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Fast Signature Spotting in Continuous Air Writing

Santosh Kumar Behera[1], Pradeep Kumar[2], Debi Prosad Dogra[1], Partha Pratim Roy[2]
School of Electrical Science, IIT Bhubaneswar, India[1]
Department of Computer Science and Engineering, IIT Roorkee, India[2]
{sb29,dpdogra}@iitbbs.ac.in[1], {pra14.dcs2014,proy.fcs}@iitr.ac.in[2]

Abstract

Development of depth sensors paves way for implementation of touch-less biometric authentication systems using 3D gestures or signatures. No keys or passwords are required in such systems to prove identities. Moreover, the systems do not suffer from various security risks such as stolen passwords or loss of passwords. In this paper, we propose such a security system that is robust in nature by allowing a user to perform random gestures before and after a signature during authentication. Since the signature can appear within any position of a gesture pattern, correct spotting of the actual signature is extremely important. In this paper, we propose a signature spotting mechanism that has been accomplished using a window-based analysis on feature sequence. An efficient searching strategy has been proposed using 3D convex hull points. Dynamic Time Warping (DTW) has been used to perform the verification of the spotted signatures. Our proposed method achieves 80% accuracy for signature spotting with less computational overhead. The method can be used on applications requiring robust authentication in a huge dataset.

1 Introduction

Over the past two decades, biometric authentication has evolved as an important field of study amongst the security research community. Authentication is a process of associating an identity with an individual. A handful of techniques have been proposed for biometric authentication. However, they are mainly of two categories, namely token-based (e.g. photo ID cards, passports, etc.) or knowledge based (e.g. PIN, password, etc.). Both token and knowledge based approaches suffer from various security risks such as stolen document/data, forgotten or misplaced data. In some cases, it is hard to differentiate between a genuine and imposter. Since these approaches [1] lack in incorporating inherent characteristics of the user.

Biometric identification is considered as a secure mechanism to perform person identification using physical or behavioral properties. Biometric identification techniques include fingerprint, iris scan, gait analysis, signature, etc. However, these traditional approaches are vulnerable to imposter attacks, where the attackers easily fool the system and gain access. Moreover, these approaches require favourable environment to perform the user identification process. For example, in medical and industrial domain, persons often wear hand-gloves, masks or jackets, such that, they are not contaminated with external environmental particles. In such scenarios, touch-screen and keyboard based security mechanism cannot be used [2]. Hence a touch-less authentication is preferred.

Recently, development of depth sensors such as Leap motion or Kinect has opened-up scopes of designing tough-less interaction systems. These devices are able to locate 3D point cloud of the observed scene and are successfully used in many Human-Computer-Interaction (HCI) applications including security [3], gesture, 3D handwriting recognition [12], rehabilitation [5], word segmentation [6, 11], etc. Leap motion device is designed to track finger and hand movements in the 3D space with the help of three infra-red LED and two infra-red sensors. Nigam et al. [7] have proposed a 3D signature based user identification methodology using Leap motion. The methodology comprises of 3D Histogram of Oriented Optical Flow (HOOF) and Histogram of Oriented Trajectories (HOT) features for matching the signatures. The system has been tested on 60 users with a user identification rate of 91%.

However, it has been observed that applying DTW on raw 3D data is time consuming. Moreover, if the number of users is extremely high, the authentication process takes a lot of time to find the result. Thus, we have used coordinates of the convex hull vertices as high-level features. Convex hull is the minimum convex polygon that encloses all the points covering a given object. It has a wide range of applications, such as in pattern recognition, collision detection, area estimation, game theory, etc. In the field of computer animation where fast computation is required, geometric structures can be helpful and they can be obtained using convex hull. In our approach, we have used Quick hull algorithm [9] to compute convex hull of the 3D points representing signature sequence. We have assumed a user can start the signature from any location of a large pattern. Therefore, we incorporate robustness in the authentication process. Even if an imposter tries to observe the finger movement, it is difficult to understand the exact location of the starting point.

In real scenario, it has been noticed that a genuine user tries to hide his/her signature from various security risks. In order to make these security systems robust, we present a methodology of user authentication by facilitating users to perform random gestures before and after their original signature in a continuous manner. This reduces the risk of imposter getting the clue about the original signature. Therefore, spotting of the actual 3D signature is very important to perform the authentication. We have adopted a window-based technique that scans the convex hull points and tries to find a best match. Once the probable location of a signature is identified, a verification using DTW is applied. Since the sequence is reduced by a significantly large factor (due to usage of convex hull vertices), the algorithm finds the result in a quick time.

Rest of the paper is organized as follows. In the next section, we present the proposed signature spot-

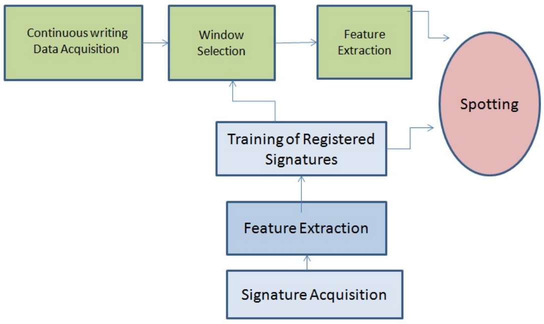


Figure 1. A flow-diagram of the proposed signature spotting methodology.

ting methodology. In Section 3, experimental results are presented. We conclude in Section 4.

2 Proposed Methodology

This section presents various intermediate processes that have been used to spot signature from continuous writing. We have adopted a sliding-window based approach to process the sequence. A flow-diagram of the proposed scheme is depicted in figure. 1. Descriptions of various intermediate stages are presented in the following sections.

2.1 Data Acquisition

In this work, we have enrolled 20 participants in the data collection process. Each user was asked to perform signature using Leap motion sensor as depicted in figure 2. To accomplish this, we have used the inbuilt API provided by the SDK. Using the API functionality, we have recorded 3D trajectories of the index finger in real-time. Each signer was instructed to repeat his/her signature 10 times. Therefore, a total of 200 genuine signatures were recorded. An example of the experimental setup is depicted in figure 2, where a user performs the signature in the 3D space. During testing, 100 continuous signatures were recorded. These signatures contained random patterns at the beginning, end or both. Another 40 samples of continuous writings have been collected by the same user where they have not put their signature within the sequence. We have used both 100 and 40 test sequences to localize the actual signatures and then DTW has been used for verification against the stored signatures.

2.2 Window Selection

We have adopted a sliding-window-based approach for spotting the signatures. Size of the sliding window over the continuous writing is considered by taking average length of the registered signatures of a user. The process is depicted through Figs. 3 and 4. The length of the sliding window is measured with the average of the distances from the local maxima (peak) to the starting point as shown in figure 3.

2.3 Feature Extraction

Feature extraction is one of the important phases in any classification process. Before feature extraction,

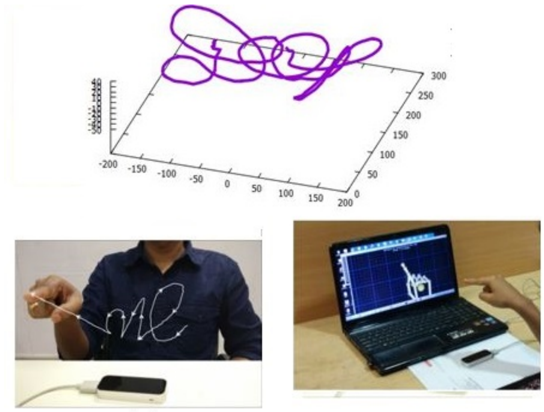


Figure 2. Setup used for capturing signature using Leap motion sensor and a typical view of a captured signature.

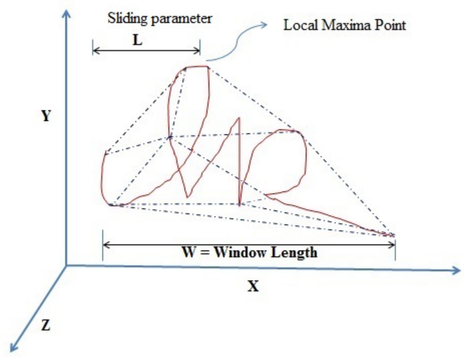


Figure 3. Convex hull representation of a registered signature.

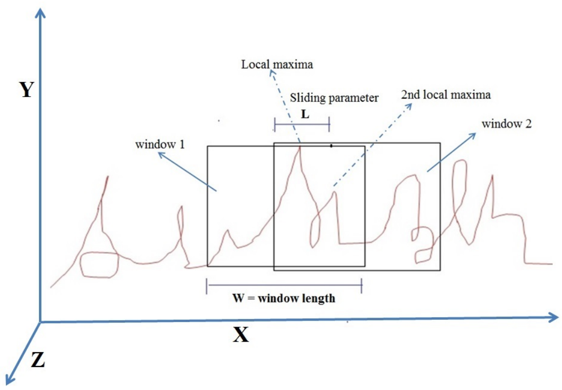
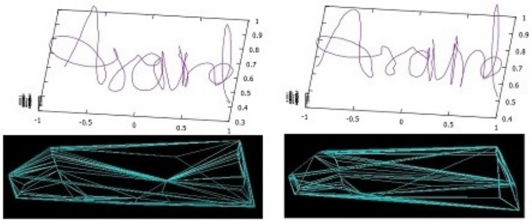


Figure 4. Continuous writing by a user and execution of sliding-window to find the signature location.

pre-processing such as noise filtration, and normalization have been applied in the original signal. In the next phase, the processed signatures are represented using convex hull vertices. We have used quick-hull algorithm to find the vertices of the convex hull. Representation of a signature using convex hull vertices look similar for a user, however they look visibly different across different users. This has been depicted in Figs. 5 and 6, respectively. Due to this, length of a given input sequence gets reduced significantly. Raw signature (3D coordinates) and extracted features (vertices of convex hull) are given in (1) and (2), respectively, where $m << n$.

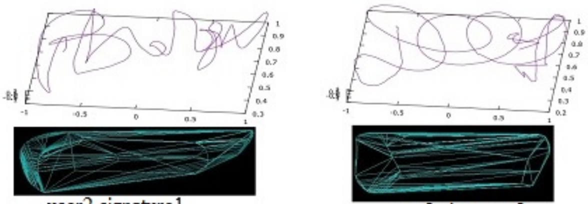
$$S = [p_1, p_2, p_3, ..., p_n]^T \tag{1}$$

$$F = [q_1, q_2, q_3, ..., q_m]^T \tag{2}$$



user1 signature1 user1 signature2

Figure 5. Convex hull representation of two signatures of a single user.



user2 signature1 user3 signature2

Figure 6. Convex hull representation of two signatures of two different user.

2.4 Training of Signatures

This section presents the training of registered signatures. During the training phase, we estimate the size of the sliding window (W), the sliding parameter (L) to find the starting point of the next window and average maximum / minimum distances between every pair of registered signatures of a user. Algorithm 1 presents the training process.

Algorithm 1 Training of Registered Signatures

Input: $S = [s_1, s_2, s_3, ..., s_m]$ where S is the set of m signatures of one user.
Output: Window size (W), Sliding parameter (L), D_{Max} and D_{Min} among all distances between the every pair of signatures.

for $i = 1$ to m **do** ▷ m: number of signature .
  for $j = 1$ to m **do**
    $D(i, j) = DTW(s_i, s_j)$ ▷ where $i \neq j$
  end for
  $D_{Max}(i) = Max(D(i, j))$ ▷ where i, $j \in m$ and $i \neq j$
  $D_{Min}(i) = Min(D(i, j))$
end for
$D_{Max} = \frac{1}{m}\sum_{i=1}^{m} D_{Max}(i)$
$D_{Min} = \frac{1}{m}\sum_{i=1}^{m} D_{Min}(i)$
$W = \frac{1}{m}\sum_{i=1}^{m} W(i)$
$L = \frac{1}{m}\sum_{i=1}^{m} L(i)$ ▷ where $W(i)$ and $L(i)$ are lengths in the x direction from starting point to end point and local maxima point respectively in ith signature as shown in figure 3

2.5 Spotting of Signatures

During this phase, we scan throughout the whole sequence using the aforementioned sliding window-based approach. In each window, we search and compute the distance of the feature vector with all registered signatures. Through comparisons with D_{Min} and D_{Max}, the algorithm takes a decision whether the signature is present or not. If it finds a signature within the present window, it computes the minimum distance using DTW with all stored signatures. In Algorithm 2, the process is described in details.

Algorithm 2 Signature Spotting

Input: C = Set of points in the continuous writing of a user, F_{train} and Window size (W), Sliding parameter (L), D_{Max} and D_{Min} of the signature of the same user.
Output: Signature Spotted Window (if signature exist) with probability of matching.

count=0
for $i = 1$ to n **do** ▷ n: number of windows.
  $W_i = [p_1, p_2..p_{n1}]$ ▷ p_i are the points inside window
  $F = [f_1, f_2, ..f_{n2}] = Feature(W_i)$ ▷ f_i are the convex hull feature points
  $D(i) = Avg(DTW(F, F_{trj}))$ ▷ $j = 1$ to number of registered signature of this user
  if $D_{Min} \leq$ D(i)$\leq D_{Max}$ **then**
    $Dist(i) = D(i)$
    count=count+1
  end if
  $X_1 = Findx(Max_y(W_i))$, X_1 is the x value where the point is in the local maxima
  $X_2 = Findx(2ndMax_y(W_i))$, X_2 is x value where the point is in the 2nd local maxima in the window after X_1.
  if x_2 is exist **then**
    $Nextwindow_{startpoint}$= X_2-L
  end if
  if x_2 is not exist **then**
    $Nextwindow_{startpoint}$= $W - L$
  end if
end for
if count==0 **then**
  Signature is not present in the sequence
else
  $D_{min} = Min(Dist(i))$ ▷ $i = 1$ to count
  $window_{no} = Window(D_{min})$ ▷ signature is present in this window
end if

3 Results and Discussion

A dataset of moderate size has been collected for experiments to verify the proposed methodology. 20 users were involved in this process for recording the signatures, where each user registered 10 signatures for training. Therefore, a total of 200 signatures were collected. In the spotting process, 100 continuous writings were collected by the the same set of 20 users, each registered 5 samples. The signers put their signatures in a continuous manner. Another 40 samples of continuous writings were collected by the same set users where they did not put their signatures anywhere within the sequence. We have trained the registered signatures and optimized the parameters using training. In the first phase, spotting has been done using the process described earlier with the training parameters, where we have observed that, in 80% cases, spotting of the signatures have been done correctly. The results of this experiments are presented in figure 7. In the next phase, we have used the dataset of 40 continuous writings, where signatures are not present. figure 8 shows that, on an average, 25% of the sequences contain signatures as per the analysis. Therefore, these cases are reported as false positives. Again for the comparison purpose, we have shown the results in figure 9 using the proposed convex hull feature against other features like coordinate points and high level features (slope, writing direction, curvature). figure 9(A) shows the computational overhead, when it searches within each window in a continuous air writing. Whereas, figure 9(B) depicts the spotting accuracies. It is evident from the figure that using the proposed feature, spotting can be done in quick time without noticeable degradation of accuracy.

Our proposed method is able to spot the signatures with higher accuracy, though some false positive cases are reported. However, this can be attributed to the fact that the dataset used in the experiments is not sufficiently large. Therefore, we believe the false positives will be further reduced if a large dataset is used. Also, we believe that robust classifiers such as HMM or LSTM can improve the verification accuracy.

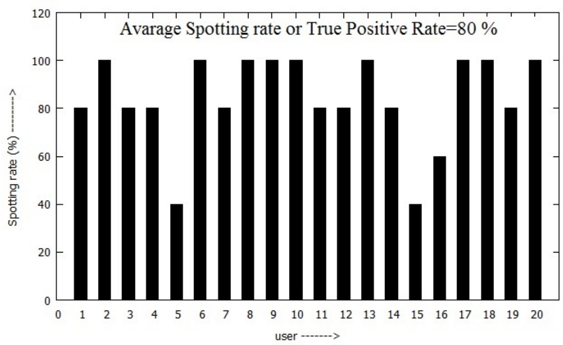


Figure 7. Results of signature spotting within continuous writing (true positives).

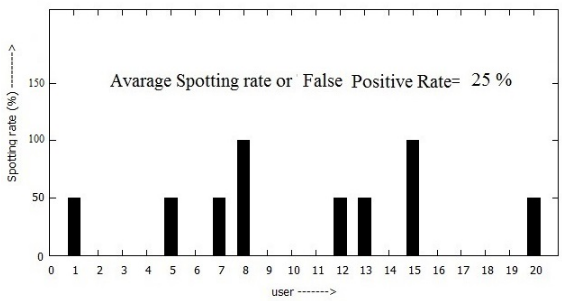


Figure 8. Results of signature spotting within the continuous writing (false positives).

4 Conclusion

The paper presents a novel approach to spot signature within a continuous air writing captured through Leap motion sensor. Our proposed algorithm is fast due to reduction of the feature vector, thus applicable for large scale authentication. Experimental results reveal that, using convex hull feature, signature can be searched even if the user performs the signature within a random sequence. This happens because, when the convex hull points are extracted from the set of original 3D coordinates of the signature trails, sequence

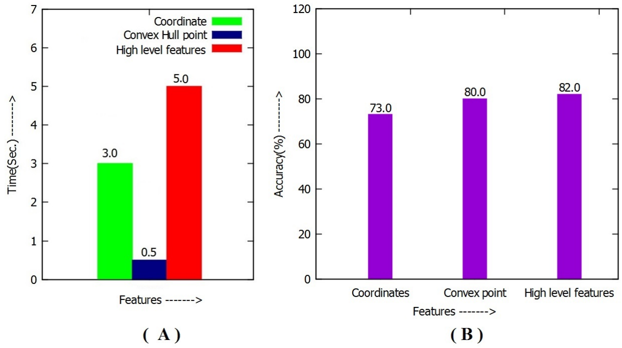


Figure 9. Comparison of performances of spotting a signature using coordinates, convex hull features and high level features.

size gets reduced significantly. Preserving the inherent characteristics of the user. The method has several applications including large scale authentication, touch-less UI designing, etc.

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