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MULTIMODAL BIOMETRIC SYSTEM FOR IDENTITY VERIFICATION BASED ON HAND GEOMETRY AND HAND PALM'S VEINS

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Abstract–This project was developed with the aim to implement a multibiometric system capable of handling hand palm images acquired using a touchless approach. This considerably increases the difficulty of the image processing task due to the fact that the images from the same person may vary significantly depending on the relative position of the hand regarding the sensor. A modular software tool was developed, providing the user a method for each of these steps: initial image preparation, the feature extraction, processing and fusion, ending with the classification, thus making the researcher's task much easier and faster. The biometric features used for identification include hand geometry features as well as palm vein textures. For the hand geometry data, an algorithm for determining finger tips and hand valleys was proposed and from there was possible to extract a handful of other features related to the geometry of the hand. The handpalm veins' texture features were extracted from a rectangle generated based on the hand's center of mass. The texture descriptor chosen was the Histogram of Gradients. In possession with all the biometric data, the fusion was done on feature level. Support Vector Machine technique was used for the classification. The database chosen for the development of this project was the CASIA Multi-Spectral Palmprint Image Database V1.0. The images used corresponds to the 940nm spectrum due to allowing the visualization of the hand palm's veins. The achieved result for the hand geometry was an EER of 4.77%, for the palm veins an EER of 3.11% and changing the threshold value a FAR of 0.50% and a FRR of 4.82% were achieved. For the fusion of both biometric systems the final result was an EER of 2.33% with a FAR of 1.30% and a FRR of 4.27%.

Keywords: biometry, hand geometry, palm veins, multimodal biometry, biometric system, support vector machines, histogram of gradients.

I. Introduction

The development of technologies to store and handle data in the digital world created the necessity for new mechanisms responsible for ensuring the safety and access controls for such operations. The most common mechanisms are the use of passwords and tokens. However, these mechanisms have proven insufficient to ensure the integrity of the user authentication process, either because the user doesn't follow a good security policy or because of the evolution of the hacking techniques. This raises the need for more secure authentication systems to protect the access to the data or the environment that contains it. It is possible to increase the security of the authentication process using biometry. Biometry is the science of establishing the identity of a person based on his physical, chemical or behavioral attributes [1]. A biometric system is defined as a pattern recognition system that operates acquiring biometric data of a person, extracting a set of characteristics and comparing them with a model in a database [1]. As these data are unique and inherent to the person, the task of hacking a system with biometric security proves itself difficult.

Some of the most recent work in hands multimodal biometric systems makes use of geometric attributes combined with tridimensional hand attributes as proposed by KANHANGAD[25] and the work of PARK and KIM [26] based on geometric attributes plus hand veins patterns.

II. Database

The image database CASIA-MS-Palmprint V1.0 [2] provided by the Institute of Automation, Chinese Academy of Sciences (CASIA). The database contains 7.200 images, acquired with a multispectral device. The resolution of the images is 72 dpi with 8 bits of grayscale levels and in JPEG format. Each one of the samples of this database has 6 images for both hands, for each one of the following electromagnetic spectrum: 460nm, 630nm, 700nm, 850nm, 940nm and white light. Fact that makes possible the extraction of one set of characteristics used in this project: the hand palm's veins patterns, acquired with the 940nm spectrum of the right hand only.

Working with touchless hand image acquisition devices is more comfortable for the user but by the other hand considerably increases the difficulty to extract the features compared to a hand fixed (such as pins) device. This is due to the fact that the variations for the same person can be significant as we may have distance, inclination and light variations, thus making it difficult to normalize the data and even leading to problems before this such as not being able to apply filters like

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image segmentation. Figure 1 depicts examples of bad positioned images.

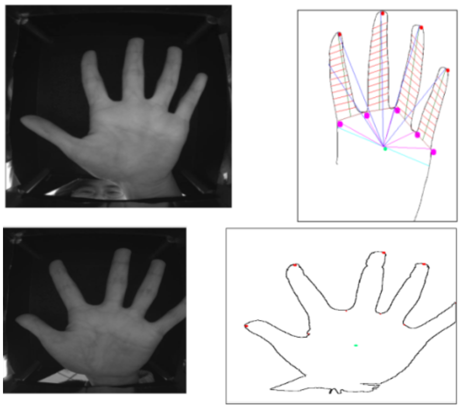

Fig. 1 – Challenges on processing images acquired through touchless devices.

Distance variations can be corrected applying a normalization method (like dividing all the attributes for the hand area or hand width). But in extreme cases (as the ones mentioned and illustrated on Figure 1) the image simply can’t be further processed and its characteristics extracted. The algorithm implemented for the geometric feature extraction tries to extract the maximum numbers of features possible. If this number is less than an established limit the image is discarded. Four images were discarded in this work.

III. Extraction of geometry characteristics set

The very first filter applied in the image was the thresholding. It is a widely used segmentation technique due to its simplicity, intuitive properties and low computational costs [3]. The Otsu [4] algorithm was selected due to the light variations on the images and it was the algorithm that handled this variety in a better way. For the border detection task, the Canny algorithm [5] was the one with best results, hence the one applied. Finally to extract the hand contour a blob filter provided by the AForge.NET image processing framework [6] was used.

After all the proper filters were applied and the contour extracted the next step was to detect the finger tips and the hand valleys. This was achieved with a proposed method that aims to divide the hand contour into 5 distinct regions. Each of these regions is defined by a pair of curves surrounding each one of the fingers. The points related to these curves were stored on a dictionary data structure which the key is a point representing the coordinate of the pixel and the value is the Euclidian distance between this point and the hand's center of mass. The dictionary of each one of the valley regions was ordered in a descending way so that the smallest distance is the center point of the valley and for the finger tips the very opposite logic was used, the points were ordered according to the longest distance from the hand's center of mass. These regions are shown on Figure 2.

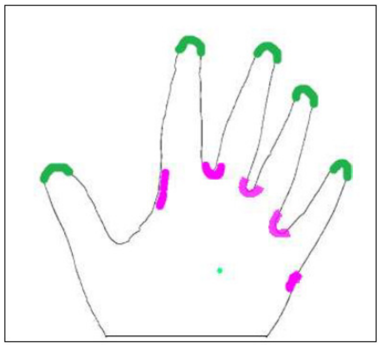

Fig. 2 – Algorithm implemented for the detection of hand valleys and finger tips. Finger tips regions on green color and valleys on pink color.

A total of 80 characteristics were extracted. They include: hand perimeter, hand palm width, distances between the fingers (base lines), Euclidian distance between the hand's center of mass and the finger's tips, as well each of the finger's valley. And for all the fingers except the thumb: 15 widths (maximum) and finger length. The Figure 3 depicts all these characteristics after the extraction algorithms were processed.

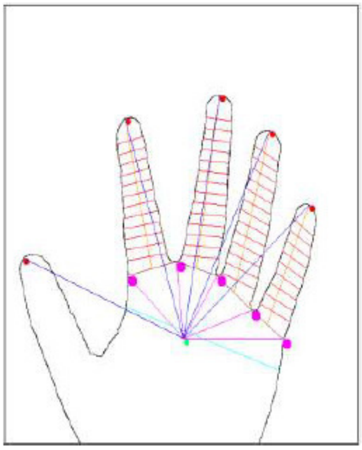

Fig. 3 – All geometric characteristics extracted.

IV. Hand palm's veins

In order to be possible to process texture, the definition of a Region of Interest (ROI) is necessary. There are plenty of methods for ROI extraction [7] including dynamic ones [8]. In the developed project, the ROI was extracted growing a rectangle from the hand palm's mass center until the maximum possible area could be extracted without extrapolating the hand palm area of all users. The resulting image was a 160x120 pixels rectangle that represents the hand palm's veins pattern as shown in Figure 4.

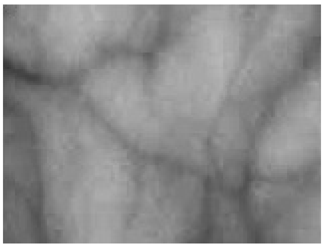

Fig. 4 – ROI of hand palm with its veins pattern.

Then the texture descriptor used was the Histogram of Oriented Gradients (HOG) introduced by DALAL and TRIGGS [9] and has been used for people detection with very good results. The HOG parameters used were 4x4 cells per block and 2x2 pixels per cell. The blocks and cells are depicted in Figure 5. The total amount of attributes generated for each hand palm image is an array of 3.780 float values for each window.

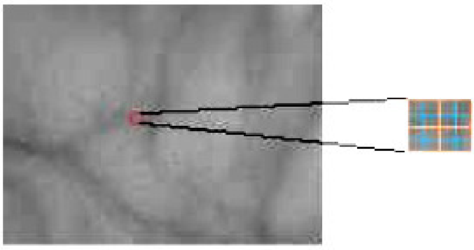

Fig. 5 – Representation of cells and blocks used in HOG texture descriptor algorithm.

On Figure 6 the representation of the veins can be visualized after a HOG texture descriptor is applied.

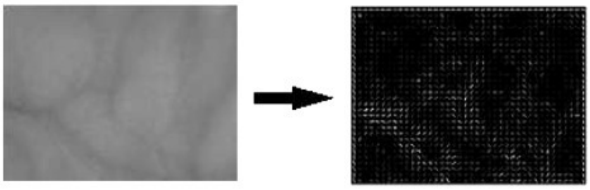

Fig. 6 – HOG representation of veins textures.

V. Fusion

The fusion process was done using the attribute level fusion method. As the geometric characteristics diverge in nature and scale from the characteristics acquired from the HOG descriptor before the fusion a normalization technique was applied. Two methods were tested: Z-Score and MinMax. The later was chosen because it achieved better results for machine learning data normalization [10]. The equation of this normalization is described below.

$$x_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \qquad (1)$$

After the data was normalized the fusion process is simple, just concatenate the two output arrays (from geometric attributes and the HOG descriptor output array) into one. For each one of the images a fused array was generated.

VI. Classification

The Supporting Vectors Machine (SVM) technique was chosen for the task of classification due to its good results regarding biometric patterns recognition. In order to achieve this, the library libSVM [11] was used together with Matlab.

Two distinct groups were created. One for training which had 500 images of 940nm from the right hand and the other group used for testing which had 100 images from the total of 600. This way for each user 5 images were used for training and 1 was used for testing.

Besides the recommended parameters from [11] the *c* parameter (that defines the size of the margin separating hiperplanes i.e. how much we want to avoid misclassification, the smaller the c parameter value the bigger the separating margin) was changed to 0.001. Also the kernel used for the current SVM implementation was the Radial Basis Function (RBF) kernel.

VII. Tests

While all the image processing and attributes fusion were done in the developed system for this project the classification was done solely in Matlab. There were 3 testing groups: geometry, veins and the fusion of both. For each one of them a Receiver Operating Characteristic (ROC) as well as False Acceptance Rate (FAR) x False Rejection Rate (FRR) curves were generated and important quality indicators of biometric systems like Equal Error Rate (EER) were calculated.

VIII. BiometricsLAB

A software was developed with the intention to concentrate all the tasks pertinent to image processing, feature extraction and data fusion in only one place. This will allow future researchers to save time by being able to do all these operations in only one software and to avoid doing those operations in different places. Also, BiometricsLAB was designed keeping in mind its extensibility and reusability so others can add to it new biometrics and new functions. It is reusable because the user can choose to use only parts of it or some of its libraries instead of use the system in its totality. The Figure 7 represents the main screen of BiometricsLAB available at [27].

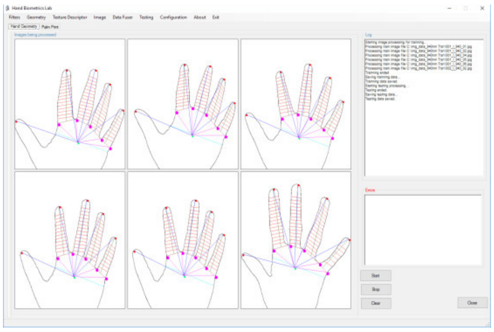

Fig. 7 – The main screen of the developed software: BiometricsLAB showing the processing of geometry hand biometrics.

IX. Results

The results for the hand geometry experiment can be visualized in Figure 7 and Figure 8.

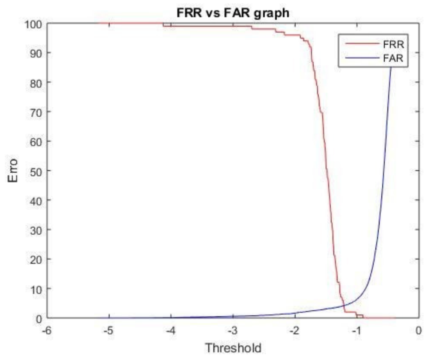

Fig. 8 – FAR x FRR curves for hand geometry biometric system.

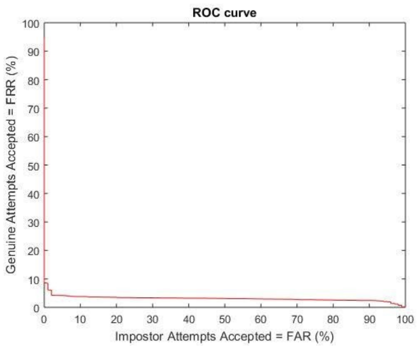

Fig. 8 – ROC curve for hand geometry biometric system.

The EER rate achieved was 4.77%. It's easy to notice that a slight variation on the threshold value it changes the system's performance significantly, thus making it unfeasible to choose security at the expense of a higher reliability.

The second experiment shows a little improvement compared to the first one. The Figures 9 and 10 depicts the performance of the hand palm's vein biometric system.

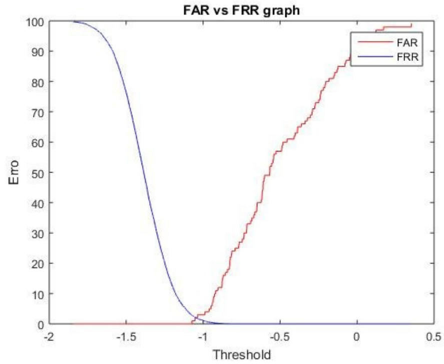

Fig. 9 – FAR x FRR curves for hand palm's veins biometric system.

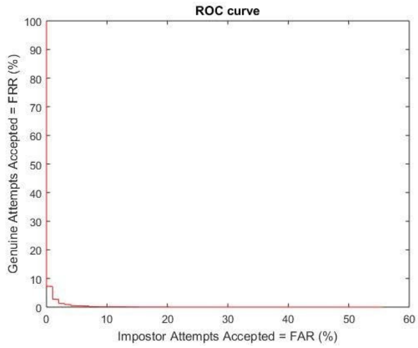

Fig. 10 – ROC curve for hand palm's veins biometric system.

For this experiment an EER rate of 3.11% was achieved which is clearly an improvement compared to the first one.

In the final experiment the multimodal biometric system proved itself more reliable and secure than both of the options that implemented only one biometry. After the fusion, the consolidated data that was generated and processed by the SVM produced even better results. These results are shown in Figure 11 and Figure 12.

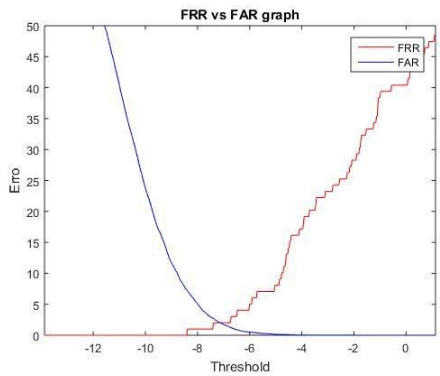

Fig. 11 – FAR x FRR curves for the multimodal biometric system (Geometry + veins).

An EER rate of 2.33% was reached and can be improved by changing the threshold obtaining this way rates for FAR and FRR of 1.30% and 4.27% respectively.

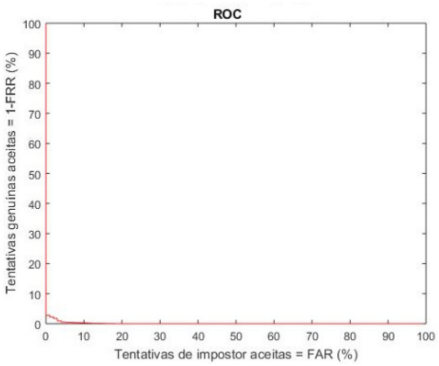

Fig. 12 – ROC curve for the multimodal biometric system (Geometry + veins).

X Discussion

Comparing the obtained results with recent works presented in Table 1, it is possible to notice that there are better results especially regarding the hand geometry.

Here it is important to mention the differences of how the images were acquired. CASIA [2] database makes use of a touchless method for data acquisition which makes it harder to process the feature extraction due to the high level of variance in the images of a same person (distance, angles, light, etc) while systems that make use of a support for this task do not have to deal with these problems.

Table 1: Recent works results

Author	Biometry	Succesrate(%)
Xin et al. (2011) [12]	Geometry	97.84
Guo et al. (2012) [13]	Geometry	96.23
Lee (2012) [14]	Veins	EER=0.44
Gangopadhyay et al. (2013) [15]	Geometry	96.67
Singh et al. (2014) [16]	Geometry	95.84
Abbas e George (2014) [17]	Veins	EER = 0.24
Wang et al. (2014) [18]	Veins	98.88
Elnasir e Shamsuddin (2014) [19]	Veins	EER = 0
Kang et al. (2014) [20]	Veins	EER = 0.996 e EER = 3.11
Yan et al. (2015) [21]	Veins	EER = 0.16

Although this work has reached good results there are some points to improve especially regarding the analysis of other types of ROI

XI. Conclusion

Looking to reduce the possibility of fraud in a system, the use of a biometric system is a viable alternative. By extracting the attributes from more than one source, the system becomes safer and less susceptible to successful hacking attempts, besides other benefits like enabling the inclusion of persons with physical limitations.

One innovation that can be stressed is the proposed method for extracting the finger tips and hand valleys. The algorithm produced very good results for the CASIA database, with 99% of successful extractions. Not only did it prove itself to be reliable and strong, but it also showed a good performance and low computational cost.

Another point, still regarding the hand geometry biometry, was the fail tolerant algorithm implemented in the feature extraction that allows obtaining the maximum number of features even when the image could not be processed completely. If the quality of the image is too low (due to noise factors) to the point that affects the extraction of canon features (like palm width, finger lengths, finger tips, etc) the algorithm will then discard the image.

The hand palm's veins biometric system was implemented with a different method from the ones used so far, the Histogram of Oriented Gradients, which has been successfully used for people recognition [12]. The HOG texture descriptor obtained good results when used for the veins textures as the results obtained proved.

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