DYNAMIC SIGNATURE VERIFICATION BASED ON HYBRID WAVELET-FOURIER TRANSFORM

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ABSTRACT

In this paper, we propose a dynamic signature verification system which integrates hybrid of Discrete Wavelet Transform and Discrete Fourier Transform (DWT-DFT) for feature extraction. In feature matching, Euclidean distance and Enveloped Euclidean distance (EED) (a variant of Euclidean distance) are used. Distances of features are fused into a final score value and used to classify whether a genuine or a forgery signature. A benchmark database, SVC2004 which compose of Task 1 dataset and Task 2 dataset validate the effectiveness of this proposed system. Experimental results reveal a 7.08% EER for skilled forgeries and 2.37% EER of random forgeries in Task 1 dataset; and 8.61% EER for skilled forgeries and 2.05% EER for random forgeries in Task 2 dataset.

Keywords: Signature Verification, Wavelet Transform, Fourier Transform, Dynamic Signature, Score Level Fusion

INTRODUCTION

With the advancements in information technology, protecting privacy and sensitive data is of increasing concern within society. Biometrics has gradually replaced the conventional password system and provides a more reliable personal authentication system. Generally, biometrics is categorized into two main categories which are physiological and behavioral biometrics. The former measures the static characteristics of an individual such as fingerprint, iris and face; while the latter, behavioral biometrics, measures the behaviors and actions that an individual makes, such as gesture, signature, voice, and key stroke.

Among the traits of biometrics, signature is the most widely used method of authentication. Signature has long been established, is widely accepted by the public and offers less privacy issues in comparison to other biometric traits (Muramatsu & Matsumoto, 2007). Signature verification can be divided as offline (static) and online (dynamic) signatures. An offline signature captures a two dimensional image of a signature while an online signature captures not only the shape but also the dynamic properties of a signature. The online signature is more sophisticated as it provides more information about the signature characteristics and is difficult to imitate. As a result, online signatures are more reliable than offline signatures (Impedovo & Pirlo, 2008).

Generally, the dynamic features of an online signature can be characterized by global and local features (Jain, Griess, & Connel, 2002) (Pippin, 2004). Global feature characterizes a signature as a whole which describing the entire signature such as the total signing duration, the number of strokes, the average pressure of the entire signature. On the other hand, local feature corresponds to individual points along the trajectory of a signature. Some of the local features are positional coordinates, pressures along the trajectory, and orientation of a digital pen. Despite the number of features in a signature, using all these features to establish authentication is time consuming, costly and is unable to guarantee the verification performance. Therefore, Lei & Govindaraju (2005) in their study addressed the discriminative power and consistency of features with the use of mean and standard deviation. As reported by the authors, a more discriminative feature is a feature which obtains a higher mean and lower standard deviation. Ketabdar, Richiardi, & Drygajlo (2005) also conducted a feature selection algorithm. In their study a large number of global features were extracted from MCYT database and a subset of global features was selected by using a modified version of the Fisher ratio cost function. In addition, the relationship between genuine-to-genuine signatures and genuine-to-forgery signatures was investigated. The results found that the availability of forgery data may have less relevance to the verification performance. Refer to Zhang, Wang, & Wang (2011) for an overview of the most recent research addressing online signatures.

PREVIOUS WORKS

Inta-class variation is always a major challange a behavioral biometric faced. Hence, same problem is also facing with dynamic signature. Two signatures that signed by a same genuine signer might be also vary in terms of duration, as a result, creates feature vector with different length. This variation creates restriction for dynamic signature to used straight forward feature matching method such as Euclidean distance. Dynamic Time Warping (DTW) has becoming a good approach to overcome the non-linear feature matching problem (Zhang, Wang, & Wang, 2011). Kholmatov & Yanikoglu (2005) employed DTW with the nearest, farthest, and template reference signatures. They had won the first place in First International Signature Verification Competition (SVC2004) (Yeung et al., 2004) by achieving 2.8% of the lowest error rate tested on skilled forgery signature. Bunke, Csirik, Gingl, & Griechisch (2011) also proposed to employ DTW to obtain the dissimilarity of acceleration signals in their system. Although DTW has been shown to perform well, the approach involves high computational costs. Faundez-Zanuy & Pascual-Gaspar (2011) replaced DTW with vector quantization (VQ). They were able to successfully reduce the computational cost by 47 times in comparison to DTW. Despite the lower computational cost, VQ is unable deal with temporal information perfectly. In the further researches, Hidden Markov model (HMM) is found to be another approach for non-linear feature vector. More details of HMM were discussed by Impedovo & Pirlo (2008), Shafiei & Rabiee (2003) and Luan, Lin, & Cheng (2009).

Fourier Transformation is a very successfully in extracting a frequency domain feature. This frequency feature can be trimmed to a fixed length vector by neglected some information which consider as least important. This action led to overcome the non-linear comparison between vectors. Besides, the merit of orientation invariant attracts the attention of researchers. Lam, Kamis, & Zimmermann (1989) carried out some of the earliest work using Fourier Transform with dynamic signatures. In this approach, the signature's signal is transformed into a frequency domain by using Fourier Transformation, however, only the first fifteen highest magnitudes of the signal are used in the discriminant analysis. The resulting error rate was reported as 2.5% False Acceptance Rate (FAR). Furthermore, Kholmatov & Yanikoglu (2006) also adopted Fourier Transform in extracting features of signature. Boundary lines (known as envelope) of each user were constructed by maximum, minimum and average values obtained from enrolled signatures. After that, dissimilarity scores were calculated by comparing a testing signature with the constructed envelope. An encouraging result was obtained with 10.4% FAR and 11.9% False Rejection Rate (FRR).

Recent years, Wavelet Transform technique has becoming more popular and been widely used in signature verification. The reason behind is the capability of multi-resolution analysis and its localization function in both space and scale. In could turn the information into a more compact form while keeping most of the important localize information of features, meanwhile, translation and rotation invariant could be also achieved. Afsar, Arif, & Farrukh (2005) extracted wavelet coefficients of global features of signature using wavelet transform. *k*-NN was then used as a classifier in accepting or rejecting a signature. They achieved with the results of 3.21% FAR and 3.37% FRR for random forgeries; while 6.79% FAR and 6.61% FRR for skilled forgeries. In the same year, Ji & Quan (2005) used the position of zero-crossing extracted by wavelet transform as a signature feature. After that, DTW and Support Vector Machine (SVM) were employed as feature matching and classification, respectively. Results of 5.25% FRR and 5% FAR were reported. Besides, DWT was also employed in the research work of Emerich, Lupu, & Rusu (2010). The authors proposed a new technique that encodes the details coefficients and approximation extracted from DWT by using TESPAR DZ method. Our research work was inspired by the work introduced by Yip, Teoh, & Ngo (2007). The authors extracted a compact features by incorporating a hybrid DWT and DFT. Features extracted were used in generate a biometric hash and a very promising results were obtained.

Fusion is a technique to combine multiple modalities into a single modality system. It is expected to be able to compensate for the limitations in performance and improve the verification accuracy for each individual biometric system. Fierrez-Aguilar, Krawczyk, Ortega-Gracia, & Jain (2005) proposed a score-level fusion for online signature verification. They applied max, product and sum rules as fusion techniques in combining score values of two separated systems; one employed DTW as feature matching method to local features and the other system used HMM to compute the score value of global features. As a result reported, sum rule fusion technique coupled with a user-dependent threshold achieved the best performance. Liu & Wang (2008) proposed a two-stage fusion method to combine global and local features. Global features were first filtered by with majority voter at the first stage. Local features were then extracted to those signatures which went through the first stage. Enhanced DTW was adopted in feature matching. The experiment results represent that this method achieved a 4.02% EER on a benchmark SVC2004 Task 2 dataset.Yanikoglu & Kholmatov (2009) had also proposed to fuse two of their previous works in which one system based on Fast Fourier Transform (FFT) and the other used DTW. The author used sum rule as fusion approach and improvement of about 8% for SUSIG database and 26% for MCYT-100 database were been reported.

PROPOSED METHOD

In general, this proposed dynamic signature verification system comprises of several components. These include raw signal selection and derivation, preprocessing, feature extraction (DWT-DFT), feature matching method, score-level fusion techniques and score normalization. Lastly, final fused score generated from previous components is used to determine whether to accept or reject a signature as a genuine signature. The outline of proposed system is illustrated in Figure 1. A more details of each component are explained below.

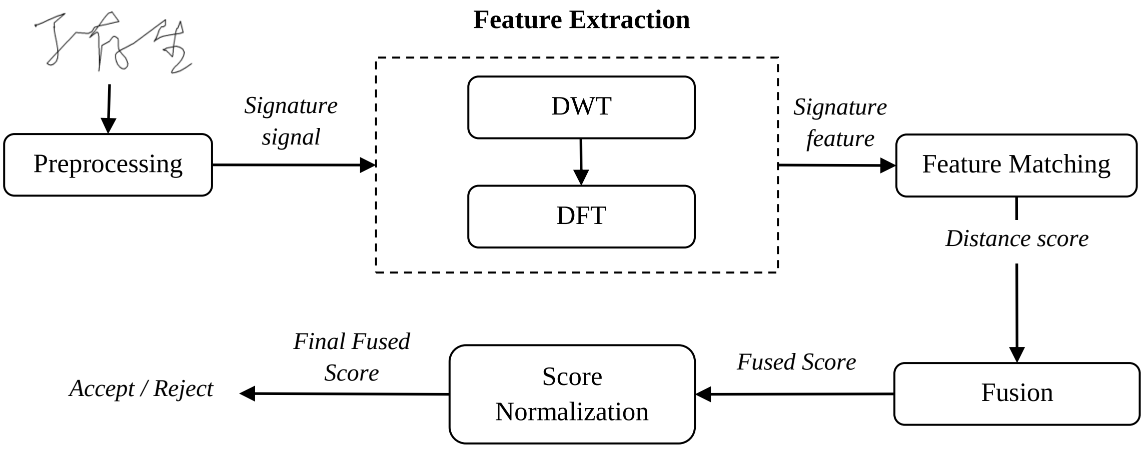


Figure 1. Outline of Proposed System

a) Preprocessing

A raw signature, captured by a pressure sensitive tablet, can be jagged and varies in scale and orientation due to an inconsistent signature signing motion. In order to address this intra-personal variation, size normalization is applied onto the raw signature. The size of a signature is normalized into a range from 0 to 1 in relation to its width (x-coordinate) and height (y-coordinate) as below:

$$x'(t)=\frac{x(t)-x_{\min}}{x_{\max}-x_{\min}} \quad \text{, where } x_{\min}\leq x(t)\leq x_{\max} \qquad (1)$$

$$y'(t) = \frac{y(t) - y_{\min}}{y_{\max} - y_{\min}} \text{ , where } y_{\min} \le y(t) \le y_{\max} \tag{2}$$

where $x(t)$ and $y(t)$ are the *x* and *y* coordinates. The subscripts of *max* and *min* correspond to maximum and minimum values of each coordinate, respectively. The results of size normalization are denote as $x'(t)$ and $y'(t)$. The lengths of both coordinates are then zero-padding to extend the length into size of 512. This fixed length is considered enough to cover all the trajectory points of signature signals.

b) Feature Extraction

An informative and discriminative feature is crucial for a signal representation. Therefore, in this work, a dual-transformation technique that integrates Discrete Wavelet transforms (DWT) and Discrete Fourier Transform (DFT) is proposed. DFT is capable of transforms a signal into frequency spectrum. It's capability of measuring the periodic patterns latent of a signal that are considered to be an important characteristic for dynamic signatures. However, frequencies of a signal are shown without knowledge of when and where they occurred, resulting in a lack of localization to support a signal. As a solution, DWT is combined. Wavelet transform uses multi-resolution technique turns to analyze the signal in different frequencies and resolutions, retaining local information in both frequency and time. This proposed method obtains a Fourier coefficient of a signal $S(k)$ which can be defined as $S(k) = FFT(DWT(f))$, where the *f* is the raw signal. Translation invariance is then can be achieved by dividing $S(k)$ with total magnitude m for Fourier Descriptor $F(k)$ as follows:

$$F(k) = \frac{|S(k)|}{m}, \text{where } k = 0, \ldots, \frac{N-1}{2} \tag{3}$$

$$m = \sum_{k=0}^{N-1} |S(k)| \tag{4}$$

where *N=512* is the length of the signal and $|S(k)|$ is the absolute magnitude value of the coefficient $S(k)$. Due to the symmetry properties created by Fourier Spectrum, the coefficient could be cut down by half of the total length. Therefore, the resulting length where *k=256* is obtained which is half of the maximum length of *N* by $\left(\frac{N-1}{2}\right)$. Figure 2 and Figure 3 show the feature vector extracted from *x* and *y* coordinates after feature extraction of hybrid DWT-DFT.

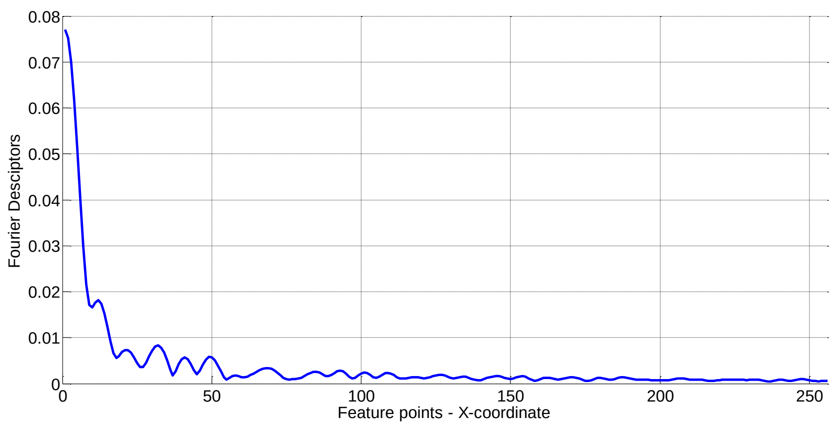


Figure 2. DWT-DFT feature vector (*x* coordinate)

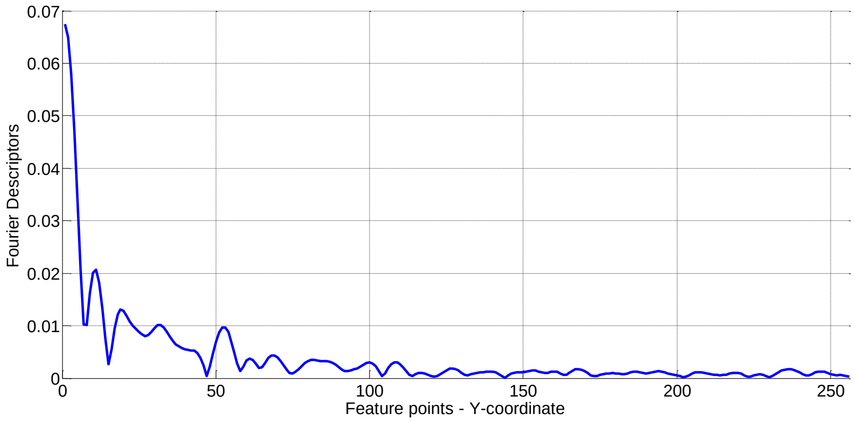


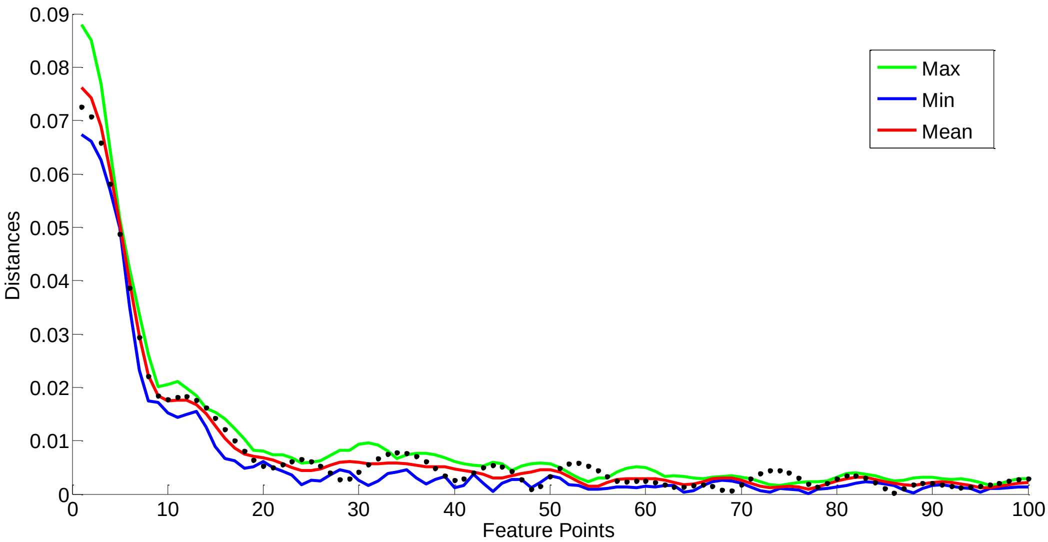
Figure 3. DWT-DFT feature vector (y coordinate)

c) Feature Matching

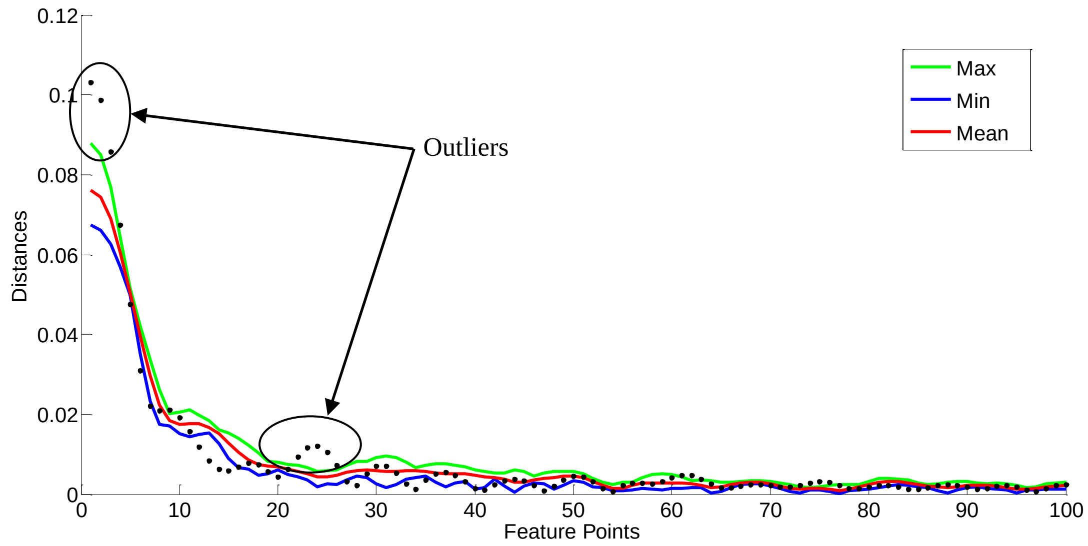
Feature matching is a process to measure the degree of dissimilarity between a test signature and reference signature template which is generated from a set of genuine signatures enrolled from contributors. In this work, Euclidean distance and Enveloped Euclidean distance (EED) are used. Euclidean distance is computed as follows:

$$D(p,r)=\sqrt{(p_1-r_1)^2+(p_2-r_2)^2+\ldots+(p_n-r_n)^2}=\sqrt{\sum_{i=1}^{n}(p_i-r_i)^2} \qquad (5)$$

where p is the feature vector of a test signature template and r is the feature vector of a reference signature template in n-dimensional space. EED is modified from Euclidean distance. It constructs a region/envelope by using the minimum and maximum values of the reference template. Most of the feature points of a genuine test signature are expected to fall inside the envelope during a matching process. Adversely, more feature points are expected to fall outside the envelope (known as an outlier) for a forgery signature.



(a)



(b)

Figure 4. Comparison between Genuine and Forgery Test Signatures
(a) Genuine, and (b) Forgery

Figure 4 (a) and (b) show the difference of genuine and forgery test signatures when put into feature matching process. The scattered black dots denote the feature points of a test signature. Feature points that fall outside the envelope will be taken into account for distance cost calculation. Assuming two feature vectors p and r **,** the distance of one single feature point can be computed as:

$$d[n]=\begin{cases}(p_i - r_{mean})^2, & r_{\min} \le p_i \le r_{\max} \\ 0 \quad , & p_i > r_{\max} \quad or \quad p_i < r_{\min}\end{cases} \tag{6}$$

where $i > 1$ is the corresponding feature point and $r_{\min}$, $r_{\max}$ and r_{mean} are the minimum, maximum and mean values of reference signature template, respectively, which used to construct the envelope. EED of a test signature feature can be computed as follows:

$$D(p,r)=\sqrt{d[1]+d[2]+\cdots+d[n]}=\sqrt{\sum_{i=1}^{n} d[i]} \tag{7}$$

The distance score of a test signature template p and a reference signature template R is then normalized by dividing by a normalization factor D_{norm} as follows:

$$Dist = \frac{D(p,R)}{D_{norm}}, \tag{8}$$

$$\text{where } D_{norm} = mean\left(\sum_{i=1}^{N-1} D_{q\overline{r_i}}(R/q)\right) \tag{9}$$

This normalization factor D_{norm} is an average of all distances which obtained by pairwisely comparing a query signature q with a reference template R with N reference signatures with the rest of other signatures in R . Therefore, the selection process is denoted as R/q in equation (9), indicating the query q is excluded from the reference set R .

d) Score-level Fusion

Score-level fusion is employed to merge the output scores from several single modalities into a single final fused score. Three common fusion techniques are applied in this work; there are sum rule, min rule and max rule. However, the distributions of a score value when putting different subjects together could be vary. The fused score value has to be normalized to reduce the wide range distribution in order to achieve a better result. *z-score* normalization which employed the mean and standard deviation of the input matching score value is used. The computation of *z-score* normalization as follows:

$$S_{norm} = \frac{Dist_i - mean(S)}{std(S)} \tag{10}$$

where $S = \{S_1, S_2, \ldots, S_i\},\ i = 1,\ 2, \ldots, n$ be a set of matching score value.

EXPERIMENTAL RESULTS

During the experiment, a benchmark dynamic signature database which was released by SVC2004 (2004) was used. This database comprises Task 1 and Task 2 datasets. Task 1 dataset consists of positional information (x and y coordinates), time stamp and pen-up status of a signature, while Task 2 dataset has not only the information mentioned in Task 1 but also with additional dynamic information such as pressure p, altitude ψ and azimuth ϕ. Both datasets were actually collected from different contributors and each contributor provided 20 genuine signatures into the dataset. A total of 20 forged signatures were also collected from at least 4 other contributors. During the collection process, forgers were given ample time for practicing. It is to ensure the process of forging could be as close as the targeted genuine signature.

In addition to these, extra dynamic signals were also derived which including *dist* (distance), *vel* (velocity), *vx* (velocity in x direction) and *vy* (velocity in y direction). Table 1 shows dynamic signals involved in two different datasets. The first column of the table is the presentation of dynamic signals, whilst the second and third columns represent the involvement of signals in a particular dataset.

Table 1. Dynamic Signals in Both Task 1 and Task 2 Dataset

Dynamic Signal	Task 1 Dataset	Task 2 Dataset	Remarks
x	Y	Y	x-coordinate
y	Y	Y	y-coordinate
xy	Y	Y	Complex input of x and y components
$dist$	Y	Y	Distance, $dist = \sqrt{x^2 + y^2}$
vel	Y	Y	Velocity, $*vel = \sqrt{{x_d}^2 + {y_d}^2}$
vx	Y	Y	Velocity of component x, $*vx = \sqrt{{x_d}^2}$
vy	Y	Y	Velocity of component y, $*vy = \sqrt{{y_d}^2}$
p	N	Y	Pressure
ψ	N	Y	Altitude
ϕ	N	Y	Azimuth

* x_d = sequential differences of x; y_d = sequential differences of y

Equal Error rate of skilled forgery (ERR-S) and random forgery (EER-R) are tested and reported in this experiment. Skilled forgery refers to a type of imitation or duplication of a genuine signature by a non-genuine user while random forgery is an act of a non-genuine user uses a signature that does not belong to him.

During the experiment process, five out of twenty genuine signatures were first randomly selected in order to generate a reference signature template. The remaining signatures (15 signatures) were used for evaluation purpose. In order to achieve a fair comparison, this process was repeated 20 times with each repetition, different set of signature were randomly chosen for the reference template generation. EER-S and EER-R were computed by averaging the error rates obtained from all repetition.

Performance Analysis

Experiments were tested with both Euclidean distance and EED feature matching methods and several fusion approaches. Performance results are also reported in this paper. Table 2 shows verification results of using sum rule fusion approach on both Task 1 and Task 2 datasets. It had shown that the best result achieved 7.08% EER-S for skilled forgery in Task 1 dataset which using Euclidean distance, meanwhile best result of 2.05% EER-R in Task 2 dataset which using EED as feature matching method.

Three fusion approaches which are sum rule, min rule and max rule were also conducted and reported in the experiment. Max rule selects a maximum value among the input features involved as its final fused score while min rule chooses the minimum value. Table 3 and Table 4 show the verification performance of both fusion approaches.

Table 2. Verification Performance of Sum Rule Fusion Approach

Task	Feature Matching	Score Combination	EER-S	EER-R
Task 1	Euclidean Distance	x, y, v, xy, vx	**7.08**	2.44
	EED	x, y, v, xy, vx, vy	7.29	**2.37**
Task 2	Euclidean Distance	x, y, v, vx, vy, ϕ	9.30	2.23
	EED	y, v, vx, vy, ϕ	**8.61**	**2.05**

Table 3. Verification Performance of Max Rule Fusion Approach

Task	Feature Matching	Score Combination	EER-S	EER-R
Task 1	Euclidean Distance	y, xy	**7.42**	**3.22**
	EED	y, $dist$, xy	8.10	3.30
Task 2	Euclidean Distance	y, xy, ϕ	9.32	4.34
	EED	y, xy, ϕ	**9.14**	**3.50**

Table 4. Verification Performance of Min Rule Fusion Approach

Task	Feature Matching	Score Combination	EER-S	EER-R
Task 1	Euclidean Distance	y, xy	**7.61**	**4.05**
	EED	y, xy	9.15	4.23
Task 2	Euclidean Distance	y, xy	12.68	5.05
	EED	y, xy	**12.09**	**4.20**

A summary of the best performance for both datasets presented in this paper are shown in Figure 5 and Figure 6, respectively. Obviously, it shows that sum rule fusion approach obtained the better performance for both Euclidean distance and EED in Task 1 dataset and Task 2 dataset, respectively. A comparison between two feature matching methods indicates that both datasets do not appear to have the same performance. Euclidean distance performs slightly better than EED in Task 1 dataset, however, Euclidean does not perform as well in Task 2 dataset. The difference in results from two different datasets can be explained by the quality of the reference signature selected. The distance of two different signatures is computed by comparing a testing signature with a reference signature template. The reference signature template is generated by a number of enrolled reference signatures. The results are unexpected if the reference signatures are randomly picked from the dataset. A low quality signature might have been selected as one of the reference signatures, which could explain the deterioration in performance in the experiment.

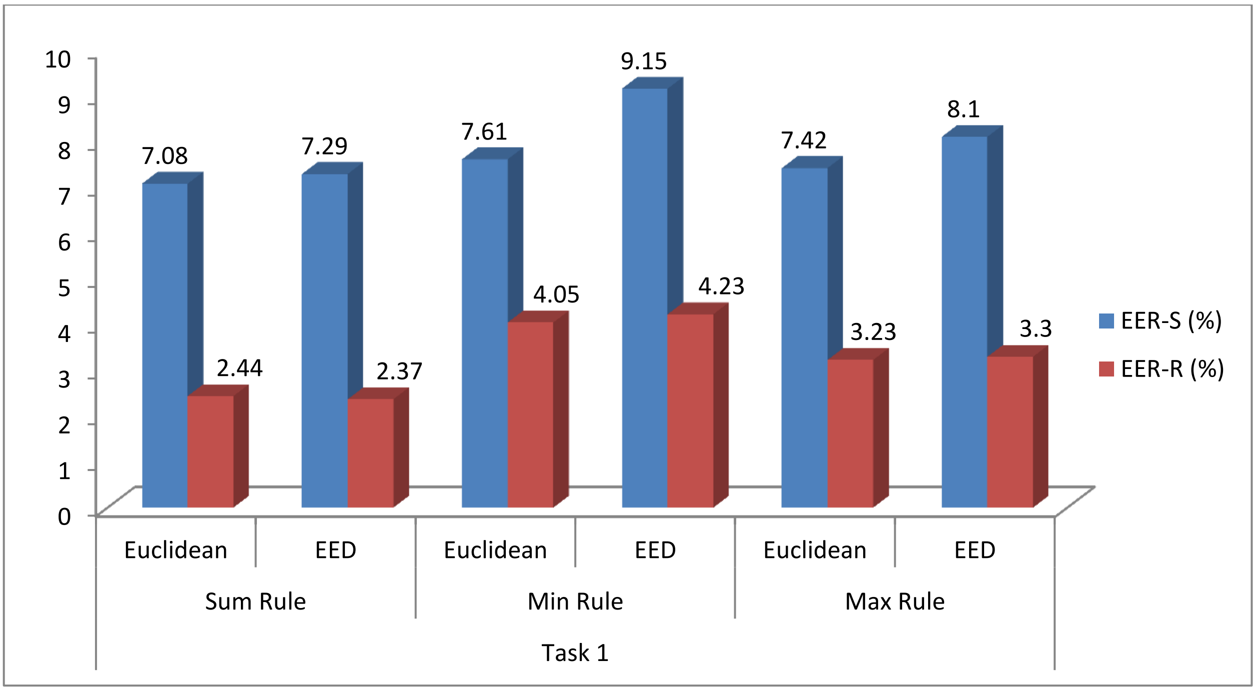


Figure 5. Summarized Results of Fusion Rules in Task 1 Dataset

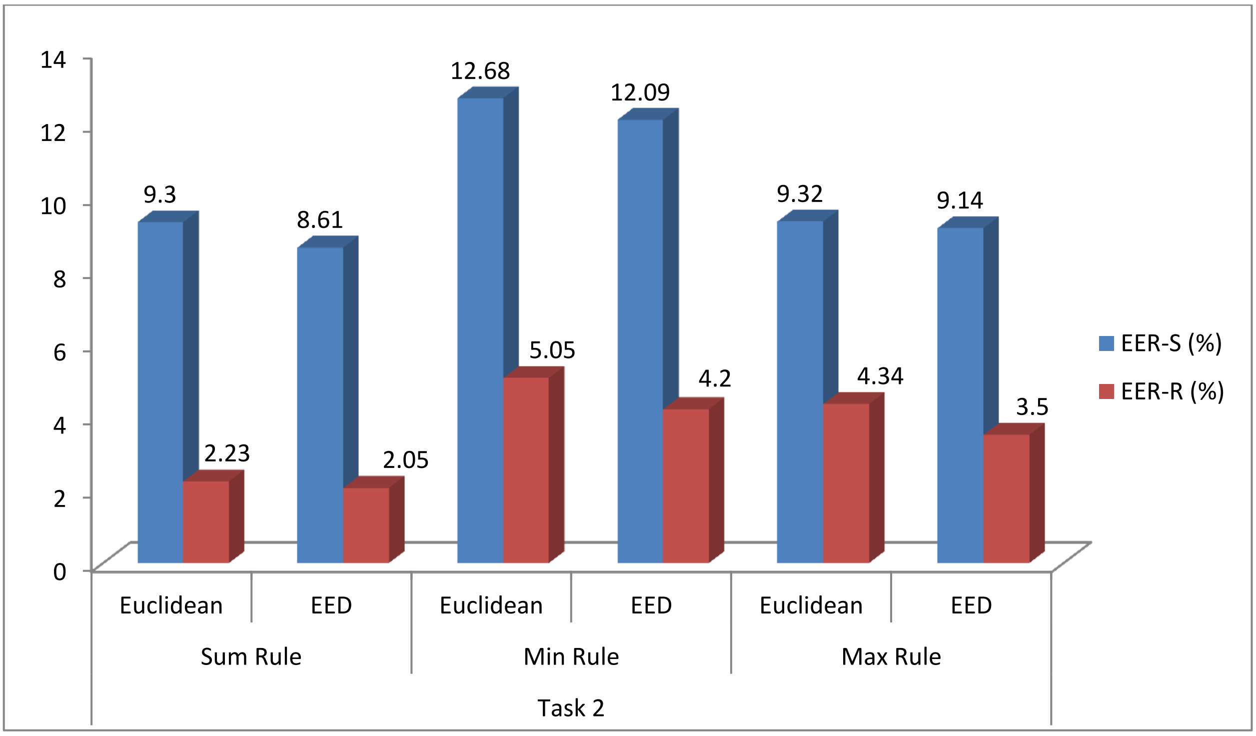


Figure 6. Summarized Results of Fusion Rules in Task 2 Dataset

A direct comparison between two experiments is usually not viable. It might be an unfair comparison when comparing experiments which difference in database used, features extracted from raw data, feature matching algorithms, experimental settings and so on. Hence, re-implementation process is essential to produce a fair comparison between experiments.

Table 5. Verification Performance between Proposed Method and Existing Research Works

Authors	Methods	Task 1		Task 2	
		EER-S (%)	EER-R (%)	EER-S (%)	EER-R (%)
Ji and Quan (2005)	DWT-SVM	9.93	4.82	8.87	2.54
Kholmatov et al. (2005)	DTW	11.91	2.35	12.01	2.11
Yanikoglu et al. (2009)	FFT	17.46	4.59	17.37	4.86
Proposed method	DWT-DFT + Sum rule	**7.08**	**2.37**	**8.61**	**2.05**

By referring to the results in Table 5, our proposed method shown better results in both Task 1 dataset and Task 2 dataset, and more obvious in skilled forgery when comparing with other methods which used the same set of database and experiment settings. As demonstrated in the result, the proposed method able to achieve a more promising performance in coping with skilled and random forgeries of signature without the available of any sophisticated fusion approaches.

CONCULSIONS & FUTURE WORK

In this research work, an approach to a dynamic signature verification system using a dual transformation of DWT-DFT is presented. Euclidean distance and Enveloped Euclidean distance were used to obtain the distance score of the extracted feature. Several fusion approaches were employed in order to fuse several score values of feature into single final score. The final score is then used to evaluate the performance of the verification system.

The experiments were tested on Task 1 dataset and Task 2 dataset which are both released by SVC2004. Results show that sum rule fusion approach obtained the best results in both datasets. It obtained the lowest error rate of 7.08% EER-S for skilled forgeries and 2.37% EER-R for random forgeries in Task 1 dataset. On the other hand, the best results were reported 8.61% EER-S and 2.05% EER-R for skilled forgeries and random forgeries, respectively in Task 2 dataset. Despite extensive research in recent years, more discriminative and informative features for signature are yet to be found. Investigation on extracting and selecting a more reliable and stable feature in dynamic signature verification is still remain a major concern in near future.

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