



Turkish Studies

International Periodical for the Languages, Literature and History of Turkish or Turkic
Volume 12/23, p. 203-218

DOI Number: <http://dx.doi.org/10.7827/TurkishStudies.12205>

ISSN: 1308-2140, ANKARA-TURKEY

Article Info/Makale Bilgisi

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COMPUTER AIDED PALM VEIN AUTHENTICATION SYSTEM BASED ON FEATURE MATCHING

Amal EJJARI - Pelin GÖRGEL** - Ahmet SERTBAŞ****

ABSTRACT

In recent years, biometric technologies have become one the most used ways to identify and confirm hand vein patterns. Because veins are a particular part of the human body; it is difficult or almost impossible to damage, alter or simulate the vascular trauma. In this study a computer aided palm vein authentication system is developed. All the data that we used in our research were taken from the CASIA database. The first two steps used in the system are entering the preprocessing stage to improve the relevant region extraction (ROI) and vessel appearance. The task of removing the palm vein feature is another challenging question in the work of infrared palm recognition. In this study; six features have been introduced to represent palm vein image. The first and second features are standard features which are mostly used in palm vein image processing: Local Binary Pattern and Zernike Moments. The remaining features are novel features which we developed for this study: Total Vessel Length, Vessel Density, Central Density and Vessel Propagation. Each extracted feature list is combined as a feature vector that is used to separate palm veins of different people. To test our system we used images of a small study group which is made of 20 volunteers. From each volunteer 6 pictures are collected. In total, the database contains 120 palm vein images. For matching performance cosine similarity has been used. According to the results obtained using all these methods, the novel features produce higher sensitivity, specificity and accuracy.

STRUCTURED ABSTRACT

In the last years, biometric technologies have become one the most used ways to identify and confirm hand tube patterns. Because veins are a particular part of the human body, it is difficult or almost impossible to damage, alter or simulate the vascular trauma. The palm vein

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compared with a finger or a hand's back face, it has a wider and more complex vessel pattern with an enriching feature for personal identification. These are personality-specific and even twins have different models. Since vascular models exist in the body, they cannot be played with photos, voice recordings or fingerprints, so this biometrics makes the authentication method more secure than the others . The functioning of the biometric system goes through two main stages: (i) the registration phase and (ii) the recognition phase. During the recording phase, the biometric system is programmed to identify a specific person. Once the descriptive information of that person is recorded, the system attempts to verify the identity of the person by comparing the images that are already saved in the database with the image that was received during recognition.

Our study aimed to identify the scanned palm image and compare it with the images in the database to determine whether the registered palm correspond to person A or B. In order to obtain a good result we followed 3 mean stage: first stage preprocessing than feature exctraxtion stage and finally we did a feature matching Total Vessel Length, Vessel Density, Vessel Center Distance and Vein Propagation four methods that were developed during this study and showed a high accuracy percentage.

Below there is some previous work about palm vein identification:

Wang and Chen (Wang and Chen, 2011, p.311-314) created a system and tested it on a database composed from 25 images that were taking from 5 women and 20 men their age is over 20 years old. Twenty images were obtained from each volunteer at different time, 10 images for right and 10 images for left hand. The presented system and framework included image enhancement, noise reduction, subtraction, thinning, skeletonization and vein subtraction tasks. The average rate of obtained result was 93.4%, 94.8% on the right hand and 91.9% on the left hand.

Another work was made by Somalia Vaid and Mishra (Vaid and Mishra, 2015). They have produced a comprehensive comparative study of basic transformations in 2015. PCA (Main Component Analysis), DCT (Discrete Cosine Transform), Walsh Transform, Inclined, DST (Discrete Sinus Transform). In this way, 128x128 pixels of palm vein images and 576 views of the database were applied to transformations. The results show that none of the applied transformations can accept any brightness and contrast image except PCA, where the brightness and contrast are 10.41% of the modified image acceptance rate. After comparative analysis of the baseline conversion, it can be said that Walsh-Hadamard has the lowest EER in the range of 0.2-17% followed by PCA with 0.6% EER followed by DCT with EER of 2.7-7%. Followed by a Slant transformation with an EER interval of 6.2-12% followed by a DST with a range of 35-37% EER. In our study we used and developed news methods for feature extraction. Despite the works that used standard feature extraction method in our work we developed news feature special for palm vein. Each extracted feature list is combined as a feature vector that is used to separate palm veins of different people.

The First phase in our study is the preprocessing. We first extracted the region of interest from the images than we used the median filter in order to remove noise from images while protecting the edges.

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The filtering was followed by the morphologique operations and binarization. The result obtained from the preprocessing is used in the second phase which is the feature extraction stage. We first tried the standart feature extraction method which are known with giving good result, we used Local Pattern Binary (LBP) and Zernike moment methods. And we developed 4 news feature extraction method which are Total Vessel Lengths this method calculates the total vessel length in the palm of the person, as for each person the structure of the veins varies in terms of thickness and length. The second method is Vessel Density: in this method the palm image is divided into four equal parts and the total vessel length on each section is counted. The third feature extraction method is Vessel Central Density in order to achieve the central density, the image passes through the erosion process which will thin the veins in the binary image than the central density of the veins is examined to determine the identity of the person. In other words, a central point is determined in the palm and it is determined how intense the veins are in this central point. It is then determined how close the vessels at the determined point are to each other. The last method is the Vessel Propagation feature extraction method. In this feature, unlike the central density feature, the propagation of the veins in the palm is handled. To determine whether the veins are uniformly distributed, openness is measured, such as the openness of the quarters, the central span. In this method, the standard deviation of the central propagation measure is calculated. Finally after obtaining the result from the feature extraction methods we pass to the last phase which is feature matching using Cosine similarity.

Leave-One-Out Cross-Validation is used to obtain a good and accurate result in our study. 120 images from the CASIA database were evaluated and their attributes were extracted. 120 images in total; for every 20 persons, 6 palm vein images were taken and all images were tested for training and test clusters. The cosine similarity is used to determine the degree of similarity between the vectors of properties of each model. And we have got the results (accuracy) like below; Local Binary Pattern 99%, Zernike Moment 98%, Total Vessel Length + Vessel Density + Central Vessel + Vessel Propagation 99.1%, authentication rates were achieved using 99% attributes. In these applications, we have achieved the highest and most reliable results by combining the four proposed features of total vessel length + vein density + central density + vein propagation.

Keywords: Palm Vein, Authentication, Local Binary Pattern, Zernike Moments, Total Vessel Length

ÖZELLİK EŞLEMEYE DAYALI BİLGİSAYAR DESTEKLİ AVUÇ İÇİ DAMAR İZİ KİMLİK DOĞRULAMA SİSTEMİ

ÖZET

Son yıllarda, biyometrik teknolojiler el içi damar görüntülerini onaylama ve kimlik tanımada en çok kullanılan yollardan biri haline gelmiştir. Damarlar insan vücudunun özel kısımları olduğundan, damar travmalarını simüle etmek, değiştirmek çok zordur hemen hemen

imkansızdır. Bu çalışmada, bilgisayar destekli avuç içi damar izi kimlik doğrulama sistemi geliştirilmiştir. Araştırmamızda kullandığımız tüm datalar CASIA veritabanından alınmıştır. Sistemin ilk iki adımı damar izini ortaya çıkarımını ve ilgili bölge çıkarımını iyileştirmek adına ön işlemlerin yapılmasıdır. Avuç içi damar izi özelliklerini yoketme görevi kızılotesi avuç içi tanıma işinde diğer iddialı açık bir nokta teşkil etmektedir. Bu çalışmada, avuç içi damar izi görüntülerini simgelemek için 6 farklı özellik kullanılmıştır. İlk 2 özellik, avuç içi damar izi görüntü işlemede en çok kullanılan Yerel İkili Şablon ve Zernike Moment adı verilen özellik çıkarım yöntemleridir. Diğer 4 özellik bizim bu çalışmada önerdiğimiz yeni özelliklerdir. Bunlar toplam damar uzunluğu, damar yoğunluğu, merkezi damar yoğunluğu ve damar iletimi özellikleridir. Herbir çıkarımlanan özellik listesi, farklı insanların avuç içi damar izlerini ayırt etmek için kullanılan bir özellik vektörü olarak birleştirilmiştir. Sistemimizi test etmek için, 20 gönüllüden oluşan küçük bir çalışma grubundan alınan görüntüleri kullandık. Her gönüllüden de 6 adet resim toplanmıştır. Toplam olarak veri tabanı 120 adet avuç içi damar izi görüntüsü içermektedir. Eşleştirme performansı için kosinüs benzerlik yöntemi kullanılmıştır. Elde edilen sonuçlara göre, yeni özellikler daha yüksek duyarlılık, seçicilik ve doğruluk değerleri üretmiştir.

Anahtar Kelimeler: Avuç İçi Damar İzi, Kimlik Doğrulama, Yerel İkili Şablon, Zernike Moment, Toplam Damar Uzunluğu

1. Introduction

Biometrics can be defined as “life measurement”. Biometrics contains automated methods of recognizing individuals based on the measurement of their physical or behavioral characteristics. A biometric system either makes identification or verifies an identity by establishing the probability that a specific physiological or behavioral characteristic is valid. It is based on the use of unique and measurable physiological or behavioral characteristics. Physiological characteristics include, but are not limited to, a person’s vein patterns, facial structures, ocular characteristics, hand geometry, or fingerprint. Behavioral characteristics are based on an individual’s unique actions captured over a period of time including (such traits as signature dynamics, voice, gait, and keyboarding dynamics) (Wilson, 2010, p.68).

Biometric systems are essentially pattern recognition applications that acquire certain biometric data from an individual, extract a salient feature set from that data, compare this feature set against the feature set(s) stored in the enrollment database, and finally execute a cognition action that based on the result of the comparison (Riera et al, 2009).

Most of the vessels in the human body can be used for personal identification (such as the vein of the retina, the face vein, the vein in the hand), but often the vessels in the hand are preferred. Since the vessel in hand, which is usually an open section, is closer to the surface than other regions, it can be easily detected, especially by low resolution cameras. It has emerged in the 1990s (Mac Cregon & Welford 1991) and has become very popular since 2000 due to its advantages. For example, the vascular braid is the largest blood vessel network found under the skin of a person. The vein pattern is difficult when compared to other Biometry species. In palm vein authentication, it works by comparing the veins in the palm of a verified person (such as dark lines) with a pattern stored in the decrypted database, and forgery is impossible. When compared with a finger or a hand's back face, it has a wider and more complex vessel pattern with an enriching feature for personal identification. These are personality-specific and even twins have different models. Since vascular

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models exist in the body, they cannot be played with photos, voice recordings or fingerprints, so this biometrics makes the authentication method more secure than the others (Mirmohamadsadeghi, 2013). Wang and Chen (Wang and Chen, 2011, p.311-314) creatively captured a vascular image, presented a new system and a new framework. This system, which includes image enhancement, noise reduction, subtraction, thinning, skeletonization and vein subtraction tasks, was tested on a database of 25 images from different ages (over 20 years old). For each individual, including five girls and twenty men, 20 images were obtained at different intervals. (10 images for right and left hand) The average rate of obtained result was 93.4%, 94.8% on the right and 91.9% on the left.

Somalia Vaid and Dhirendra Mishra (Vaid and Mishra, 2015) have produced a comprehensive comparative study of basic transformations in 2015. PCA (Main Component Analysis), DCT (Discrete Cosine Transform), Walsh Transform, Inclined, DST (Discrete Sinus Transform). In this way, 128x128 pixels of palm vein images and 576 views of the database were applied to transformations. The results show that none of the applied transformations can accept any brightness and contrast image except PCA, where the brightness and contrast are 10.41% of the modified image acceptance rate. After comparative analysis of the baseline conversion, it can be said that Walsh-Hadamard has the lowest EER in the range of 0.2-17% followed by PCA with 0.6% EER followed by DCT with EER of 2.7-7%. Followed by a Slant transformation with an EER interval of 6.2-12% followed by a DST with a range of 35-37% EER.

The palm-vein literature has been highly focused on the verification problem with known feature extraction methods. Therefore, this paper has also presented new feature extraction methods and compared it with the traditional ones. The rest of the paper is organized as follows: Section II presents the details on the preprocessing steps and features extraction approach. The experimental results are presented in Section III. Finally, the key conclusions from this paper are summarized in Section IV.

2. Methods

2.1. Preprocessing

Preprocessing stage is known to be the most primary and principal stage in the biometric system. In the context of vein pattern images, articulation movement and rearrangement of parts for the same vein pattern in different images is minimal due to the temporal stability nature of the vein patterns. However, for FIR images, due to uneven heat distribution, some parts of the veins will be occluded in some images.

Similarly for FIR images, due to uneven illumination, some parts of the veins will be invisible in some images (Wang and Chen, 2011, p.311-314). So, the preprocessing stage is considered as very important and fundamental stage in the vein recognition system. Normally, the vein image is prepared for feature extraction after several preprocessing stages.

2.1.1. Median Filter

Median filtering is a nonlinear method used to remove noise from images. It is commonly used because it is very effective at noisy areas while protecting the edges. The noise from the 'salt and pepper' type is particularly effective at lifting. The median filter works by moving the image pixel, replacing each value with the median value of the neighboring pixels. The pattern of the neighbors is called the "window" that scans the entire image with a pixel. The median is calculated by first changing all pixel values from the window to the numerical sequence and then modifying the pixel, which is replaced by the median pixel value (Dipti and Sipi, 2015, p.138).

Median filtering output:

$$g(x, y) = \text{med}\{f(x-i, y-j, i, j \in W)\} \quad (1)$$

Since the median filter is a nonlinear filter, mathematical analysis is quite complex for an image with random noise. For an image with zero mean noise under normal distribution, the noise variance of the median filter is approximately:

$$\sigma_{med}^2 = \frac{1}{4nf^2(n)} \approx \frac{\sigma_i^2}{n + \frac{\pi}{2} - 1} \cdot \frac{\pi}{2} \quad (2)$$

Where, input σ is the noise power (variance), n is the size of the median filtering mask, $f(n)$ denotes the function of noise density. And the noise variance of the mean filter is:

$$\sigma_o^2 = \frac{1}{n} \sigma_i^2 \quad (3)$$

2.1.2. Morphologic Operations

Morphology deals with the structure of materials. It extracts image components that are useful to represent and describe shape boundaries, skeletons, and so on. Also, to achieve pre or post processing the morphology techniques such as morphological filtering, thinning, and pruning are very beneficial (Gonzales and Woods, 2011). In an image a structuring element is compared with appropriate neighborhood of pixels.

2.1.3. Binarization

Image binarization converts an image from gray levels to a black and white image. After local brightness mapping, thresholding become a good choice for binarization purpose because the produced vein image will have better background brightness.

2.2. Feature Extraction

In order to provide accurate recognition of individuals, the most discriminating information representing the view pattern must be extracted. The extracted representing information is gathered in a features vector to distinguish the person from others (Matyas and Ríha, 2002, p.227-230).

In this work, we used six different feature extraction methods:

2.2.1. Local Binary Pattern

The Local binary pattern (LBP) operator is a texture descriptor originally proposed in 1994 (Ojala et al, 1994, p.582-585). This operator is based on the gray level comparison of a neighborhood of pixels. The original operator considers a 3×3 neighborhood of 8 pixels around a center pixel. This neighborhood is threshold by the value of the center pixel and the result is considered as a binary number or its decimal equivalent where $s(u)=1$ if $u \geq 0$ and 0 otherwise. Each decimal number is considered as a micro-pattern's type. These micro-patterns are generally represented in histograms whose bins each contain one kind of pattern. The LBP operator was modified to be more sensitive to

certain types of spatial patterns. (Ojala, Pietikainen and Maenpaa, 2002, p.980-983). The operator size is specified as the number of neighbour pixels P at radius from center point R (as seen in Fig. 1).

LBP output:

$$LBP_{p,R}(I_c) = \sum_{p=1}^P s(Z_p - Z_c) 2^{p-1} \quad (4)$$

$$s(u) = \begin{cases} 1, u \geq 0 \\ 0, u < 0 \end{cases} \quad (5)$$

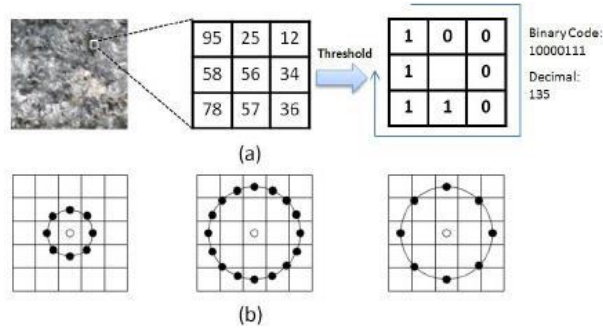


Figure 1. (a) original LBP operator, (b) circular (8,1), (16,1) and (8,2) neighbor.

2.2.2. Zernike Moment's

Zernike Moment's are shape descriptors which are subcategory of the region-based descriptors (Sharma Ashok et al, 2013). Region based descriptors use all the pixels inside an area to build the descriptors. Zernike moments project an image onto a set of complex Zernike polynomials and these polynomials are orthogonal to each other. For computing Zernike moment's two steps should be considered. The first step is calculating the Zernike basis functions and the second step is computing the Zernike moments by projecting an image to the basic functions (Sharma Ashok et al, 2013). The set of these complex polynomials called Zernike basis functions are denoted by $V_{nm}(x,y)$, and defined as follows:

$$V_{nm}(x,y) = V_{nm}(\rho, \theta) = R_{nm}(\rho) \exp(jm\theta), \quad (6)$$

Where R_{nm} is :

$$R_{nm}(\rho) = \sum_{s=0}^{\frac{n-|m|}{2}} (-1)^s \cdot \frac{(n-s)!}{s! \left(\frac{n+|m|}{2} - s\right)! \left(\frac{n-|m|}{2} - s\right)!} \rho^{n-2s} \quad (7)$$

2.2.3. Total Vessel Lengths

The palm vein reading system is now being used in ATMs, banks and especially in private hospitals. It has spread rapidly and even with the decision of the Constitutional Court, it cannot be

examined by the SSI which entered into force in 2015 and is not registered to the system. The palm vein shows various differences in each individual. For example, even twin sisters have fingerprints as well as vascular structures. The structure of the veins varies from person to person in terms of thickness and length. Our method calculates the total vessel length in the palm of the person, as shown in Fig. 2 using Eq. (8 and 9) where L is the total vessel length and χ_A is the palm image. The thickness and length of the palm vein are evaluated as the identity of the individual in the identification or recognition system. The error rate of the system is very low because the vessel length of people is variable.

$$\chi_A(a_{ij}) = \begin{cases} 1, a_{ij} \in A \\ 0, a_{ij} \notin A \end{cases}, A = \{1\} \quad (8)$$

$$L = \sum_{i=0}^m \sum_{j=0}^n \chi(a_{ij}) \quad (9)$$

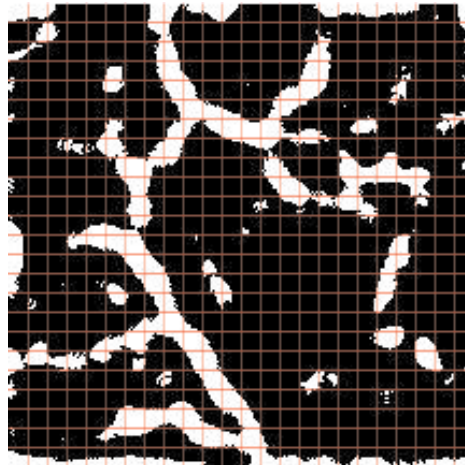


Figure 2. Total Vessel Length

2.2.4. Vessel Density

Vessel density is the part of the palm vein that filters out and uses as part of the self. The palm image is divided into four equal parts ($P1, P2, P3$ and $P4$). The total vessel length on each section is counted. The most intense (i) vein image is detected from the scanned sections in Fig. 3.

$$\chi_A(a_{ij}) = \begin{cases} 1, a_{ij} \in A \\ 0, a_{ij} \notin A \end{cases} \quad (10)$$

$$P1 = \sum_{i=0}^c \sum_{j=0}^d \chi(a_{ij}) \quad (11)$$

$$P2 = \sum_{i=0}^e \sum_{j=0}^f \chi(a_{ij}) \quad (12)$$

$$P3 = \sum_{i=0}^g \sum_{j=0}^h \chi(a_{ij}) \quad (13)$$

$$P4 = \sum_{i=0}^o \sum_{j=0}^p \chi(a_{ij}) \quad (14)$$

$$i = \max(P1, P2, P3, P4) \quad (15)$$

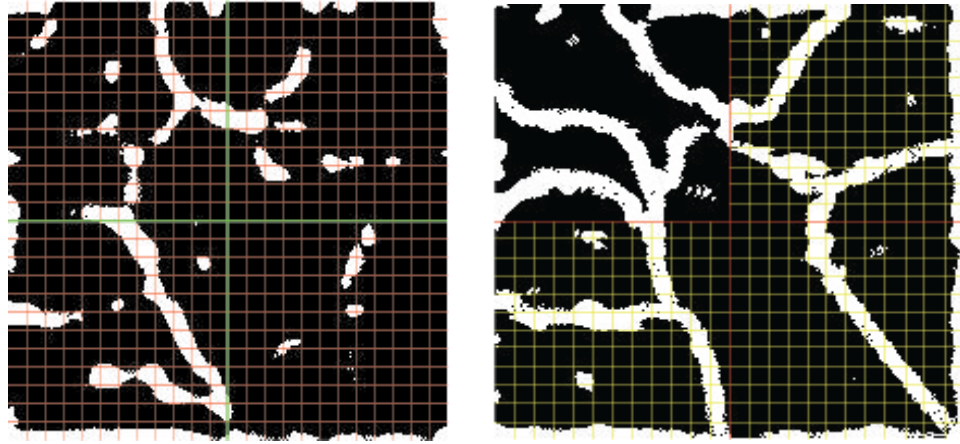


Figure 3. Vessel Density Images for Feature Extraction

2.2.5. Vessel Central Density

To achieve the central density, the image passes through the erosion process as seen in Fig. 4. Erosion will thin the veins in a binary image. Considering the clusters A and B, the erosion defined by building element B is defined (Zhou, Wu and Zhang, 2010, p.100-110) as:

$$A \ominus B = \bigcap_{b \in B} (A)_{-b} \quad (16)$$

$$A \ominus B = \{z | z + b \in A, \forall b \in B\} \quad (17)$$

The density of palm veins, vessel shapes and vessel thicknesses are unique to the person and show differences in each individual. In this method, the central density of the veins is examined to determine the identity of the person. In other words, a central point is determined in the palm and it is determined how intense the veins are in this central point. It is then determined how close the vessels at the determined point are to each other. After the image taken from the palm of the hand is passed through the preprocessing phase, the central vessel density is regarded as the separating feature as shown in Fig.5.

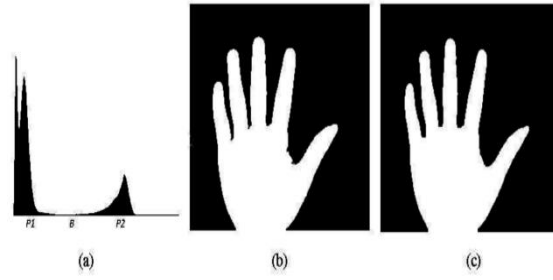


Figure 4. Illustration of a binary image after dilation and erosion processes.



Figure 5. Vessel Central Density

2.2.6. Vessel Propagation

In this feature, unlike the central density feature, the propagation of the veins in the palm is handled. To determine whether the veins are uniformly distributed, openness is measured, such as the openness of the quarters, the central span. In this method, the standard deviation of the central propagation measure is calculated using Eq. (18) where S is the standard deviation, M is the mean distance, X is the current pixel's distance to the center and n is the number of points. The standard deviation tells how the veins are spreading. Unlike the central density feature, in which veins are located closer to each other in the center, the distances between the veins are used as a separating feature.

$$S = \sqrt{\frac{\sum (X - M)^2}{n - 1}} \quad (18)$$

2.3. Feature Matching

Biometric mapping refers to the process of measuring the degree of match between two biometric samples (usually in the form of a match score). One is usually aggregated at the biometric registration phase, the other at the biometric verification or identification stage (Michael, Connie and Teoh, 2010).

Distance or similarity measures are necessary to solve many different recognition problems such as classification, clustering and retrieval problems. A similarity measure should be chosen to

decide how close a vector is to another vector. This task can be transformed to compute the discrepancy between the two vectors x, y . Although there are many similarity measures, the proposed method is cosine similarity which is formulated in Eq. 19.

$$\text{Cos } \theta = \frac{AB}{\|A\| \|B\|} \quad (19)$$

3. Experimental Results

In this study, the data set used to train and test the algorithms is the CASIA multi-spectral Palm print Image Database V1.0 (CASIA database), tested using a volunteer database. The age distribution of the volunteers is between 17 and 60 years and the samples are collected in two separate sessions. This data set is images captured at a wavelength of 850 nm.

The first step of the preprocessing is image adjustment. We take an image from the database as an input for the contour detection algorithm (Shapiro and Stockman, 2000, p.132-140) (Konukoglu et al, 2006, p.1804-1809). This method chooses a random starting point in the hand contour and then searches for all the contour pixels. The contour is important for identifying the region of interest and other reference points. The hand boundary or contour can be seen in Fig. 6.

The acquisitions of key point are obtained by the combination of two different methods, the contour curve gram and the radial distance to a fixed point (Lin, Chuang and Fan, 2005, p. 2639-2652). Both methods identify the valleys and the fingertips and between the fingers.

The radial distance obtains the Euclidean distance between boundary pixels and a constant point, which is the middle point of the region where the wrist crosses the edge of the image. The contour curve gram analyzes the intensity of the curvature along the contour, and can be constructed by using a technique called difference-of-slopes (Lin, Chuang and Fan, 2005, p. 2639-2652) (Polli et al, 2011, p.302-309).

Both methods have some drawbacks and benefits, but if they are used together they constitute a more robust set of reference points. In order to obtain an approximation of the final reference points, the radial distance to a fixed point is the technique used firstly. After the raw key points are obtained, the contour curve gram is used near the obtained locations. The last obtained positions are the final finger-valley locations and fingertip.



Figure 6. Hand contour.

The additional reference points demonstrated with yellow dots in Fig. 7, are useful to extract ROI of the palm. By discovering index, thumb and pinkie fingers, these additional reference points are detected.

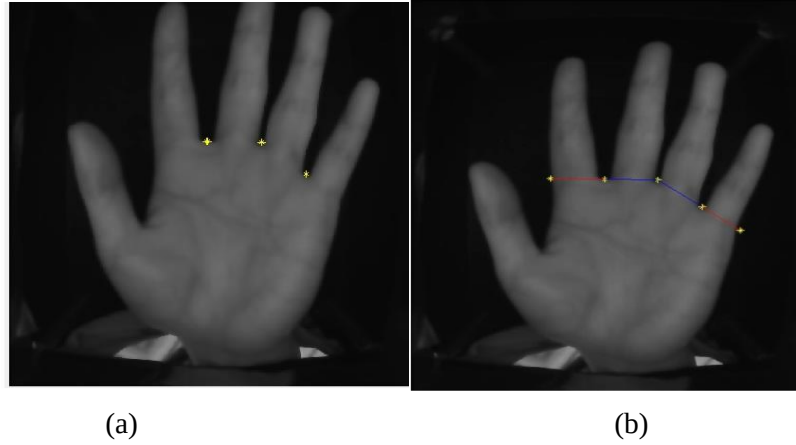


Figure 7. (a) Hand reference points (b) Final set of hand reference points.

The five fingertips are used to compose the final set of hand reference points, the valleys of four fingers and the three additional reference points. After determining the reference points, the ROI square is obtained (Fig. 8). The position of the square is specified through a line segment which is drawn from the index to the pinkie finger.

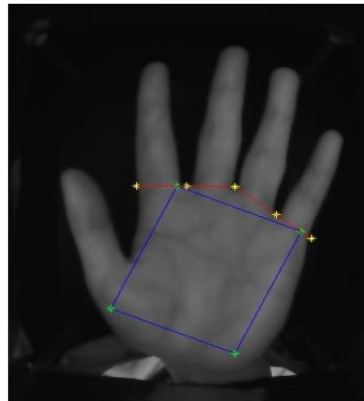


Figure 8. Region of interest.

Different palms will create squares of different sizes and orientations that will need to be normalized to reach purposes. In order to obtain a standard the ROI is rotated to a vertical position and adjusted to a standard dimension. The ROI's are size of 216x216, according to the results that will be mentioned in the performance evaluation section. After the rotating step the image is filtered and converted to binary. The ROI extraction step can be seen in Fig. 9.

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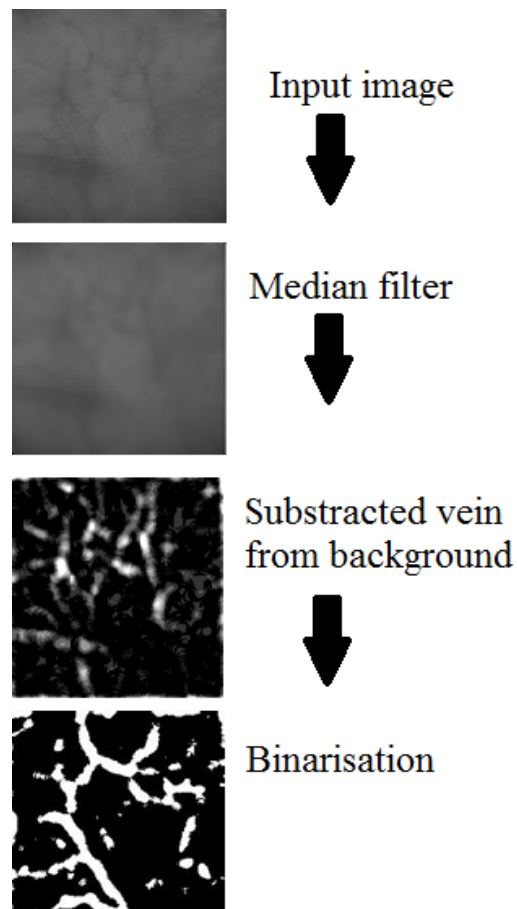


Figure 9. Illustration for the outcomes of preprocessing stage.

After the feature extraction phase the matching is done according to the tools above:

Specificity, sensitivity, and accuracy are common tools to test the system's performance. Sensitivity (True positive rate) demonstrates the relationship between false negatives and true positives as shown in Eq. 20 (Prabu and Sivanandam, 2013, p.695) (Yingbo and Ajay, 2011, p.1247-1259):

Sensitivity:

$$\frac{TP}{TP + FN} \quad (20)$$

True positives (TP) mean the people correctly identified.

Specificity (True negative rate) demonstrates the relationship between false positives and true negatives; formula is given

Specificity:

$$\frac{TN}{TN + FP} \quad (21)$$

Accuracy represents the relationship between true positives, true negatives, false positives and false

negatives (Polli et al, 2011, p.302-309) as shown below:

$$\frac{TP + TN}{TP + FP + TN + FN} \quad (22)$$

Cross-validation analysis was conducted to obtain a good and accurate result in our study. Leave-One-Out Cross-Validation is used as the cross validation method. One-way cross-validation (LOOCV) is a special case of p-inferential cross-validation with $p=1$. 120 images from the database were evaluated and their attributes were extracted. 120 images in total; for every 20 persons, 6 palm vein images were taken and all images were tested for training and test clusters. The cosine similarity is used to determine the degree of similarity between the vectors of properties of each model. The feature vector of the first palm vein image of person A was taken and compared with the feature vector of the other 5 images, and compared with the feature vector of the remaining 19 people. As a result, if the comparison is correct for each person; person A gets 1 True Positive and gets 19 true Negative. If person A is paired with person B, then 1 False Positive, 1 False Negative and 18 True Negative remain. As seen in Table 1. the highest sensitivity (91.6%), the highest specificity (99.5%), the lowest false positive rate (0.004%), and lowest false negative rate (0.08%) are obtained by our proposed features, total vessel length + vessel density + center density + vessel propagation.

In Table 2, the confusion matrix is given.

Table 1. Verification results.

Characteristics Methods and Features	Sensitivity (%)	Specificity (%)	False positif rate (%)	False negatif rate (%)	Accuracy (%)
PROPOSED FEATURES TVL+VD+CD+VP	91.6	99.5	0.004	0.08	99.1
Zernike Moment	80.8	98.9	0.01	0.19	98
Local Binary Pattern	90	99.4	0.005	0.1	99

Table 2. Confusion matrix.

Methods and Features \	True Positif (TP)	True Negatif (TN)	False Positif (FP)	False Negatif (FN)
PROPOSED FEATURES TVL+VD+CD+VP	110	2270	10	10
Zernike Moment	97	2257	23	23
Local Binary Pattern	108	2268	12	12

As stated in Table 2, the best method is total vessel length + vessel density + central density + vessel propagation. Verification total test number was 2400, determined as 110 images TP (True positive) from 2400 tests, namely the person himself and 10 images FP (False positive).

4. Conclusion

In this study, an identification system based on a human biometric characteristic of palm vein structure and based on palm image analysis has been realized. In our study, authentication performance was evaluated from palm vein images. And we have got the results like below; Local Binary Pattern 99%, Zernike Moment 98%, Total Vessel Length + Vessel Density + Central Vessel + Vessel Propagation 99.1%, authentication rates were achieved using 99% attributes. In these applications, we have achieved the highest and most reliable results by combining the four proposed features of total vessel length + vein density + central density + vein propagation.

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