Un système de vérification de signature manuscrite en ligne basé sur la décomposition modale empirique

Online handwritten signature verification system based on the empirical mode decomposition

Toufik Hafs *, Layachi Bennacer & Mohamed Boughazi

Laboratoire d'étude et recherche en instrumentation et communication avancée L.E.R.I.C.A, Université Badji Mokhtar, BP 12, 23000, Annaba, Algérie.

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ملخص :

التوقيع بخط اليد هي طريقة بيومترية تستخدم في تحديد هوية الشخص. هذا العمل يدخل في نطاق اعداد نظام للتحقق المباشر من التوقيع بخط اليد. قمنا باستخراج نموذج التوقيع بخط اليد باستعمال طريقة تحليلية قائمة على أساس تجريبي هي *(EMD) Empirical Mode Decomposition*. النظام المقترح مجهز بوحدة للتدريب وقاعدة للتوقيعات. النتائج المحصل عليها تدل على نجاعة الطريقة المتبعة حيث تمكنا من الحصول على نسبة التعرف الصحيح للتوقيعات تصل إلى 98٪، مع نسبة قبول خاطئ *(FAR)*تقدر بـ 3.33٪، ونسبة الرفض الخاطئ*(FRR)* تساوي 4.67٪ ¤وعلى نسبة الخطأ المتساوي *(EER)* مقدرة بـ 1.83٪.

الكلمات المفتاحية: *التوقيع بخط اليد، التحقق، البيومترية، طريقة تحليلية*.

Résumé

La signature manuscrite est une modalité biométrique utilisée pour l'identification d' une personne. Ce travail s'inscrit dans le cadre de l'élaboration d'un système de vérification de signatures manuscrites en ligne. Nous modélisons la signature manuscrite par une approche analytique basée sur la décomposition modale empirique (EMD). Le système proposé est muni d'un module d'apprentissage et d'une base de signatures. Le protocole d'évaluation mis en œuvre montre l'intérêt de la méthode adoptée et permet d'obtenir un taux de reconnaissance allant jusqu'à 98%, avec un taux de fausse acceptation(FAR) de 3.33%, un taux de faux rejet (FRR) de 4,67% et un taux d'erreur égal (EER) à 1,83%.

Mot clés : *signatures en ligne, vérification, biométrie, approche analytique.*

Abstract

The handwritten signature is a biometric method used to verify the identity of a person. This work deals with an online handwritten signature verification system. We model the handwritten signature by an analytical approach based on the Empirical Mode Decomposition (EMD). The organized system is provided with a training module and a base of signatures. The implemented evaluation protocol points out the interest of the adopted method and allows obtaining a recognition rate going up to 98%, with a false acceptance rate (FAR) of 3.33%, a false rejection rate of 4.67 % and an equal error rate (EER) of 1.83 %.

Key words: *online signature, verification, biometrics, analytical appr*oach.

Auteur correspondant : hafstoufik@gmail.com

1. INTRODUCTION

The signature is the most common way used to authenticate documents, people, banking and financial transactions. The handwritten signatures verification is the process of people identification by means of their signatures. The signature verification systems are systems that deal directly with manuscripts : they are divided into two categories: the "online" and "offline" systems. The problem of cursive handwritten signatures verification can be approached on two main approaches one probabilistic (analytical) and another structural. So, two methodologies for signature recognition can be distinguished: global methods [1, 2, 3, 4] and local ones [5, 6, 7]. The global methods consist on the recognition of a signature through the extraction of its global characteristics such as the average velocity, the total time of signing and the ratio (height/width) of the signature, which are considered as general information of the signature since they are not accurate. In other words, a global parameter contains little information without being very discriminating. To enrich the quantity of information, the global approach must extract more global parameters (about 50 to 100) to reach acceptable performances. The advantage of the global approach is that all the signatures are represented by vectors of the same length. Unlike the global methods, the local ones aim to extract several parameters in each point of the signature. A portion can be delimited by local minima or maxima of the ordinate, speed or acceleration. The signature is finally represented by a sequence of great dimension vectors. Several works were already carried out in the field of online signature verification, especially these last years. We will quote some works which marked this field. A state of art about signature verification can be found in [8]. In [9] a novel method based on determining extrema position points for the verification of online handwritten signature is presented. L. Nanni and A. Lumini [10] present a new approach by developing local information of the signature, they also use the discrete 1-D wavelet transform (WT) to perform that. Another approach based on wavelet transform for the extraction of features and neuronal network to do the classification is presented in [11].The online signature recognition algorithm proposed in [12] calculates all of local, regional and global information by using three approaches which are Dynamic Time Warping (DTW), Hidden Markov Model (HMM) and the Linear Programming Descriptor (LPD). A different philosophy was developed in [13] when the authors used Zernike moments for online signature authentication.

Being a very personal graph, the online handwritten signature undergoes modifications naturally depending on the personality of its provider, his state of stress, or its psychological state in a general way. In this respect, looking for the EMD impact on this modality is the crucial issue presented herein. To perform this task, this paper proposes a new method for online signature verification based on the empirical mode decomposition. The main contribution of our system is to consider the effect of the empirical mode decomposition in decreasing data storage and keeping, at the same time, error rates as lower as possible.

The rest of this paper is organized as follows. In Section 2, we explain the details of our proposed system for the handwritten signature verification. Section 3 and section 4 illustrate the mechanisms of training and verification selected respectively. Section 5 reports the experimental results, and Finally, Section 6 presents the conclusion and the prospects which this work underlies.

2. PRINCIPLE FUNCTION OF THE STUDIED SYSTEM

In the proposed online handwritten signature verification system, the users are first introduced into the system by recording some samples of their signatures which are used as references (enrolment phase). Then, when a user who claims to be a particular customer of the system presents his signature for the verification, it will be compared to his reference signatures. Following this comparison, a score measuring the similarity between two signatures is provided. If the score of similarity is higher than a threshold fixed at training stage of the system, the user is accepted. Otherwise, he will be rejected. The diagram block of the system considered is illustrated by the diagram of figure 1. This system was separated into two blocks: a training block and a verification one. We describe in what follows the principal parts which compose these two blocks. We should mention that the acquisition and pre-processing operations of the signatures are identical for the two blocks considered.

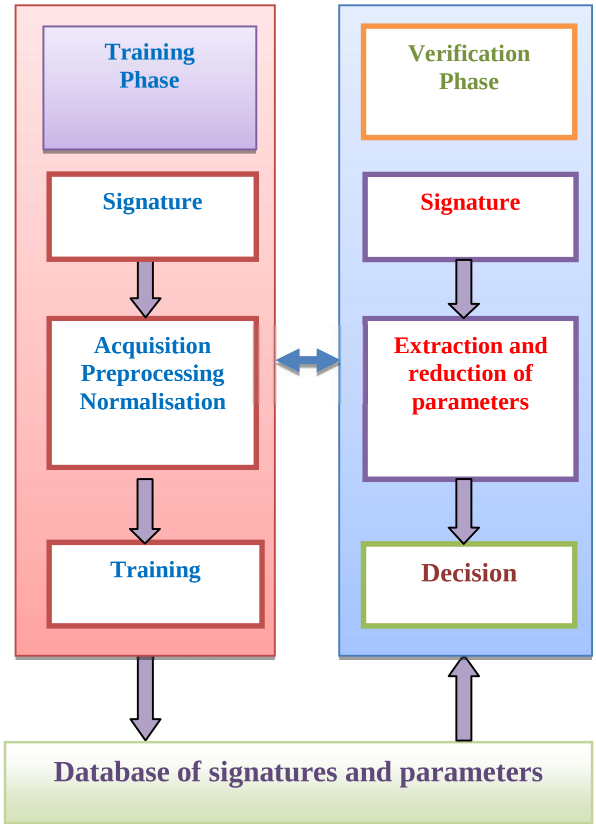


Figure 1: General organization of the proposed system.

3. TRAINING MECHANISMS

3.1 Acquisition and pre-processing of the signatures

The acquisition is performed using a digitizing tablet (OCE G6451). The phase of pre-processing (Fig. 2) is intended to eliminate the writing noise and the redundancy of information. It is based on the use of both distance and angular filters.

The first one removes the pen shaking during the writing (Fig. 2b) and can be achieved using one dimensional Gaussian filter in both x and y directions. The last one is used to sample the signature while preserving, at the same time, its general form (Fig. 2c). Once this phase is done, it is followed by a normalization phase which consists on making the signature standard in a specific field like the size, the position and the duration. To normalize a signature in position, we have chosen the approach which consists in aligning the signatures through their centers of gravity [14]. The figure 2d illustrates an alignment example of two signatures by their gravity centers.

The normalization in size consists on returning all the signatures included in a box of fixed size. This last processing investigates preserving only certain significant points of the signature. The interest is multiple here, it allows to reduce the size of the signature and, thus, to accelerate treatments. It allows decreasing storage space required for the profile as well.

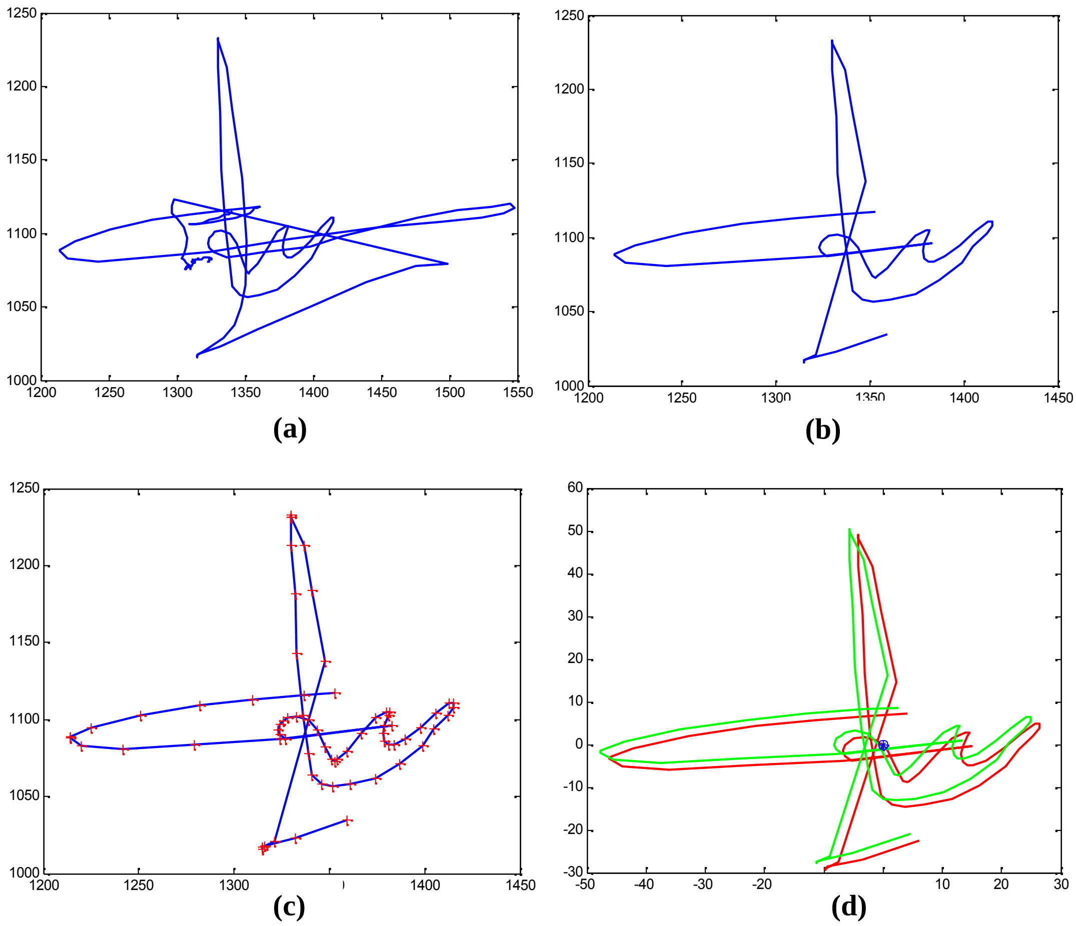


Figure 2: Pre-processing of a signature: (a) the original signature (b) the signature after distance filtering (c) the signature after angular filtering (d) the alignment of two signatures by their centers of gravity

3.2 Enrolment

This stage aims to create the user's profile. After a necessary training of the acquisition peripheral, the user provides five signatures to the system. If any problems occur during the acquisition, the user can cancel the operation and start again. The system carries out also a control to avoid any problem during the creation of the user profile. This verification consists on requiring five new signatures of the signatory. The similarity between two signatures is evaluated according to a definite criterion (cf section 4.4). Once the five signatures are valid, they undergo the treatments above (cf section 3.1) then they are stored as reference signatures.

4. VERIFICATION

During this phase, a user wishing to be authenticated must undergo the preprocessing operations described in (section 3.1).

The obtained test signature will be compared with the reference signature in order to determine whether the signatory is the one that he claims to be.

The comparison is done using the Euclidean distance which will give a similarity score between the two signatures. Before proceeding to this stage, a procedure intended for the extraction of the signature parameters by EMD approachis presented.

4.1 Extraction of the parameters by EMD approach

The online signature is represented by a set of numerical signals according to time. The obtained parameters depend on the type of signature acquisition peripheral. The basic parameters obtained directly from the acquisition peripheral are the coordinates (x(t) and y(t)) of the pen at each acquisition point. Starting from these two basic parameters, several other parameters representing the dynamic of the signatures which increase discrimination between them can be extracted [15]. In our case, the concept of the empirical modal decomposition (EMD) is used to extract other parameters that can discriminate the signatures between each other. The EMD is a technique suggested by Huang et al. [16]. It is an approach of breaking down a signal into a group of functions defined only starting from the signal. These functions are called "intrinsic mode functions (IMF)". The IMFs are obtained using an iterative process called sifting process (SP). The algorithm of obtaining IMFs is described in the next section (cf session 4.2).

4.2 EMD algorithm

Given a mono-dimensional signal S(n) with $0 < n < N-1$: The following steps show the calculation of IMFs:

Step1: Initialization: r = S, k = 1
Step 2: Calculation of the average envelope E of r (E is the average of the minima envelope and the maxima envelope of R)
Step 3: We put $P_i = r - E$.
Step 4: While pi is not an IMF repeat calculate average envelope e_i of P_i

$P_{i+1} = P_i - e_i$;i = i + 1

Step 5: $d_k = P_i$, $r = r - d_k$
Step 6: if R is not monotonous, return at step2 and we put k = k + 1, else the decomposition is finished. Once the decomposition is finished, “S” can be written as:

$$s[n] = \sum_{k=1}^{K} d_k\left[n\right] + r\left[n\right] \ , \quad K \in N^* \qquad (1)$$

The signal "r" is called the residue of the decomposition. As mentioned above, the online signature is represented by x(t) and y(t). The empirical modal decomposition of these two signals allows to characterize the signature by new parameters which are IMFs of x (t) and y(t).These parameters are gathered in a vector Vemd= [IMFx, IMFy]. Consequently, a signature can be decomposed and rebuilt from these new parameters. In this context, the rebuilding can be perfect (obtained from the sum of all IMFs), closer (sum of some IMFs) weighted (sum of some IMFs weighted). The weights are determined experimentally. In the following, we focus on the case of a signature rebuilding starting from the sum of all these IMFs. Figure 3 illustrates the result of signature decomposition and rebuilding.

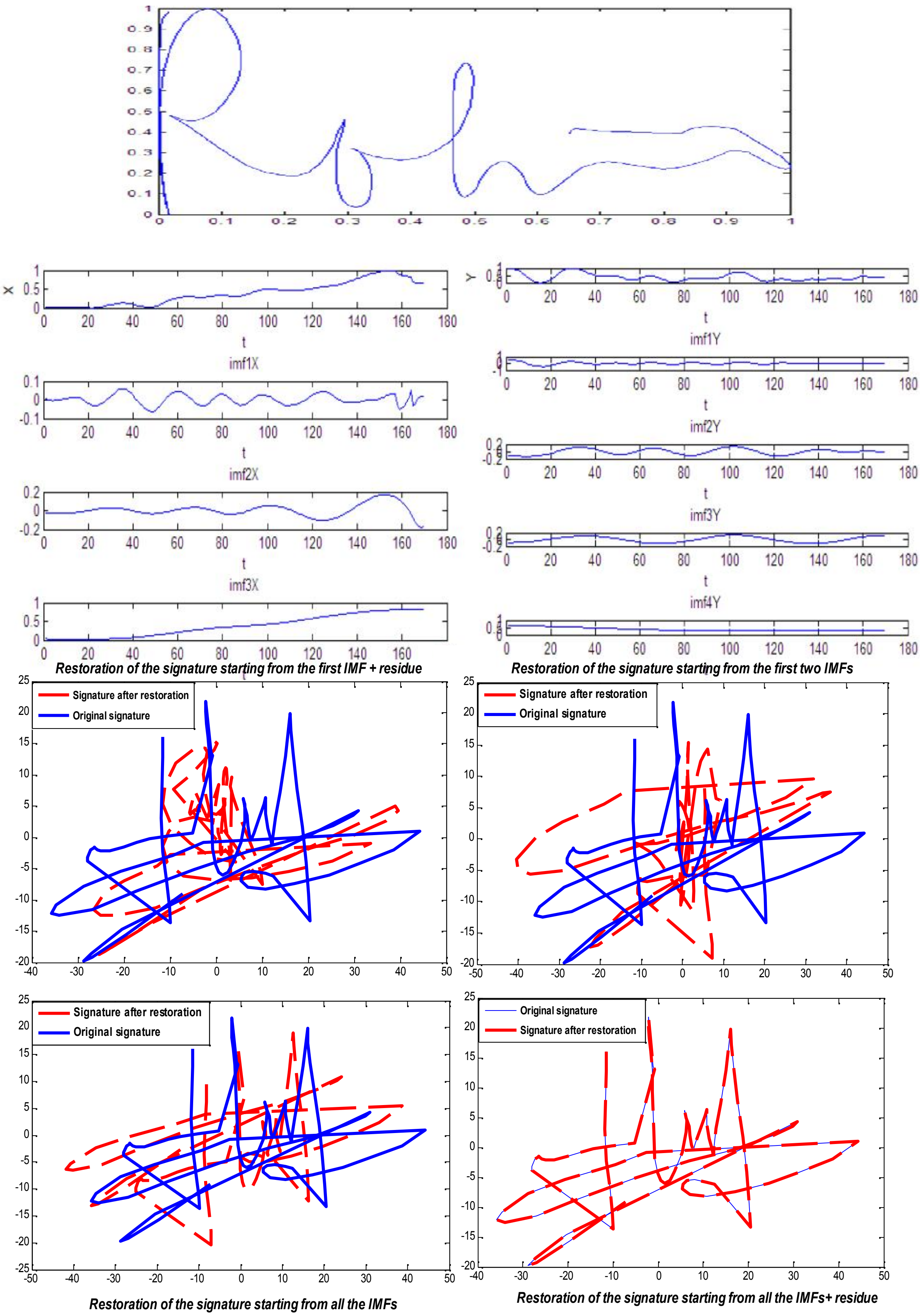


Figure 3: (a) Decomposition of a signature with the EMD (b) Restoration of a signature starting from IMFs combinations.

4.3 Reduction of the parameters space

The parameter vector Vemd defined previously cannot be used to characterize a signature because of the large volume occupied for each recorded IMF. To solve this problem, a new vector (VemdN), made up only of the maxima and minima of IMFs composing each signature, is defined. We note that a removal proceeding of false maxima and minima is achieved during the extraction of maximas and minimas. The new vector characterizing a signature is described by:VemdN=[extrema IMFx, extrema IMFy].This vector will allow rebuilding the original signal in an approached way using a selected technique of interpolation (spline cubic interpolation in our case). Figure 4 illustrates the principle of rebuilding a signature starting from VemdN. Figure 5 illustrates an example of signature rebuilding starting from IMFs of x(t).

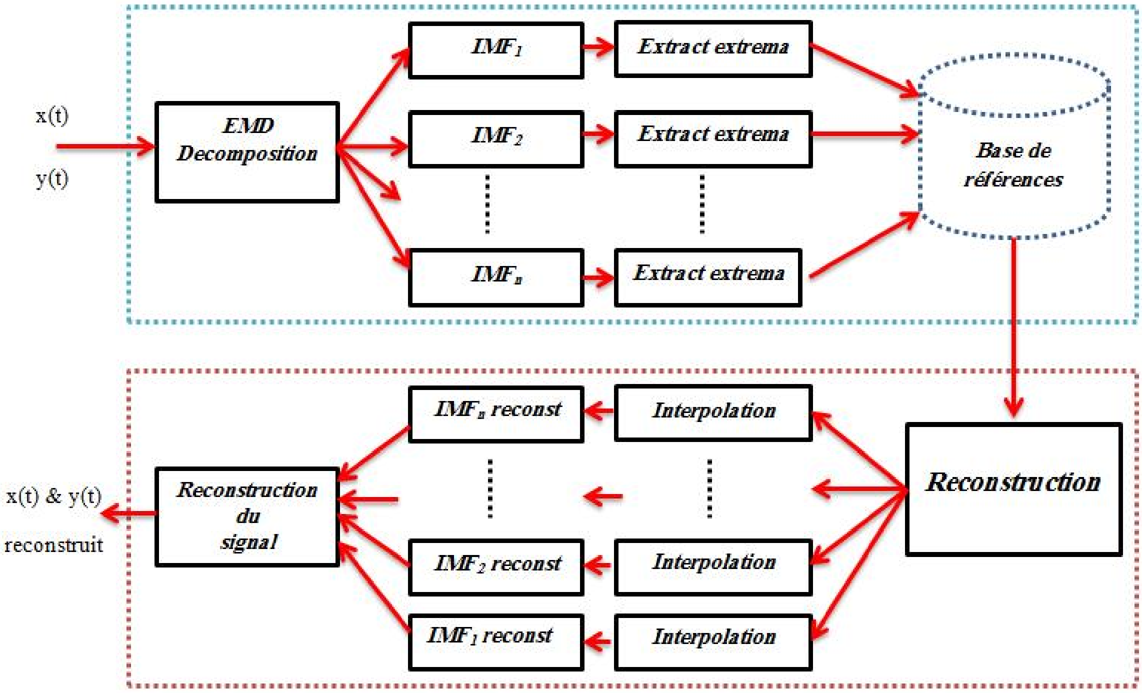
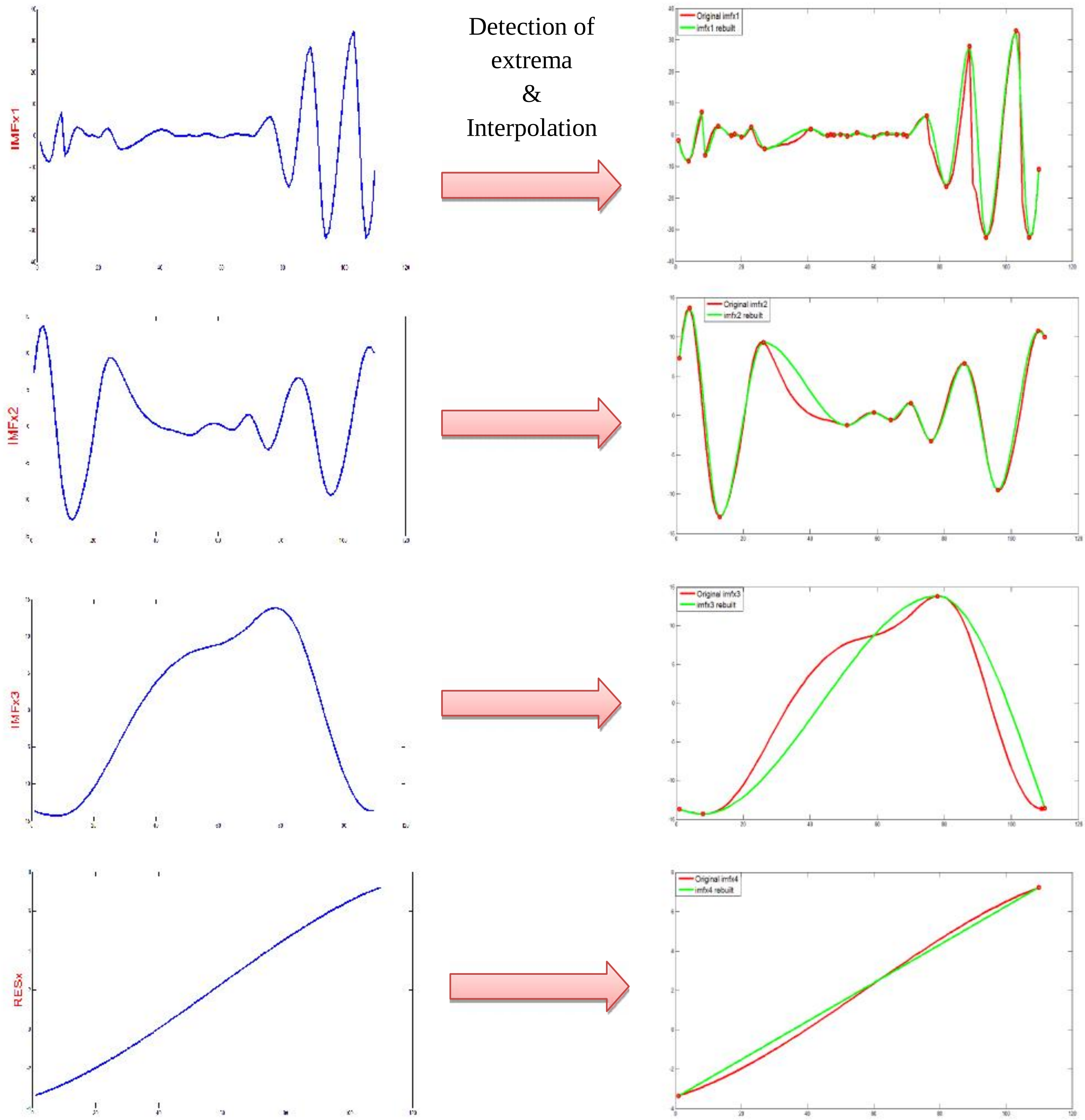


Figure 4: Principle of a signature rebuilding starting from extrema of the IMFs.



(a) **(b)**

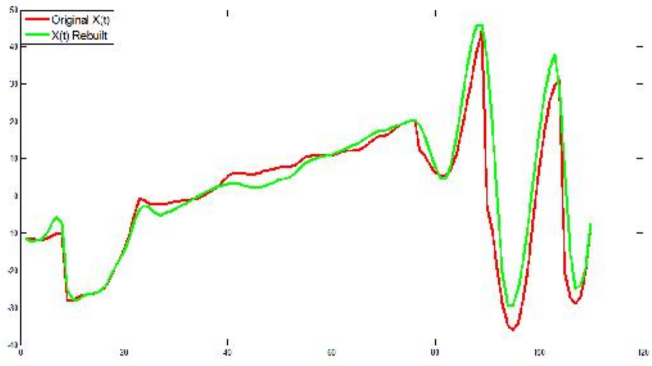


Figure 5: Example of rebuilding x(t) starting from the extrema of its IMFs: (a) IMFs of signal x(t), (b) interpolation of extrema (red curve) and (c) rebuilding of x(t) starting from the extrema of IMFs (red curve).

This stage attributes a test signature into one of two classes: genuine or impostor according to a similarity score. The decision is taken according to the comparison of the verification score to the decision threshold fixed in the stage of system enrolment.

The comparison is achieved by calculating the Euclidean distance between both rebuilt test and reference signatures. The following points constitute the essential part of our contribution in the decision block:

1. Presentation of signatures base (in our case it is about the base "task1" from SVC2004 [17]).
2. Associate with each signature from the base a VemdN vector intended to do the rebuilding of a signature starting from its extrema (cf session 4.3).
3. Obtaining the reference signature. Being given the first five signatures of each user [S1 (x1, y1) ... S5 (x5, y5)]. The user's reference signature is defined by the following expression:

$$S_{ref} = \frac{S_1 + S_2 + S_3 + S_4 + S_5}{5} \quad (2)$$

4. Define two matrices: One of size (N×M) called MATDIST and the other of size (K× M) called MATIMP where: N represents the number of test signatures, K the number of imitated signatures (impostors) and M the number of reference signature. Matrix MATDIST gathers the whole of the calculated distances between the test and the reference signatures. Matrix MATIMP gathers the whole of the calculated distances between the imitated signatures (impostors) and the reference signatures.

The establishment of these two matrices informs us about the signatures with higher degrees of similarity and those with lower degrees of similarity.

5. Calculation of the Euclidian distance between the test and reference signature rebuilt starting from their extrema: If Ui designates any user, and Vref = [Vref1, Vref2,......VrefN] indicates the whole of the reference signatures, the Euclidian distance between the test and the reference signature is defined by:

$$D\left(U_i, V_{ref}\right) = \begin{bmatrix} D\left(U_i, V_{ref1}\right), D\left(U_i, V_{ref2}\right), \\ D\left(U_i, V_{ref3}\right), ..D\left(U_i, V_{ref_N}\right) \end{bmatrix} \quad (3)$$

$$D\left(U_i, V_{ref\,i}\right) = \begin{bmatrix} \sqrt{\left| U_i - V_{ref1} \right|} & \sqrt{\left| ,Ui - V_{ref2} \right|} \\ \sqrt{\left| U_i - V_{ref3} \right|} & \sqrt{\left| ..U_i - V_{refN} \right|} \end{bmatrix} \quad (4)$$

6. Choice of the security level: The genuine signatures with higher degrees of similarity are associated with an interval: RESS = [RESSMIN RESSMAX], and those with lower degrees of similarity are associated with an interval DISS = [DISSMIN DISSMAX]. The intervals RESS and DISS are experimentally determined.

7. Comparison Test: It consists on comparing the similarity score with a variable threshold for each user.

5. EXPERIMENTAL RESULTS

5.1 Test Protocol

To evaluate our online handwritten signature verification system, we have used the base "task1" from SVC2004 (Signature Verification Competition 2004). The information collected from signatures are: the coordinates x(t) and y(t). This base contains signatures collected from 40 signatories. For each user, there are 20 genuine signatures and 20 skilled forgeries with a total of 1600 signatures. The first five signatures are used as reference signatures and the remaining signatures are used as test signatures. The performances of the system are evaluated in term of Equal Error Rate (EER). Figure 6 shows the matching scores distributions of our system.

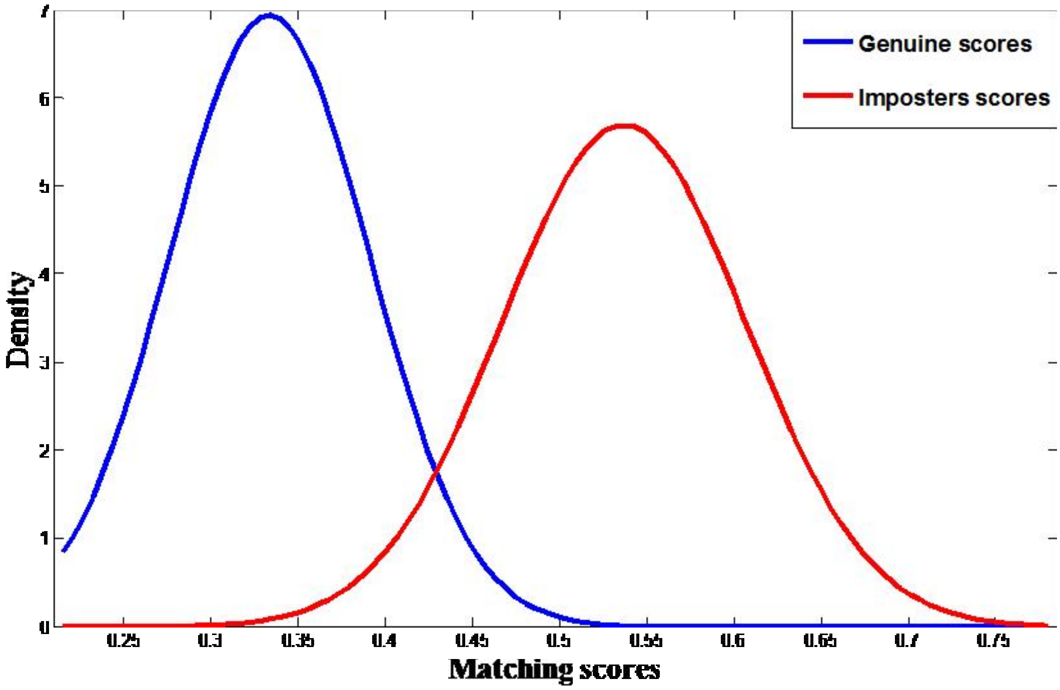


Figure 6: The scores distributions of our system

5.2 Evaluation of the system performance

The main objectify throw our work is to compare the contribution of our method with others. The results obtained in our case after obtaining MATDIST, MATIMP, RESS and DISS matrices are: False Rejection Rate (FRR) equal to 4.67 %, False Acceptation Rate (FAR) equal to 3.33%.This corresponds to Equal Error Rate (EER) equal to 1.83 %. Figure 7 illustrates the detection error tradeoff (DET) graph of our proposed system.

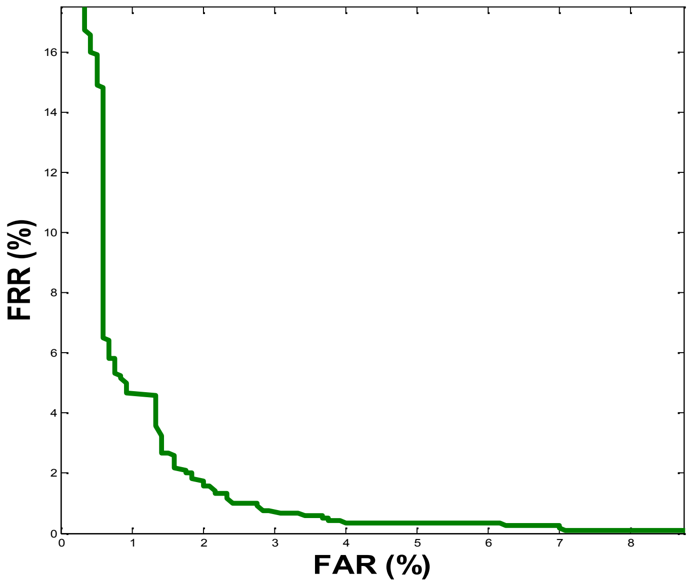


Figure7: The detection error tradeoff (DET) graph of our proposed system.

Thus, we have compared our results with those obtained by [18, 19, 20, 21] which had been tested on the same database (SVC2004) used in our work. Table1 summarizes their performances in term of equal error rate (EER). The results obtained show the effectiveness of the adopted approach in comparison to others.

Table1 Comparison with other methods

Methods	EER (%)
[18]	3.61
[19]	3
[20]	2.84
[21]	2.12
This approach	1.83

6. CONCLUSION AND PROSPECTS

In this paper, we have proposed a novel method for online signature verification that supports on the empirical mode decomposition (EMD). First, we have performed many kinds of normalizations before extracting the most important features of the signature using the method quoted below. Then, the matching process was supported on calculating of a similarity score using the Euclidian distance. At last, we have obtained very satisfactory results. Our research confirmed the success of the proposed approach where the empirical mode decomposition was applied for the first time on online signature and shows success because of its simplicity and adaptability. The other major advantage of our approach is its reduced time when compared to the wavelet decomposition for example .The major contribution of our system is reducing the probability that an imposter can be accepted and, at the same time, that a genuine is rejected by the system which confirms the effectiveness and the promising of our system. Finally, we will apply our approach on online signatures that have particular characteristics like Arabic signatures for example. This will make the object of our future works.

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