Human Identification Using Normalized Energy Based Spectrum Eigenpalms

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Abstract

Biometrics, is defined as the since of Human recognition based on his/her physical or behavioral traits, is beginning to used as Human added computer method for determining an individual's identity. The human hand presents the sorce for a numerous of physiological biometric features. Palmprint, hand geometry, finger geometry and the vein pattern on the dorsum of the hand, are mostly used in many fields for different applications. Lines and points are extracted from palms for individual identification in original image or frequency space. In this paper, the normalized energy based spectral eigenpalms is used for human identification. The correlation distance is used as a similarity measure. A threshold value is used to prevent the imposter form being identified. The experimental results point up the effectiveness of the method in varying noisy types.

Keywords: Biometrics, Human Identification, Normalized Energy, spectrum Eigenpalms, Correlation.

الخلاصة

المحددات البايولوجية تعرف على أنها علم تميز الأشخاص بالاعتماد على السمة الفيزيائية أو التصرف، أصبحت تعرف على أنها طريقة وثقى في تمييز الأشخاص. يد الإنسان تمثل مورد للعديد من السمات الخاصة بالمحددات الفيزياوية. راحة اليد، شكل اليد، شكل الأصابع ، أنماط الأوردة على ظهر اليد، والتي تم استخدامها في العديد من التطبيقات. الخطوط والنقاط يتم استخلاصها من صورة راحة اليد بصورة مباشرة أو بعد تحويلها إلى الفضاء الترددي. في هذا البحث تم أستخدم تمثيل الطاقة المعدل المبني باستعمال تحويل فورير السريع لمحددات الوجه الطيفية في تمييز الاشخاص. تم استخدام مسافة الارتباط لقياس. تم استخدام حد لمنع الصور الدخيلة من أن تميز داخل المنظومة. نتائج الاختبارات عبرت عن مدى فعالية الطريقة الجديدة المطبقة في حالة الأنواع المختلفة من الضوضاء.

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1. Introduction

Computer-based personal identification, via biometric mean, attempts to recognize a person by his/her body or behavioral characteristics. The human hand includes a broad diversity of measurable characteristics possible to be used by biometric identification systems. These characteristics are in general extracted from the visible and infrared images of the hand. Compared with the other physical characteristics, palmprint based identifiers have several advantages [1]: low-resolution imaging, low intrusiveness, stable line features and high user acceptance. A palmprint image captured by a CCD camera, with a very low resolution (65 dpi) is depicted in Figure (1). The palm is defined as the inner surface of the hand between the wrist and the fingers. The main patterns in a palmprint are principal lines: These are usually three principal lines in a palmprint “the heart line, the head line, and the life line”. Wrinkles are much thinner than the principal lines and much more irregular. Creases are the relatively detailed features that exist all over the palmprint, just like the ridges do in a fingerprint.

Palmprint based identifier can be categorize as: off-line palmprint, where all palmprint samples are inked on paper, then transmitted into a computer via a digital scanner, and online palmprint: samples are directly obtained by a palmprint scanner. The classification of palmprint-based biometric (on-line or off-line) systems is according to the applied feature-generation method into systems that extract features in the original image space or in the transformed image space [3].

The palmprint identification system consist of six modules, palmprint acquisition, preprocessing, feature extraction, post processing, matching and decision-making, and two mode, enrollment and identification [1]. Figure (2) depict a block diagram to describe the relationship between the six modules, and two modes for identification process.

With the works that appear in the literature based on transformed image space are eigenpalms [4], Gabor filters [1], Fourier Transform [5], Wavelets [6], and. Radon transform is proposed [7], which can extract principal lines effectively and efficiently even in the case that the palmprint images contain many long and strong wrinkles.

In this paper, a spectrum eigenpalms feature vectored is extracted from palmprint image for individual identification. The result feature vector is post-processing using min-max normalization to the range [0, 1]. The remaining sections are organized as follows: Backgrounds are mentioned in Section 2. The proposed normalized energy based spectral eigenpalm feature in Section 3. Scheme Phases in section 4. Finally, Section 5 conclusions and summaries to the main results of this paper.

2. Background

2.1. Palmprint Pre-processing

A coordinate system of a palmprint is used, via gaps between the fingers as reference points, next central square part is extracts, as depicted in Figure (3), and the pre-processing algorithm is summarized below:

Input: Palmprint image of 256 gray levels

Output: Central square part of a palmprint

Process:

Step1: Apply a low-pass filter for the input image.

Step2: binarylized the palmprint image using a threshold method.

Step3: Find the contours of the hand shape.

Step4: Extract the anchor points, which represent the minimum mean radial distance from all the points on the hand contour to the hand centroid.

Step5: The origin of the coordinate system is defined as the point between index and middle finger and the point between the middle and pinky finger.

Step6: The slop of the line passing through the anchor points is determined and each hand image is rotated in the direction of the slope around the anchor midpoint.

Step7: Extract a sub-image with the fixed size on the basis of coordinate system, which is located at the certain part of the palmprint.

2.2. Normalized Energy

The normalized energy is computed for each row according to the following relation:

$$Energy = \frac{norm^2}{N} \quad ,.................. \quad (1)$$

$$norm^2 = \sum_i x_{ij}^2 \quad ,........................ \quad (2)$$

Where x_{ij} is the $_{ij}$th pixel value of the images, and N is the data size.

2.3. Discrete Fast Fourier Transform

Once the signal has been acquired and digitized, it can be converted to the frequency domain by using fast-Fourier-transformed (FFT). The FFT results can be either real and imaginary, or magnitude and phase, functions of frequency. The choice of output format belongs to the user. The transform and inverse transform pair given for vectors of length N by [8]:

$$X(k) = \sum_{j=1}^{N} x(j)\psi_N^{(j-1)(k-1)} \quad ,.......... \quad (3)$$

$$x(j) = \frac{1}{N}\sum_{k=1}^{N} X(k)\psi_N^{-(j-1)(k-1)} \quad ,..... \quad (4)$$

Where $\psi_N = e^{(-2\pi i)/N}$ is an Nth root of unity.

2.4. Correlation Implementation Using FFT

Let X, and Y be data sets such that, correlations based FFT is defend as: take FFT of X, and FFT of Y, multiply one resulting transform by the complex conjugate of the other, and inverse transform the result product such as [9]:

$$Corr(X,Y) = IFFT(FFT(X) * FFT(Y)) \quad ,.......... \quad (5)$$

2.5. Eigenpalm

Eigenpalm or the Principle Component Analysis (PCA) is a statistical measurement method, which operates in the linear domain and can be used to reduce the dimensionality of an image. A palmprint image can be viewed as vectors and represented in matrix form. This method can be described as follows [10]:

Let I denote a $n_1 \times n_2$ gray scale image. Represent I by a means of a vector, $x = n_1 \times n_2$, which can be seen as a point in R^n . When performing PCA on these vectors, the eigenvectors obtained from the sample covariance matrix are called *Eigenpalms*. Here are the steps to computing these Eigenpalms:

1. Obtain palmprint images $I_1, I_2,.,I_M$.
2. Represent every image I_i as a vector x_i.
3. Compute the average palmprint

$$\psi = \frac{1}{M}\sum_{i=1}^{M} x_i \quad ,.......................(6)$$

4. Subtract the mean palmprint

$$\varphi_i = x_i - \psi_i \,, \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (7)$$

5. Compute the covariance matrix

$$C = \frac{1}{M}\sum_{n=1}^{M}\varphi_n\varphi_n^T = AA^T \,, \ldots\ldots\ldots \quad (8)$$

6. Compute the eigenvectors u_i of AA^T:
   6.1 Consider matrix AA^T as an MxM matrix.
   6.2 Compute the eigenvectors v_i of AA^T such:

$$A^T A\gamma \Rightarrow \mu_i v_i \Rightarrow AA^T A\gamma = \mu_i A\gamma \Rightarrow Cu_i = \mu_i u$$

Where $\mu_i = Av_i$,................ (9)

   6.3 Compute the M best eigenvectors of AA^T:

$$\mu_i = Av_i \,, \ldots\ldots\ldots\ldots\ldots\ldots \quad (10)$$

7. Keep only K eigenvectors.

2.6. Palmprint Post-processing

A feature is normalized by scaling its values so that they fall within a small-specified range, such as 0 to 1. Min-max normalization performs a linear transformation on the original data. Suppose that mina and maxa are the minimum and the maximum values for feature A. Min-max normalization maps a value v of A to v' in the range [new_{min}, new_{max}] by computing:

$$v' = \left(\frac{(v - mina)}{(maxa - mina)}\right) \times (new_{max} - new_{min}) + new_{min}$$

, ……………..…………………….. (11)

2.7. Eigenpalm Matching

Let X and Y be two spectral eigenpalm feature vectors where, $x_i \in$ X, $y_i \in$ Y, i=1,…,n. to calculate the degree of association, a correlation distance is defined as [6]:

$$R = 1 - r, \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (12)$$

Where r is the linear correlation coefficient which is given by the formula [6]

$$r(X,Y) = \frac{\sum_{i=1}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}(y_i - \bar{y})^2}} \,, \ldots (13)$$

Where $\bar{x}$ the mean of the vector is X, and $\bar{y}$ is the mean of the vector Y.

The correlation distance determines the genuine or forged query sample; it is easy to verify the input pattern by a pre-defined threshold value T. If the value R is smaller than threshold T, then the owner of query sample is claimed to be individual X. Otherwise, the query sample is classified as a forged pattern.

2.8. Threshold Selection

In any palmprint identification system, it is essential to pick a suitable threshold (T), for a good performer results. To this end, an approach based on intra-class and inter-class information collected from the Enrolment database. The intra-class (D) measures the distances between images of the same individual, therefore it gives an indication of how similar the images of the same individual are. The intra- distance is defined as:

$$d_{ik}^{ik'} = (1 - r(\Omega_{ik}, \Omega_{ik'})), \ \ldots\ldots\ldots \ (14)$$

Where $i \in I,\ I, k' \in K$, and $K \neq K'$

The inter-class (P): The distances between the images of an individual are measured against the images of other individuals in the Enrolment database. Therefore it gives anindicates how different each image of an individual is when compared to images of other individuals in the Enrolment database. The inter-distance is defined as:

$$p_{ik}^{ik'} = (1 - r(\Omega_{ik}, \Omega_{jl})), \ \ldots\ldots\ldots \ (15)$$

Where $j \in I$, $i \neq j$, and $l, k \in K$

A threshold (T) is then calculated from intra-class and inter-class information as described in [11]. The estimation of threshold (T) depends mainly on the number of images per individual in Enrolment, therefore as in [10], every individual should have at least 4 images for Enrolment database. The algorithm for the maximum intra-class, and the minimum inter-class calculation is described as:

Input: $I = \{1,...I'\}$, where I' = number of individuals, $K = \{1,...,K'\}$, where K' = number of images per individual, F_{ik}= normalized palmprint image feature vector i $\in$ I and k $\in$ K

Ω = feature matrices of training images for each image

Output: D_{max}=*Maximum intra*-class, *and* P_{min}=*minimum* inter-class

Process:

Step1: Do while the $(\text{Fik} \neq 0)$

Step2: Compute the intra distances, and the inter distances

Step3: End of while

Step4: Store the intra-class (D), and the inter-class (P) in ascending order

Step5: Compute $D_{\max}$, and $P_{\min}$.

Step6: End.

2.9. Eigenpalm Identification Process

An unknown query palmprint can be represented as a linear combination of the best K Eigenpalms of the obtaining eigenvectors for a given dataset. In Palm identification, the eigenpalms are used once again in order to compute a distance from the query in the palm space. The algorithm is summarized below:

Input: an unknown image vector x

Output: matching result

Process:

Step1. Compute

$$\varphi = \mathrm{x} - \mathrm{y}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (16)$$

Step2. Compute

$$\varphi^{\wedge} = \sum_{\mathrm{i}=1}^{\mathrm{k}} w_{\mathrm{i}} u_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (17)$$

Where $w_i = u_i^T \varphi$,

Step3. Compute

$$\mathrm{D_e} = \left\| \varphi - \varphi^{\wedge} \right\|, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (18)$$

Step4. If $\mathrm{D_e} < \mathrm{T}$, then x is a palm.

Where $\mathrm{D_e}$ is the distance from palm space.

3. The proposed Normalized Energy based Spectral Eigenpalm Feature

The new proposed idea of applying the FFT in the implementation for Eigenpalm is by using FFT in the implementation of the correlation, as an alternative of conventional ideas of converting the intensity of the image palmprint data into the spectral domain, followed by applying the Eigenpalm. The new proposed idea is named as the spectral based eigenpalm feature.

The correlations can be computed by using the FFT as follows: FFT the two data sets, multiply one resulting transform by the complex conjugate of the other, and inverse transform the product. The method is implementing via the normalized energy instead of converting the input image into one dimensional vector.

Let I denote a $n_1 \times n_2$ gray scale palmprint image. Represent I by means of a vector, $x = n_1 \times n_2$, which can be seen as a point in R^n . Here are the steps to computing these Eigenpalms:

1. Obtain palm images I_1, I_2... I_M.
2. Represent every image I_i as a vector x_i, by using a normalized energy for each n_1
3. Compute the average palmprint $$\psi = \frac{1}{M}\sum_{i=1}^{M} x_i$$
4. Subtract the mean palmprint $$\varphi_i = x_i - \psi_i$$
5. Compute the covariance matrix $$C = IFF(FF(\varphi)FF(\varphi^T)) = AA^T$$
6. Compute the eigenvectors u_i of AA^T :

6.1 Consider matrix AA^T as an $M \times M$ matrix.

6.2 Compute the eigenvectors v_i of AA^T such that:

$$A^T A v_i \Rightarrow \mu_i v_i \Rightarrow A A^T A v_i = \mu_i A v_i \Rightarrow C u_i = \mu_i u_i$$

Where $\mu_i = A v_i$

6.3 Compute the M best eigenvectors of AA^T: $\mu_i = A v_i$

7. Keep only K eigenvectors.

4. Scheme Phases

4.1 Enrolment Phase

100 palmprint images collected from 10 individuals, a sample of 10 images depicted in Figure (4(a-j)), 4 of them are female, 6 of them are male. Each of them is asked to provide abut 10 images for their left palm. Originally, the collected images have size, 584 × 484 pixels with 75dpi resolution. The gathered palmprints images belong to individuals place their hands freely on the platform of the scanner when scanned. This results in palmprint images with different shifts and rotation. Therefore, some pre-processing operations are required to correct the orientation of the image. Next, a sub-image which represents the central part of the palm is extracted so that the feature extraction process can be performed on a fixed size of image. The size of the central part for each palmprint image is 256× 256 pixels.

A normalized energy is computed for each sub-image. Next the spectrum Eigenpalms is applied. A min-max normalization take place to convert the result feature vector to an element between [0,1]. The results normalized feature vector is labeled manually, and 40 samples (4 for each individual) where used to form a database, which named the Enrollment Database EDB, the other 60 samples where used to perform the identification. A threshold value T, is computed using the intra-classes and inter-classes, T is equal to (4.2915e-007) and stored in the enrolment database for the identification phase.

4.2 Identification Phase

A comparison based on using the correlation distance for each of the rest 60 query samples with the other10 normalized distribution centers extracted from the 40 reference in EDB. Table (1) depicts the number of success identification for each of the 60 query samples.

The robustness of the normalized energy spectral eigenpalms identification algorithm over noise image with different noise types is investigated. Taple (2) represents the parameters of the used varying types of noise. Table (3) represents the result of the identification.

The robustness of the normalized based spectral eigenpalms identification algorithm is studied, with different unknown palmprint images for boyes and griles, Table (4) depict result.

5. Conclusion

The palmer presents a physiological biometric feature for an individual's identity, are mostly used in many fields for different applications. Lines and points are extracted from palmers for personal identification in either original or frequency space palmer image. This paper is devoted to presents the normalized energy based spectral eigenpalms as means used for human identification. As a result there are some conclusions, from these:

1. The gathered palmprints images belong to individuals who place their hands freely on the platform of the scanner when scanned. This results in palmprint images with different shifts and rotation. Therefore, some preprocessing operations are required to correct the orientation of the image. Next, a sub-image which represents the central part of the palm is

extracted so that the feature extraction process can be performed on a fixed size of image
2. To reduce system complexity, a horizontal projection is adopted to obtain 1-D energy profile palmprint image. To exploit the benefits driving from concentrated energy, every column is accumulated as energy palmprint image.
3. For accurate feature vector extraction a normalized energy is implemented for each energy palmprint image.
4. The distanced methods, normalization helps to prevent features with initially large ranges from outweighing features with initially smaller ranges.
5. The proposed system is implemented for identification 10 individuals, with success of identification rate of 96.6%. Table (1) depicts the effectiveness of the proposed method.
6. A different noise types as in depicted in Table (2) are used to investigate the application of spectrum eigenpalm in different noise levels, and the method gives a success identification of 96.6%. Table (3) depicts the effectiveness of the proposed method.
7. A threshold value (4.2915e-007) is used to prevent the imposter form being identified. Table (4) depicts the effectiveness of the proposed method.

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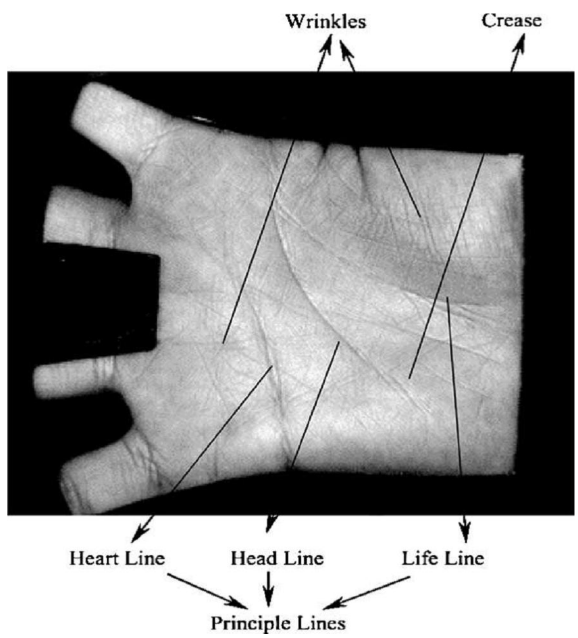

Figure (1): The main patterns in a palmprint [1].

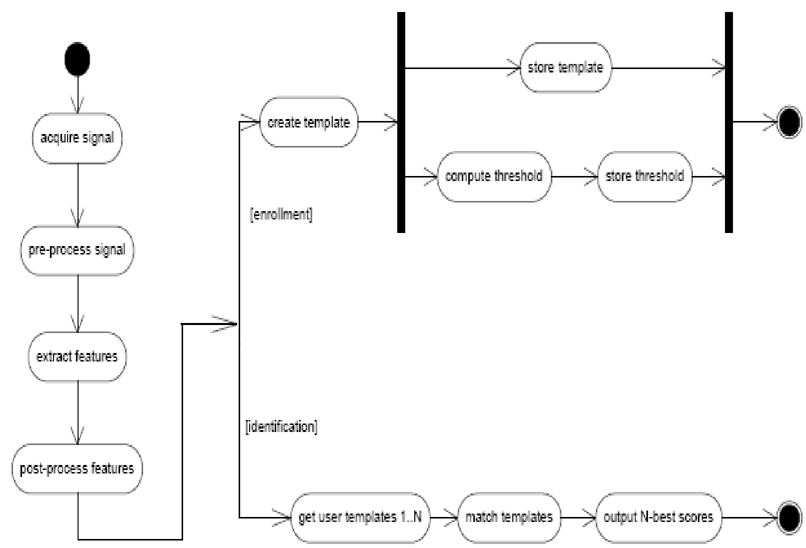

Figure (2): The palmprint Identification System [2].

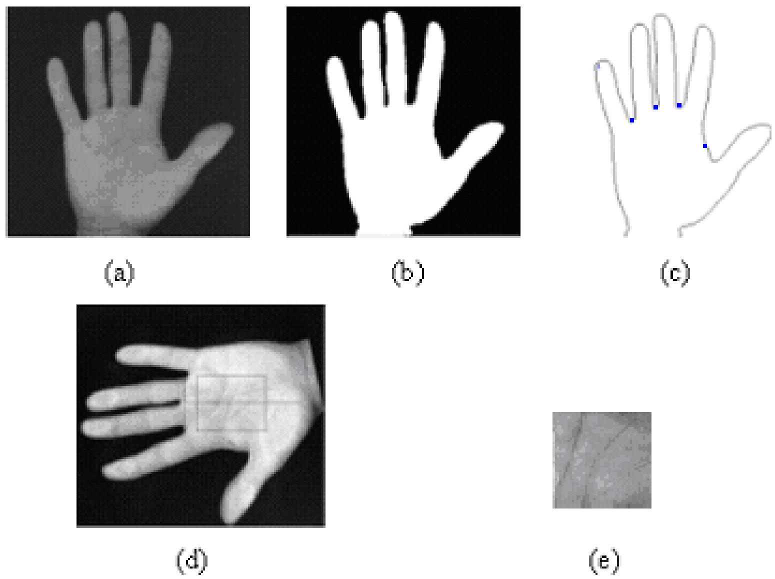

Figure (3(a-e)): The preprocessing steps

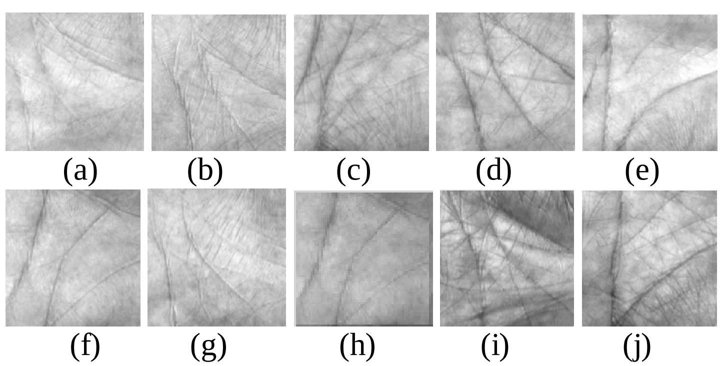

Figure (4(a-j)): The images from the databases.

Table (1): The success identification for EDB

	Palm1	Palm2	Palm3	Palm4	Palm5	Palm6	Palm7	Palm8	Palm9	Palm10
No. of Success Identification	6/6	6/6	6/6	6/6	6/6	6/6	6/6	6/6	5/6	6/6

Taple (2): The parameters of the used noise types.

Salt and Piper	Gaussian	Poisson
Noise Density = 0.01	Mean = 0, and Variance = 0.01	-

Table (3): The number of success identification

	Palm1	Palm2	Palm3	Palm4	Palm5	Palm6	Palm7	Palm8	Palm9	Palm10
No. of Success Identification	6/6	6/6	6/6	6/6	5/6	6/6	6/6	6/6	5/6	6/6

Table (4): The number of success refused identification

	Palm1	Palm2	Palm3	Palm4	Palm5	Palm6	Palm7	Palm8	Palm9	Palm10
No. of Success refused Identification	3/3	3/3	3/3	3/3	3/3	3/3	3/3	3/3	3/3	3/3