WAVELET PERFORMANCE IN BIOMETRIC IDENTIFICATION SYSTEM ACCORDING TO USERS INCREASE

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Abstract: This work shows a simple and robust biometric identification system through the use of the palmprint. It proves the efficiency of the wavelet transform regardless of users' number. Firstly, the hand palm image with scale, rotation and translation invariance is isolated from the hand image recorded. Then, the "wavelet transform" is used to extract the texture features from gray-scale images. Three wavelet families, haar, daubechies and biortogonal are studied in order to get the best recognition rate. 1440 hand images of 144 people with 10 samples each one have been acquired by means of a commercial scanner with 150 dpi resolution. Support Vector Machine (SVM) is the main classifier used as identifier in closed mode. A recognition rate of 99.83% for 50 users and 99.76% for 144 users demonstrate the strong performance of wavelet transform in biometrics according to users increase.

1 INTRODUCTION

In the competitive business world today, the need and demand for a biometric physical security solution has never been higher. Common biometric techniques include fingerprints, hand or palm geometry, retina, iris, or facial characteristics. Behavioural character includes signature, voice (which also has a physical component), keystroke pattern, and gait among others. Nowadays, most of the security systems developed into the society are based on hand image analysis (Masood et al., 2008; Pavesic et al., 2004), especially in the texture of the hand palm since they provide people with higher security in relation to authentication systems (Zhang, 2004) and offer a good balance of performance characteristics while they are relatively easy to use. Palmprint analysis offers many advantages similar to the other technologies such as small data collection, resistant to attempt to fool a system, ease of use and difficult technology to emulate a fake hand. In this context, wavelet analysis plays an important role in biometric systems: the wavelet filter allows the users to extract the main features of their hands and to be differentiated between them (Zhang et al., 2007).

There are however several challenges to beat. Besides high proprietary hardware costs and size, the aging of the hands of individuals, the lack of accuracy of the technology and the biometrics inability to not recognize a fake hand pose a challenge. To overcome these drawbacks, Liu et al., 2007, showed a research about the use of wavelet transform in palm-print. Classifying with the ISODATA algorithm got a 95% of identification accuracy with 180 palm-print from 80 people. Masood et al., 2008, developed a palm-print system using wavelet transforms. 50 people took part in the session (10 samples per person), reaching a 97.12% of accuracy with the combination of different wavelet families. Before, Goh et al., 2006, had presented a palm-print system made up of 75 individuals. It was based on wavelet transform and Gabor filter, with a verification result of 96.7% and an Equal Error Rate (EER) close to 4%. Other authors have also proposed different techniques of palm-print analysis: Guo et al., 2009, described a BOCV system, (Binary Orientation Co-Occurrence Vector) based on the linking of six Gabor features vectors. 7752 samples from 193 people were taken. The error rate was 0.0189%. Zhang et al., 2009, presented a novel 2D+3D palm-print biometric system made up to 108 individuals. The EER was 0.0022%. Badrinath and Gupta, 2009, proposed a prototype of robust biometric system for verification which uses features extracted using Speeded Up Robust Features (SURF) operator of human hand. The system was tested on IITK database and PolyU database. It had FAR = 0.02%, FRR = 0.01% and an accuracy of 99.98% at original size. The system addressed the robustness in the context of scale, rotation and occlusion of palm-print.

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Zhang et al., 2010, presented an online multispectral palmprint system with the requirements of real-time applications. A data acquisition device is designed to capture the palmprint images under Blue, Green, Red, and near-infrared (NIR) illuminations in less than 1 s. The results show that the Red channel achieves the best result, whereas the Blue and Green channels have comparable performance but are slightly inferior to the NIR channel. Recently, Yue et al., 2011, proposed an algorithm to speed up the identification process, where the intrinsic characteristics of the templates of each subject are used to build a tree, and then, perform fast nearest neighbor searching with assistance of the tree structure. The proposed two strategies are 30%-50% faster than brute force searching. Li et al., 2011, showed a simple efficient scheme for 3-D palmprint recognition. After calculating and enhancing the mean-curvature image of the 3-D palmprint data, line and orientation features are extracted. Then, the features are fused at either score level or feature level, reaching a recognition rate of 99.79%.

This paper focuses on the use of 2-D Discrete Wavelet Transform (DWT) in order to get a simple and robust biometric identification system using the texture of the hand palm. Firstly, the hand palm image processing with scale, rotation and translation invariance (ROI) is obtained. Then, it will discussed and analyzed several wavelet biometric families providing its advantages and disadvantages, showing identification and verification results, and concluding with the biometrics of the future.

The general block diagram of the system is shown in Figure 1. After getting the ROI and applying different filter levels, the recognition rate will be reached with Support Vector Machine (SVM) (Steinwart & Christmann, 2008), a supervised classifier used to authenticate people.

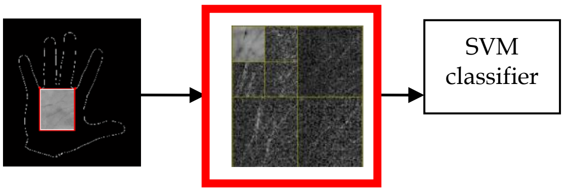

Figure 1: Functional block diagram of the system.

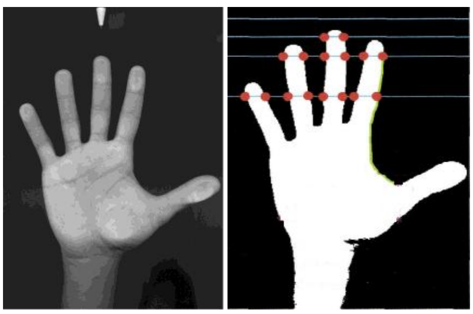

Figure 2: (a) Database hand image, (b) Fingers detection of the hand.

This paper is set up as follows: section 2 introduces the image processing necessary to extract the palm features presented in section 3; section 4 shows the classification system used in this work and section 5 explains the experiments performed; finally, a brief conclusion is given in section 6 together with the future work.

2 IMAGE PROCESSING

The 1440 hand-images belonging to the 144 users are acquired thanks to a 150 dots per inch general scanner, and they are stored with 256 gray levels, 8 bits per pixel (Figure 2 (a)). The size of these images is set to 1403x1021 pixels after scaling them by a factor of 20% to facilitate later computation (see Table 1). When a hand is detected, it is pre-processed to extract the hand-contour and then, the region of interest (ROI) of the palm. It let us analyze the palm-print texture and consequently the identity of the people.

Table 1: Properties of database hand images.

Properties of the hand images contained in the database	
Size	80% original size
Resolution	150 dpi
Colour	256 grey levels
File size	1405 Kbytes
Data matrix dimension	1403×1021

Firstly, we convert each image from 256 gray levels to a binary image through and adaptive threshold obtained empirically with training samples. To work out the biometric features, we localize the 4 fingers of the hand through 8 initial points of the Figure 2 (b) to detect the tops and the valleys of the fingers.

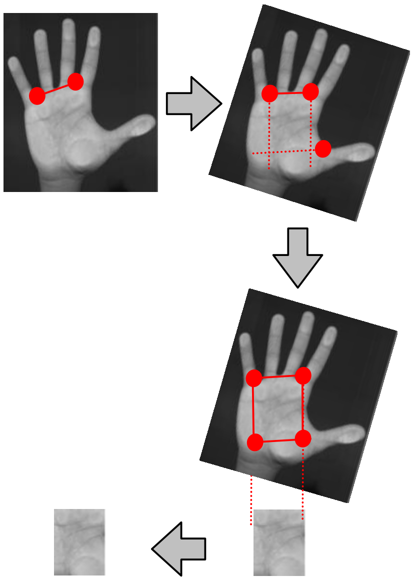

Figure 3: Palmprint extraction from hand images: detection of the valleys.

Finding out the maximum of the contour between the 2 points of each finger the ends are obtained. Finding out the minimum between the 2 consecutive points of different fingers the valleys are obtained. At this time, the ROI is extracted after lining up the valley of the little finger with the valley of the hearth-index finger (Figure 3), in order to not depend with the hand position. It has a vertical size of 300 pixels and the horizontal size can vary some pixels depending on the fingers gap.

3 FEATURE EXTRACTION: DISCRETE WAVELET TRANSFORM (DWT)

Next step is to process the hand palm image with the purpose of emphasizing its discriminative characteristics. The Discrete Wavelet Transform (Villegas & Pinto, 2006) filters the image separating the thin details from the thick details of the palm-print image. In this work, 3 wavelet families have been compared: 'haar' or 'db1', 'daubechies5' and 'biortogonal5.5' (see Figure 4 for different wavelet waveforms).

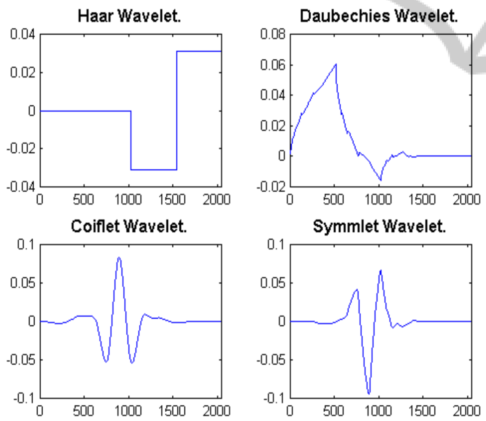

Figure 4: Several wavelet families: haar, daubechies, coiflet and symmlet.

We have used a successive chain of low filters with cutoff=π/2. It lets to emphasize the difference between the diverse gray levels. The size of the palm-print images is reduced to a different set of values after applying the successive filters. The DWT of a signal f(t) has the form of (1), where ψ(t) is a family of wavelet functions (Gonzalez and Wood, 2008):

$$DWT(j,k) = \int_{-\infty}^{+\infty} f(t)\cdot \psi_k^j(t)dt \qquad (1)$$
$$\psi_k^j(t) = 2^{\frac{-j}{2}}\cdot \psi(2^{-j}\cdot t - k) \qquad j,k \in Z$$

Taking one user palmprint approximation A_{k-1}, we can obtain the *k-th* level factorization applying a successive chain of filters, resulting in the approximation (A_k), horizontal (H_k), vertical (V_k) and diagonal (D_k) detail images (Figure 5). In this work, the original palmprint has been split in approximation and diagonal images, studying the response of the first one due to its high recognition rate.

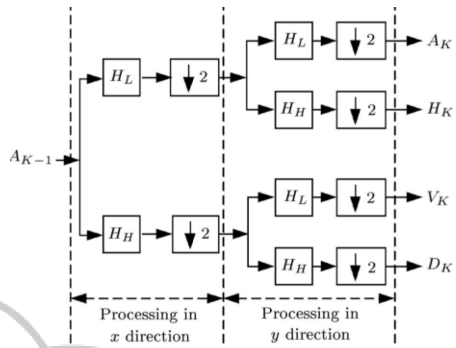

Figure 5: Block diagram of the filter to split the palmprint into the four images.

After applying filter levels, the image is reduced to several image sizes to facilitate people recognition. In the results section, the system accuracy will be shown according to image size, emphasizing the best wavelet level.

4 CLASSIFICATION SYSTEM: SUPPORT VECTOR MACHINE

A general supervised identification/verification system is divided into two fundamental blocks: training and test, just as it is shown in the Figure 6. In that figure, the data capture and the extraction of biometric information are observed. With these parameters it is modelled a feature score which is used in the test step.

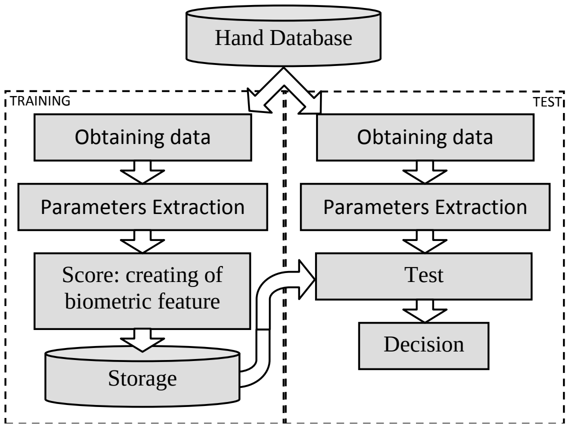

Figure 6: Block diagram of a general supervised identification/verification system.

To evaluate the hand features we have used a support vector machine (SVM) as classifier (Steinwart & Christmann, 2008). RBF kernel is used in SVM with the Gaussian function $K(\bar{x},\bar{y}) = e^{-g^2(\bar{x},\bar{y})}$ when it works as identifier in closed mode where only known users can appear in the test data and are taken into account for the systems performance evaluation. Also the lineal kernel is studied.

To identify that an input hand belongs to a fixed identity, we calculate the distance of the input hand features to the separator hyperplane of the SVM which models the hand of each identity. The highest distance belongs to the accepted identity.

It would be possible to say that SVM builds a hyperplane of separation in the entrance space in two possible modes: in the first, it is converted the input space into higher dimension characteristics space, by means of a (nucleus) non lineal transformation; in the second, it is built the optimum hyperplane of separation (MMH, Maximal Margin Hyperplane). This hyperplane maximizes the distance of the vectors which belong to different classes. Thus, if S is a set of N vectors $\overline{x}_1 \in R^n$ where i=1...N, each vector $\overline{x}_1$ belongs to one of the two identifying classes as $y_i \in \{-1,1\}$. If the two classes are linearly separable, then a unique optimum hyperplane defined by equation 2 exists:

$$\overline{w} \cdot \overline{x} + b = 0 \qquad (2)$$

It provides a greater margin of separation among the classes, and it divides S leaving all the vectors of the same class in the same side of the hyperplane. Support Vector Machines (SVM) are based on a bi-class system, where only two classes are considered. In particular for this work, we have worked on identification system, and for this reason, we have built a one-versus-all strategy for SVM, where the second class will consist of the rest of the classes, under closed mode (Bin et al., 2000). To express the similarity between biometric patterns, in our case palm-print modality, we have used the recognition rate. The higher the recognition rate, the better the system performance.

5 EXPERIMENTS AND RESULTS

In this section we have evaluated the response of three wavelet families for 50 and 144 users. Four images of each user are chosen randomly as training samples and the remaining six images are used to test the system. The results are shown in average (%) and typical deviation (std). Each test has been done 10 times using lineal and RBF SVM kernels, finding the result through a cross-validation strategy. The supervised classification has been carried out with SVM_light (Cortes & Vapnik, 1995). Figure 7 ilustrates the result after applying the 3^{rd} level of wavelet filter.

At this time, the extracted and filtered palmprint is reduced to different image sizes in order to get a faster system while the accuracy increases. Then, the image is introduced to the classifier in order to get the recognition rate. In figures 8 and 9 the performance rate of the *haar* wavelet according to size increase after applying the second and third filter levels for 144 users are shown.

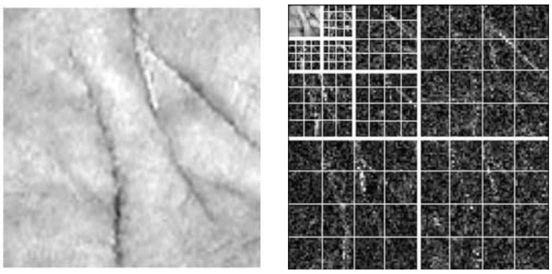

Figure 7: Left, the original palmprint. Right, palmprint factorization in the third wavelet level.

When the fourth level was applied to palmprints the recognition rate decreased considerably up to 84.14% ± 2.80 and 86.33% ± 1.33 with lineal and RBF classifier.

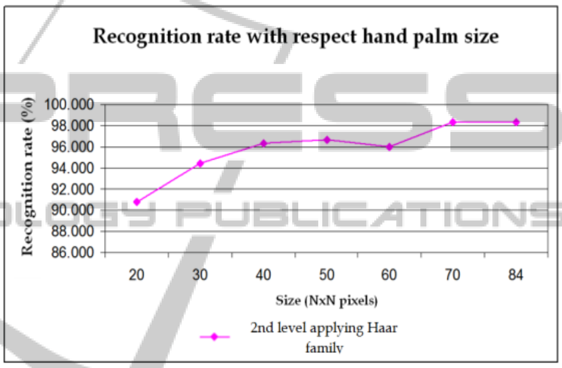

Figure 8: Identification rate for second level applying Haar wavelet: progress according to palmprint sizes.

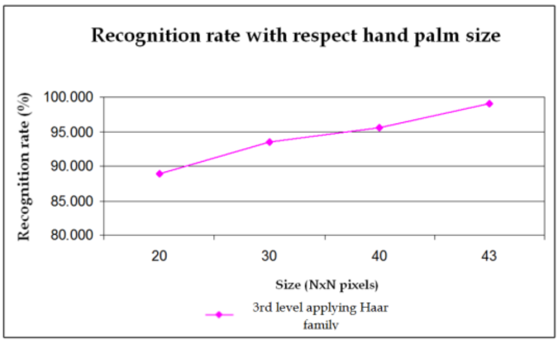

Figure 9: Identification rate for third level applying Haar wavelet: progress according to palmprint sizes.

Once the image is filtered, the higher the palmprint size the better the system recognition. This happens because important discriminative features are ruled out when the image is reduced to a small size. When the applied filter is daubechies5 or biortogonal5.5, the recognition rate progress is similar to haar filter. In Tables 2 and 3 the highest recognition rate with lineal and RBF kernels for 50 and 144 users and the three wavelet families are shown.

Table 2: Wavelet identification results for 50 users.

IDENTIFIER – 50 USERS		
Features	**Lineal Recognition Rate**	**RBF Recognition Rate**
Wavelet Haar 3 filters	99.33% ± 0.00	99.17% ± 0.06
Wavelet db5 3 filters	99.66% ± 0.22	99.50% ± 0.06
Wavelet bior5.5 3 filters	**99.83% ± 0.06**	**99.67% ± 0.22**

Table 3: Wavelet identification results for 144 users.

IDENTIFIER – 144 USERS		
Features	**Lineal Recognition Rate**	**RBF Recognition Rate**
Wavelet Haar 3 filters	99.54% ±0.01	**99.73% ± 0.03**
Wavelet db5 3 filters	99.54% ± 0.01	99.31% ± 0.12
Wavelet bior5.5 3 filters	**99.76% ± 0.01**	99.65% ± 0.02

According to tables 2 and 3, the recognition rate is similar regardless of database users' number, unlike other texture algorithms like derivative method. The best recognition rate for 144 users (99.76% ± 0.01) is reached with lineal kernel for biortogonal5.5 wavelet. This result is similar to 99.83% reached for 50 users. The third level of the low pass filter provides the suitable value of the texture to maximize the interclass relationship in order to get the large discriminative information. This is possible because it makes better use of the frequency-space resolution, and consequently the classifier is able to differentiate the users properly.

We can compare the wavelet performance with other algorithms applied to the same database (Travieso et. al 2011), as the derivative method, where if the number of users increases, the recognition rate decreases considerably (see Table 4).

Table 4: Comparison with other algorithms for 50 and 144 users.

IDENTIFIER – 50 & 144 USERS		
Algorithm	**Recognition Rate (50 users)**	**Recognition Rate (144 users)**
Wavelet Haar 3 filters	99.83% ± 0.06	99.76% ± 0.01
Derivative method	99.99% ± 0.01	99.46% ± 0.13
Gabor filter	99.66% ± 0.01	99.73% ± 0.02

In next section we will discuss about these results and the system performance. It will be also introduced the future work and possible improvements in our work.

6 CONCLUSIONS AND FUTURE WORK

In this paper, a deep study about the performance of wavelet transform in a biometric identification- system is shown. A recognition rate of 99.76% is reached using palmprint features of the users' hand.

The results depict the reliability of the filters due to the high rates obtained for the three wavelet families for 50 and 144 users. It makes the growth of the database possible independently the number of users, reaching similar recognition levels.

The hand palm texture extraction algorithm is intuitive, simple and quick, with a computational load similar to geometrical parameter extraction.

It is important to obtain the palmprint with the method explained in the section 2, with scale, rotation and translation invariance. It lets the classifier differentiate the users. Moreover, the proposed biometric feature is well adapted to the SVM classifier, which identifies the feature degree of simplification necessary for the best performance. This is very important for the system successful, and it happens for both 50 and 144 users.

A higher accuracy system could be built combining Wavelet transform with other texture algorithms or with geometrical methods. Fuertes et al., 2010, and Ferrer et al., 2007, proposed two studies about the performance of geometrical and texture methods were shown, demonstrating the improvement of the system when some algorithms were merged. It is possible to combine them at score or decision level, getting a safer and higher accuracy system respectively.

One drawback we have to mention it is the necessity of operating with clean hands. Painted or dirty hands would cause an identification mistake. In this case a combined geometric/palm biometric feature would be more advisable.

Many applications and algorithms have been proposed in the last years, but few of them are really used. Our future work is focusing on new 2D+3D technologies, and in the improvement of reliable algorithms which can be merged with other techniques, as face recognition. Specifically for this research line, it will be interesting a deep study about the stability of the wavelet algorithm for many users. It is not the same to test a system with 100 or 1000 users in order to get a system regardless of number of users. If the number of users is long and unknown, wavelet analysis can be an excellent technique to recognize people.

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