Biometric analysis of the palm vein distribution by means two different techniques of feature extraction

R. Castro-Ortega[a], C. Toxqui-Quitl[a], J. Solís-Villareal[b], A. Padilla-Vivanco[a] and J. Castro-Ramos[c] .

[a]Universidad Politécnica de Tulancingo, Ingenierías 100, 43629 Hidalgo, México.
[b]Universidad Autónoma del Estado de México, Instituto Literario 100 Col. Centro, 50000 Estado de México, México.
[c]Instituto Nacional de Astrofísica, Óptica y Electrónica, Calle Luis Enrique Erro No. 1, 72000 Puebla, México.

ABSTRACT

Vein patterns can be used for accessing, identifying, and authenticating purposes; which are more reliable than classical identification way. Furthermore, these patterns can be used for venipuncture in health fields to get on to veins of patients when they cannot be seen with the naked eye. In this paper, an image acquisition system is implemented in order to acquire digital images of people hands in the near infrared. The image acquisition system consists of a CCD camera and a light source with peak emission in the 880 nm. This radiation can penetrate and can be strongly absorbed by the desoxyhemoglobin that is presented in the blood of the veins. Our method of analysis is composed by several steps and the first one of all is the enhancement of acquired images which is implemented by spatial filters. After that, adaptive thresholding and mathematical morphology operations are used in order to obtain the distribution of vein patterns. The above process is focused on the people recognition through of images of their palm-dorsal distributions obtained from the near infrared light. This work has been directed for doing a comparison of two different techniques of feature extraction as moments and veincode. The classification task is achieved using Artificial Neural Networks. Two databases are used for the analysis of the performance of the algorithms. The first database used here is owned of the Hong Kong Polytechnic University and the second one is our own database.

Keywords: Biometric analysis, feature extraction, Artificial Neural Networks, vein patterns

1. INTRODUCTION

Nowadays systems employed for people recognition have been based its performance in digital sensors. These devices can acquired information from personal identification numbers (*PIN's*), smart card, passwords, keys, and so forth. These methods of identification give users limited security because they can be easily violated[3,9,13,14]. Other devices use physiological or behavioral people characteristics for identification purposes. These characteristics are useful for biometric analysis, because they have a higher level of security[2,12]. This type of identification can minimize the disadvantages with respect to classical identification systems[3]. Hence, biometric identification of a person is unique and unalterable, making it more safe, comfortable and reliable for the user. Moreover fingerprint, iris of the eye, shape of the face and ear, voice, hand geometry, gait, dynamic keyboard, and the signature are used by many systems as a immediate reference biometric. However, these kinds of systems have some drawbacks when they need a rigorous identification method of individuals because there is not still an algorithm capable of recognizing a person with a maximum degree of accuracy[2,9,13]. This is because as they increase the technicals for security, also are increased the techniques to hide or impersonate. Given the growing need to improve security and access controls, the biometric family has begun to displace the older systems of identification by new and better high-performance systems based on the authentication process in the recognition of new traits. Some identification systems based on images use the structures of the veins of the palm or back

Further author information: (Send correspondence to R. Castro-Ortega.)
R. Castro Ortega: E-mail: raul.castro@upt.edu.mx, Telephone: +51(776) 1107307

Applications of Digital Image Processing XXXVII, edited by Andrew G. Tescher, Proc. of SPIE Vol. 9217, 92171W
 · doi: 10.1117/12.2061085

of the hand. These features are useful as personal identification data and since they are physiological biometric indicators they satisfy important properties as: Universality, Uniqueness, Permanence, and Quantification[3,11]. Because the distribution of veins in the palm and back of the hand of each person are different, the biometric methods offer advantages to find many features which make them unique. This fact is used for adquiring hand images where some blood flows are registered. With this, it is almost impossible to identity impersonation through the use of spoofing techniques, therefore, is hard to duplicate since veins are hidden underneath the skin and are mostly invisible to the human eye, furthermore, is less susceptible to damage and contamination[7,13]. In addition, several studies show that the distribution of veins in the hand are unique for each individual, even for twins, likewise, this distribution is different in both hands. Also, the vein pattern does not change with growth only is extended[16].

Hand vein pattern recognition is one of the focus in the field of biometric identification in recent years. This technique appeared in 1990's, and has been popular since 2000 by the security advantages it offers[4]. Apart from safety purposes, the distribution of veins may be used in the field of health. In this field, there are people who have hidden veins, therefore, when the doctors perform a venipuncture these people, it takes time to find veins, causing a high degree of stress and anxiety in patients[5].

The near infrared (NIR) lights (700 - 900 nm) are often used in palm vein image acquisition systems because they can penetrate the palm of the hand and be absorbed greatly by the deoxyhemoglobin in veins[3,5]. In anatomy, palm veins form a network along a palm and this network cannot be broken unless some veins suffer rupture[8]. Some of the typical stages of a biometric system based on vein pattern recognition are: image acquisition, image enhancement, segmentation, feature extraction and validation[3,5,6,10,15].

The content of this paper is organized as follows: Section 2 presents the optical setup for the image acquisition. We describe in Section 3, the stages of pre-digital processing for improve the images of the veins. Following this, in Section 4, we presented the different techniques used for feature extraction from the vein patterns. The results are summarized in Section 5. Finally, in Section 6 shows the conclusions of this work.

2. OPTICAL SETUP FOR THE IMAGE ACQUISITION

To acquire the image of the vein distribution in the near infrared, a computer vision system is implemented in order to display and acquire images of the vein pattern palm and back of the hand. To achieve optimal results, it is essential that in the stage of image acquisition, the capture of the pattern must be the best possible, because the preprocessing and classification depends on it. As shown in Figure 1, the image acquisition system proposed is composed by a multi-spectral CCD camera, this device acquires images in the infrared and visible channel, also our system contains a light source in the near infrared, a base for people to put their hand, and a computer for image capture and processing.

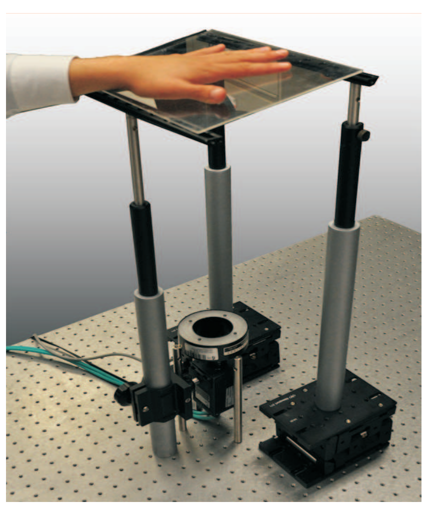

Figure 1. **Image acquisition system proposed**

Taking as an advantage the effect of the infrared radiation absorption by the veins of the hand, it is used an illumination source in ring shaped. The technical specifications of light source show that the peak of intensity radiation emitted by this is 880nm, the working distance is 10.16 cm, also it has 60 LED's infrared diodes distributed in two concentric circles. The external circle consists of 36 LED's and the inner circle consists of 24 LED's. This IR light source can be used to illuminate the palm and back of the hand.

A Digital 2CCD Progressive Scan Multispectral Camera is used to capture images. This camera can capture simultaneously visible and near infrared through the same optical path, the size of the acquired image is 1024(H) x 768(V) pixels, each pixel is a square of size 4.65μ, it has a resolution of 800K pixels as well as a GigaE high-speed connection, this allows fast communication with the computer. The camera is positioned in the center of the light source and 47 cm from the base of the hand positioning.

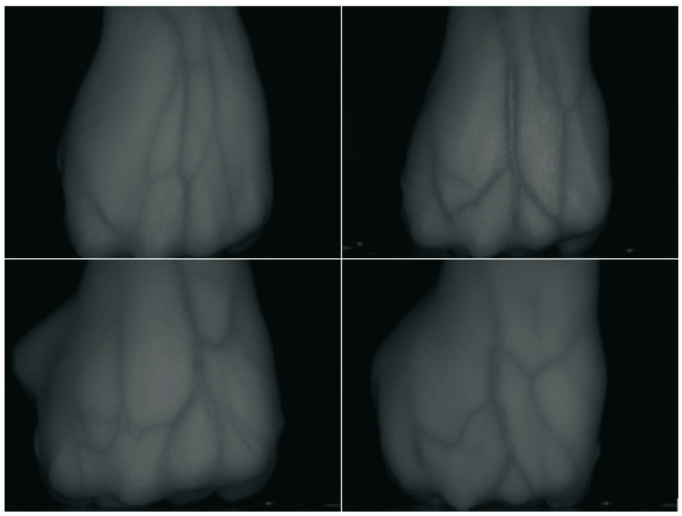

Figure 2. **Images of the back of the hand using the proposed system**

This camera is based on a dichroic prism, this allows precise separation of the visible (color) and the near infrared parts of the spectrum into two separate channels. The range of wavelength for the visible channel (channel 1) goes from 400nm to 650nm, and for near-infrared (channel 2) from 760nm to 1000nm. Both channels can be configured to operate separately or synchronously.

Figure 3. **Images of the palm using the proposed system**

The PolyU Multispectral Palmprint Database owned of Hong Kong Polytechnic University is utilized, this database contains images of 500 people with 12 versions each in 4 channels, Red, Green, Blue and Infrared (RGB-IR). Of these 4 channels, Green (G) and Blue (B) are discarded because the veins are not displayed, only shows the presence of folds or wrinkles of the hand. The red channel (R) in the same way is discarded because although the vein distribution is shown, there is still the presence of folds. In the case of images acquired in the infrared (IR), the vein pattern distribution is more visible and folds are mostly eliminated, therefore, these images are used in this work. Figure 4 shows how it is organized this database, just as the differences for two people between the 4 channels that are composed.

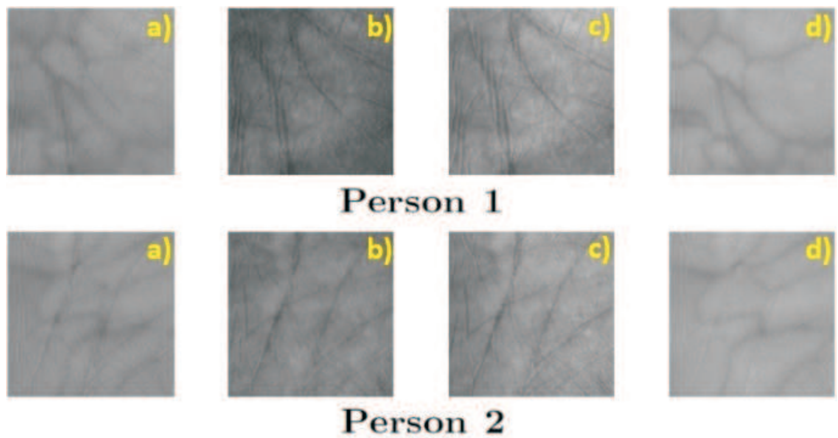

Figure 4. **a) Red (650nm), b)Green (490nm), c) Blue (460nm) and d) Infrared (850nm).**

3. PREPROCESSING OF INFRARED IMAGES

In this section we describe the operations and transformations applied on the digital images after they were captured. The main objective is to improve and highlight items of interest and thus to eliminate unnecessary information.

3.1 ROI extraction

Before performing the stages of preprocessing and extraction characteristics of the digital images, it is necessary to segment a portion of the original image with which we will work on the steps of preprocessing and feature extraction. The extraction of this portion is known as ROI (region of interest). With this in mind, the size of the area to be analyzed is also reduced as the processing time. In order to achieve greater reliability and accuracy for the feature extraction of images of the veins in the hand, it is necessary to guarantee that the features are in a similar region for each image acquired.

Generally, some devices use delimiters forcing to maintain the hand in a fixed position during the capture making it easier to obtain specific reference points and delimit the region. Based on the original image acquired, the ROI extraction is made through the following steps:

1. Change the dimensions of the image by 50%
2. The centroid of the palm and back of the hand are obtained.
3. From the centroid, we seek the coordinates of the 4 points (E1, E2, E3, E4) which will form the ROI.
4. After obtaining these coordinates we cut off the image where finally, the region of interest is located.
5. We save the new image that contains the highest amount of information from the vein pattern.

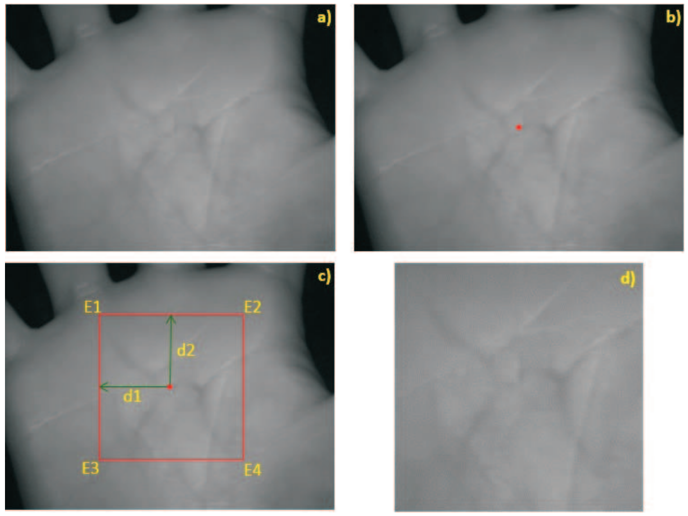

Figure 5. **a) Original Image, b) Reduced image and computation the Centroid, c) ROI Computed and d) ROI Extraction.**

3.2 Image enhancement

In the preprocessing stage, the vein pattern is extracted from the segmented images which contain more information on the ROI. To obtain the distribution of veins a segmentation algorithm is proposed to separate the pattern formed by the veins of the rest of the surface as well as an algorithm for its representation. We applied techniques of digital image processing such as spatial filtering based on convolution in order to remove unnecessary information and highlight the characteristic elements in the image, as well as histogram equalization to adjust the contrast of each image.

In general, linear filtering of an image f of size $M \times N$ with a kernel w of size $m \times n$ is given by,

$$g(x,y) = \frac{1}{M * N} \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x+s, y+t). \tag{1}$$

The result of applying a low pass filter $w(s,t)$ to an image $f(x,y)$ is simply the average of the pixels contained in the neighborhood of the mask used. Let $f(x,y)$ an image function and $w(s,t)$ an average filter, both functions are convolved as Eq. (1), the explicity filter expression is defined as follows

$$w(s,t) = \frac{1}{m \times n} \begin{bmatrix} 1 & \dots & 1 \\ \vdots & \ddots & \vdots \\ 1 & \dots & 1 \end{bmatrix}, \tag{2}$$

where $m \times n$ is the size in pixels of the mask. The effect produced by the average filter on image pixels is the smoothing, because each pixel in the filtered image is averaged with their neighbors. Typically, this type of filter is used to eliminate noise in the image, where is taking into account the size of the mask and it is commonly linked to the amount of noise to be eliminated.[1]

In the second step, a histogram equalization is used to adjust the contrast by using the histogram of each image. The histogram acts as a graphic representation of the gray level distribution of the image. If we plot the gray value for each pixel, the vertical axis represents the gray level values and the horizontal axis, the number of pixels with the corresponding gray level. This technique is commonly implemented to calculate the probability of occurrence of gray level r_k in an image and it is computed by,

$$P_r(r_k) = \frac{n_k}{n} \qquad k = 0, 1, 2, 3, ..., L-1 \tag{3}$$

where n is the total number of pixels in the image, n_k is the number of pixels which has the gray level r_k, and L is the total number of gray levels in the image. The transformation given in Eq. (4) is called *histogram equalization* or *histogram linearization*.[1]

$$s_k = T(r_k) = \sum_{j=0}^{k} p_r(r_j) = \sum_{j=0}^{k} \frac{n_j}{n} \tag{4}$$

$$k = 0, 1, 2, 3, ..., L-1$$

As part of the binarization techniques, adaptive binarization can be used. This kind of binarization is applied to the acquired images because the veins and tissues have different gray-level variations between consecutive images. So that, the use of some global thresholding techniques are not appropriate for this application, therefore a method based on adaptive thresholding is much better. In this method, it is assigned a threshold value for each pixel of the image based on the gray levels of its neighbors. For this case, the threshold value corresponds to the average gray level in a set $N \times N$ around each pixel. This procedure can be computed using the following expression,

$$g(x,y) = \left\{ \begin{matrix} 1 & if\ f(x,y) \geq f_{prom}(x,y) - T_g \\ 0 & other\ case \end{matrix} \right\} \tag{5}$$

where $f(x,y)$ is the original image, $f_{prom}(x,y)$ is the average image of $f(x,y)$, T_g is a threshold and $g(x,y)$ is the resulting binarized image. The threshold value T_g is determined by trial and error because not all the images have a similar distribution of grayscale values. This can be verified obtaining the histogram of each image[3,6].

The binarization process is important because it allows us to convert the grayscale values of the image to only two values 0 and 1, the result is a bidimensional image, in which the value 0 is assigned to the background and the value 1 to the information of the vein distribution. After making the process of image binarization, this still contains unnecessary information, so it is applied the morphological operation of thinning to obtain the contour of the vein pattern distribution and to remove the noise present in the binarized image.

The morphological operation of dilation is applied to thicken this pattern and unite small ruptures of veins. As of the images with the dilatation, feature extraction techniques are used to obtain descriptors for each of the processed images. Figure 6 shows the procedure performed to the images in the preprocessing stage, in this image is shown the process sequence for two people in which it can be seen that the vein pattern distribution is different for each one. Figure 7 shows the procedure performed to the images in the preprocesing stage, in this image is shown the process sequence for one person as part of the back of the hand.

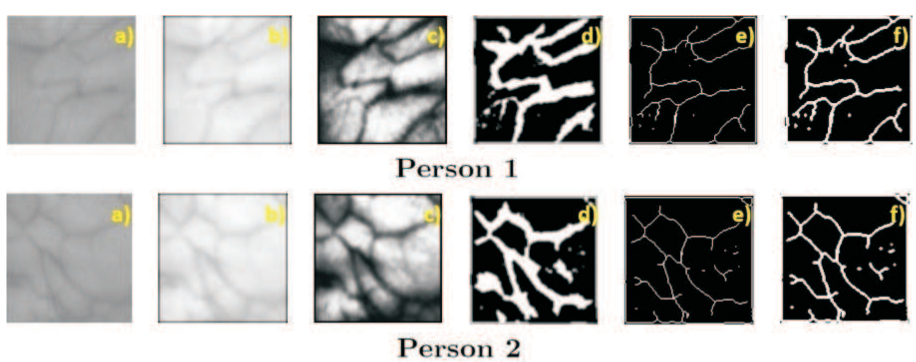

Figure 6. **a) Original Image, b) Spatial Filtering, c)Histogram Equalized, d) Adaptive Binarization, e) Thinning and f) Dilation.**

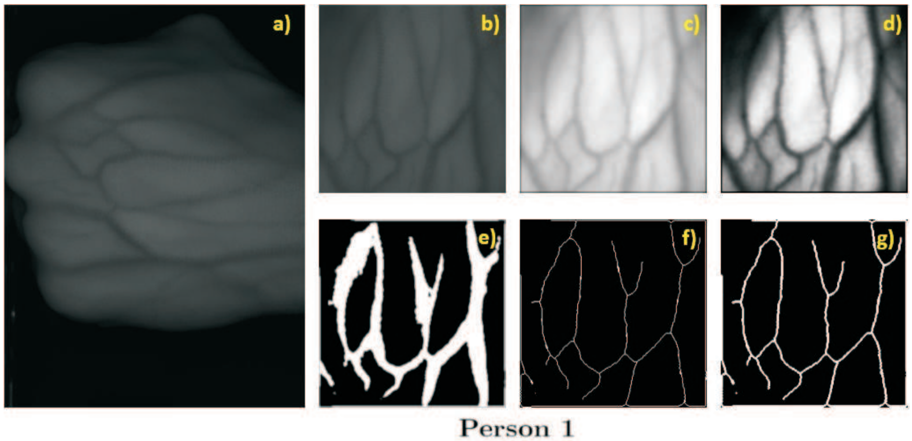

Figure 7. **a) Original Image, b) ROI Extraction c) Spatial Filtering, d)Histogram Equalized, e) Adaptive Binarization, f) Thinning and g) Dilation.**

4. FEATURE EXTRACTION

In this stage, the main objective is getting descriptors of the processed images in order to extract information of discriminant features of vein pattern distributions of people. To extract these descriptors, it is implemented some feature extraction techniques based on Geometric Moments, Hu Moments, and VeinCode. These feature extraction techniques are briefly described below.

4.1 Geometric moments

Moments are numerical descriptors which can be obtained from a given image. Using moments enough information of an image can be obtained. This method has the advantage that it uses only the silhouette of an object, but takes into account all pixels of the same image. Moments are currently used to recognize the shape of objects inside images. The theory of moments provides an interesting and useful alternative for the representation of object shapes. To calculate the geometric moments in the discrete case the next expression can be used,

$$m_{p,q} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x^p y^q f(x,y) \qquad p,q = 0,1,2,3,..., \tag{6}$$

where p and q are the orders and $M \times N$ is the image size. The most useful application of the moments are the values which can be drawn from them, they are invariant to geometric transformations such as the shift. Additionally, there exist the central moments which are used to recognize an object independently of its orientation in a coordinate axis. The current expression of central moments is as follows,

$$\mu_{p,q} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^p (y-\bar{y})^q f(x,y) \qquad p,q = 0,1,2,3,..., \tag{7}$$

where $\bar{x}$ and $\bar{y}$ are the centroid of the object in the x and y axis. Normalized moments are used for object recognition, regardless of its rotation, size or position in image plane.

So that, normalized moments are defined by,

$$\eta_{p,q} = \frac{\mu_{p,q}}{\mu_{0,0}^{\gamma}} \qquad p,q = 0,1,2,3,..., \tag{8}$$

where $\gamma = \frac{p+q}{2} + 1$. With geometric moments, the area of a figure can be computed independently of its orientation and with the central moments is possible to distinguish an object despite if it was moved. Further, the normalized moments can be used to recognize objects regardless of the size inside its image.

4.1.1 Invariants of Hu

From the normalized moments can be obtained seven standardized invariant moments. The set of these seven moments are known as Hu Moments. These moments are used to calculate the invariant moments to rotation, translation and changes in the scale of an object. This set of moments are defined as follows,

$\phi_0 = n(_{2,0}) + n(_{0,2})$
$\phi_1 = (n(_{2,0}) - n(_{0,2}))^2 + 4(n(_{1,1}))^2$
$\phi_2 = (n(_{3,0}) - 3n(_{1,2}))^2 + (3n(_{2,1}) - n(_{0,3}))^2$
$\phi_3 = (n(_{3,0}) + n(_{1,2}))^2 + (n(_{2,1}) + n(_{0,3}))^2$
$\phi_4 = (n(_{3,0}) - 3n(_{1,2}))(n(_{3,0}) + n(_{1,2}))[((n(_{3,0}) + n(_{1,2})))^2 - 3(n(_{2,1}) + n(_{0,3}))^2] + (3n(_{2,1}) - n(_{0,3}))(n(_{2,1}) + n(_{0,3}))[3((n(_{3,0}) + n(_{1,2})))^2 - (n(_{2,1}) + n(_{0,3}))^2]$
$\phi_5 = (n(_{2,0}) - n(_{0,2}))[((n(_{0,3}) + n(_{1,2})))^2 - (n(_{2,1}) + n(_{0,3}))^2] + 4n(_{1,1})(n(_{3,0}) + n(_{1,2}))(n(_{2,1}) + n(_{0,3}))$
$\phi_6 = (3n(_{2,1}) - n(_{0,3}))(n(_{3,0}) + n(_{1,2}))[((n(_{0,3}) + n(_{1,2})))^2 - 3(n(_{2,1}) + n(_{0,3}))^2] + (3n(_{1,2}) - n(_{0,3}))(n(_{2,1}) + n(_{0,3}))[3((n(_{3,0}) + n(_{1,2})))^2 - (n(_{2,1}) + n(_{0,3}))^2]$

4.2 VeinCode Method

This method consists in performing a count of pixels which are presented in a region through a subsampling of the image with the vein pattern dilated. After that, it is divided into small square blocks of equal size. With this procedure, we obtain a characteristic vector of each image with a smaller amount of data to which it contains the input image data but it maintain the discriminant information of the vein pattern. The expression to obtain the vein code is given by,

$$VC = \begin{Bmatrix} 1 & if\ Np \geq \delta \\ 0 & other\ case \end{Bmatrix}, \tag{9}$$

where Np is the number of pixels in a small square block, δ is a cutoff threshold and VC is the resulting vector.

5. ARTIFICIAL NEURAL NETWORK

This is the last stage in which is performed the most important task, the main objective is to obtain an indicator of authentication for the automatic recognition of people.With the purpose of make a comparative analysis of the performance of feature extraction techniques, we propose the use of artificial neural networks for identification purposes. We use a multilayer artificial neural network using a Backpropagation learning algorithm with a sigmoidal activation function in which the neurons or input layers receive descriptors of the images of the vein pattern distribution. For the output layer, the number of neurons must be equal to the number of classes to be recognized, one for each person. If the number of people recognize is higher, the neural network is made largest, therefore, the rate of correct classification rate decreases and increases computing time.

6. RESULTS

The results obtained in this work using the PolyU Miltispectral Palmprint Database are:

Table 1. Classification Results

Processed people	Geometric Moments	Hu Moments	VeinCode
	Correct Classification	Correct Classification	Correct Classification
25	72 %	16.33 %	98.33 %
50	55.67 %	9 %	96.5 %
100	49.92 %	6.25 %	96.17 %
150	45 %	5.06%	95.72 %
200	—	—	94.83%

7. CONCLUSIONS

In this work, an image acquisition system with near infrared illumination source and a multispectral camera is implemented. The location and extraction of region of interest on the palm and back of the hand is obtained using geometric moments. This fact is done in order to reduce the time of preprocessing and the feature extraction. In the region of interest is concentrated the most significant information. The algorithm based on geometric moments ensures the extraction of the region of interest in a similar zone for each image. Preprocessing algorithms were programmed to enhance the acquired images and the function moments are used as algorithms for feature extraction, they are implemented in order to obtain descriptors for each image. For 200 people with 12 versions each one and 64 descriptors, were used 2400 test images of the palm of the hand giving a percentage of correct classification of 94.83 %, the descriptors were obtained from the algorithm of VeinCode. The VeinCode algorithm results to be a good technique for feature extraction of the processed images, also with increasing the number of people within the neural network, significantly increases the computational cost. In this work, the similarity of the vein pattern distribution of two or more people was studied, verifying that the pattern is unique and unrepeatable for everyone even in the case of twins and also it is different in the right and left hand. It was verified that, in the case of the back of the hand, adversely, the hair have a negative effect in the stage of preprocessing and feature extraction, and therefore the classification. In the case of the palm, the factors that affect the visibility of veins are: amount of adipose tissue, depth of veins as well as the presence of scars and warts.

8. ACKNOWLEDGEMENT

The author would like to thank the National Council for Science and Technology (CONACyT) for the scholarship number 303672.

REFERENCES

[1] Rafael C. Gonzalez and Richard E. Woods. *Digital Image Processing*, Prentice Hall, 2da Edición, (2002).

[2] Qiushi Zhao, Wei Bu, Xiangqian Wu, and David Zhang, "Design and implementation of a contactless multiple hand feature acquisition System," *Proc. of SPIE* vol. 8371, 2012.

[3] Óscar Fernando Motato Toro and Humberto Loaiza Correa, "Identificación biométrica utilizando imágenes infrarrojas de la red vascular de la cara dorsal de la mano," *Revista Ingeniería e Investigación*, vol. 29, pp. 90-100, 2009.

[4] MacGregor, P., Welford, R., "Veincheck: imaging for security and personnel identification," *Adv. Imaging 6 (7)*, pp. 52-56, 1991

[5] Aída Marcotti, Belén Hidalgo and Ladislao Mathé, "Método de detección no invasivo utilizando luz infrarroja," *Universidad Nacional de Córdoba, Argentina, Master Degree Thesis*, 2012.

[6] Lingyu Wang, Graham Leedham and David Siu-Yeung Cho, "Minutiae feature analysis for infrared hand vein pattern biometrics," *Pattern Recognition*, vol. 41, pp. 920-929, 2008.

[7] Yun-peng Hu, Zhi-yong Wang, Xiao-ping Yang and Yu-ming Xue, "Hand vein recognition based on the connection lines of reference point and feature point," *Infrared Physics & Technology*, vol. 62, pp. 110-114, 2014.

[8] Jinfeng Yang and Yihua Shi, "Finger-vein ROI localization and vein ridge enhancement," *Pattern Recognition Letters*, vol. 33, pp. 1569-1579, 2012

[9] Jen-Chun Lee, "A novel biometric system based on palm vein image," *Pattern Recognition Letters*, vol. 33, pp. 1520-1528, 2012.

[10] Ahmed M. Badawi, "Hand vein biometric verification Prototype: A testing performance and patterns similarity," *International Journal of Biomedical Sciences*, pp. 141-148, 2007.

[11] Maleika Heenaye- Mamode Khan, "A multimodal hand vein biometric based on Score Level Fusion," *Procedia Engineering*, vol. 41, pp. 897-903, 2012.

[12] Deepak Prasanna.R, Neelamegam.P, Sriram.S and Nagarajan Raju, "Enhancement of vein patterns in hand image for biometric and biomedical application using various image enhancement techniques," *Procedia Engineering*, vol. 38, pp. 1174-1185, 2012.

[13] Zhi Liu, Yilong Yin, Hongjun Wang, Shangling Song and Qingli Li, "Finger vein recognition with mainfold learning," *Journal of Network and Computer Applications*, vol. 33, pp. 275-282, 2010.

[14] Jian-Da Wu and Siou-Huan Ye, "Driver identification using finger-vein patterns with Radon transform and neural network," *Expert Systems with Applications*, vol. 36, pp. 5793-5799, 2009.

[15] Byung Jun Kang and Kang Ryoung Park, "Multimodal biometric authentication based on the fusion of finger vein and finger geometry," *Optical Engineering SPIE*, vol. 48, 2009.

[16] Masaki Watanabe, Toshio Endoh, Morito Shiohara and Shigeru Sasaki, "Palm vein authentication technology and its applications," *Proceedings of The Biometric Consortium Conference*, 2005.