Hand Recognition using Texture Histograms
A Proposed Technique for Image Acquisition and Recognition of the Human Palm

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Abstract: This paper presents a technique for biometric identification based on image acquisition of the palm of the human hand. A computer system called Palm Print Authentication System (PPAS) was implemented using the technique exposed, it identifies human hand palm by processing image data through texture identification and geometrical data by employing the Local Binary Pattern (LBP) method. The methodology proposed has four steps: image acquisition; image pre-processing (normalization), and segmentation for biometric extraction and hand recognition. The technique has been tested utilizing 50 different images and the tests have proven promising results, showing that the approach is not only robust but also quite efficient.

1 INTRODUCTION

Biometrics refers to individual recognition based on biological and behavioral traits. Recently, this technology has been widely adopted. Due to the market expansion, private and corporate investments, research in this technology no longer relies on government support and costs related to this technology have been decreased.

Today, researches present several interesting ways of biometric identification using the human hand. For instance, (Khan and Khan, 2009) proposed user identification and authentication by mapping blood vessels obtained from infrared techniques. Similarly, other studies employ hand geometry, applying geometric calculation in the hand shape as source of biometric data. Additionally, several forms of image acquisition devices, such as scanners, digital cameras and CDC cameras are available today, simplifying the adoption of biometric identification by human hand images. However, by analysing studies regarding palm fingerprints, it is clear that the hand position is a crucial factor to consider while acquiring an image that permits biometric identification. For example, (Li et al., 2009) propose extraction of images from the region of interest (ROI), showing that geometric calculation makes it possible to extract data from the hand palm with any placement of the fingers or hand rotation.

In the same way, a research from (Bakina, 2011) implements an application using a webcam for image acquisition and considers that images from fingers can be captured together or apart, with no restriction on hand rotation. This uses key points as biometric data, extracting them from the top of the fingers to end of the wrist, in a circular pattern of a binary image; this technique has an accuracy check of 99% with high false acceptance rate (FAR). Also, the low FAR is 0% when the system becomes bimodal by combination of voice features.

Also, in the study conducted by (Jemma and Hammami, 2011), first the image is represented in binary format and then hand contour is used as a reference. After a Euclidian method is employed for extracting the ROI. This technique divides the palm in subregions to discover regions with more un-continuous data. In order to extract the features, the LBP method is used the identified regions, which has shown satisfactory identification performance and saves store space.

Furthermore, in the system proposed by (Ribarc, 2005), a scanner captures the hand image with no restriction on its position, making the system easier for its users. This implementation also increases the system efficiency by turning it in a multimodal system employing both the hand palm and fingers as biometric data.

In addition, according to (P.K. and Swamy, 2010), for people recognition, single mode systems are more profitable, but less efficient. Therefore, multimodal

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systems (Ribarc, 2005) have a higher accuracy rate, reaching up to 100% rate. Although, the results obtained by (Kumar and Shen, 2003), using only the hand palm as biometric data was able to reach a success rate of 98.67%. Another remarkable research was conducted by (Wu et al., 2004), it proposes a method without biometric recognition, but using the classification of the lines from the hand palm and was able to obtain 96.03% of accuracy.

Likewise, this work proposes a tool for extracting biometric data from the palm of hand, using image processing techniques and a protocol to acquire the images. This protocol is explained in section 2. Then, sections 3 and 4 present the methodology with the techniques and results obtained from the tests. Finally, conclusions are presented in Section 5.

2 IMAGE ACQUIRING PROTOCOL

To validate the algorithms and techniques exposed, the presented work employed a hand-made device designed to acquire images from hands.

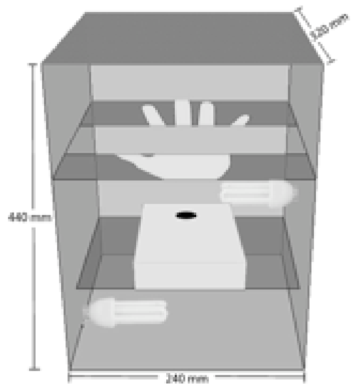

Figure 1: Device diagram with camera and lamps.

Furthermore, the proposed algorithms were implemented in C programming language using the Open Source Computer Vision Library (OPENCV, 2011), an open source computer vision and machine learning software library built to provide infrastructure for image processing applications. Additionally, the designed device accessed a camera connected to a personal computer.

The device case was assembled in medium-density fiberboard (MDF), an engineered wood product popularly used in furniture. It consisted in a 240 mm x 440 mm box, 320 mm depth, containing a 5-megapixel webcam and two compact fluorescent lamps of 5 and 7 watts, to produce stable light source and avoid shadows, brightness and contrast variation. To use the device to capture images, the hand must be placed on the delimited area in the upper side of the device (see Figure 1). After that a bitmap (.bmp) image is captured in RGB scale with 640 x 480 pixels of resolution.

The following rules were defined to capture images:

a) The distance between the camera and the hand should not change as empirical tests show that it affects texture recognition,

b) The device must be closed so its light sources can produce enough light to avoid variance in the image due to the external light,

c) The camera needs predefined settings to avoid changes due to automatic adjustment,

d) Considering that every camera has distortion, it is fundamental to use a reference (as the delimited area on the top of the device) and

e) The image captured must be oriented vertically and needs to present part of the fingers. These must be apart, as shown in Figure 2.

Figure 2: Original image obtained from the device.

3 METHODOLOGY

The methodology can be described in the following steps: first, the image acquisition step is responsible for capturing the image through the device, then pre-processing techniques use several pre-processing approaches to obtain the hand boundaries using mathematical morphology.

Afterwards, techniques to locate the reference points take place. Next, the located reference points are used to normalize the image. After, geometric data is extracted to and then hand texture based on the region of interest can be read. Finally, textures are compared based on techniques and methods to compare the texture histograms.

3.1 Image Acquisition

To ensure the efficacy of the algorithms implemented, the image must be acquired following the image acquiring protocol presented in section 2. In addition, the time spent by the device to capture each image was 0,001 second.

3.2 Pre-processing Techniques

This step presents methods to obtain the hand boundaries, which will be used to locate the reference points, normalization and to acquire geometric data. To accomplish it, initially the image is converted into grey scale, then a $19x19$ smoothing Gaussian filter (Figure 3) is applied to improve the outline definition during its binarization process and to reduce noise that could prevent contour identification.

Figure 3: Grey scale image with Gaussian filter.

Further, the image can be transformed in a binary image employing Otsu's method (Otsu, 1979), then active pixels (white) represent the palm while inactive pixels (black) represent the background as shown in Figure 4.

Figure 4: Otsu image.

In figure 4, it is possible to notice that the image edges are well defined, this effect is attributed to the proposed low-pass filter. Next, mathematical morphology operations (Gonzalez and Woods, 2007) (Facon, 1996) are used to identify the image contour. To accomplish it, a morphological dilation process is applied to the image using a $3x3$ cross-shaped structuring element. Second, a morphological erosion process is applied, also using a $3x3$ cross-shaped structural. Finally, to detect the contour, a XOR logical operator is used between the resulting images as shown in Figure 5.

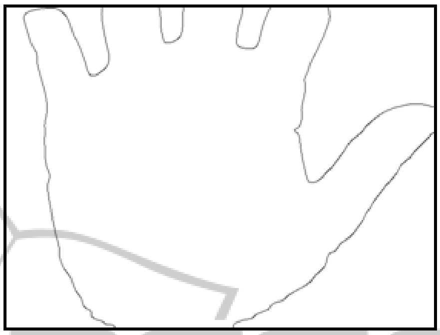

Figure 5: Palm contour.

3.3 Reference Point Technique

Now is presented a technique to identify statistically stable reference points used during the image normalization, to accomplish it, an algorithm scans the hand contoured image from the top until find the first line where 8 intersection points from the fingers can be found, as shown in Figure 6.

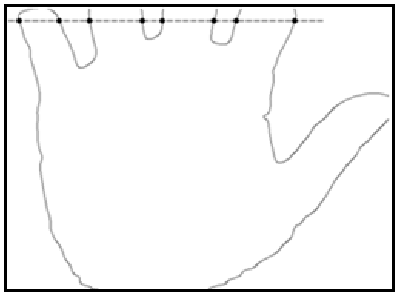

Figure 6: Identify points intersecting with fingers.

Next, it is necessary to identify the midpoints (Ma, Mb, Mc) between the fingers, starting from the initial line as reference as shown in Figure 7.

After the reference points can be found in the longer distance between them and the midpoints (Ma, Mb, Mc) as illustrated in Figure 8.

Although, a better understanding of the solution is necessary once the reference points (A, B, C) do not always exist, they can vary depending on the hand position or characteristics. In addition, stabilizing the reference points using only the longer distance criteria (Ojala et al., 2002) was not efficient in this work. From the 50 tested images, 23 had a considerable variation in their position. To circumvent this issue,

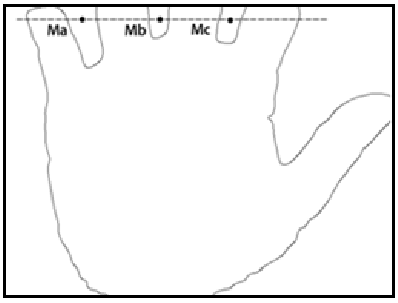

Figure 7: Midpoints identification.

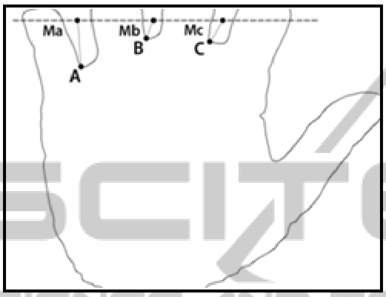

Figure 8: Reference point identification.

was used an algorithm that measures the longer distance from the midpoint until the finger curve, using a $1x3$ mask that scans the finger curve and moves down a 1 pixel for each distance measurement and stops when no pixel from the contour can be detected in this mask. This way, point stability (A, B, C) is ensured. The mask action is shown in Figure 9.

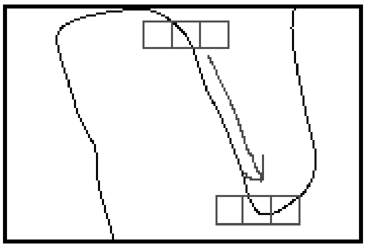

Figure 9: Identification from point to curve using a mask.

This method presented stability in all images tested. Besides, it is worth to mention that the algorithm has shown to be efficient even when applied in 10% of the images photographed wearing a ring.

3.4 Image Normalization Technique

Once the reference points are identified, the image normalization can be performed. After image normalization, it is possible to extract the geometric data.

To perform normalization, a right triangle is represented from points A, C and D. Its segments CD and AD length determine the angle (a) using arctangent from CD and AD ratio. Then the grey scale image (without Gaussian filter), is inverse-rotated from point A to be normalized, as shown in Figure 10.

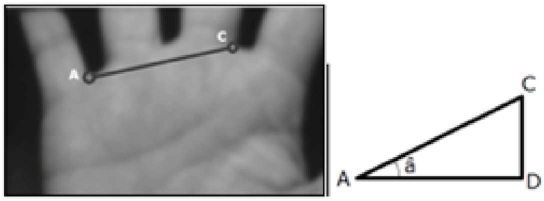

Figure 10: Identification of the Inclination skew.

Figure 11: Normalized image.

Next, the algorithm used to find the reference points must be re-applied. Its important to notice that if there is variation greater than 3 pixels in point A in images from the same source, the procedure will not work properly. The Figure 11 shows normalized image.

3.5 Geometric Data Acquisition Technique

This section presents statistically stable geometric data, which can be used in a biometric recognition system.

After acquiring the contour from the normalized image, 3 stable geometric data are available: the hand width (EF segment), the distance from points A to C and the distance from point B to segment AC. Defining X as half of the segment AC length, the line EF must have X pixels length and be projected below the segment AC (see Figure 12).

Moreover, the geometric measures selected demonstrated to be efficient discrimination criteria in the 50 images used in the tests. A set of 10 different people was selected, as a result, a test executed with 5 images per person displayed great stability, with less than 5-pixel variation. It is important to notice that finger width was not considered due to wide variation range found during the tests in images with rings, finger swelling or other finger size variation.

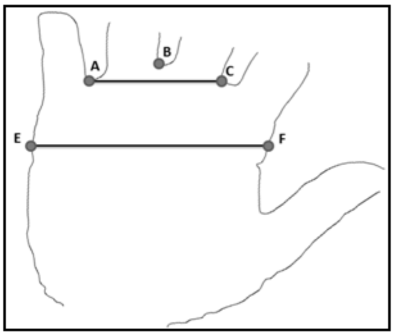

Figure 12: Geometric data.

3.6 ROI Acquisition and Texture Extraction Techniques

Here is suggested a region of interest (ROI) employed to extract hand texture characteristics applying a technique to obtain the texture with histograms resulted from the Local Binary Pattern (LBP) processing. The LBP is an operator, proposed by (Ojala et al., 1996) (Ojala et al., 2002), which describes bi-dimensional textures by using its spatial patterns and greyscale contrast. This operator assigns binary values to the pixels of an image by thresholding the neighbors of every pixel that configures the image. A resulting binary sequence is then used to create a histogram that can be used to classify or analyze the texture. Then, to define the ROI using the LBP operator, it is necessary to draw a square with side L, where L is equal to segment AC length, as shown in Figure 13.

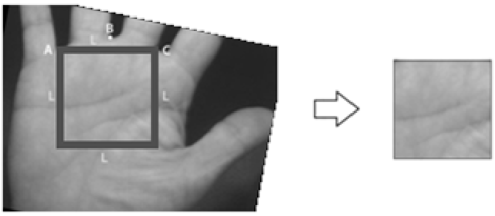

Figure 13: Extracting the ROI.

After finding the ROI, the hand texture data is extracted by applying the LBP descriptor. Additionally, to execute the LBP, the ROI must be divided in a $3x3$ matrix as illustrated in Figure 14.

The LBP application result in the histograms concatenation and each histogram is an element from this matrix. Afterwards, the data is stored in a vector with 2304 positions (256 for each square). The relevant characteristic in this procedure is that no features are selected during LBP execution.

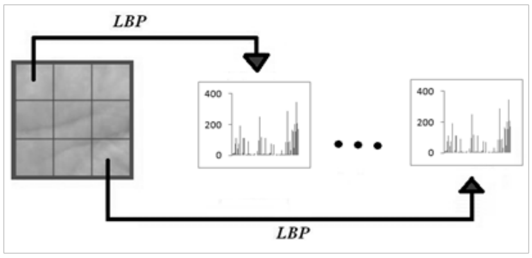

Figure 14: ROI divided for LBP application.

3.7 Texture Comparing Techniques

This section explains approaches to compare the texture histograms stored in the concatenated histograms vector explained before. First, images are selected from an image database for online recognition. Then, the comparison is done employing Chi-square distribution method in the LBP histograms of the selected images. To use point-to-point comparison in the histogram vector Chi-square distribution method needs a threshold. To define it, a considerable quantity of images either from the same as from different individuals are essential. This ensures that the FAR rate (false-positive recognition) is almost eliminated.

4 RESULT ANALYSIS

This experiment used 30 images from different individuals to test the recognition operation through the proposed methods and a previously registered image was used to test the comparison. First, the images are compared employing the Chi-square distribution. As shows Figure 15, the position 26 indicates that the system correctly identified the person with 2546 features, using a LBP texture comparison.

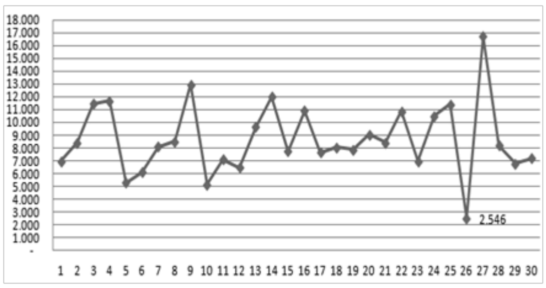

Figure 15: Results from Chi-square identification method.

To Chi-squares comparison, the threshold was previously defined as 2900. As shows Figure 15, position 26 indicates that the system correctly identified the individual with 2546. Besides, no other individual had a comparison less then 2900, indicating a correct operation of the system.

The FAR and FRR rates tested are zero, once no false acceptance or rejection could be found.

5 CONCLUSIONS

In conclusion, the results presented in the paper show that it is possible to implement a biometrical recognition system using human hand palm images acquired by simple low-cost devices. Further, although the presented technique analysis would be certainly improved by using a larger image dataset, the initial analysis evidences promising results with a reduced number of images. Thus, increasing the size of the testing image collection is evidently the next step to continue assessing the system performance and its accuracy as well as compares it to methods adopted by similar systems.

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