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Application of Microlectures Based on WeChat in Rehabilitation Nursi ng Teaching

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Abstract - People may now connect into an app using biometric identification on a wide variety of devices thanks to advancements in mobile technology and the usage of smartphones. In the field of biometrics, device interoperability is a difficult subject that merits additional investigation. Since this biometric feature has gained significant traction in the financial and commercial sectors in recent years, we decided to concentrate on interoperability device compensation for online signature verification in this study. The two primary steps of the suggested method are outlined below. A preprocessing step is used to standardise signals from diverse devices, so that they may be compared to one other. The second method relies on a feature selection process that considers the interoperability of the devices being used, in order to identify characteristics that will hold up well under such settings. An online signature verification system based on global features and another based on temporal functions has both been successfully implemented using this method. Researchers are testing two alternative scenarios simulating real-world operating situations utilising dynamic signature data sets from Biosecure DS2 (a Wacom pen device) and DS3 (a mobile device for a Personal Digital Assistant). An average relative increase in performance of 60.3 percent and 26.5 percent Equal Error Rate (EER), respectively, has been achieved for random forgery scenarios by the suggested global features-based and temporal functions-based systems, compared to baseline systems. For skilled forgeries, a merger of the suggested methods has yielded a further significant improvement in device compatibility. When compared to a time functions-based system, the suggested fusion system exhibited an average relative improvement of 27.7 percent EER. These findings demonstrate the resilience of the suggested technique and open the way for future investigations employing devices like smartphones or tablets, which are widely used today.

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Keywords - Device interoperability, on-line signature, time functions-based system, global featuresbased system, fusion, DTW, Biosecure.

I. Introduction

One of the most widely acknowledged biometric qualities is the handwritten signature. For more than a century, they have been used in financial and legal agreement situations [1], [2]. Multiple electronic devices (such as pen tablets, PDAs, grip pens, cellphones, etc.) can now readily take signatures [3]. Biometric traits like this one have been more popular in recent years, notably within the financial and commercial sectors, as seen by recent occurrences. a pair of two However, one of the most difficult aspects of signature verification is the wide range of possible signatures. High intra-class diversity in authentic signatures might be a problem, although expert forgeries may be almost identical to real signatures (low inter-class variability). Additionally, there are extrinsic sources of unpredictability like device compatibility that may have a significant impact on recognition performance.

People may use a variety of devices to access an app, for example, owing to the rising use of smartphones in business apps to enable payments [4]. A dynamic signature verification system is analysed and improved in an interoperable manner for these reasons.

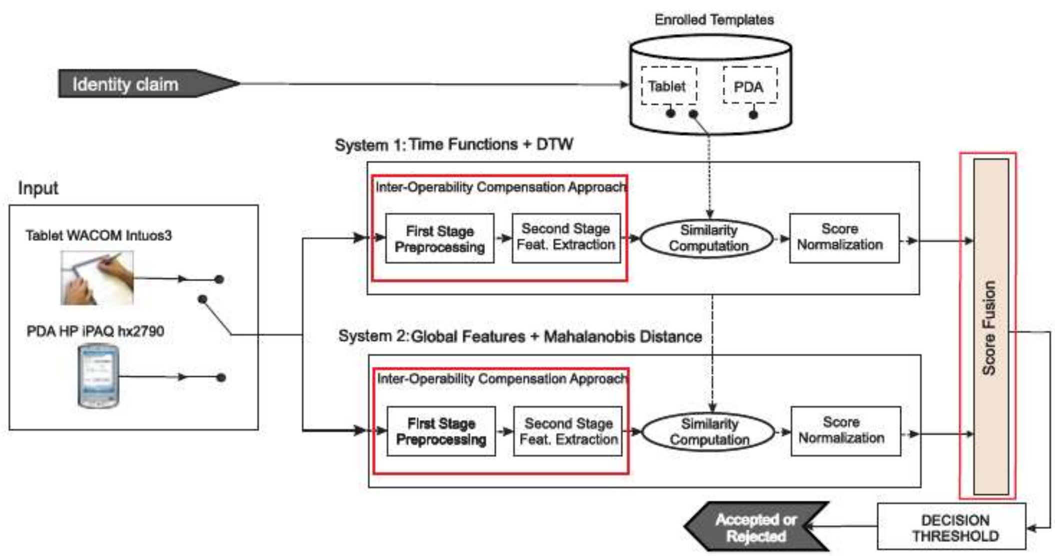

Figure 1. Design of the suggested device interoperability compensation plan

Both temporal functions and global features are used in the proposed technique, which consists of two steps of data preprocessing and feature selection. Both suggested systems are fused at the score level, which further enhances system performance in general, but especially for device compatibility. The suggested phases (stage 1 and stage 2) and the score fusion from both systems are noted in red boxes in this paper.

Global featuresbased systems (often known as global systems) capture global information (e.g. signature duration, number of pen ups, etc.) in order to produce a holistic feature vector for on-

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line signature verification [5][7]. The signature time functions (e.g. X and Y pen coordinates, pressure, etc.) are used for verification in time function-based systems (often known as local systems). Historically, systems based on temporal functions have outperformed systems based on global features in terms of recognition performance [5, [9], [10]]. There are a variety of statistical classifiers often used in global features-based systems, such as Gaussian Mixture Model [11] and the Mahalanobis distance [12]. [12]

There are DTW (Dynamic Time Warping), HMM (Hidden Markov Models) [8], [14], NN (Neural Networks) [15] and SVM (Support Vector Machines) in time function-based systems. The benefit of DTW is that user models do not need to be trained beforehand. Device interoperability for dynamic signature recognition seems to be a relatively new topic [17][19]. In [17], the interoperability of two tablet PCs is explored using signatures from both devices in an access control scenario.

Linear interpolation was used to downsample signatures to a sampling frequency of 100 Hz. The performance of a time-functions-based system based on HMM with 14 discrete-time functions is assessed. Sensor enrollment and fusion for monosensors and multisensors are both studied. Tablet PCs, cellphones, and tablets, on the other hand, are included in a recent research [18]. Interoperability devices are tested utilising a DTW-based time functions-based system with four discrete-time functions for random (zero-effort) forgeries to evaluate the system's performance

Preprocessing normalizations based on time and location are used to improve the comparability of signatures from diverse devices. There was no specific design for correcting for device interoperability in that effort, other from the normalisation step. We recently [19] proposed a time-functions-based system solution to solve the problem of device interoperability in dynamic signature recognition. A 26.5 percent average boost in random forgeries and a 14.2 percent gain in expert forgeries was found when comparing the results to having a system customised to each device. This study builds on previous work by examining two systems (global features-based and time-based systems) and merging them. Multi-session situations and access control scenarios, in which users must sign while standing with the device in one hand, are also taken into consideration.

Figure 1 depicts the two-stage design of the suggested technique to account for device compatibility (data preprocessing and feature selection). Two widely used systems for online signature recognition are given a try using this strategy (local and global systems). Finally, the suggested systems are fused at the score level, which improves system performance in general, but especially when it comes to device compatibility. The suggested technique has two parts, the first of which is a data preprocessing step used to achieve high similarity between signatures generated by various devices.

In order to limit the impact of device compatibility, a global feature and time function selection phase is recommended after this data preparation stage. The Sequential Forward Feature Selection (SFFS) method has been used for this purpose [20]. The system based on global features employs 100 global features in total and the Mahalanobis distance technique, whereas the system based on time functions employs 21 time functions in total and the DTW method.

Another substantial increase in interoperability is provided by a weighted sum of the matching scores, which merges both global features-based and temporal functions-based systems.

Experiments are conducted using the biosecure DS2 (Wacom pen tablet under access control scenario) and DS3 (HP PDA under mobility scenario) datasets, each with 120 users. There have been several contests like the Biosecure Signature Competition Campaign (BSEC 2009) [23] that have focused on the quality of signatures, and the final solution provided for all comparison instances includes 28 global characteristics and seven temporal functions. Therefore, it is vital to point out that the final suggested system performs well and operates correctly in both scenarios of device interoperability and non-interoperability. Here are the sections of the paper. The database utilised in the experiments is described in Section II. Using two primary steps and a signature verification method, this paper proposes a two-stage technique. There's a lot of experimentation in Section IV. Section V concludes with a look at what's to come.

II. Significance Inventory

DS2 and DS3 from the Biosecure [24] database were utilised to perform the experiments reported in this research. As an added benefit, DS2 datasets were collected in a sitting-signing situation; on the other hand, mobile datasets (DS3) were taken when users were standing and holding the device in one hand, simulating actual operational settings. Biosecure DS2 and DS3 datasets feature two distinct sessions separated by a three-month time gap, therefore the issue of intra-class variability is also taken into account. Figure 2 depicts the DS2 dataset recorded using a digitising pen tablet WACOM Intuos3 A6 digitizer at a sampling rate of 100 Hz as well as writing on a paper sheet concurrently, as seen in Fig. 3.

In the experimental study presented here, a subset of 120 common users in DS2 and DS3 is analysed in order to analyse and adjust for the effect of device interoperability. Biosecure DS2 provides X and Y pen coordinates, pressure, pen angular orientation (azimuth and altitude angles), and timestamp information. There are just X & Y pen coordinates, as well as a time stamp, in Biosecure DS3. For the two datasets (DS2 and DS3), two distinct sessions of acquisition (i.e., multi-session) were used to capture the signatures. We have 30 real signatures for each user in the dataset (which is 15 real signatures per session) as well as 20 forgeries that are good enough to fool the system (which is 10 forgeries that are good enough each session). When it came to forging signatures for expert forgers, users were able to see the dynamics of the signing process.

Figure 2. (a) Pen tablet capture in Biosecure DS2 – Access Control Scenario. (b) Biosecure DS3 - Mobile Scenario PDA signature capturing procedure.

III. Interoperability Device Signature Verification System

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A Data Preprocessing Stage

The goal of this first step is to collect signatures that have the same sort of information (e.g. X and Y coordinates, pressure, etc.) and time and spatial location standard formats so that the system may perform better in a device interoperability instance.. Due to discrepancies in geometry, many statistical data normalising methods were investigated (see Fig. 3).

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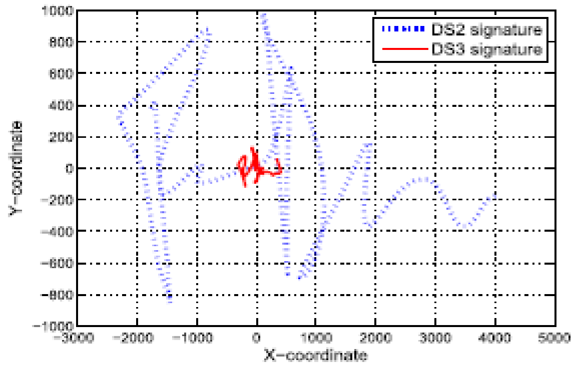
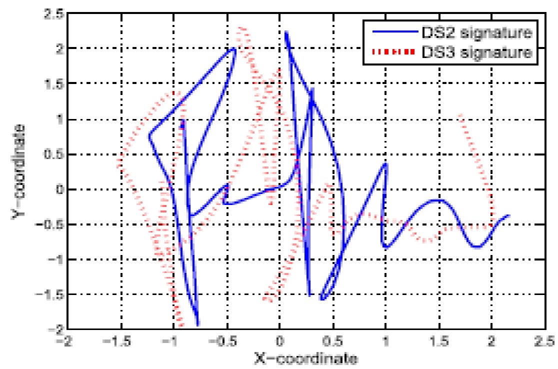


(a)



(b)

Figure 3. DS2 and DS3 signatures. (a) Difference in DS2 and DS3 spatial resolution. (b) Normalized DS2 and DS3 signatures.

Biosecure's signature collection technique required users to sign in various boxes on a piece of paper (see Fig. 2(b)) for DS2, however the differences in size between DS2 and DS3 signatures might be attributed to the devices' varying screen resolutions (see Fig. 3(a)). This is especially true for DS2. Both systems were normalised using the mean and standard deviation to enhance their performance in the interoperability example, which was shown to be the most effective. In Fig. 3(b), we show the normalised signatures from DS2 and DS3. An extra preprocessing step is required in the DS3 dataset to address sampling errors based on splines [25]. (missing samples). In addition, this study solely takes into account X and Y spatial coordinates. To concentrate on the interoperability of the system, pressure and pen angular orientation have been deleted since these information is not given by the DS3 device.

Table 1. This work's time functions. [6] and [8] tables modified.

#	Feature
1	X-coordinate: x_n
2	Y-coordinate: y_n
3	Path-tangent angle: θ_n
4	Path velocity magnitude: v_n
5	Log curvature radius: ρ_n
6	Total acceleration magnitude: a_n
7-12	First-order derivate of features 1-6: $\dot{x_n}, \dot{y_n}, \dot{\theta_n}, \dot{v_n}, \dot{\rho_n}, \dot{a_n}$
13-14	Second-order derivate of features 1-2: $\ddot{x_n}, \ddot{y_n}$
15	Ratio of the minimum over the maximum speed over a 5-samples window: v_n^r
16-17	Angle of consecutive samples and first order difference: α_n, $\dot{\alpha_n}$
18	Sine: s_n
19	Cosine: c_n
20	Stroke length to width ratio over a 5-samples window: r_n^5
21	Stroke length to width ratio over a 7-samples window: r_n^7

In addition, the PDA does not capture information from pen-ups to pen-downs. It was thus decided to remove this data in DS2 (but not in IV-B1 to examine the suggested data preprocessing step) in order to establish comparable processing conditions in both devices.

B *Feature Extraction And Selection Stage*

Obtaining a set of global characteristics and time functions that can stand up to data comparisons with and without device interoperability is the primary goal of the proposed system's second stage. In this paper, a system based on global features and a system based on time functions, with 100 global features and 21 time functions, respectively, is examined. Previous works [26, 27] are used in both systems. The 21 time functions for each signature are shown in Table 1. Due to space constraints, no information on the 100 global characteristics examined in this study could be shown. See references [26, 27] for further information.

Sequential Forward Feature Selection (SFFS) technique [20] is used to choose a subset of the 100 global features and 21 temporal functions that increases the system's performance in terms of Equal Error Rate (EER) in a particular actual situation (percent). Because it doesn't take into consideration all potential combinations of attributes, this method provides an inferior answer. This is the algorithm's primary purpose. Optimization criteria have included the EER (energy efficiency ratio).

By modifying the algorithm's criteria, which takes into consideration the EER of all comparison instances (including those with and without device interoperability) simultaneously, the suggested technique aims to achieve good system performance in interoperability scenarios (see Sec. IV-B4).

C *Global Features Based Verification System*

When comparing two signatures, the Mahalanobis distance [28] is used to determine how similar the two are to one other. A training collection of signatures is used to build a user model. It is defined as C = $(\mu, \Sigma,)$, where μ is a feature vector containing the mean of feature vectors taken

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from each signature of this user and Σ is a diagonal covariance matrix. The inverse of the Mahalanobis distance between the input signature feature vector x and the claimed user model C is used to calculate the matching score: xC.

$$s(x, C) = \left((x-\mu)^T(\Sigma)^{-1}(x-\mu)\right)^{-1/2} \qquad (1)$$

As long as the score is greater than or equal to the threshold (s(x;C), it's regarded authentic). As a result, the system rejects it.

D *Time Functions-Based Verification System*

Time functions from signatures are compared using the DTW method [13]. As follows:

$$score = e^{-D/K} \qquad (2)$$

When utilising the DTW technique, the D and K values reflect the cumulative distance and the number of points aligned between two signatures, respectively.

E *Fusion Of Global Features-Based And Time Functions-Based Systems*

The best global feature/time function vectors provided in this study (see Section IV-B4) are combined with the global and local systems through a weighted sum of the match scores [29]. Global and local scores are standardised in a range of [0,1] using tanh-estimators before fusion is applied [30]. It is possible to calculate the fusion score sf as follows:

$$s_f = k \cdot s_g + (1-k) \cdot s_l \qquad (3)$$

In this equation, sf represents the national score, while the global score is equal to sg, and the local system score is equal to sl. The fusion weighting coefcient k is calculated heuristically based on the development signature set's EER performance (see Sec. IV-B5).

IV. Experimental Work

A *Experimental Protocol*

Inter-class variability must be taken into consideration when training signatures are employed, thus the 15 valid signatures from the second session are used for testing. As a result, our trials do not include any of the 10 legitimate signatures from the first session. The training signatures are compared to one of the remaining users' genuine signatures to provide random (zero-effort) forgeries scores, while skilled forgeries scores are obtained by comparing the training signatures to the 20 accessible skilled forgeries signatures for the same user. To arrive at a final score for the global verification system based on features, signatures are compared to a user model created using the first five authentic training signatures, while the final score for the time function verification system is calculated by averaging the results of two one-to-one comparisons. The following is an explanation of the terminology used in this paper:

$a-b-c$

B and c, respectively, are the devices used for training and testing in circumstances of skilled or random forgeries, as shown by a (DS2 or DS3). The first 50 users of the chosen datasets are utilised for system development and training, while the remaining 70 users are used for system evaluation.

EXPERIMENT 1 - DATA PREPROCESSING STAGE

The purpose of this experiment is to determine whether or not the first suggested pre-processing step (see Section III-A) is necessary to compensate for the interoperability issue.

A frequent practise in on-line signature verification is that systems for both global features and temporal functions are altered without regard to device compatibility. For the DS2 and DS3 datasets, an SFFS method was applied to enhance the EER scores for each person. These two vectors (global features and temporal functions) for each system, one for DS2 dataset and one for DS3 dataset, are tuned to authenticate the most difficult cases of forged documents.

A comparison of both systems' performance is shown in Table 2. For time-function-based systems, the performance of the system that applies the first suggested step is noticeably better than that of the system that does not apply this first preprocessing stage. Since this first preprocessing step is critical to device interoperability, the system's performance in such circumstances is quite low, with EER values of approximately 50% in the majority of cases. A device interoperability case should take into account the relevance of this pre-processing step in this experiment (as was the only case considered in [18]). Studying cases where there was no interoperability revealed that the system's performance was nearly identical for systems based on global features or on time functions, with or without applying the preprocessing stage, in both cases. In fact, in time functions-based systems without applying the preprocessing stage, the performance was even better because information between the pen up and the pen down was not removed. However, if the system is trained for DS3 (DS3-DS3) utilising the suggested preprocessing step, it performs better since sampling errors are rectified using interpolation based on splines [25].

Experiments 2, 3, and 4 were meant to demonstrate the system's improved performance when the second step of preprocessing was applied after the significance of the first stage had been assessed in a device interoperability instance. In order to pick features and time functions that are resistant to data comparisons in scenarios with and without device interoperability, this second step relies on feature/time function selection strategies.

Table 2. Experiment 1 results: EER (%) for global features-based system (top) and temporal functions-based system (bottom) on development set of 50 users (bottom). Comparison of results with and without the first pre-processed step suggested here.

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Global System	*Skilled forgeries*	
Training vs Testing	Without stage 1	With stage 1
DS2 - DS2	4.3	4.1
DS3 - DS3	25.3	14.8
DS2 - DS3	30.6	23.5
DS3 - DS2	49.3	46.9
Local System	*Skilled forgeries*	
Training vs Testing	Without stage 1	With stage 1
DS2 - DS2	7.1	8.6
DS3 - DS3	28.6	17.1
DS2 - DS3	45.5	27.3
DS3 - DS2	56.6	17.6

EXPERIMENT 2 - BASELINE SYSTEM

Global features and temporal functions both use the approach described above, which uses a first preprocessing step as its baseline. This is how online signature verification always works. Using the SFFS method, the EERs for the DS2 and DS3 datasets were improved, and two different vectors (one for the DS2 dataset and another for the most problematic scenario of skilled forgeries) were taken into consideration in each system (global features-based and temporal functions-based systems). Using this system as a baseline, we can see how much better we can go with the second step described in the tests to come. Using the rst step of the proposed technique, these baseline systems are shown in Table 3 for both global features-based (referred to as global) and temporal functions-based (referred to as local) systems (see Sec. III-A).

Table 3 shows that the system's performance for DS2 datasets is much better than DS3 datasets for both platforms when looking at no interoperability instances. There are many reasons for this, including the fact that the Wacom pen tablet DS2 is a superior quality device that is better suited for collecting signatures, and that participants in the DS3 dataset had to sign while holding their phone in one hand. A closer look into interoperability conditions shows that in both systems, the system's performance decreases dramatically, especially when it is trained for devices (DS2 - DS3) where the system's performance is over six times worse in some instances. For this reason it seems that training and testing with a variety of devices has a higher impact on performance, and the key circumstance is when the testing and training devices have varying quality. Recent research for random forgeries [18] have examined the system's performance in an interoperability situation, but no strategy for correcting the interoperability between various grade devices other than the preprocessing step has been proposed.

As a result, the following experiment's goal is to find an ideal feature vector that performs well in every situation.

EXPERIMENT 3 - INDIVIDUALLY OPTIMIZED SYSTEM

The purpose of this experiment is to determine which system, when tuned individually, performs at its optimal level. To be clear, this is not something that could be done in an application. It has

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been applied to each system (global features and time functions-based systems) independently and for each comparative instance. SFFS algorithm (4 for random and 4 for skilled forgeries).

Compared to the baseline system, an improved system performs much better in interoperability scenarios. This is because the SFFS algorithm in these independently designed systems has taken the interoperability situation into consideration. An application would not be able to use this since it evaluates 16 alternative optimum feature vectors (one for each scenario and system). As a consequence of these findings, we now have a better notion of the optimal performance we should aim for.

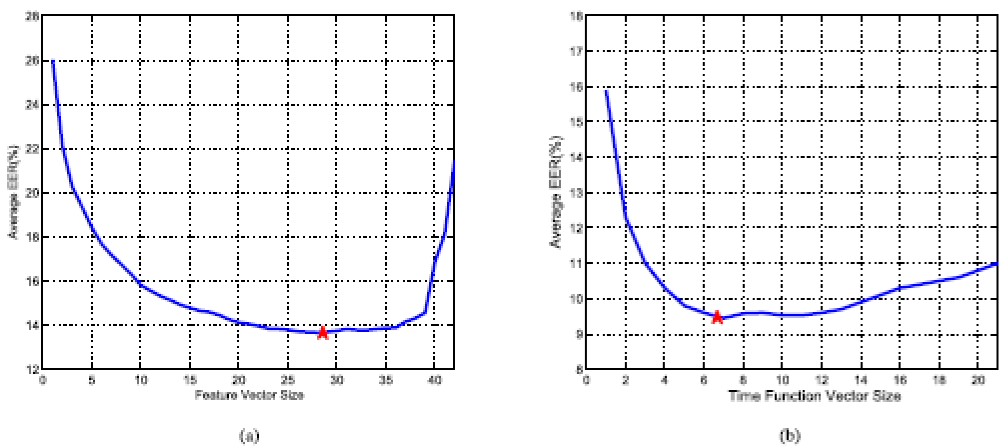

Figure 4. AVERAGE EER (%) OF SYSTEM SELECTED BY SFFS USING NEW CRITERIA FOR GLOCAL FEATURES AND TIME FUNCTION SYSTEMS the system is global in nature. (b) Time-based system

It's worth pointing out that the system's performance is higher when it's trained and tested using DS3 and DS2 devices (DS3 - DS2), respectively, for the skilled forgeries scenario in both systems (based on global features and time functions) (DS3 - DS3). This indicates once again that the DS3 device and the mobility scenario on the DS3 dataset are of lesser quality than on the DS2 dataset. If you look at both systems, the lowest performance in all circumstances comes from DS2 and DS3 forgeries, thus this is the most problematic issue for the next experiment to take into consideration.

EXPERIMENT 4 - PROPOSED SYSTEM

For each system (global features-based and time function-based systems), the goal of this experiment is to create an optimum feature/time function vector that does well in all comparisons at the same time (with and without interoperability). According to Section IV-B3 of this work, the algorithm SFFS has been tweaked to achieve the lowest overall EER (the average of all the comparison cases' eer), as well as to get the lowest feasible EER for expert forgeries, DS2 - DS3. This new criterion reflects the average performance of SFFS algorithm-based systems for global features-based and temporal functions-based systems. With a subset of 28 global features and seven time functions, both global features-based systems and time functions-based systems achieved the best performance. Y-coordinate and velocity are the best time functions for the time

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functions-based system, whereas geometry, speed, and acceleration are the most significant features for the global features-based system.

A time functions-based system will benefit from the suggested method of selecting features.

An average relative improvement of 40.5 percent EER is achieved for competent forgeries and 60.3 percent EER for random forgeries when compared to the baseline system. Even in the most challenging situations, the EER has grown by 3.5 percent compared to the baseline system (skilled-DS2-DS3).

However, the proposed system delivers an average relative improvement of 14.0 percent EER for skilled forgeries and 26.5 percent EER for random forgeries in comparison to the baseline system when testing interoperability scenarios for the time functions-based system. Due of its prevalence, I'd want to include:

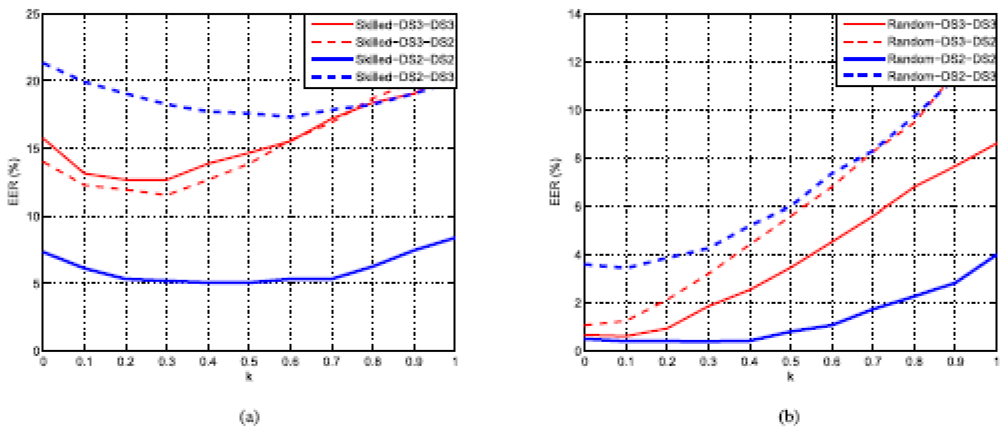

Figure 5. Experiment 5: System verification performance for fusion of local and global systems at the score level for various fusion weighting coefficients k. Forgery case (a) b) Forgeries at random.

Table 3. Exploration 5: EER (%) for global and local systems on a development set of 50 users for global and local systems, respectively (proposed in the Experiment 4).

	Skilled forgeries			*Random forgeries*		
Training vs Testing	Global	Local	Fusion	Global	Local	Fusion
DS2 - DS2	8.3	9.3	5.2	4.0	0.9	0.4
DS3 - DS3	20.5	18.1	12.7	8.6	1.5	1.9
DS2 - DS3	20.0	22.9	18.3	13.7	4.3	4.3
DS3 - DS2	21.9	15.7	11.5	13.2	2.9	3.2

A time-function-based system, on the other hand, gives an average relative improvement in EER of 14.0 percent for skilled fraud and 26.5 percent in the event of random fraud, according to the suggested system's analysis of interoperability. The most difficult situation (skilled forgeries DS2 - DS3) also increases in absolute numbers the EER by 4.4% when compared to the baseline system, as it does for the global system.

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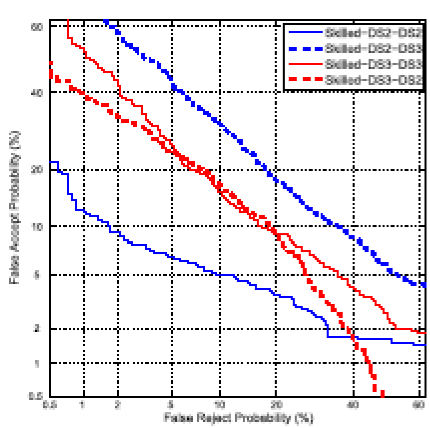
EXPERIMENT 5 - FUSION OF THE PROPOSED SYSTEMS

Using the ideal feature/time function vectors derived in Section IV-B4 and a merger of global features-based and time-functions-based systems, the purpose of this experiment is to significantly increase device interoperability.

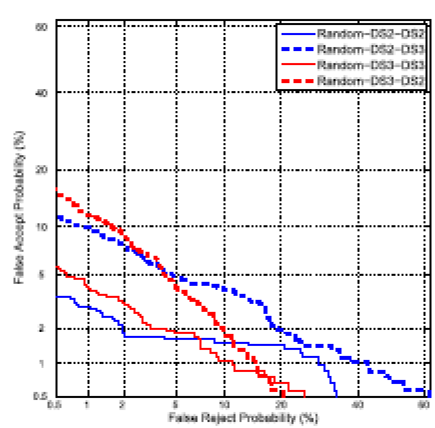
The fusion of systems was carried out in accordance with Section III-E of this document. The fusion weighting coefcient k was chosen by analysing the system's performance in terms of the EER and taking into consideration all the examples simultaneously. Fig. 6 shows how the fusion system performs with various k values. For random and skilled forgeries, system performance goes worse when we pick a large value of k, whereas for skilled forgeries, system performance gets worse when we choose a low value of k. It's for this reason that 0.3 is picked as the best value for k, since it performs well in all instances simultaneously. Because of this, the temporal functions-based system has a greater impact than the global features-based system. A fusion weighting coeffcient of k D 0:3 is shown in Table 4 to highlight how global features-based and temporal function-based systems perform independently. Even for highly skilled forgeries, which have an average relative improvement of 27.7 percent EER compared to time functions-based systems, suggested fusion system outperforms both systems independently in terms of performance.

B *Validation Experimental Results*

On the remaining 70 users of Biosecure datasets, we assess the verication performance system using the ideal fusion method that was developed throughout the development period. Fig. 7 shows a DET plot depicting system performance. It is shown in Table 5 how much better EER is for the baseline system and the proposed system with the weighting coefficient k D 0:3 (for both systems, this is the best value). Comparing the EER for skilled forgeries and random forgeries, the proposed system improves EER by an average of 11.0 percent on average and 37.3 percent on average when compared to the baseline system. It is clear from this comparison that the suggested method is resilient, as shown by the similarity of these findings to those from the development phase.



(a)



(b)

Figure 6. Data from Biosecure DS2 and DS3 assessment sets, as well as device interoperability situations, were used to validate the final signature recognition system. Case of expert forgery b) Forgeries at random

Table 4. Results of the validation set of 70 users for the fusion of global and local systems using a weighted total of scores. Comparison of results from baseline and suggested systems using k = 0.3 for fusion.

Fusion of Systems	*Skilled forgeries*		*Random forgeries*	
Training vs Testing	Baseline	Proposed	Baseline	Proposed
DS2 - DS2	7.1	6.2	3.4	2.0
DS3 - DS3	11.3	12.8	2.6	2.7
DS2 - DS3	21.5	18.9	10.6	4.9
DS3 - DS2	14.8	13.4	4.7	4.7

V. Conclusion

Because of today's widespread use of electronic devices (such as pen tablets, PDAs, grip pens, smartphones, etc.) and the increasing use of dynamic signature verification in banking and commercial applications, this paper aims to analyse and compensate for the very challenging problem of device interoperability for dynamic signature verification. In addition, it's worth noting that there aren't many books devoted to this pressing issue.

A mobile scenario is also included in this study, which simulates genuine operation circumstances since the user must sign while standing and carrying the device in one hand in a mobile situation. As an added bonus, we used Biosecure DS2 and DS3 datasets, which comprise data from two sessions separated by three months, to test for the issue of intra-class variability as well.

In order to address the issue of interoperability, this paper proposes two steps. For starters, there's the data preparation step, in which information gathered from various sources is combined to produce digital signatures that are strikingly similar in appearance. Selecting the optimal characteristics in order to minimise the impact of device compatibility is the second step of the process. There are two primary system techniques in on-line signature verification that this methodology has been effectively applied to.

An average relative improvement of 27.7 percent EER has been obtained by the suggested fusion system compared to the best performance of time functions-based system for skilled forgeries, as compared to the best performance of time functions-based system. When it comes to interoperability, this shows the system's resilience, which was the primary goal of this research. To observe how the system performs in interoperability scenarios, as well as with newer devices like tablets and smartphones, it will be fascinating to watch how the system performs in the future. For security applications, a dynamic signature verification system that doesn't employ X and Y coordinates is intriguing to examine since it would be a far more resilient system against assaults.

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