Dynamic Signature Verification Using Sensor Based Data Glove

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Abstract

Handwritten signature verification is a well-established and potential area of research with numerous applications such as commercial (e.g., Credit card, bank check verification etc.), government (e.g., National ID card, Driver’s license, passport control etc.) and forensic (e.g., corpse identification) application. In this paper, we propose a new approach to deal with the problem of handwritten signature verification and forgery detection using data glove. The technique is based on linearly projecting the glove signature into a low-dimensional space, through the Singular Value Decomposition (SVD). The Euclidean distance between the different groups of singular values is used to measure the authenticity of the tried signatures. The reliability and efficiency of the proposed system against forgeries are tested and reported. A comparative analysis has also been shown for data gloves with 14, 5, and 4 sensors respectively.

1. Introduction

Handwritten signature verification is the process of confirming the identity of a user based on the handwritten signature of the user as a form of behavioral biometrics. Online handwritten signature verification is not a new problem. Many early research attempts were reviewed in the survey papers. Two categories of verification systems are usually distinguished: off-line and online systems for handwritten signature authentication and verification.

Off-line approaches for signature recognition: In off-line systems for which the signature is captured once the writing process is over, and thus only a static image is available. As for the verification processing, there are many approaches that are used nowadays, for example, Neural Networks, the Euclidean Distance Classifiers, Elastic Image Matching and others. Most of the earlier work on off-line signature verification involves the extraction of features from the signature images by various schemes. Qi et al. used local grid features and global geometric features to build multi-scale functions for verification. Sabourin et al. used an extended shadow code as a feature vector to incorporate both local and global information into the verification decision. Fang et al. used positional variances of the 1-dimensional projection profiles of the signature patterns and the relative stroke positions of two-dimensional patterns. Meenakshi et al. used a quasi-multi-resolution technique using GCS (Gradient, Structural and Concavity) features for feature extraction. An important issue in signature recognition is the effect of insufficient samples available for training in classification accuracy. It is well known that
when the ratio of the number of training samples to the number of the feature dimensionality is small, the estimates of the statistical model parameters are not accurate, and therefore the classification results may not be satisfactory. This problem is especially significant in off-line signature verification where usually only a few samples can be available for training such as 2-4 signatures when one opens a bank account [17][18][19].

On-line approaches to signature recognition: Input devices in this category include digitizing tables or smart pens and hand gloves. In digitizing table-based systems, both global and local features that summarize aspects of signature shape and dynamics of production are used for signature verification. In Pen-based systems, a smart stylus pen is used to collect data such as pen-tip positions, speeds, accelerations, or forces while a person is signing. The invisible pen-up parts of the signature are used to construct a signature verification system. Trajectories left in pen-up situation, which are called virtual strokes, are used to extract the optimal features that represent the personal characteristics of the authentic signature and affect the error rate greatly [20][21]. In on-line system for which the signature signal is captured during the writing process, thus making the dynamic information available [22].

Data glove - a new dimension in the field of signature verification represents an easy-to-use device that can reflect the identity of a person and that renders the forging process nearly impossible. Glove signature is a virtual-reality-based environment to support the signing process. Application in banks and Internet-based applications could be widely enhanced by manufacturing light and wireless data gloves. While most input devices offer one-, two-, or three-degrees of freedom, the data glove is unique in that it offers multiple degrees of freedom for each finger and the hand as well. This permits a user to communicate to the computer a far richer picture of his or her intentions than most other input devices. The dynamic features of the data glove provide information on: (a) Patterns distinctive to an individual's signature and hand size, (b) Time elapsed during the signing process, and (c) Hand trajectory-dependent rolling. Thus, the glove as a tool for signature recognition allows authentication of people not only through the biometric characteristics of their signatures but also through the sizes of their hands. The virtual signature acquired by the glove can be used to make Internet transactions or bank transfers secure, because it unequivocally authenticates a person. It is well known that the Virtual Signature is the most reliable method for signature authentication, especially when the signing process takes place on a digitizing table as well. This combination results in all possible useful features like finger and hand dynamics, speed, time, acceleration, and the effect of hand size.

2. Data Acquisition

We designed database into three separate categories. Database consists of (i) 14 sensor-based, (ii) 5 sensor-based, and (iii) 4 sensor-based.

When one signs a signature using data gloves, three types of information are captured: (i) the coordinate values \( x(n), n=1,2,\ldots,n_s \) based on each of the sensor position, (ii) timing information tagged to each of \( x \)-coordinate values based on the number of sensors that are used to acquire the data, and (iii) total time elapsed during the completion of the signature. Here we have collected three categories of signature for skilled forgery: (i) using 14 sensors, (ii) using 5 sensors and (iii) using 4 sensors. After the data acquisition, the data of the signature to be authenticated is compared against the SVD-based signature verification technique.

3. SVD-Based Handwritten Signature Verification Technique

Consider a data glove \( m \) sensors each generates \( n \) samples per signature, producing an output data matrix, \( A(m \times n) \). Matrix \( A \) that represents the feature contents of a signature and its Singular Value Decomposition is given as

\[
A = USV^T .
\]

where \( U(m \times m) \) and \( V(n \times n) \) are orthogonal matrixes, and \( S(m \times n) \) is a diagonal matrix. The columns \( u_i \) and \( v_i \) of \( U \) and \( V \) are the left- and right-singular vectors, respectively, and the diagonal elements of \( \sigma_i \) of \( S \) are called the singular values. Where the singular values are arranged on the main diagonal in the following order

\[
\sigma_1 \geq \sigma_2 \geq \sigma_3 \cdots \geq \sigma_{r+1} = \cdots = \sigma_p = 0 ,
\]

where \( r \) is the rank of matrix \( A \), and \( p \) is the smaller of the dimensions \( m \) or \( n \).

Because of their sensitivity to content change in \( A \) and their uniqueness representation of the matrix itself, we propose to use the \( l \)-largest singular values of \( A \) as feature contents of the signature. Therefore, the whole signature is represented by highly discriminate feature vector of dimension \( 1 \times l \). Now, having used the \( l \)-largest singular values of the signature-data matrix as an indicator to signature contents, a Euclidean distance may be used to measure the distance between each pair of singular values for signature verification system. In general, the distance between points \( x \) and \( y \) in Euclidean space is given as

\[
d = \sqrt{\sum_{j=1}^{l} |x_j - y_j|^2} .
\]
4. Performance Evaluation

To verify the efficiency of the proposed technique in handwritten signature verification, we have taken total 200 sample signatures for each of the categories of database. Twenty skilled people are trained on mimicking the authentic signature. First, 10 authentic signatures are tried and the corresponding singular values of the data matrix $A_{m \times n}$ are calculated. The Euclidean distance between the 10 groups of authentic singular values and the reference ones is calculated. Similarly, the average of the 10 groups of authentic used as reference for signature verification and calculated the Euclidean distance for each of the forged-signatures to verify the performance evaluation of our proposed technique.

5. Results and Discussion

By comparing the results shown in Table 1, using 14 sensors the maximum value of Euclidean distance between the mean authentic signature and the 10 authentic trials is 10756 and minimum is 1541, whereas the maximum and minimum values of Euclidean distance between the mean authentic and the 10 skilled forgery are 247730 and 16691 respectively. On the other hand, using 5 sensors, the maximum value of Euclidean distance between the mean authentic signature and the 10 authentic trials is 6329 and minimum is 1118, whereas the maximum and minimum values of Euclidean distance between the mean authentic and the 10 skilled forgeries is 91376 and 7056 respectively. For 4-sensors category, the maximum value of Euclidean distance between the mean authentic signature and the 10 authentic trials is 4480 and minimum is 930, whereas the maximum and minimum values of Euclidean distance between the mean authentic and the 10 skilled forgery include 60137 and 4067. On the contrary, the results shown in Figures 1 and 2 indicate that the Euclidean distances for skilled forged signatures using 14- and 5-sensors’ data can easily identify from the authentic one by the graph trend. Whereas in 4-sensors data, Euclidean distances of the skilled forged signatures have crossed the graph trend line of authentic one. From the experimental results, it is obvious that 14- or 5-sensor data glove can significantly produce the signal data, which can easily identify the forged signature using our SVD based approach.

It is worth mentioning that the computational time of the algorithm is significantly small and directly related to singular value decomposition of the data matrix $A_{m \times n}$. This makes a solid ground to suggest the above technique that reflects the required potential for real-time implementation.

Table 1: Comparison of maximum and minimum values of Euclidean distance between the authentic (genuine) and skilled forged trials using 14-, 5- and 4-sensors-based data gloves.

|       | 14 sensor | 5 sensor | 4 sensor |
|-------|-----------|----------|----------|
|       | Max       | Min      | Max      | Min      | Max      | Min      |
| Genuine | 10756     | 1541     | 6329     | 1118     | 4480     | 930      |
| Skilled| 247730    | 16691    | 91376    | 7056     | 60137    | 4067     |

![Figure 1: Euclidean distance between the genuine and skilled forged signatures using 14-sensors](image1)

![Figure 2: Euclidean distance between the genuine and skilled forged signatures using 5-sensors](image2)

![Figure 3: Euclidean distance between the genuine and skilled forged signatures using 4-sensors](image3)
6. Conclusion

In this paper, we described a new real-time technique for the recognition of handwritten signature. The technique is based on linearly projecting the signature space of data glove into a low-dimensional space, through the use of Singular Value Decomposition (SVD). The resulting projections maximize the total scatter across all classes, i.e., across all signals of all signatures and results in a much simpler and efficient approach for signature recognition and verification. 20 skilled people are trained to forger the signature. The Euclidean distances between their respective singular values and the authentic ones are calculated and found that it can easily identify the forged signature from the authentic ones.

7. References

[1] Nalwa V.S. "Automatic On-line Signature Verification", Proceedings of the IEEE, 85(2): 215–239, 1997.
[2] Jain A., Bolle R. and Pankanti S. Biometrics: Personal Identification in Networked Society. Kluwer Academic Publishers, Boston, MA, USA, 1999.
[3] Jain A.K., Griess F.D. and Connell S.D. “On-line signature verification”, Pattern Recognition, 35(12), pp. 2963–2972, 2002.
[4] Plamondon R. and Lorette G. “Automatic Signature Verification and Writer Identification-The State of the Art”, Pattern Verification, 22(2), pp. 107–131, 1989.
[5] Leclerc F. and Plamondon R. “Automatics Signature Verification: The State of the Art, 1989–1993”, Pattern Verification and Artificial Intelligence, Special Issue Signature Verification, 8(3), pp. 643–660, 1994.
[6] Proceedings of Workshop on Biometric Authentication - ECCV’02.
[7] Pirlo G. "Algorithms for Signature Verification", Fundamentals in Handwriting Recognition, ed. S. Impedovo, Springer Verlag, Berlin, pp. 433-454, 1994.
[8] Plamondon R. and Srihari S.N. “On-Line and Off-Line Handwriting Recognition: A Comprehensive Survey”, IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(1), pp. 63-84, 2000.
[9] Plamondon R. (ed.), “Progress in Automatic Signature Verification”, World Scientific Publication, Singapore, 1994.
[10] Yacoubi A. E., Justino E.J.R., Sabourin R. and Bortolozzi A.F. "Off-Line Signature Verification Using HMMs and Cross-Validation, Neural Networks for Signal Processing X, 2000.Proceedings of the 2000 IEEE Signal Processing Society Workshop, 2, pp. 859–868, 2000.
[11] Yacoubi A. E., Sabourin R., and Suen C.Y. "Unconstrained Handwritten Word Verification Using Hidden Markov Models", IEEE Transactions on Pattern Analysis and Machine Intelligence, 21(8), pp. 752–769, 1999.
[12] Yang L., Winjaja B.K. and Prasad R. “Application of Hidden Markov Models for Signature Verification”, Pattern Verification, 28(2), pp. 161–170, 1995.
[13] Qi Y. and Hunt B.R. “Signature Verification Using Global and Grid Features”, Pattern Recognition. 27(12), pp. 1621-1629, 1994.
[14] Sabourin, R., Genest G., Préteux F., “Off-line Signature Verification by Local Granulometric Size Distributions”, IEEE Trans. Pattern Analysis and Machine Intelligence. 19(9), pp. 976-988, 1997.
[15] Fang, B., Leung C.H., Tang Y.Y., Tse K.W., Kwok P.C.K. and Wong Y.K. “Offline Signature Verification by the Tracking of Feature and Stroke Positions”, Pattern Recognition, 36(1), pp. 91–101, 2003.
[16] Meenaschi K. K., Sargur S. and Xu A. "Offline Signature Verification and Identification using Distance Statistics", International Journal of Pattern Recognition and Artificial Intelligence. 18(7), pp. 1339-1360, 2004.
[17] Ammar M. “Progress in Verification of Skillfully Simulated Handwritten Signatures”, International Journal of Pattern Recognition and Artificial Intelligence. 5(1), pp. 337-351, 1991.
[18] Raudys S.J. and Jain A.K. “Small Sample Size Effects in Statistical Pattern Recognition”. IEEE Tran. Pattern Recognition and Machine Intelligence. 13(3), pp. 252-264, 1991.
[19] Fang B. and Tang Y.Y. “Reduction of Feature Statistics Estimation Error for Small Training Sample Size in Off-line Signature Verification”, First International Conference on Biometric Authentication, Lecture Notes in Computer Science, 3072, pp. 526-532, Springer-Verlag, Berlin Heidelberg New York, 2004.
[20] Plamondon R. “The Design of an On-line Signature Verification System: From Theory to Practice”. International Journal of Pattern Recognition and Artificial Intelligence, 8, 1994.
[21] Paulik M., Mark J. and Mohankrishnan N. “Sequence Decomposition Based, Autoregressive Hidden Markov Model for Dynamic Signature Identification and Verification”, 1993.
[22] Rhee Taik H., Cho Sung J. and Kim J. H. “On-Line Signature Verification Using Model–Guided Segmentation and Discriminative Feature Selection for Skilled Forgeries”, Proceedings Sixth International Conference in Document Analysis and Verification, pp. 645–649, 2001.