Wavelet-based Compared to Function-based On-line Signature Verification

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Abstract. We implemented two direct methods for on-line signature verification. First, data produced by a graphics tablet describing a signature to be tested are treated with wavelet transforms to generate features to be nonlinearly confronted with a reference signature chosen among 10 previously stored tryings from the same writer. In order to recover the time dependence lost in the wavelet treatment, we included the level of departure from the diagonal line in the warping function as a complementary measure of distance. In a second approach, the functions x(t) and y(t) describing position in time of each pixel of the same test signature were directly (though nonlinearly) compared to their counterparts from the reference. We concluded that both approaches showed good fidelity to all details in the signatures, with acceptable false rejection rates (we obtained around 30% FRR) to this kind of biometry. On the other hand, the inclusion of the wavelet transform turned out to be an essential step for the achievement of low false acceptation rates. It was only with the inclusion of the wavelet transform, at the right level of resolution, that we managed to completely prevent trained forgeries to be accepted (0% FAR) in the cases studied.

1. Introduction

This work deals with practical issues related to the safety of digital signatures. Under normal conditions, a digital signature is just an alphanumerical password which confirms authenticity of a document in electronic form based upon solely on the information that this document contains. All the security associated with this scheme relies on the assumption that only the person who signed the document knows the right password (Schneier [10]). However, since the copy of an electronic password cannot be easily distinguished from the original, it is highly recommended the inclusion of additional mechanisms to connect a digital signature and its author, such as the use of tokens (smart cards, for example) or the verification of some physical or behavioral trace (biometrics) collected at the moment of signing. Among all methodologies related to biometrics, we decided to choose signature verification. This choice can be justified because it is very well accepted outside electronic media. People are used to sign papers to confirm authenticity and the signature verification process is not different or intrusive, as the most part of other biometrics (Newham [1]). On the other hand, Ruggles [13] states that a person's signature is prone to variability and this would imply that systems for signature recognition must allow for a wide range of possibilities, being not very reliable.

Signature verification can be performed on-line or off-line. These two approaches and several other practical aspects related to the more general theme of handwriting recognition are discussed at length in the survey from Plamondon [12]. On-line verification signature verification methods can be further divided into two groups (see Plamondon [12]): direct methods (using the raw functions of time) and indirect methods (using parameters). In the first case, the signature is stored as a discrete function to be compared to a standard from the same writer, previously computed during an enrolment stage. Such methods simplify data acquisition but comparison can become a hard task. On the other hand, indirect methods require a lot of effort preparing data to be processed, but the comparison is quite simple and efficient. Examples of the implementation of indirect methods can be found in the papers from Lee et al. [15] and Griess[16].

Sato and Kogure [3] present one of the first direct methods to be successful. They propose a system that relies on three pseudo-distance measures (shape, motion and writing pressure) derived from coordinate and writing pressure functions through the application of a technique known as Dynamic Time Warping (DTW). They report reasonable error taxes (over 90% success) applying their system to japanese signatures, using forgeries trained for 10 minutes. Some authors tried to improve this idea. Wirtz [4] presents a very similar system but with verification based on strokes (rather than points) as the structural units of the signature. There is also Munich and Perona [8], who propose a continuous DTW as an improvement of precision in the comparison process and Huang and Yan [11], who segment the signature based on the writing velocity before applying the DTW. None of the modifications seems to represent any significant improvement over the original idea of Sato and Kogure.

Lam and Kamins [5] propose the Fast Fourier Transform as an alternative to time warping. Basically, they suggest that working in the frequency domain would eliminate the need to worry about temporal misalignments between the functions to be compared. They achieve good results and conclude that the FFT can be useful as a method for the selection of features for signature verification. On the other hand, Sundaresan and Keerthi [6], while studying possible ways of representing characters of an indian language called Tamil, discovered that, because differences among Tamil characters can be very subtle, the best way to represent them is with the aid of wavelet transforms. They noted that Fourier coefficients would not be a good alternative because they are not very sensitive to small variations in style or shape.

The idea of employing wavelet transforms as a means of generating features from signatures appears also in the work from Deng et al. [9]. They propose an off-line verification system that uses wavelet transforms for the decomposition and analysis of the coordinate functions and the tangential angle of points obtained from a signature image. Deng et al. acquire their data from scanned samples of signatures, so they must use image processing techniques to identify closed contours which conveniently represent each signature. Coordinates of the points that compose each contour are stored as polar functions of angles measured counterclockwise with respect to some reference internal to the contour. The functions obtained are submitted to a wavelet transform and the authors take zero-crossings of the detail function in a certain level as features. They complement this set of features with integrals between consecutive zero-crossings and corresponding amplitudes to the same abscissa in the approximation function one resolution up. Experimenting with occidental signatures, these authors were able to achieve error taxes as low as 5,6 % false rejection rate (FRR) and 10,98% false acceptation rate (FAR), thus showing the applicability of the wavelet transform to this kind of problem.

Wavelet transforms can also be found in works related to other biometrics. Boles [7], for example, presents a security system that uses the wavelet transform for iris recognition. In order to extract features that are unique to the gray level profiles of the iris image, the author uses (similarly to Deng et al. [9]) the zero-crossings of the detail function and the integrals between consecutive zero-crossings in a certain level of the wavelet transform.

The present work describes an extension of the work from Deng et al. [9] to the case of on-line signature verification. Though a powerful technique, their method for off-line verification cannot be directly applied to the on-line case, mainly because it was developed to deal with situations in which the only available information is the complete signature image. Data obtained on-line do not demand image processing techniques to be used but, besides shape, they provide important additional information which should be considered, such as the order in which points were created in the original signature and the writing velocity. Specifically, we compare the functions x(t) and y(t) describing a test signature with their counterparts in a reference signature, previously chosen in an enrolment stage. Our aim is to determine if this test signature can be taken for original. This comparison is based on dissimilarity measures between features that are obtained from the wavelet transform of the functions x(t) and y(t) through the calculation of certain parameters related to the zero-crossings of the detail function in the right level of resolution to this problem (level 4). These parameters (described below) contain, theoretically, the same amount of information associated to the complete set of coordinates (x(t),y(t)). If these dissimilarity measures between the test signature and the reference lie into an acceptable range, established in a previous enrolment stage with 10 original signatures, the test signature is accepted as true.

Before the calculation of the dissimilarity measures, the functions x(t) and y(t) from the test signature must be aligned in time with the corresponding functions in the reference signature. This is accomplished with the Dynamic Time Warping from Sato and Kogure [3]. The information related to the writing motion, lost in a preparation process to the wavelet transform, is recovered with the inclusion of an additional dissimilarity measure, directly extracted from the graphic of the warping function between zero-crossings, given by the area between this function and the diagonal in the dynamic programming diagram. It is similar to the second pseudo-distance of Sato and Kogure, but including the wavelet transform and represents a good measure because forgeries tend to produce warping functions stronger deviated from the diagonal than original samples of the same signature.

Finally, in order to confirm the need of such a sophisticated tool as a wavelet transform in the verification process, we implemented a second method, in which the features are simply the coordinates x(t) and y(t), normalized but not transformed. Similarly to the wavelet approach, the main tool in this case is the warping function that results after the use of the DTW to dynamically align features. Besides the distance that naturally comes out of the alignment process, we also included the area between the warping function and the corresponding diagonal as a dissimilarity measure. This should take into account, in an indirect way, the information associated with the writing motion in this analysis.

2. Data acquisition

Data acquisition is accomplished with a graphics tablet Graphire from Wacom [14], with 12.76×9.28 cm^2 active area and maximum data transmission rate of 100 points per second. Budget restrictions prevented us from testing with a LCD pad, which would allow the same kind of feedback provided by usual media (paper and pen). However, the effectiveness of the proposed system does not depend on this factor and the only influence that could be expected from a better quality data acquisition device would be the acquirement of better error taxes in the experimental phase of this work.

The data consisted of original signatures from 4 people (2 right-handed and two left-handed). We took 30 samples from each person and we generated also 30 trained forgeries to each signature. These forgeries were created with free access to all available information, such as shape and sequence of writing of each original signature and with no limitation in time for training. False acceptation rates were computed only with trained forgeries. We used random forgeries in preliminary tests, just to be sure that our system was correctly implemented, but we did not include these results in the FARs reported. Random forgeries are not representative of real situations and their inclusion would tend to dissimulate the error taxes computed. Furthermore, a system that presents a good performance in preventing trained forgeries to be accepted must be effective with random forgeries too.

3. Overview of the system

The signature to be tested is collected from an electronic pad as two functions in time (x(t),y(t)) and is numerically processed to generate numbers that represent the distance between it and a reference signature (standard), computed in a previous enrolment stage. If this distance lies inside a statistically acceptable range, the test signature is recognized as being original. The numerical treatment includes resampling to a uniform mesh, correction of elementary distortions between curves (such as spurious displacements and rotations), applying wavelet transforms to produce features and finally nonlinear comparison in time (Dynamic Time Warping).

3.1 Preprocessing

Initially, raw coordinate functions $x_*(t_*)$ and $y_*(t_*)$ are obtained as sequences over a non-uniform mesh in time, presenting an average of 200 points each. These functions are immediately resampled to a uniform mesh with twice the number of nodes in time. Then these resampled data are submitted to the same normalization to location and rotation used by Sato and Kogure [3], producing an effect like the one showed in Figure 1.

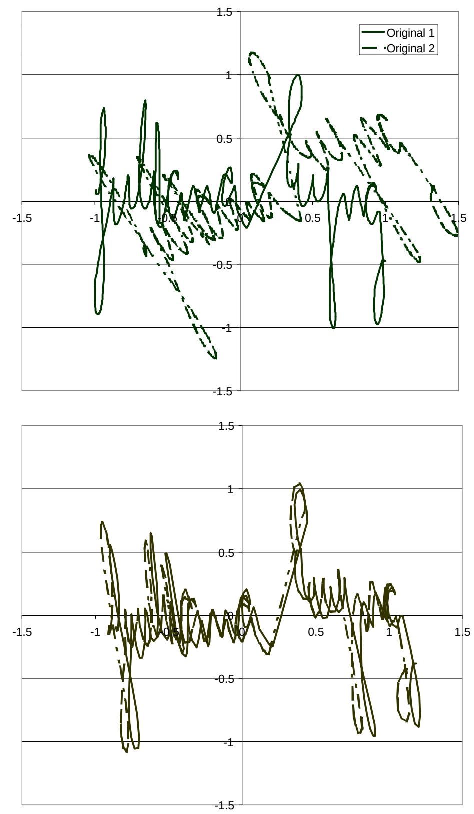


Figure 1 Effect of preprocessing over spurious displacement and rotation.

Specifically, time is changed to the unit interval [0;1] and x(t) and y(t) are changed to [-1;1]. In the next step, an auxiliary complex valued function z(t)=x(t)+i.y(t) is defined, whose origin is then situated over the centroid with $\overline{z}(t) = z(t) - z_C$, where z_C is defined as:

$$z_C = \int_0^1 z(t)dt \qquad (1)$$

The signature is then aligned with one of its principal axes, with:

$$\hat{z}(t) = \overline{z}(t).e^{-i.\arctan\alpha} \qquad (2)$$

where $\alpha = -\beta + \sqrt{1+\beta^2}$ is the inclination angle of the principal axis, for a value of β given by:

$$\beta = \frac{\mathrm{Re}\left[\int_0^1 (\hat{z}(t))^2 \, dt_*\right]}{\mathrm{Im}\left[\int_0^1 (\hat{z}(t))^2 \, dt_*\right]} \tag{3}$$

3.2 Wavelet-based feature extraction

Considering the good results presented by Deng et al. [9], we decided to use the wavelet transform as the main tool for feature extraction. The wavelet transform is also a good choice because of its capability to allow hierarchical decomposition of functions in different levels of resolution, separating in each level a an approximated shape from the details that complement it. It is a reasonable assumption to suppose that an authentic signature must be consistent with a standard pattern in the details, at a suitable level of resolution. We considered also to use Fourier Transform in place of wavelets, but this option was discarded in view of the remarks from Sundaresan and Keerthi [6]. Fourier coefficients would tend to increase the (false) acceptation of forgeries, since they would not be able to indicate changes of style during the signing process, while these changes can be identified in a natural way in the detail functions of a wavelet transform.

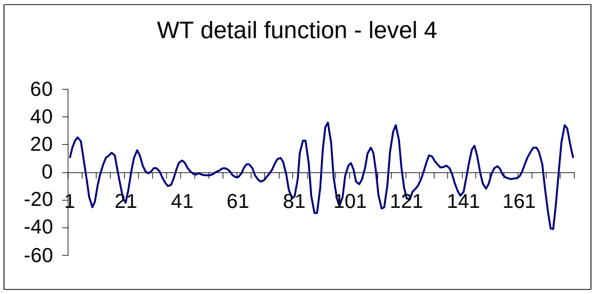
The decomposition of the functions x(t) and y(t) with wavelet transform generates approximations and details like those showed in Figure 2 to an original example of x(t). To each zero-crossing of the detail curve at the 4th level of resolution (this level was chosen empirically, by trial and error), three parameters are extracted: its abscissa, the integral between consecutive zero-crossings (WD4 is the wavelet detail function at the 4th level):

$$vi_k = \int_{ZC_{k-1}}^{ZC_k} WD4(t)dt \tag{4}$$

and the corresponding amplitude to the same abscissa in the approximation function one resolution up (WA3 is the wavelet approximation function at the 3rd level):

$$va_k = WA3(zc_k) \tag{5}$$

As it has been demonstrated that this information suffices to a complete reconstruction of the non-transformed curve (see Deng et al. [9]), these parameters can be used as highly significant features.



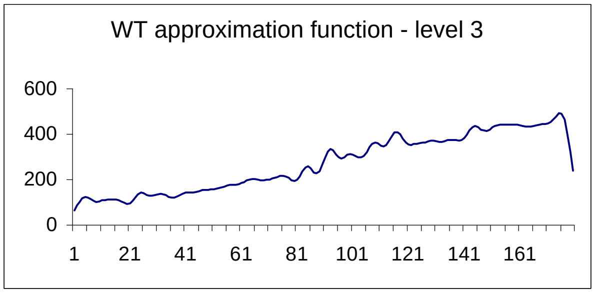


Figure 2 Example of a function x(t) after the wavelet transform.

3.3 Calculation of the dissimilarity measures

The main goal of the feature extraction is to allow for the dissimilarity between two signatures to be quantified. However, even for original samples, it is almost impossible to have two original signatures with exactly the same shape and velocity profiles, so that the right pairs of zero-crossings to be associated will never occur at the same time and sometimes they will not be even close to each other. So, before measuring distances, it is necessary to identify a suitable correspondence between zero-crossings, which is accomplished with the Dynamic Time Warping (DTW) algorithm from Sato and Kogure [3]. It consists of a linear programming technique, in which the time axis of the reference curve is fixed, while the time axis of the test curve is nonlinearly adjusted, so as to minimize the norm of the global distance between the curves. This optimization tool, described by Rabiner [2], is also used in speech recognition to identify different utterances from the same phoneme.

Typically, this DTW is executed between two discrete functions, having or not the same number of points, to find the best correspondence between these points. In our context, the best correspondence is the one in which the sum of the euclidean distance between selected points is minimum. This is accomplished through the assignment of costs (distance between points) to each association between points in different curves. These costs are organized as a matrix [A], whose element a_{ij} contains the value of the euclidean distance between point i in some curve f(x) and point j in some g(x). This matrix can be viewed as a diagram with $T_f \times T_g$ points and an algorithm of linear programming indicates which pairs of points compose the path that leads to the best global correspondence. Typically, the optimization solution deviates from the main diagonal of the diagram, meaning that some "warping" had to be imposed.

A recursive algorithm that finds the best path in a diagram with T_f X T_g points, starting at (1,1) and finishing at (T_f,T_g), can be described by the three steps below (d_{ij} means local cost between points i and j and D means global cost from (1,1) until (i,j), following an optimal path), extracted from Rabiner [2]:

1. Initialization: $D_{(1,1)} = d_{(1,1)}.m_{(1)}$, where m contains weights that empirically impose some preference among possible paths (see Figure 3).

2. Recursive step: search on a tree of possible paths. Starting by the last point (T_f,T_g), for each intermediary combination (i_f,i_g), search among allowed candidates (i'_f,i'_g), the one which, after the addition of the local cost between (i_f,i_g) and (i'_f,i'_g), leads to a global distance from (1,1) to (i_f,i_g) that is minimum. Since the alternative paths tend to grow exponentially, only the 3 paths that conform to the restriction rule showed in Figure 3 are considered. Mathematically, this can be stated as: for $1<i_f<T_f$, $1<i_g<T_g$, compute, over all (i'_f,i'_g) allowed by the restriction,

$$D(i_f,i_g) = \min_{i'_f,i'_g}\left[D(i'_f,i'_g) + d((i_f,i_g),(i'_f,i'_g))\right] \qquad (6)$$

The computation of $D(i'_f,i'_g)$ depends on the verification of the optimal path that reaches (i'_f,i'_g) itself, so that this step must be recursively repeated until point (1,1) is reached.

3. At the end, the distance between functions receives the value of the accumulated minimum cost, normalized in order to take weights into account:

$$\mathrm{dist}(T_f,T_g) = \frac{D(T_f,T_g)}{T_f + T_g} \qquad (7)$$

Figure 4 shows a typical result of an application of DTW. In a practical sense, the nonlinear alignment suggested by the DTW algorithm allows for abstracting from the analysis small behavioral variations during writing. The effect of the alignment produced by the DTW between the zero-crossings of two functions x(t) derived from authentic samples of signatures from the same writer is showed in Figure 5.

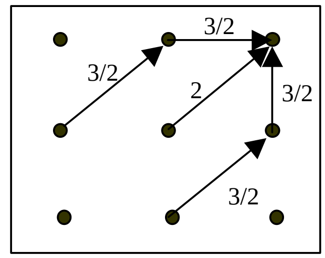


Figure 3 Local restriction used in the DTW algorithm.

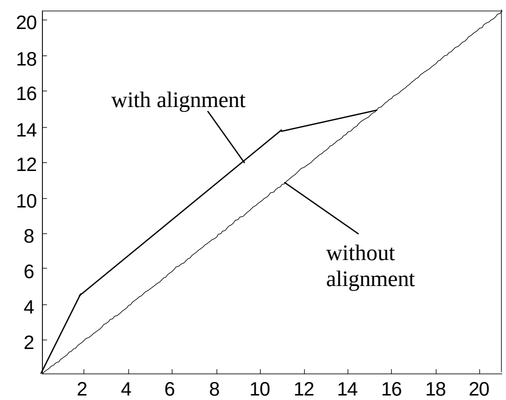


Figure 4 Typical optimal path suggested by DTW to align features originated from wavelet transforms.

The output of the DTW algorithm includes the optimal correspondence between points in the two curves and the value of the minimal distance. The optimal path is the two-column matrix $[CAM_{(i,j)}]$, where each line contain one pair of points associated by DTW.

Once the optimal correspondence is established, distances can be conveniently measured. The comparison process is based on four distances, defined as:

1. The minimum produced by the DTW algorithm, $d(T_f,T_g)$, given by equation (7).

2. The norm of the differences of integrals between consecutive zero-crossings, di^x for x(t) and di^y for y(t), calculated from:

$$di^{x} = \left\| vi^{x,1}_{CAM_{k,1}} - vi^{x,2}_{CAM_{k,2}} \right\| \quad (8)$$

$$di^{y} = \left\| vi^{y,1}_{CAM_{k,1}} - vi^{y,2}_{CAM_{k,2}} \right\| \quad (9)$$

where $[CAM_{i,j}]$ is the matrix containing the optimal path and $[vi_k]$ is given by equation (4).

3. The norm of the differences between amplitudes in the approximation function at the 3rd level, da^x, for x(t) and da^y, for y(t), calculated from:

$$da^{x} = \left\| va^{x,1}_{CAM_{k,1}} - va^{x,2}_{CAM_{k,2}} \right\| \quad (10)$$

$$da^{y} = \left\| va^{y,1}_{CAM_{k,1}} - va^{y,2}_{CAM_{k,2}} \right\| \quad (11)$$

where $[va_k]$ is given by equation (5).

4. The area of the difference between the warping function and the corresponding diagonal (see Figure 3). We assume that this last parameter recovers the information related to the velocity that is lost during the resampling process to an uniform mesh. This assumption is based on the simple idea that bigger differences in speed during signing between two signatures demand bigger deviations from the diagonal in the warping function.

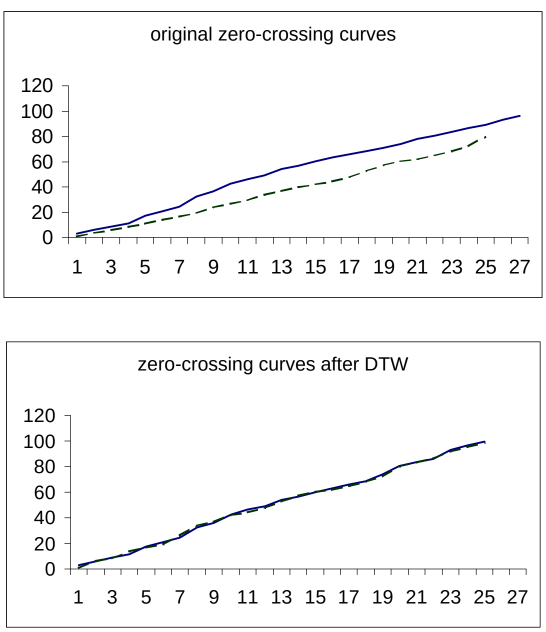


Figure 5 Effect of DTW over zero-crossings extracted from original samples of signatures from the same writer.

3.4 Function-based feature extraction

Basically, the method that includes the wavelet transform consists of the computation of distances between sets of features aligned with DTW. In this second approach, we extract the features directly from the normalized curves x(t) and y(t) that describe the signature, without any transformation. In this case, there are only two distances that can be defined: the minimum that returns from the DTW between the non-transformed curves and the area of the difference between the warping function and the corresponding diagonal. This drastically simplifies feature extraction, but the DTW has now to be applied over a much bigger number of points than when the only points to be considered were the zero-crossings from function WD4. To deal with this great amount of points in an efficient manner, we developed a non-recursive version of the DTW algorithm. Accordingly, in this case the warping function presents shapes like the one showed in Figure 6 (in comparison to Figure 4). We are again assuming that two signatures produced with too different writing velocity profiles tend to present a much more pronounced warping effect.

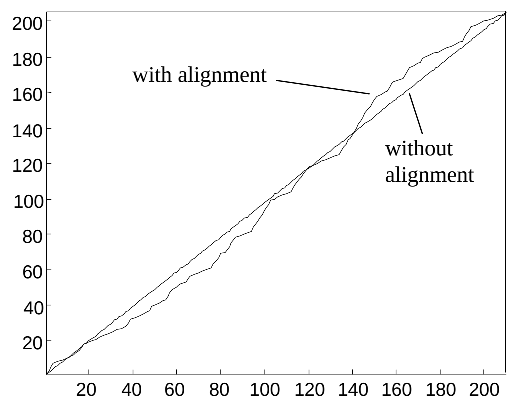


Figure 6 Typical optimal path obtained with DTW directly applied to the coordinate functions x(t) and y(t).

3.5 Reference signatures

During an enrolment stage, 10 sample signatures from each writer to be enrolled are collected and pairwise distances between them are computed. Based on these distances, a reference signature is selected as the one that presents minimal overall distance to the others. Actually, to each of the 10 signatures, we create a 9×8 matrix containing the 8 distances defined (4 for x(t) and 4 for y(t)) to each of the other signatures. The reference is the signature whose distance matrix presents the minimal norm.

The distances calculated in this step are also used to produce the 8 thresholds to be tested during the verification stage. Each threshold is computed from the averages ($\bar{d}$) and standard deviations (s) of all possible pairwise distances associated with the 10 sample signatures, according to:

$$L = \bar{d} + 1.96 \times s \qquad (12)$$

where the value 1.96 is chosen to assure that, assuming normal distribution for the distances originated from the same writer, 97.5% of the distances between original signatures and references lie under this threshold.

3.6 Verification

A test signature, after passing through preprocessing and feature extraction, is compared with the reference signature to that writer. The verification consists of checking if all defined 8 distances thus obtained lie under the thresholds given by equation (12).

4. Experimental results

The proposed methodology was tested with the original signatures and the forgeries previously acquired. The tests consisted in determining false acceptation rates (FAR) and false rejection rates (FRR) to each of the 4 writers enrolled during data acquisition. Tests were executed with the mother wavelets Daubechies 1 (Haar), Daubechies 6 (db6), Daubechies 10 (db10) and Biorthogonal 5.5 (Bior. 5.5), at different levels of resolution (3, 4 and 5). We included also a test in which the 4^{th} dissimilarity measure (area between warping function and diagonal) was not considered.

According to preliminary tests, we chose a standard configuration as: db 6 and level of resolution 4. Results for this configuration are presented in Table 1. Although the FRR may be significant, there was no acceptation of forgeries at all. It should be noted that, according to practical considerations, it would be possible to decrease FRR by relaxing the thresholds, but in this case the FAR would increase. The standard configuration was chosen in order to provide maximum security aginst forgeries, without taking into account any troubles to the writer by having original signatures rejected.

Table 1. db 6, level 4, including distance 4.

	Writer 1	Writer 2	Writer 3	Writer 4
FAR	0%	0%	0%	0%
FRR	37%	23%	30%	40%

The tests showed in Table 2 justify the adoption of level 4 as the reference. Although presenting a light decreasing in FRR on the average, the data in Table 2 show unacceptable values to the FAR, meaning that at levels other than the 4^{th} , this verification system would be unsafe for the cases studied.

Table 2. Mother wavelet db6, levels 3 and 5, including distance 4.

Resolution level	Error taxes	Writer 1	Writer 2	Writer 3	Writer 4
3^{rd}	FAR	0%	23%	3%	23%
	FRR	23%	13%	40%	37%
5^{th}	FAR	0%	53%	0%	7%
	FRR	30%	33%	33%	27%

We also performed an investigation to check if a substitution of the mother wavelet Daubechies by others would produce better results. To this end, the same tests from the standard case were re-executed, just replacing db6 successively by db1, db10 and bior 5.5. Our results, showed in Table 3, indicate that, even though it is possible to find some improvement in FRR, there are again some important security failures due to high FAR, meaning that db6 was effectively the most indicated in this case.

Table 3. Mother wavelets db1, db10 and bior 5.5, level 4, including distance 4.

Mother wavelet	Error taxes	Writer 1	Writer 2	Writer 3	Writer 4
Db1 (Haar)	FAR	0%	50%	0%	13%
	FRR	20%	7%	30%	20%
Db10	FAR	0%	27%	0%	23%
	FRR	7%	23%	30%	37%
Bior 5.5	FAR	0%	20%	0%	0%
	FRR	40%	27%	30%	20%

To check if the information associated with writing motion is really relevant in the methodology with wavelets, a test was devised, in which the 4^{th} dissimilarity measure (area between warping and diagonal) was ignored. The results to this case, shown in Table 4, reveal that the 4^{th} measure of distance is an essential parameter to prevent forgeries to be accepted.

Table 4. Mother wavelet db6, level 4, without distance 4.

	Writer 1	Writer 2	Writer 3	Writer 4
FAR	0%	3%	0%	3%
FRR	37%	17%	23%	27%

Finally, the wavelet transform was removed and the distances were obtained directly from the coordinate functions x(t) and y(t). In this case, the difference in the number of points between a test signature and the reference can become very large, so we had to include a "filter", based on two global parameters: total duration time of the signature and its total length. Even with the inclusion of this filter the FAR obtained in this case were not satisfactory at all and showed that, for the cases studied, the wavelet step is essential to ensure security.

Table 5. Function-based, with filter.

	Writer 1	Writer 2	Writer 3	Writer 4
FAR	3%	70%	0%	3%
FRR	13%	13%	23%	17%

5. Conclusions

We concluded that the error taxes obtained were at acceptable levels for this kind of biometry. This shows that the chosen methodology, consisting basically in the application of the Dynamic Time Warping algorithm on features extracted with the application of wavelet transforms, is suitable to on-line signature verification. The need of a wavelet transform step was tested by comparison with a simplified system based solely on the coordinate functions x(t) and y(t). We concluded that it is worth to include the wavelet transform in the analysis. The main tool to comparison of signatures is undoubtedly the DTW, but the inclusion of the wavelet transform was an essential step for the achievement of low false acceptation rates. It was only with the inclusion of the wavelet transform, in the right level of resolution, that we managed to completely prevent trained forgeries to be accepted (0% FAR) in the cases studied. This result was expected, since, through wavelet transforms, it is possible to analyze the problem in a resolution level suitable to the problem of comparison of signatures.

6. Acknowledgements

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