ABSTRACT

Accurate protection systems capable of replacing the traditional passwords and ID cards are essential, for commodity and for security reasons. A hand-vein pattern recognition system is just one of a vast group of biometric techniques under research, in order to become the reference recognition system.

This paper presents a hand vein biometric recognition system that uses the hand blood vessels pattern to identify an individual. All biometric systems have an immense application potential, as they present advantages over the traditional identification systems. They are able to work with patterns that are very hard to duplicate, since they are different from person to person, and it is also impossible to lose or forget them, since the biometric characteristics are intrinsically attached to the human body.

The developed approach was created with the intent of providing an effective protection system despite having been designed and implemented using inexpensive hardware, in comparison with the biometric recognition systems presently offered at a commercial level. The results show that a reliable system can be produced at a low cost and can be used standalone or in combination with other systems.

Keywords

Hand-based biometrics, biometrics recognition, palm veins, hand geometry, palm vein acquisition system, palmprint, web-camera.

1. INTRODUCTION

Nowadays, we can access our personal data from almost everywhere. This is very convenient but entails increasing risks since the probability of phishing credentials increases with the number of users. More sophisticated protection systems are required to control possible harassments, like ID cards cloning, theft or compromised passwords.

When thinking about digital protection, one which immediately comes to mind is the use of passwords and smart cards, since they are used daily for almost everything. Despite being used very frequently, passwords and smart cards are a relatively insecure method of protection and access control.

2. DIFFERENT BIOMETRIC RECOGNITION SYSTEMS

There are several approaches that exploit the hand biometric characteristics to identify an individual. Mauricio Ramalho [2] in his palmprint recognition system used an operating point that achieves 9.5% for the False Reject Rate (FRR), 0.1% for False Accept Rate (FAR) and 3.29% for the Equal Error Rate (EER) using an expensive camera.

Nuno Moço [3] in his palmprint recognition system for cellphones used an operating point that achieved 9.87% of FRR and 0.03% of FAR with an EER of around 5%.

Huan Zhang and Dewen [1] on theirs hand vein recognition system achieved an EER of 1.82% with an AD-080CL camera that costs around 3000€.

3. PROPOSED HAND VEIN RECOGNITION SYSTEM

The proposed biometric recognition system is unimodal and uses the hand vein pattern as the biometric trait. The architecture of the developed system is presented in Figure 5. It includes the
following main modules: image acquisition, pre-
processing, feature extraction, matching and decision. 
The following paragraph gives a summarized 
description of the approaches taken.

To do the image acquisition in the developed system a 
modified low cost camera is used. After the image 
acquisition the captured image is resized in order to 
reduce the required computational power, turning the 
pre-processing less demanding and consequently 
saving processing time. After resizing the acquired 
image, is preprocessed in order to reduce the amount 
of noise. The detection of the region of interest is 
obtained through some reference points in the hand 
contour. The feature extraction and template creation 
sections are based on the Orthogonal Line Ordinal 
Features (OLOF) [4] technique. The OLOF method 
turns the veins representation robust against 
illumination variations. It also makes the matching 
stage effortless since the dissimilarities between two 
palmprints can be measured through the differences in 
the binary bits from the two templates with a simple 
XOR operator, which can be computed almost 
instantly.

3.1 Image Acquisition

The image acquisition module developed for this 
dissertation uses a low cost (around 20€) webcam 
(Logitech QuickCam Pro 9000) that is installed in a 
special assembly (see Figure 1), in order to operate in 
controlled illumination conditions. Since the system 
performs recognition based on vein images, the 
illumination is obtained using 15 near IR leds (OSRAM – SFH4550). The box is a cube with 26 cm side. The 
top of the box was painted black in order to reduce the interference instigated by the visible light coming from 
the exterior of the assembly.

In order to be able to capture the near infrared light, 
necessary for the vein acquisition, the low cost web-
camera requires the removal of the infrared filter that 
is placed behind the lens, as illustrated in Figure 2.

The main problem associated with the removal of the 
IR filter is that the auto-focus functionality of the web-
camera becomes damaged, which turns the capture 
of good quality images at long distances impossible. 
This problem won't affect the image acquisitions of 
the developed system since they are captured from a 
small distance.

As the camera needs to detect only infrared light, a 
visible filter has been applied. An old fashioned 
photographic revealed film was used for this purpose, 
as shown in Figure 3.

After removing the IR filter in the back of the lens and 
assembling the visible light filter in front of it, the 
camera is ready to do the acquisition of near infrared 
images, Figure 4.
3.2 Pre-processing

The pre-processing stage prepares the image for the feature extraction phase. This is obtained through several stages: image adjustment, filtering, segmentation, contour detection, key point's detection and region of interest extraction, as represented in the architecture illustrated in Figure 6.

The first step of the pre-processing stage is image adjustment. During this step the raw image is resized from 240x320 to 192X256, in order to reduce the computational power required through the process. After resizing the raw image, the color space is converted from rgb to grayscale since the luminance information is enough for the image segmentation—see Figure 7.

The second step of the pre-processing chain is the filtering, used to reduce the noise of the image and to smooth the areas with little variance. This is obtained using a Wiener filter, see Figure 8.

The third module performs image segmentation, where the image is segmented into foreground and background through a pre-defined threshold. Thresholding is a very fast way of identifying the hand using the contrast with the black background. After thresholding the image it is converted to binary. One example of a segmented image obtained is depicted in Figure 9.
The segmented image is the input of the contour detection algorithm [5]. This algorithm chooses a random starting point in the hand boundary and then searches for all the boundary pixels. The contour is essential for identifying the region of interest and the reference points. The hand contour can be seen in the Figure 10.

The key point’s acquisitions are obtained through the combination of two different techniques, the radial distance to a fixed point and the contour curvegram. Both methods identify the fingertips and the valleys between the fingers.

The radial distance to a fixed point technique calculates the Euclidean distance between every contour pixel and a fixed point, which is the middle point of the region where the wrist crosses the image edge.

The contour curvegram analyzes the intensity of the curvature along the contour, and can be constructed by using a technique called difference-of-slopes [6]. The two methods have their benefits and drawbacks, but together they create a stronger set of reference points. The radial distance to a fixed point is the first technique used in order to get an approximation of the final reference points. After obtaining the raw key points, the contour curvegram is used around the obtained locations. The final obtained positions are the final fingertip and finger-valley locations.

In order to obtain a good location of the fixed point, to be used in the radial distance method, an ellipse (Figure 11) with the same normalized second central moment as the hand region is drawn. Through the hand contour input, the ellipse’s parameters like the major and minor axes, center position, end-points and lengths, orientation (given by the angle between the major and minor axes) are calculated.

After obtaining the parameters that define the ellipse, it is necessary to find out in which side of the minor axis the wrist is located. This verification is obtained through the counting of the contour points that lie on each side of the axis. The wrist is located on the side with fewer points. Knowing the axis' side on which the wrist lies, the fixed point (Figure 12) in the wrist is defined as the intersection point between the major axis and the edge of the image.

The additional reference points, represented as yellow dots in the Figure 13, are necessary to extract the palm’s region of interest. These additional reference points are determined by discovering, the thumb, index and pinkie fingers.

The final set of hand reference points, is composed by the five fingertips, the four finger valley and the three additional reference points.
After finding the reference points, the square that represents the ROI is obtained, Figure 14. The square position is defined through a line segment that is drawn between the index and the pinkie finger. Different hands will create squares with different sizes and orientations that will need to be normalized for matching purposes. In order to do the standardization the ROI is rotated to a vertical position and resized to a standard dimension. The standard ROI dimension chosen is 128x128 due to the results that will be presented in the performance evaluation section. Decreasing the dimensions would reduce the computational effort but would also reduce the detail of the image. After the rotating step the image is binarized and filtered and then a thinning method is applied in order to thin and repair the vein line. The ROI treatment step can be seen in the Figure 15.

Figure 15 - ROI treatment steps.

After being thinned the standardized ROI is converted into a vector consisting in luminance values. Through the reference points illustrated on Figure 16, the value of 35 hand geometry characteristics will be calculated in order to provide the geometrical information of the hand. The characteristics used are the finger widths (20), perimeters (5) and lengths (10). After acquiring the 35 hand geometry characteristics, a mean of the 35 values is calculated. This mean summarizes the geometrical information of the hand, so each user in the database will have one mean associated. At the identification stage, the mean of the recently acquired template under identification will be compared with the remaining geometrical information (means) of the previously acquired data in the database. Instead of comparing templates randomly, the most probable will be compared first. The most probable users will be the ones that have similar hand geometry. If the vein pattern under identification does not fit the one from the user with the most similar geometry, the algorithm searches the next most similar and so on, until finding the one with the same vein pattern. The delay obtained by calculating the hand geometry characteristics is almost irrelevant, due to the simple calculations required. The geometry similarity is not crucial for a positive matching, but helps sorting the most probable hands.

Figure 16 - Reference points used to calculate the hand geometry characteristics values.

3.3 Feature Extraction

The feature extraction module will output the biometric template, which will be used in the matching stage. The feature extraction technique used in the developed system is the Orthogonal Line Ordinal Features (OLOF) [4]. The one-dimension vector obtained in the preprocessing module will be the input of the OLOF method that will generate a one bit feature code that is going to be the template stored in the database. The OLOF approach uses a 2D Gaussian filter to acquire the weighted average intensity of a line-like region, equation (1) [4].

\[
f(x,y,\theta) = e^{-\left(\frac{(x-x_0)\cos(\theta) + (y-y_0)\sin(\theta))^2}{\delta_x^2}\right)^{\frac{1}{2}} \left(\frac{(x-x_0)\sin(\theta) - (y-y_0)\cos(\theta))^2}{\delta_y^2}\right)^{\frac{1}{2}}} \tag{1}
\]

In equation (1), \(\theta\) symbolizes the orientation of the 2D Gaussian filter, \(\delta_x\) the filter’s horizontal scale and \(\delta_y\) the filter’s vertical scale. Equation (2) represents the orthogonal line ordinal filter, designed to compare two orthogonal line-like palmprint image orientations for the same region [4].

\[
OF(\theta) = f(x,y,\theta) - f(x,y,\theta + \frac{\pi}{2}) \tag{2}
\]

The filtering of the ROI is accomplished using three orthogonal line ordinal filters through three different orientations (\(\theta\)), in this case: \(OF(0)\), \(OF(\frac{\pi}{6})\) and \(OF(\frac{\pi}{2})\). The filter parameters used were \(\delta_x = 9\) and \(\delta_y = 3\). The filter is centered at \((x_0, y_0) = (17,17)[4]\).
The output of the feature extraction phase using the OLOF extraction method are three bit ordinal codes based on the sign of the filtering results, (Figure 17).

![Figure 17 - OLOF output in the three directions, $\theta = \frac{\pi}{6}, \theta = \frac{\pi}{3}$ and $\theta = 0$.]

3.4 Matching System

A successful or unsuccessful recognition of an individual is based on the calculation of the bitwise Hamming distances of the recently acquired template and all the others in the database. The Hamming distance between two vectors is the number of coefficients in which the corresponding symbols differ. If two vectors are exactly equal the Hamming distance will be zero. To calculate the Hamming distance a bitwise XOR operator is used. The validation or refusal of the matching is defined by a predefined threshold.

4. EXPERIMENTAL RESULTS

The experimental results of the developed biometric system are evaluated by the Receiver Operation Characteristic (ROC) curve which plots the FAR against the Genuine Accept Rate (GAR) (or 1-FRR) and by the Equal Error Rate (EER), which is defined as the error rate when the FAR and the FRR are equal.

A recognition attempt might have the following results:

<table>
<thead>
<tr>
<th>Type of user</th>
<th>Match</th>
<th>Non-Match</th>
</tr>
</thead>
<tbody>
<tr>
<td>Genuine</td>
<td>Correct Accept</td>
<td>False Reject</td>
</tr>
<tr>
<td>Impostor</td>
<td>False Accept</td>
<td>Correct Reject</td>
</tr>
</tbody>
</table>

Table 1 - Possible recognition attempts results.

4.1 Test Conditions

In order to test the performance of the developed system, the first step was to create a hand palm vein database containing 30 registered people. For each person, five different acquisitions from each hand were performed. For the testing purposes each hand is considered as a different user. 30 registered people represent 300 different templates.

4.2 Performance Evaluation

The system performance was tested using the database mentioned above, using a ROI size of 128x128 and the features were extracted with the OLOF technique.

The obtained ROC curve is shown in the Figure 18. The ROC curve is near the perfect point (0,100) which shows the good matching performance of the system. The ROC curve and the table show that GAR is near 85% when the FAR is 0%.

For applications like opening doors for non-high secure areas values of FAR above 0% can be used despite the slope suggesting that there is no benefit on using an operating point that has a GAR above 85%.

For ATM machine operations the FAR must be around 0% so values of GAR around the 85% or inferior are mandatory.

![Figure 18 - Receiver Operation Characteristic curve for a ROI with 128x128 pixels.]

An alternative way of evaluating the performance of a biometric system is through the EER. A low EER means that is possible to get both low values of FRR and of FAR and thus the lower the EER, the better the performance is. Despite being a good reference point, the EER might not be the ideal operating point for a given system. The system might require a lower FRR or FAR for special application conditions. A system that requires high security conditions like the ATM machine will require a really low FAR which will possibly imply a higher FRR.
Figure 19 shows the FAR and FRR curves produced as functions of the threshold. The figure shows that when the threshold value increases the FRR decreases and the FAR increases. The figure also shows that if the threshold is lower that 40% the FAR is near zero. Through the figure it is perceptive that the EER of the developed system is near 9% and the associated threshold is about 45%.

![Figure 19](image1.png)

**Figure 19 - FAR and FRR at different operating thresholds.**

In order to test which ROI size should be used, three ROC curve were created. The three sizes tested were, 32x32, 64x64 and 128x128 pixels. The obtained result is depicted in the Figure 20.

![Figure 20](image2.png)

**Figure 20 - ROC curve for different ROI dimensions.**

From the Figure 20 is obvious that the ROI size of 128x128 pixels and 64x64 obtain the best results in terms of matching. The ROI size of 32x32 pixels clearly underperforms both in the ROC curve as well in the EER (see Figure 21).

![Figure 21](image3.png)

**Figure 21 - FRR (%) against FAR (%) to obtain EER for different ROI dimensions.**

The ROI size chosen was 128x128 pixels due to the better matching performance.

### 4.3 Operating Point

The operating point used depends on the application. It must be chosen taking into account the system recognition performance and his security. The developed system can be used on several applications, like ATM machine operations, opening doors or even to unlock a computer.

<table>
<thead>
<tr>
<th>Threshold(%)</th>
<th>FAR(%)</th>
<th>FRR(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>35</td>
<td>0,000</td>
<td>19,667</td>
</tr>
<tr>
<td>35,5</td>
<td>0,002</td>
<td>18,833</td>
</tr>
<tr>
<td>36</td>
<td>0,009</td>
<td>18,167</td>
</tr>
<tr>
<td>36,5</td>
<td>0,011</td>
<td>18,000</td>
</tr>
<tr>
<td>37</td>
<td>0,020</td>
<td>17,500</td>
</tr>
<tr>
<td>37,5</td>
<td>0,038</td>
<td>16,167</td>
</tr>
<tr>
<td>38</td>
<td>0,072</td>
<td>15,167</td>
</tr>
<tr>
<td>38,5</td>
<td>0,113</td>
<td>14,667</td>
</tr>
<tr>
<td>39</td>
<td>0,199</td>
<td>14,000</td>
</tr>
<tr>
<td>39,5</td>
<td>0,337</td>
<td>13,833</td>
</tr>
<tr>
<td>40</td>
<td>0,508</td>
<td>13,333</td>
</tr>
</tbody>
</table>

**Table 2 - Values of FAR and FRR for different operating points.**
5. CONCLUSIONS

This paper presents a unimodal biometric recognition system that used the hand vein patterns to do the identification of an individual. It was developed in Matlab and implemented to work on a Windows operation system.

The developed system has proved to have several operating points that can be used in different scenarios. In addition it has the advantage of being a low-cost, requiring an investment around 50€, and is simple to assemble.

The EER of the developed system is near 9%. The ROI dimension used is 128x128 pixels due to the best matching results during the tests. The OLOF templates dimensions used is 32x32.

REFERENCES


