Verification stage.

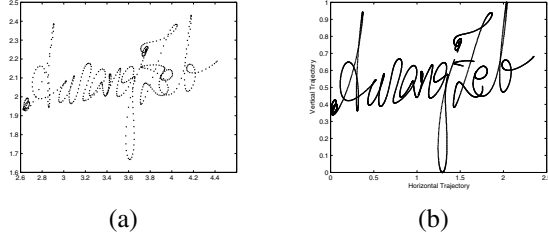


Figure 1. a) Base Signatures, b) another genuine signature after applying all preprocessing steps suggested in [6], [5].

A. Training Stage

Before the exploitation of inter-feature dependencies within a signature, there is a need to develop the one-to-one correspondence between the base-signature b^i and all the signatures including genuine and forgeries of the i th signer. For this purpose dynamic time-warping (DTW) has been performed between the base velocity v_b^i and velocity profiles v_j^i of j th signature of signer i as suggested in [5].

After the elimination of one-to many relationship, the horizontal x_j^i and the vertical trajectories y_j^i are divided into two partitions based on the velocity profile of base-signature b^i by using the Eq. 1:

$$\begin{aligned} mvb^i &= \frac{1}{N} \sum_{n=1}^N vb^i(n), \\ indl^i &= find(vb^i \leq mvb^i), \\ indh^i &= find(vb^i \geq mvb^i), \end{aligned} \quad (1)$$

where N is the total number of samples in v_b^i , $indl^i$ represents the indices corresponding to low-velocity and $indh^i$ represents the indices corresponding to high-velocity respectively. Now the spatial areas (x_j^i, y_j^i) corresponding to $indl^i$ and $indh^i$ are extracted and we named them as: low-velocity horizontal trajectory xvl_j^i , high-velocity horizontal trajectory xvh_j^i , low-velocity vertical trajectory yvl_j^i and high-velocity vertical trajectory yvh_j^i . Empirically, it has been observed that high-curvature curve segments falls in the low velocity partition whereas the low-curvature curve segments falls in high velocity partition as shown in Fig. 2. So it is more feasible and useful to analyze the signature by decomposing its trajectories into two parts based on the velocity of the signer during the signing process and further analyzing each partition directionally. For the forger, it is easy to maintain the curvature or the velocity of the signer individually, but it is hard for him to maintain both at the same time. After the velocity based partitions, we have calculated the relative angles for each j th signature of the i th signer. Relative angle is formed by taking the angle between the slope of two consecutive points in the shape of signature. All the calculations are done for the base-signature b^i of the i th signer. Mathematically, relative angles can be calculated as:

$$Ar_b^i = mod(arctan(y_b^i, x_b^i) + 2\pi, 2\pi), \quad (2)$$

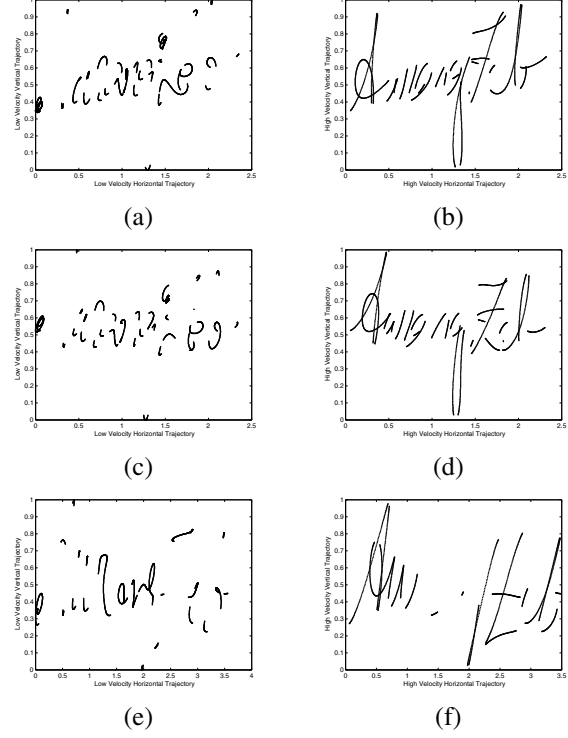


Figure 2. a),b),c) and d) are spatial areas of genuine signatures corresponding to low and high velocities, e) and f) are spatial areas of forgeries. We see a lot of similarity among four genuine signature areas, whereas forgery signature areas are quite different from genuine.

where Ar_b^i is a vector of M relative angles for base-signature b^i of the i th signer. Once the relative angles for base-signature b^i of the i th signer are calculated, we picked the indices of the Ar_b^i that corresponds to xvl_j^i , xvh_j^i , yvl_j^i and yvh_j^i and named them as Ar_{bl}^i and Ar_{bh}^i . Finally, the spatial areas xvl_j^i , xvh_j^i , yvl_j^i and yvh_j^i corresponding to Ar_{bl}^i and Ar_{bh}^i are decomposed into two velocity-based relative angle partitions by using the equations given below:

$$\begin{aligned} indal_n^i &= \frac{\pi(n-1)}{N} \leq Ar_{bl}^i \leq \frac{\pi n}{N} \\ \cup \frac{\pi(n-1)}{N} + \pi &\leq Ar_{bl}^i \leq \frac{\pi n}{N} + \pi, \end{aligned} \quad (3)$$

$$\begin{aligned} indah_n^i &= \frac{\pi(n-1)}{N} \leq Ar_{bh}^i \leq \frac{\pi n}{N} \\ \cup \frac{\pi(n-1)}{N} + \pi &\leq Ar_{bh}^i \leq \frac{\pi n}{N} + \pi, \end{aligned} \quad (4)$$

where $n = 1, 2$ and N represents the total number of partitions i.e. two in our case. After decomposing the base-signature of each i th signature into partitions based on $indal_n^i$ and $indah_n^i$, we have decomposed all the horizontal and vertical trajectories of each j th signature of the i th signer into partitions based on these index vectors. Mathematically it can be given as:

$$\begin{aligned} xpartln_j^i &= xvl_j^i(indal_n^i), \\ ypartln_j^i &= yvl_j^i(indal_n^i), \\ xparthn_j^i &= xvh_j^i(indah_n^i), \\ yparthn_j^i &= yvh_j^i(indah_n^i), \end{aligned} \quad (5)$$

where $n = 1, 2$ and $xpartn_j^i$, $ypartn_j^i$ represents n th directional partition in low-velocity horizontal trajectory (xvl_j^i) and low-velocity vertical trajectory (yvl_j^i), respectively, and $xparthn_j^i$, $yparthn_j^i$ represents n th directional partition in high-velocity horizontal trajectory (xvh_j^i) and high-velocity vertical trajectory (yvh_j^i). It is clear from Fig. 3 and Fig. 4 that angle partitions of genuine signatures are similar to each other but are different from forgery partitions, which supports our claim that the velocity-based directional analysis of an on-line signature helps in better exploitation of inter-feature dependencies.

For a better understanding of our proposed directional

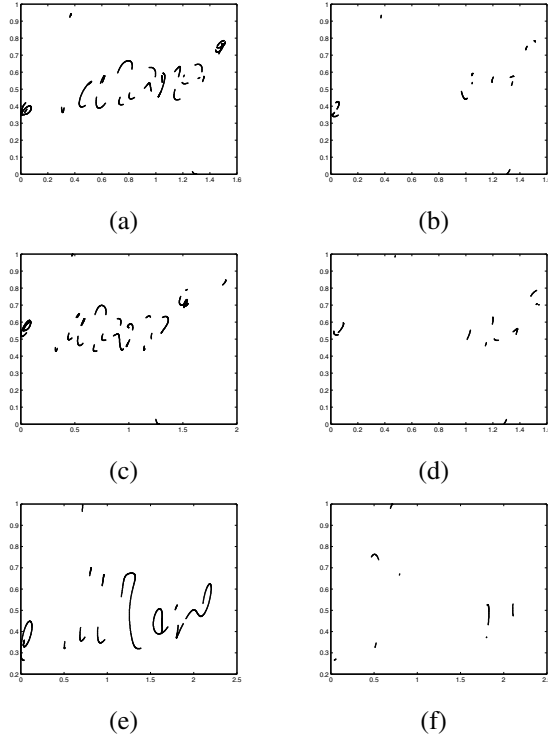


Figure 3. Angle partitions based on low-velocity regions: a), c) first angle partitions of two genuine signatures, b), d) the second angle partitions of two genuine signatures, e), f) are the first and second angle partitions of one of forgery signatures.

analysis method, we have directly applied the first stage of DDFB to an image of signature and also our proposed directional partitioning method to the signature trajectories as shown in Fig. 5. It is clear from the Fig. 5 c), d) that the artifacts has been produced by increasing the order of the filter which can be misleading in the verification process. Fig. 5 e), f) represents the results of the proposed method. We can say that theoretically, the outputs of our proposed method are equivalent to the outputs of DDFB, but due to the limitations on the order of filter in case of DDFB and due to the non-ideal nature of the filter, visually these outputs are not identical to our proposed method. We cannot have ideal response of filters due to limitation on the order of

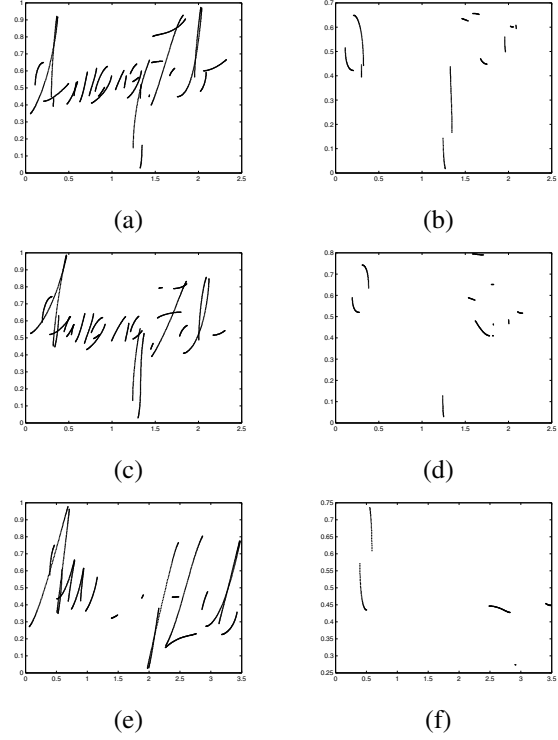


Figure 4. Angle partitions based on high-velocity regions: a), c) first angle partitions of two genuine signatures, b), d) the second angle partitions of two genuine signatures, e), f) are the first and second angle partitions of one of forgery signatures.

filter in case of DDFB but it is possible in our proposed method where directional analysis is done by calculating the relative angles and doing the partitions in the same manner as done by DDFB without converting the trajectories into an image. Thus, by having the ideal responses as well as keeping the discriminative information in each independent trajectory, our proposed method provides better directional analysis of on-line signature than DDFB [7]. The next step of our training stage is to create templates that are generated by using the equation given below:

$$temp_{abc}^i = \frac{1}{T} \sum_{t=1}^T abc_t^i, \quad (6)$$

where $a \in \{x, y\}$, $b \in \{partl, parth\}$, $c \in \{1, 2\}$ and T represents total number of genuine signatures used for training of i th signer.

Once the templates are generated, the next step is to use the forgery samples to find a decision boundary between genuine and forgery class for each i th signer. During the training stage, we don't have any information of forgery class, so for each i th signer, we have used the genuine training signatures for the rest of the signers as random forgeries. This gives us enough number of random forgery samples to find a decision boundary for each i th signer during the



Figure 5. a), b) Binarized directional outputs of the first stage of DDFB with order $n=80$, c), d) binarized directional outputs the first stage of DDFB with order $n=120$, e), f) are the directional outputs of our proposed method.

training stage. For this purpose, the Euclidean distance of all the genuine training signatures and random forgeries are calculated from their respective templates ($temp_{abc}^i$). Finally, these distances are used to train the Support Vector Machine (SVM) for finding a decision boundary between random forgery and genuine class for each i th signer.

B. Verification Stage

In verification stage, when any test signature $test^i$ comes, it is passed through all the preprocessing steps as mentioned in [5]. After performing the preprocessing steps, the test signature is decomposed into partitions based on $indal_n^i$ and $indah_n^i$. Then the distance of sample points of $test^i$ corresponding to each partition from their respective templates are calculated. Finally, these distances becomes an input to the Support Vector Machine (SVM) [8], which is used to classify the genuine test signatures and skilled forgeries for each i th signer.

IV. Experimental Results and Conclusion

For the experimental results, we have used our own private database (reported in [5], [6], [7]), containing 600 genuine and 200 forgery signatures for 25 signers. We have evaluated the performance of our proposed system through Equal Error Rate (EER). The average EER for our proposed system is 0.016, where as average EER in [5], [9] and [7] are 0.0239,

0.059, and 0.073 respectively, when 200 genuine signatures were used for the training purpose. All of the above referred algorithms were tested on our own database.

In this paper, each independent trajectory of the signature was decomposed into two velocity-based partitions and further these velocity-based partitions were analyzed directionally. We observed based on the experimental results that the improved performance of our system lies in the better exploitation of velocity and angles of signature trajectories. The main purpose of this paper was not to find the optimum number of partitions but to find an optimal way of analyzing the signature directionally without converting the shape information (horizontal trajectory, vertical trajectory) into a static 2-D image.

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