A Sensor-Based Approach for Dynamic Signature Verification using Data Glove

Shohel Sayeed shohel.sayeed@mmu.edu.my
Faculty of Information Science and Technology,
Multimedia University,
Jalan Ayer Keroh Lama,
75450 Melaka, Malaysia.
**Corresponding author*

Nidal S. Kamel nidalkamel@petronas.com.my
Department of Electrical & Electronic Engineering,
Universiti Teknologi PETRONAS,
Bandar Seri Iskandar,
31750 Tronoh, Perak, Malaysia.

Rosli Besar rosli@mmu.edu.my
Faculty of Engineering and Technology,
Multimedia University,
Jalan Ayer Keroh Lama,
75450 Melaka, Malaysia.

Abstract

Data glove is a new dimension in the field of virtual reality environments, initially designed to satisfy the stringent requirements of modern motion capture and animation professionals. In this paper we try to shift the implementation of data glove from motion animation towards signature verification problem, making use of the offered multiple degrees of freedom for each finger and for the hand as well. The proposed technique is based on the Singular Value Decomposition (SVD) in finding *r* singular vectors sensing the maximal energy of glove data matrix **A**, called principal subspace, and thus account for most of the variation in the original data, so the effective dimensionality of the data can be reduced. Having identified data glove signature through its *r*-th principal subspace, the authenticity is then can be obtained by calculating the angles between the different subspaces. The SVD-signature verification technique is tested with large number of authentic and forgery signatures and shows remarkable level of accuracy in finding the similarities between genuine samples as well as the differences between genuine-forgery trials.

Keywords: Data glove, Signature verification, Singular value decomposition, Euclidean distance.

1. INTRODUCTION

Biometry offers potential for automatic personal verification and differently from other means for personal verification, biometric means are not based on the possession of anything or the knowledge of some information. Of the various biometrics, signature-based verification has the advantage that signature analysis requires no invasive measurement and is widely accepted since signature has long been established as the most diffuse mean for personal verification in our daily life, including commerce applications, banking transactions, automatic fund transfers, etc. A wide variety of feature extraction and classification methods have been applied to the signature recognition. Two categories of verification systems are usually distinguished: off-line and online systems for hand written signature authentication and verification.

Off-line approaches for signature recognition: In off-line systems for which the signature is captured once the writing processing is over, and thus only a static image is available. As for off-line signature verification processing, most of the earlier work involves the extraction of features from the signatures image by various schemes. Y. Qi et al. [1] used local grid features and global geometric features to build multi-scale verification functions. Sabourin et al. [2] used an extended shadow code as a feature vector to incorporate both local and global information into the verification decision. B. Fang et al. [3] used positional variances of the 1 dimensional projection profiles of the signature patterns and the relative stroke positions of two-dimensional patterns. K. Meenakshi et al. [4] used a quasi-multiresolution technique using GCS (Gradient, Structural and Concavity) features for feature extraction.

On-line approaches to signature recognition: Input devices in this category are either 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 signature production are used for signature verification. In Pen-based systems a smart 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, called ‘‘virtual strokes,’’ are used to extract the optimal features, which represent the personal characteristics of the authentic signature and affect the error rate greatly [5],[6],[7],[8],[9].

2. DATA GLOVE

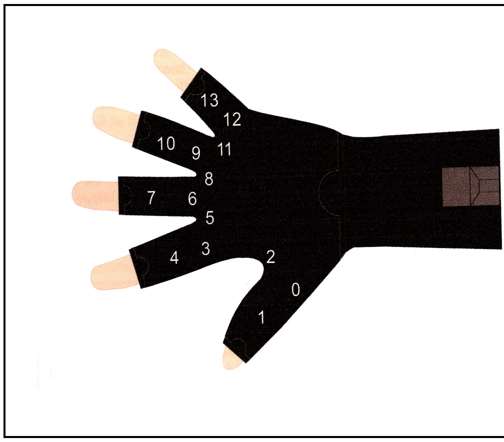
Data glove is a new dimension in the field of signature verification, which can reflect the identity of a person and that renders the forging process nearly impossible. Glove signature is a virtual-reality- based environment to support the signing process and it offers multiple degrees of freedom for each finger and for the hand as well [10].

The dynamic features of the data glove provide information on:

1. Patterns distinctive to an individuals’ signature and hand size
2. Time elapsed during the signing process
3. 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 size of their hands. Figure 1 shows the data glove [11] and location of sensors. Figure 2 shows signals from the data glove during signing process.

In our research, we proposed a new approach for handwritten signature verification using 14 sensor-based data glove. The technique is based on correlation measure through the use of Singular Value Decomposition (SVD) of different signature groups.



Sensor #	Location
0	Thumb Near
1	Thumb Far
2	Thumb/Index
3	Index Near
4	Index Far
5	Index/Middle
6	Middle Near
7	Middle Far
8	Middle/Ring
9	Ring Near
10	Ring Far
11	Ring/Little
12	Little Near
13	Little Far

FIGURE 1: Sensor Mappings for 5DT Data Glove 14 Ultra

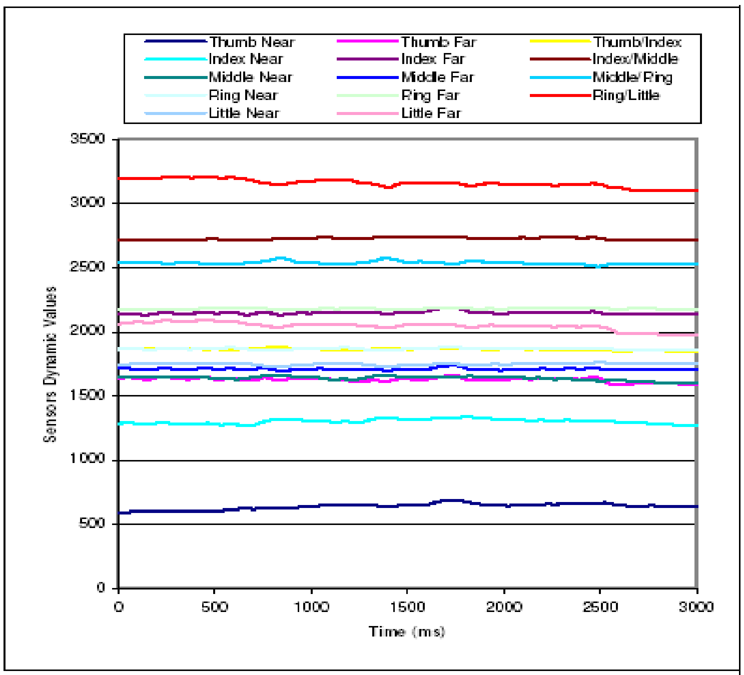


FIGURE 2: Signals From The Data Glove Of A Signature

3. SVD-BASED SIGNATURE VERIFICATION TECHNIQUE

Singular value decomposition (SVD) provides a new way for extracting algebraic features from the signature data using data glove. SVD has been used in many fields such as data compression, signal processing, and control system and pattern analysis. Consider a data glove of m sensors each generates n samples per signature, producing an output data matrix, $A(m\times n)$. Usually $n >> m$, where m denotes the number of measured channels while n denotes the number of measurements.

The properties of the singular values are described in detail in the following:

Theorem 1. Singular Value Decomposition- If $A \in R^{mxn}$, then there exists the diagonal matrices

$U = [u_1, \Lambda, u_m] \in R^{mxm}$ and $V = [v_1, \Lambda, v_n] \in R^{nxn}$ so that $U^T AV = diag(\sigma_1, \Lambda, \sigma_p)$

where $p = \min(m,n), \quad \sigma_1 \geq \sigma_2 \geq \Lambda \geq \sigma_p \geq 0$

$\sigma_i, \quad i = 1,2,...p,$ are the singular values of A.

The singular values are the square roots of eigenvalues λ_i of AA^H or $A^H A$, that is $\sigma_i = \sqrt{\lambda_i}$

Theorem 2. The stability of Singular Value:

Assume $A^{mxn}, B^{mxn} \in R^{mxn}$, and their singular values are $\sigma_1 \geq \sigma_2 \geq \Lambda \geq \sigma_n, \quad \tau_1 \geq \tau_2 \geq \Lambda \geq \tau_n$, respectively, then $|\sigma_i - \tau_i| \leq \|A - B\|_2$. This means that there is a disturbance at A, the variation of its singular values is not more than the $\|.\|_2$-norm of the disturbance matrix.

Theorem 3. The scaling property- If singular values of A^{mxn} are $\sigma_1, \sigma_2, \Lambda, \sigma_k$, the singular values of $\alpha * A^{mxn}$ are $\sigma_1^*, \sigma_2^*, \Lambda, \sigma_k^*$, then $|\alpha|(\sigma_1, \sigma_2, \Lambda, \sigma_k) = (\sigma_1^*, \sigma_2^*, \Lambda, \sigma_k^*)$

Theorem 4. The rotation invariant property- If P is the unitary matrix, then the singular values of PA are the same as those of A.

The above properties of SVD are very desirable in signature verification, when signature data are taken using data glove.

3.1 Distance Measurement for Signature Data Sets

By establishing the properties of SVD, we extracted the first r left singular vectors (U) of glove data matrix A, which is account for most of the variation in the original data. This means that with m × n data matrix that is usually largely over determined with much more samples (columns) than channels (rows): n >> m the singular value decomposition allows to compact the most of signature characteristics into r vectors.

Now, having identified each signature through its r-th principal subspace, the authenticity of the tried signature can be obtained by calculating the Euclidean distance between its principal subspace and the genuine reference. The Euclidian distance for every genuine or forged signature $X_i \in \{x_1, x_2, ..., x_k\}$ with the reference signature $Y_i \in \{y_1, y_2, ..., y_k\}$ is calculated by given equation:

$$Dis\,tance\,(X_i, Y_i) = \left(\sum_{i=1}^{k} |X_i - Y_i|^2 \right)^{1/2}$$

3.2 Model for the SVD-based Signature verification Technique

The model for the proposed signature verification technique is shown in Figure 3. The whole system is divided into two phases:

Enrollment phase:

- Use data glove to provide the system with 10 genuine samples of his/her signature.
- Out of the collected 10 genuine samples select the reference signature.
- Extract the *r*-principal subspace of the reference signature and save it in the database for matching.

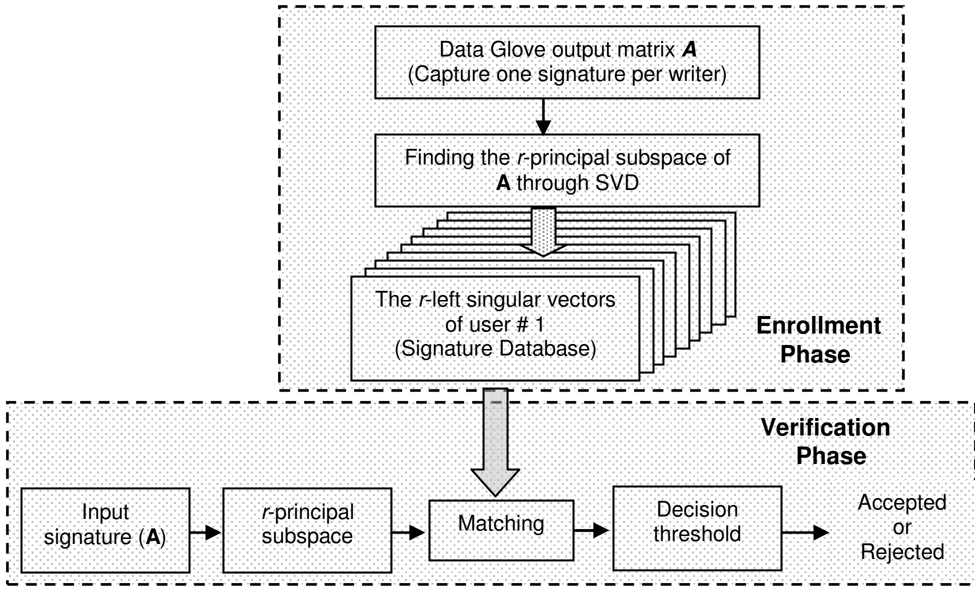


FIGURE 3. Proposed Model for the SVD-based Signature Verification Technique

Verification phase:

- Use data glove to input the signature of the user (one sample).
- Calculate the *r*-principal subspace of the claimed identity using SVD.
- Match the principal subspace of the claimed identity to the enrolled models in the database through the similarity factor.
- Compare the similarity factor with the decision threshold for ACCEPT or REJECT.

Some typical signatures along with their forgeries are given in Figure 4.

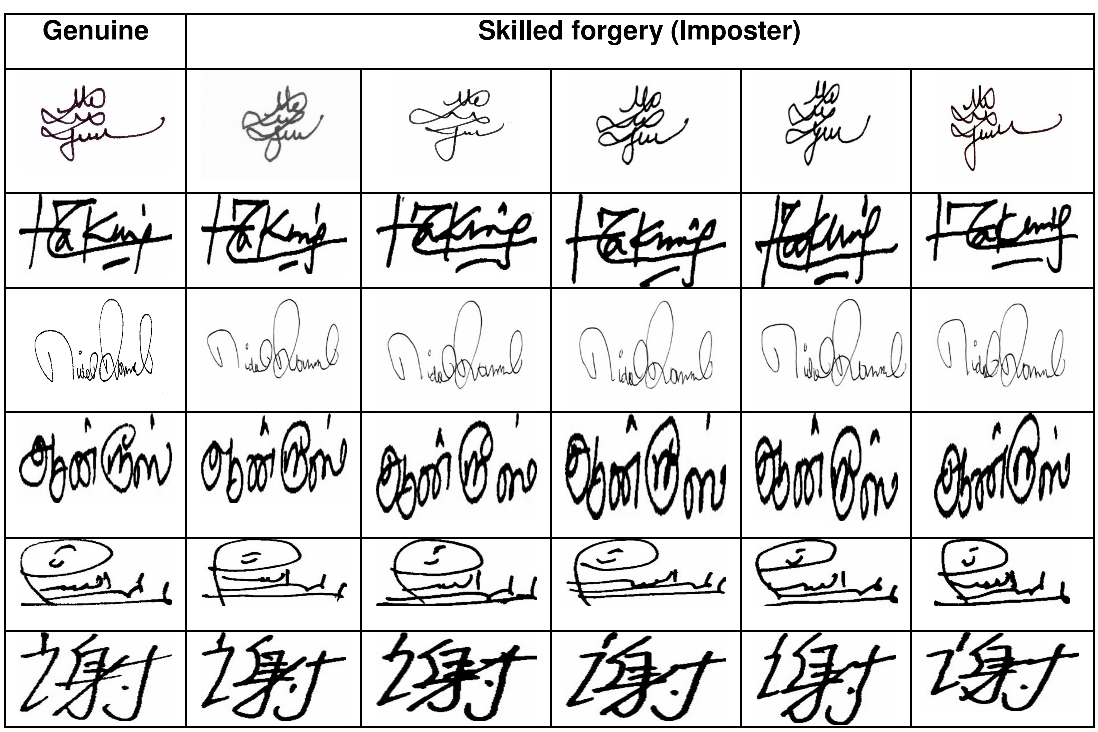


FIGURE 4: Some Example Of Genuine Signatures And Their Typical Skilled Forgeries

4. EXPERIMENTAL RESULTS AND DISCUSSION

To verify the efficiency of the proposed technique in handwritten signature verification, the 5DT Data Glove 14 Ultra is used. This glove is using 14 sensors to measure finger flexure (two sensors per finger) as well as the abduction between fingers. Glove data is acquired using 8-bit resolution (256 positions) for each figure as well as for the axes of the tilt sensor roll and pitch. The roll and bitch angle of the glove are measured using tilt sensor through a ±60o linear range. The 5DT Data Glove starts up in command mode. The full hand (five fingers, roll angle, pitch angle) can be sampled at least at 60 samples per second. The system interfaces with computer via cable to USB port. The SVD-signature verification algorithm is written in MATLAB 7.01 and run on a machine powered by Intel Core 2 Duo processor. The CPU time is about 80 ms.

In the first experiment we asked 40 writers to repeat their signature 25 times creating 25 authentic samples per writer. Then we randomly mixed up the 25 genuine samples of each writer creating 50 pairs genuine of samples. This scenario is extended towards the available 40 genuine writers to create $50 \times 40 = 2000$ pairs of genuine signatures. The SVD-based signature verification technique is then run with each of the 2000 genuine trials and the Euclidean distances between the extracted features of the different signatures are calculated and included as similarity factor in percent in Table 1.

In the second experiment we take one sample from each of the 40 genuine writers and consider it as a baseline. Next, we collect 10 forgery samples for each baseline from 20 skilled forgers, producing 200 forgery samples per baseline. The baseline sample for each genuine writer is then paired with each of 200 forgery trials to generate 200 pairs per baseline. This scenario is extended over the available 40 baseline samples generating $200 \times 40 = 8000$ genuine-forgery pairs. The SVD-based signature verification technique is then run with each of the 8000 imposter trials and the Euclidean distances between the extracted features of the different signatures is calculated and included as similarity factor in percent in Table 1.

Similarity factor In percentage	**Glove-based**	
	Genuine	**Imposter**
(91-100)%	35%	0
(86-90)%	26%	0
(81-85)%	23%	0
(76-80)%	16%	0
(71–75)%	0	0
(66–70)%	0	1%
(61-65)%	0	19.7%
(51–60)%	0	53.65%
< 50%	0	25.65%

Table 1: The Similarity Factor In Percentage For Genuine and Imposter Samples.

Table 1 shows clearly that with the different 2000 genuine pairs of samples the SVD-signature verification technique using data glove produces 100% samples with similarity factor > 76% and approximately zero samples for similarity factor lower than 76%. This simply means that, for the worst case of repetition of a signature by the same writer, the SVD-based signature verification technique manages to recognize the similarity with other genuine one by at least 76% and for average quality of repeated samples the similarity factor is about 90%.

Table 1 also shows the good capability of the SVD-based signature verification technique using data glove in identifying forgery samples from genuine. Where, out of the 8000 forgery samples the suggested technique produces 0% number of trials with similarity factor greater than 70%, making it nearly impossible for any skilful forger to exceed this threshold.

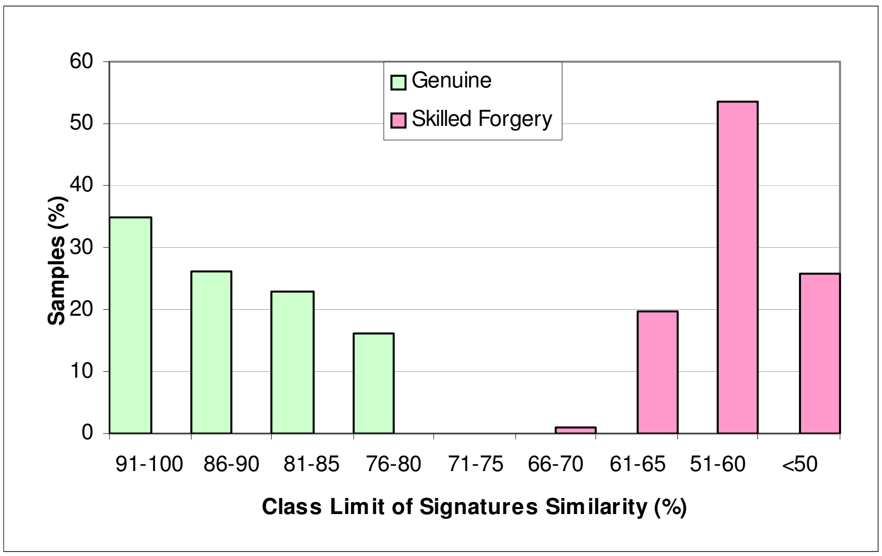


FIGURE 5: Similarity Measure Between The Mean Genuine Signature And Skilled Forgery Trials Using Glove-Based Signature Data

In summary it can be said that the suggested SVD-based signature verification technique using data glove compare to corresponding signature images is showing quite powerful performance in recognizing the similarities between genuine signatures with lower bound of 76% and upper bound of approximately 97%. On the other hand it recognizes the differences between forgery and genuine samples with upper bound of 70% and lower with less than 50%. This performance creates gap between the two cases (genuine-genuine & genuine-forgery) large enough to easily and safely distinguish between authentic and forgery trials with approximately zero error.

In evaluating the performance of a signature verification system, the FAR and FRR factors are used to assess the performance of the suggested technique.

For further evaluating the performance of a signature verification system, we adopt the equal error rate (EER), that is the error rate when the false rejection rate (FRR) of genuine signatures and the false acceptance rate (FAR) of forgery signatures assume the same value; it can be adopted as a unique measure for characterizing the security level of a biometric system. Figure 6 shows that the EER of our proposed technique. The FAR and FRR are calculated for the normalized threshold values ranging from 0 to 1. FAR and FRR are calculated by

$$FAR = \frac{Total\ number\ of\ accepted\ forgeries}{Total\ number\ of\ tested\ forgeries} X\,100$$

$$FRR = \frac{Total\ number\ of\ genuine\ rejected}{Total\ number\ of\ tested\ genuines} X\,100$$

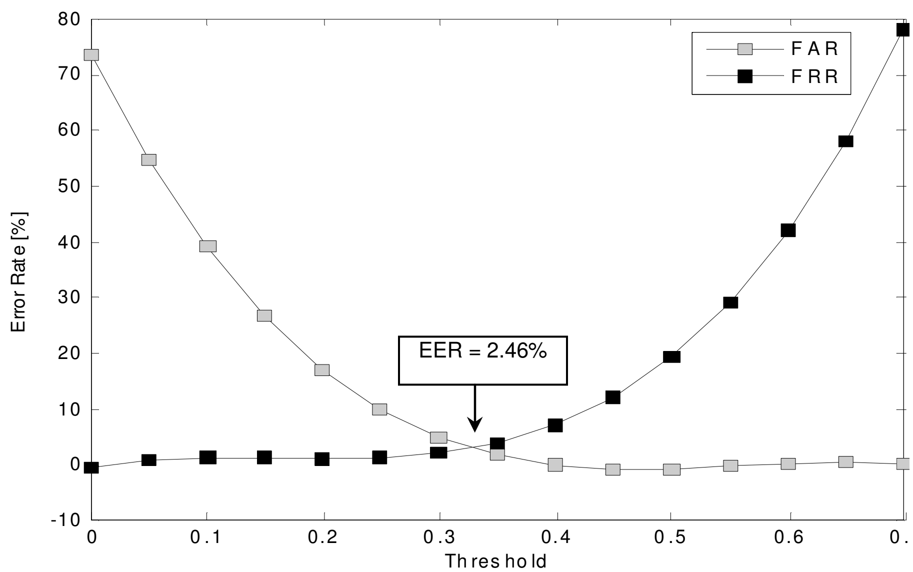


FIGURE 6: False Acceptance Rate (FAR) And False Rejection Rate (FRR) As A Function Of A Decision Threshold

Figure 6 shows that the Equal Error Rate (EER) of the SVD-based signature verification technique using data glove is 2.46%.

5. COMPARISON WITH OTHER ON-LINE METHODS

It is difficult to make comparison between different signature verification techniques based on different databases [12]. Hence, here we just compared the performance achieved by some of the suggested signature verification techniques. An automatic handwritten signature verification system based on a serial multi-expert architecture obtained false acceptance rate (FAR) and false rejection rate (FRR) for skilled forgeries 19.8% and 2.04% respectively, and EER of 10.92% [13]. On-line handwritten signature verification system using Hidden Markov Model (HMM) has achieved a false acceptance rate (FAR) of 4% and a false rejection rate (FRR) of 12% for both random and skilled forgeries and EER of 11.5% [14]. Dynamic alignment distance based on-line signature verification method presented by Amac et al. [15] has achieved 7.83% for EER with data set of skilled forgeries. In addition to the aforementioned verification techniques, the First International Signature Verification Competition (SVC2004) has tested more than 15 systems from industry and academia and found that the best equal error rate is 2.84%, achieved by [16].

Our proposed technique comparing with others, the equal error rate value of the SVD-based signature verification technique (EER =2.46%) is considerably acceptable level than the most of the suggested techniques.

6. CONSLUSION & FUTURE WORK

In this research paper we have summarized and critically discussed the main issues to be taken into account for the evaluation of the accuracy and performance of signature verification technique. The real-time signature identification and verification is necessary in most practical application. Our proposed SVD-based signature verification technique can process glove-based signature data in high speed and obtained a significant result. Its effectiveness and significant performance has been proven by the experiments. In order to compare the proposed technique using data glove with other on-line signature verification technique, the equal error rate value of the SVD-based signature verification technique is calculated and proved to be significantly lower (EER = 2.46%) than the other on-line techniques. Hence, from the experimental point of view, our proposed technique for signature identification and verification need low computational time as well as produce high level of accuracy. So, the SVD-based signature verification technique using data glove may represent a new trend in real-time signature verification system.

In future, the structure of the data glove can be further simplified by interfacing with the computer wirelessly by means of Bluetooth technology as well as increase the database size and reduce the number of sensors.

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