

Spatial Topology of Equitemporal Points on Signatures for Retrieval

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Abstract. In this paper, we address the problem of quick retrieval of online signatures. The proposed methodology retrieves signatures in the database for a given query signature according to the decreasing order of their spatial similarity with the query. Similarity is computed based on orientations of corresponding edges drawn in between sampled points of the signatures. We retrieve the best hypotheses in a simple yet efficient way to speed up the subsequent recognition stage. The runtime of the signature recognition process is reduced, because the scanning of the entire database is narrowed down to contrasting the query with a few top retrieved hypotheses. The experimentation conducted on a large MCYT_signature database [1] has shown promising results.

Keywords: Signature retrieval, Spatial similarity, Online Signature.

1 Introduction

Handwritten signature is one of the earliest biometrics used for general authentication. Its simplicity, ease to capture and the flexibility that it provides for human verification, makes it the most widely used biometric. Offline signature (conventional signature) is supplemented by other features like azimuth, elevation and pressure in case of online signature. The online signature is more robust as it stores additional features, other than just signature image. Any biometric identification problem [2] has two distinct phases: i) recognition and ii) verification. In verification, the query signature is contrasted with a limited set of signatures of the class whose identity is claimed. At the recognition phase, presence of an identity in the database is ascertained [3]. It involves matching stage that extends to entire dataset/database, which is more time consuming. Gupta and McCabe [4] have presented a review on online signature verification. Found et al, [5] investigated spatial properties of handwritten images through matrix analysis. Martinez et al., [6] compare support vector machines and multilayer perceptron for signature recognition.

Essentially any signature recognition system can be optimized when the query signature is matched with best hypotheses than the entire database. Hence signature retrieval mechanism that retrieves the best hypotheses from the database

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attains importance. Efficient retrieval of handwritten signatures is still a challenging work if the signature database is large. Unlike fingerprint, palm print and iris, signatures have significant amount of intra class variations, making the research even more compelling.

In so far the only work on signature retrieval is by Han and Sethi [7]. They work on handwritten signatures and use a set of geometrical and topological features to map a signature onto 2D-strings [8]. However, 2D-strings are not invariant to similarity transformations and any retrieval systems based on them are hindered by many bottlenecks citenine. There are several approaches for perceiving spatial relationships such as nine-directional lower triangular matrix (9DLT) [12], triangular spatial relationship (TSR) [13] and Similarity measure (SIM_R) [10]. In order to overcome the said problem, we propose an online signature retrieval model in this paper based on SIM_R . The proposed methodology retrieves signatures quickly from the database for a given query in the decreasing order of their spatial similarity with the query. Consequently the proposed system can be used as a preprocessing stage which reduces the runtime of the recognition process as scanning of the entire database is narrowed down to contrasting the query with a top few retrieved hypotheses during recognition. Experimentation has been conducted on a MCYT_signature database [1] which consists of 8250 signatures and it has shown promising results.

The remaining part of the paper is organized as follows. The proposed methodology is explained in Section 2. The details of the experimental results are given in Section 3, and finally in Section 4 some conclusions are drawn.

2 Proposed Model

Our approach involves sampling of online signature at equitemporal interval for x , y coordinates, to get n sample points. The first sampled point is labeled as '1' and the second as '2' and so on and so forth until n , the last sampled point. A directed graph of n nodes is envisaged where directions originate from the node with smaller label to the one with larger label as shown in 1 for $n = 5$. A vector V consisting of the slopes of all the directed edges forms the symbolic representation of a signature and is given by:

$$V = \theta_{12}, \theta_{13}, \dots, \theta_{1n}, \theta_{23}, \theta_{24}, \dots, \theta_{n-1n} \quad (1)$$

Where θ_{ij} is the slope of the edge directed from node i to node j , $1 \leq i \leq n-1$, $2 \leq j \leq n$, and $i < j$.

Let S_1 and S_2 be two signatures and V_1 and V_2 be the corresponding vectors representing the slopes of the edges in S_1 and S_2 . Now the similarity between S_1 and S_2 is analogous to the similarity between the vectors V_1 and V_2 . Let

$$V_1 = \{s^1 \theta_{12}, s^1 \theta_{13}, \dots, s^1 \theta_{1n}, s^1 \theta_{23}, s^1 \theta_{24}, \dots, s^1 \theta_{ij}, \dots, s^1 \theta_{n-1n}\} \quad (2)$$

$$V_2 = \{s^2 \theta_{12}, s^2 \theta_{13}, \dots, s^2 \theta_{1n}, s^2 \theta_{23}, s^2 \theta_{24}, \dots, s^2 \theta_{ij}, \dots, s^2 \theta_{n-1n}\} \quad (3)$$

Let $\Delta V = |V_1 - V_2|$, i.e.

$$\Delta V = \{\Delta \theta_{12}, \Delta \theta_{13}, \dots, \Delta \theta_{1n}, \Delta \theta_{23}, \Delta \theta_{24}, \dots, \Delta \theta_{ij}, \dots, \Delta \theta_{n-1n}\} \quad (4)$$

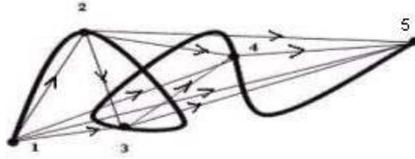


Fig. 1. Online signature with nodes and edges

Here, ΔV represents the vector of the absolute differences in the slopes of corresponding edges in signatures S_1 and S_2 . The total number of edges is $(n)(n - 1)/2$. Assuming a maximum possible similarity of 100, each edge contributes a value of $100.00/(n)(n - 1)/2$ towards the similarity. If the difference in the corresponding edge orientations of the two signatures is zero then the computed similarity value is maximum. When the differences in corresponding edge orientations tend to be away from zero, then the similarity between the two signatures reduces. In this case contribution factor [10] towards similarity from each corresponding edges directed from node i to node j in S_1 and S_2 is

$$\frac{100}{n(n - 1)/2} \left[\frac{1 + \cos(\Delta\theta_{ij})}{2} \right] \tag{5}$$

where $\Delta\theta_{ij} = |s_1\theta_{ij} - s_2\theta_{ij}|$, $1 \leq i \leq n - 1$, $2 \leq j \leq n$, and $i < j$.

Consequently the similarity [10] between S_1 and S_2 due to all edges is

$$SIM(S_1, S_2) = \frac{100}{n(n - 1)/2} \sum_{ij} \left[\frac{1 + \cos(\Delta\theta_{ij})}{2} \right] \tag{6}$$

where $1 \leq i \leq n - 1$, $2 \leq j \leq n$, and $i < j$.

Rotation invariance is achieved by aligning the first edge of the query signature with that of database signature before contrasting. The computation complexity of the proposed methodology is $O(n^2)$. During retrieval, the query signature is sampled and slopes of the edges are extracted to form a query vector. The query vector is contrasted with the training vectors in the database. Signatures are retrieved according to the similarity ranks and top K retrievals are selected for further matching for accurate recognition.

In the proposed methodology, we have considered the orientations of edges between the two corresponding sampled points of query and database signatures. For the sake of comparison with the proposed methodology, we have also considered the orientations of edges among three sampled points, forming triangles as shown in Fig.2 for six sampled points. The computation of triangular spatial relationship [9] among all possible triangles is $O(n^3)$ time complexity. Therefore we considered the orientation of edges of only successive triangles of query and database signatures for matching as it is of $O(n)$. We refer this method as successive triangle matching. Triangles formed among sampled points are $\Delta 123$,

$\Delta 234$, $\Delta 345$ and $\Delta 456$. The corresponding triangles are contrasted sequentially between query and database signatures for similarity computation. In general let $1, 2, 3, \dots, n$ be equitemporal sampled points of online signature. From n points, we can form $n - 2$ triangles by considering three successive points at a time. During matching process, the correspondence is drawn between sides of the respective triangles of query and database signatures.

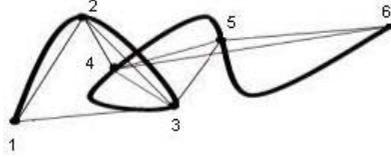


Fig. 2. Successive Triangle Matching

3 Experimental Results

The dataset: The MCYT_signature corpus [1] consists of 50 signatures; 25 are genuine and remaining 25 are forgeries for each of the 330 individuals. Totally it forms a signature database of 8250 (i.e. 330×25) genuine and 8250 (i.e. 330×25) forged online signatures. The online signature consists of x-y co-ordinate positions, pressure(P), azimuth(AZ) and elevation(EL) signals. An x-y plot of an online signature is shown in Fig. 3, along with pressure, azimuth and elevation information plots. For our experimentation only spatial relationships of x, y sampled points are considered. The comparison of retrieval performances of the

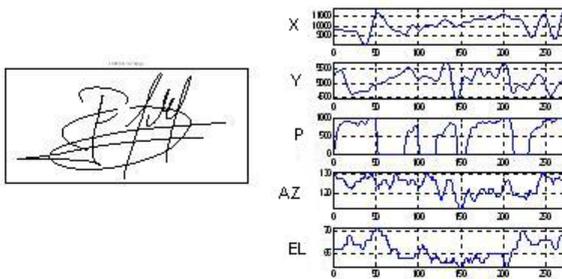


Fig. 3. Sample online signature from MCYT_signature corpus

proposed method and successive triangle method is made through a series of extensive experimentation in this section. Retrieval experiments are conducted for different number of sample points n : 10, 20 and 30. For each sampling, 10 signatures were considered as queries keeping the remaining 15 in the database,

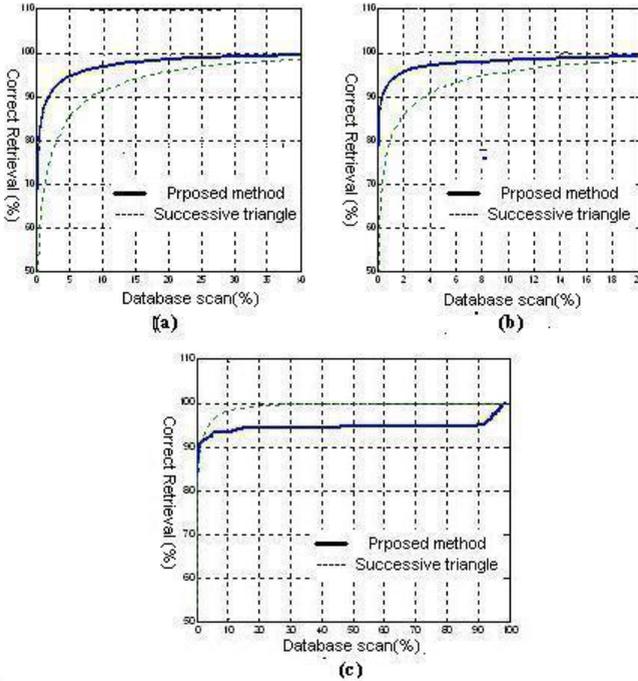


Fig. 4. Retrieval performance with 15 database signatures and 10 queries per class for different sample points: (a) for 10 sample points (b) for 20 sample points and (c) for 30 sample points

Table 1. Query and database signatures combination

Combination	Number of database signatures	Number of Query signatures
(a)	15	10
(b)	10	15
(c)	5	20

out of 25 genuine signatures per class. In all 3300 (*i.e.* 330×10) queries and 4950 (*i.e.* 330×15) database signatures comprised the test set for experimentation. The retrieval results are as shown in Fig. 4.

The output of the retrieval system is the top K hypotheses. In our experiments we have set $K = 10$. We define the correct retrieval (CR) for the performance evaluation of retrieval system as

$$CR = (K_c/K_d) \times 100 \quad (7)$$

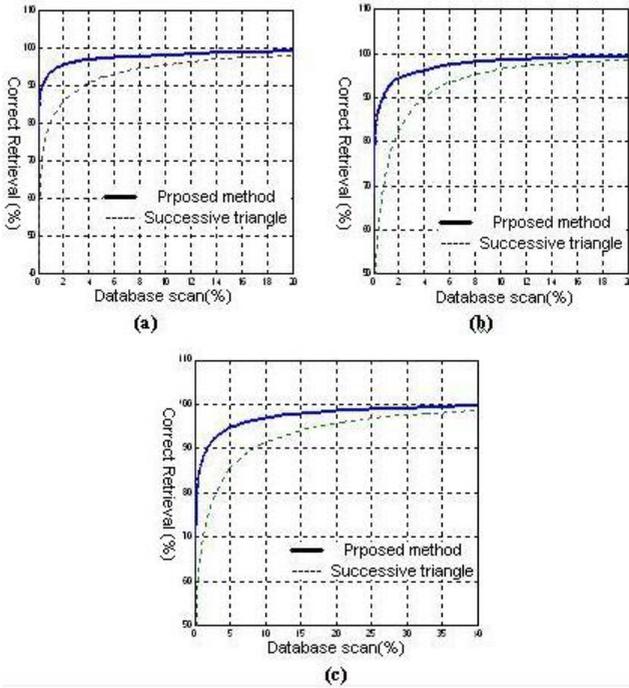


Fig. 5. Retrieval performance (correct retrieval v/s database scan) with 20 sample points for different number of queries and database signatures: (a) 15 database signatures and 10 queries per class. (b) 10 database signatures and 15 queries per class. (c) 05 database signatures and 20 queries per class.

where K_c is the number of correctly retrieved signatures, K_d is the number of signatures in the database. The retrieval performance is best for 20 sample points per signature (Fig. 4b).

We have conducted another set of experiments for different numbers of database signatures for 20 sample points per signatures (Fig. 5). Experiments were carried out for the different numbers (see Table 1) of database signatures (out of 25 signatures) for each class and remaining signatures as queries to the system. The system shows the good retrieval performance for 15 database signatures per class (fig.5 (a)). That shows the best performance is obtained for higher number of database signatures. Correct retrieval is 98% for 5% database scan and correct retrieval 99% for 10% of database scan.

To evaluate the retrieval performance of the proposed methods for the combination of queries and database signatures as in Table 1, we compute the Precision and Recall ratios. For all these experiments, 20 sample points per signature is used. Proposed methodology based on edge orientation shows better precision compared to successive triangle matching method. The results are shown in Fig.6.

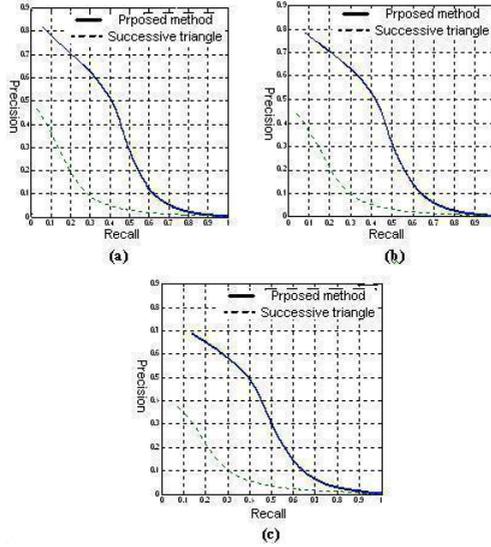


Fig. 6. Precision ratio v/s recall ratio for 20 sample points and for different number of queries and database signatures: (a) 15 database signatures and 10 queries per class. (b) 10 database signatures and 15 queries per class. (c) 05 database signatures 20 queries and per class.

4 Conclusions

Experiments were conducted for quick retrieval of online signatures and results are presented. The retrieval performance of the proposed method based on edge correspondence is compared with the retrieval method based on successive triangle matching. The proposed method is simple, efficient and outperforms the retrieval system based on successive triangle match with respect to all parameters (Precision, Recall and Correct Retrieval).

The MCYT₁₀₁ signature dataset used here consists of signatures whose $x - y$ sample length varies from 400 points to around 6000 points. However, our retrieval system is fast as it employs just 20 sample points per signature with promising results in retrieving top K hypotheses. The minimum percentage of database scan required to retrieve relevant signatures for all queries is supposed to be fixed experimentally. This is essentially a K -nearest neighbor problem and K best hypotheses should be retrieved. An attempt has been made in the work of Ghosh [11] in this regard where the parameter K is fixed without experimentation. Hence, the decision of arriving at the optimal percentage of database scan where all the authentic queries find a match can be fixed up analytically.

Acknowledgement

Authors thank Dr. Julian Firrez Aguilar, Biometric Research Lab-AVTS, Madrid, Spain for providing MCYT_signature dataset.

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