

Retina Identification Based on the Pattern of Blood Vessels Using Angular and Radial Partitioning

Mehran Deljavan Amiri, Fardin Akhlaqian Tab and Wafa Barkhoda

Department of Electrical and Computer Engineering

University of Kurdistan, Sanandaj, Iran

deljavan@ieee.org, f.akhlaqian@uok.ac.ir, w.barkhoda@ieee.org

Abstract. This paper presents a new human identification system based on features obtained from retina images using angular and radial partitioning of the images. The proposed algorithm is composed of two principal stages including feature extraction and decision making. In the feature extraction stage, first all of the images are normalized in a preprocessing step. Then, the blood vessels' pattern is extracted from retina images and a morphological thinning process is applied on the extracted pattern. After thinning, two feature vectors based on the angular and radial partitioning of the pattern image are extracted from the blood vessels' pattern. The extracted features are rotation and scale invariant and robust against translation. In the next stage, the extracted feature vectors are analyzed using 1D discrete Fourier transform and the Manhattan metric is used to measure the closeness of the feature vectors to have a compression on them. Experimental results on a database, including 360 retina images obtained from 40 subjects, demonstrated an average true identification accuracy rate equal to 98.75 percent for the proposed system.

1 Introduction

The recent advances in digital technology and increasing security concerns cause a requirement to use intelligent person identification systems based on the human's biological features. Biometric is the science of recognizing the identity of a person based on the physical or behavioral attributes of the individual. The popular used biometric features in identification purposes are fingerprint, face, facial thermo-gram, iris, retina, palm print, hand geometry, gait, ear, voice, signature, teeth, hand vein, etc. These features are unique in every individual and can be used as identification tools [1–4]. Among these features, retina may provide higher level of security due to its indigenous robustness against imposture. Uniqueness of retina comes from uniqueness of blood vessels' pattern distribution at the retina. From the other hand, the retina pattern of each person undergoes less modification during his life. Therefore, we can say that the retina pattern is a good candidate to be used in identification systems. The retina pattern of each person can be identified even among genetically identical twins [5].

Several researches on retina identification have been reported in the literature [6–8]. The first retina based identification system named EyeDentification 7.5 was introduced by EyeDentify Company in 1976 [6]. In [7] Xu et al. obtained vector curve of blood vessels' skeleton using the green channel gray-scale retina images. They defined a set

of feature vectors for each image including feature points, directions, and scaling factor. Although they have reached a good recognition result, but the major drawback of their method is its computational cost, since a number of rigid motion parameters should be computed for all possible correspondences between the query and enrolled images in the database. Ortega et al. [8] used a fuzzy circular Hough transform to localize the optical disk in the retina image. Then, they defined feature vectors based on the ridge endings and bifurcations from vessels obtained from a crease model of the retinal vessels inside the optical disk. For matching, they used a similar approach as in [7] to compute the parameters of a rigid transformation between feature vectors which gives the highest matching score. This algorithm is computationally more efficient with respect to the algorithm presented in [7]. However, the performance of the algorithm has been evaluated using a very small database including only 14 subjects. Recently, Tabatabaee et al. [9] presented a new approach for human identification using retina images by localizing the optical disk using Haar wavelet and active contour model and they used it for rotation compensation. Then, they used Fourier-Mellin transform coefficients and complex moment magnitudes of the rotated retinal image for feature definition. Finally, they applied a fuzzy C-means clustering for recognition and tested their approach on a database including 108 images of 27 different subjects.

Chalechale et al. have introduced a sketch-based method for image similarity measurement using angular partitioning (AP) [10, 11]. In their method, a hand-drawn rough black and white query sketch is compared with an existing database of full color images. Although, this method have been proposed for natural and hand-drawn images retrieval, but it could be modified to be used in other image matching systems. In this paper, we are going to propose a new approach for identifying retina images based on angular and radial partitioning (RP) of images. The identification task in the proposed system is invariant from the most of the common affine transformations (e.g. rotation, scale changes and translation). The proposed system eliminates any constraint regarding the shape of the objects and the existence of any background. Also, segmentation and object extraction are not needed in this approach. So, the computational complexity of the image matching algorithm is low and the proposed system is suitable for secure human identification especially in real-time applications.

The rest of this paper is organized as follows: Section 2 introduces the angular and radial partitioning briefly. Section 3 presents the proposed system. The feature extraction procedure and decision making process is discussed in this Section. In Section 4, some details about the simulation of the proposed algorithm are given and experimental results of are presented in this Section. Finally, Section 5 concludes the paper.

2 Angular and Radial Partitioning

Chalechale et al. [10, 11] have defined angular partitions (slices) in the surrounding circle of the image I . The angle between adjacent slices is $\varphi = 2\pi/K$, where K is the number of angular partitions in the image (see Figure 1). Any λ slices rotation of a given image, with respect to its center, moves a pixel at slice S_i to a new position at slice S_j where $j = (i + \lambda) \bmod K$, for $i, \lambda = 0, 1, 2, \dots, K - 1$. They used the number of edge points at each slice of the image to represent the slice feature.

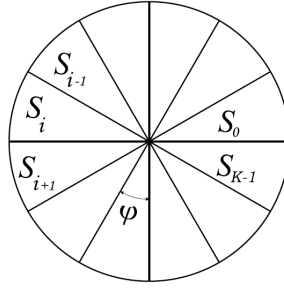


Fig. 1. Angular partitioning partitions the image into K successive slices.

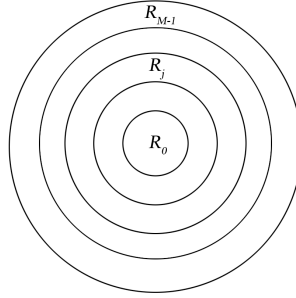


Fig. 2. Radial partitioning partitions the image into M concentric circles.

$$f(i) = \sum_{\theta = \frac{i2\pi}{K}}^{\frac{(i+1)2\pi}{K}} \sum_{\rho=0}^R I(\rho, \theta)$$

R is the radius of surrounding circle of the rotated image. The feature extracted above will be circularly shifted when the image I is rotated $\tau = l2\pi/K$ radians in counterclockwise direction ($l = 0, 1, 2, \dots$).

It can be shown that for an image I and a rotated version of it, I_τ , using 1D discrete Fourier transform (DFT) of $f(i)$ and $f_\tau(i)$ and based on the property $|F(u)| = |F_\tau(u)|$ we can use the $\{|F(u)|\}$ and $\{|F_\tau(u)|\}$ as the rotation invariant features in images I and I_τ [10, 11].

The radial partitioning, partitions a given image I into the multiple concentric radial partitions (circles). The number of circles could be adjusted in the applications to reach the best performance (see Figure 2). During the rotation process for a given image with respect to its center, the local information of the image at each circle (e.g. the number of edge points, gray levels histogram, neighborhood information, etc.) are not changed.

To increase the delicacy of the extracted features in this paper, a combination of the AP and the RP was used in feature extraction. The details of the feature extraction process will be discussed in Section 3.

3 The Proposed System

Similar to the most of the pattern recognition algorithms, the identification task in the proposed system can be divided into two stages: 1- Feature extraction. 2- Decision making. The following subsections describe the details of steps.

3.1 Feature extraction

The overview of feature extraction process in the proposed system is depicted in Figure 3. This process is done for every enrolled and query images. As Figure 3 shows, the feature extraction stage consists of some steps. In the preprocessing step, first, to achieve translation invariant features, the extra margins of the input image are cropped and the bounding box of retina is extracted from the input image. Also, to achieve the scale invariancy, the cropped image is normalized to $J \times J$ pixels (see Figure 4 (b)). At the next step, the pattern of the blood vessels' in the retina image should be detected. There are several vessels' pattern detection algorithms in the literature. Here we adopted a similar approach as in [12] to reach the vessels' pattern (see Figure 4 (c)). A morphological thinning procedure [13] is employed for thinning the vessels' pattern in the pattern image (see Figure 4 (d)). This task is based on the fact that usually there are thick lines in the pattern and thinning these lines helps to increase the performance of the system. At the next steps, two modes of feature extraction based on AP and RP are applied to the thinned pattern image in parallel (see Figures 4 (e) and 4 (f)). At each mode, first, the thinned pattern image is partitioned using the related partitioning method (AP or RP) and the number of pattern points is counted at each partition (slices in AP and circles in RP) as the partition feature. The results of these two parallel processes are two feature vectors (AP feature vector and RP feature vector) for each image. The resulting two vectors are the feature set of each image.

3.2 Decision making

Similarity measurement is a key point in pattern recognition algorithms. One of the most important tasks in image based identification systems is search the image database to find an image or some images similar to a given query image. To compare the database's images and the query image, the feature vectors extracted from the database's images and from the query image are passed through a distance measurement metric to find out the degree of closeness. There are several metrics in the literature to measure the closeness of two feature vectors. The most common metrics among this family are the Manhattan and Euclidean metrics [14–16]. The weighted Manhattan and weighted Euclidean metrics are widely used for ranking in image retrieval [17–19].

As described in Section 3.1, in the proposed system, two feature vectors are extracted from every image (AP based and RP based feature vectors). To compare the

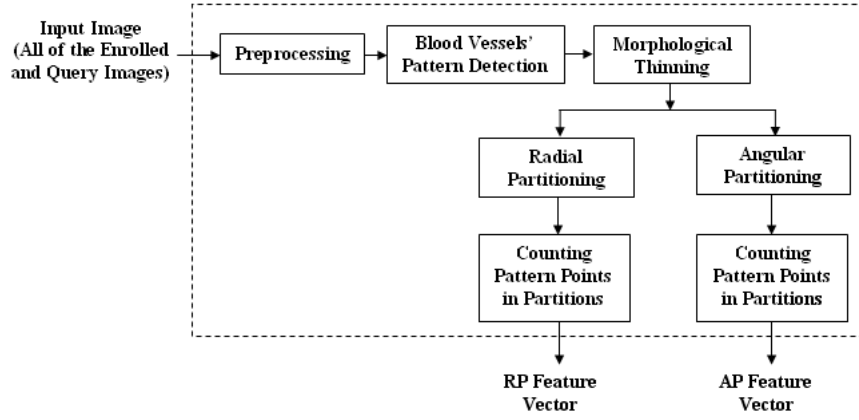


Fig. 3. The overview of the feature extraction process in the proposed system.

feature vectors, first a 1D DFT is applied on each feature vector and the absolute value (Abs) of each DFT vector is calculated. As described in Section 2, this action is done to stultify the effect of rotation on the feature vectors and consequently results a rotation invariant identification system. Then, the Manhattan metric is used to measure the distance of feature vectors. Because of the existence of two feature vectors for each image, two Manhattan distances will be produce here. To have a total distance, the two Manhattan distances are combined with a simple summation (see Figure 5).

$$\text{Distance}_{Total} = \text{Distance}_{AP} + \text{Distance}_{RP}$$

The closest image in database to the query image is the one that have the minimum distance from the query image.

4 Experimental Results

The proposed system was fully software implemented and has been tested on a database including 40 retina images from DRIVE database [12]. To do the following experiments, the size of the preprocessed images was set to 512×512 ($J = 512$). To apply the AP on images, the angle of each partition was set to 5° . Therefor each image is divided into 72 ($360^\circ/5^\circ$) slices and the *AP Feature Vector* have 72 elements (features). The number of circles in RP was chosen to be 8. So, the *RP Feature Vector* has 8 elements.

To produce test images (query images), each image in the database was rotated 8 times using various degrees to obtain 320 new query images. Table 1 shows the results of identification of the query images in the proposed system.

As the Table 1 shows, the proposed system has an average accuracy equal to 98.5 percent.

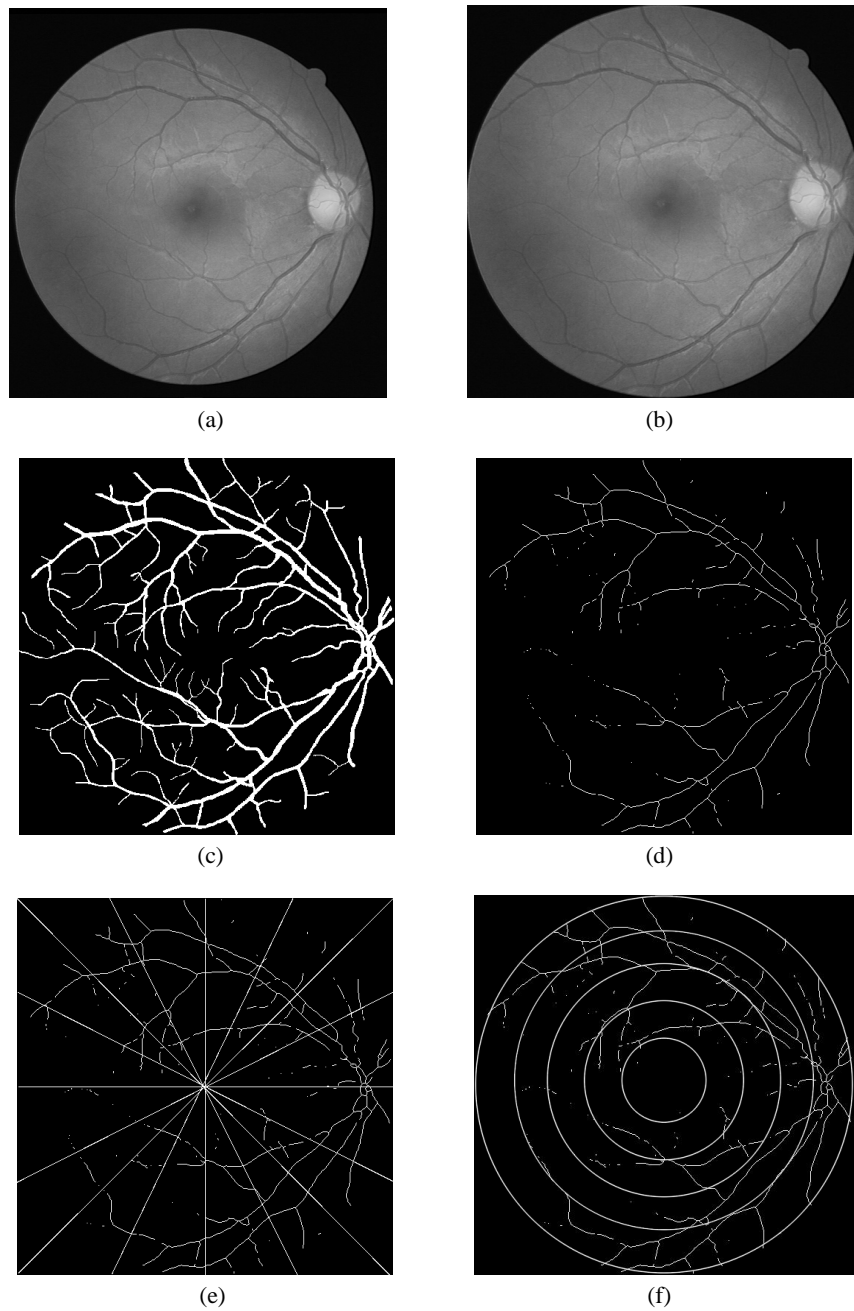


Fig. 4. (a). A sample retina image, (b) Preprocessed image, (c) The blood vessels' pattern, (d) Morphological thinned pattern, (e) Angular partitioning of the thinned pattern, (f) Radial partitioning of the thinned pattern.

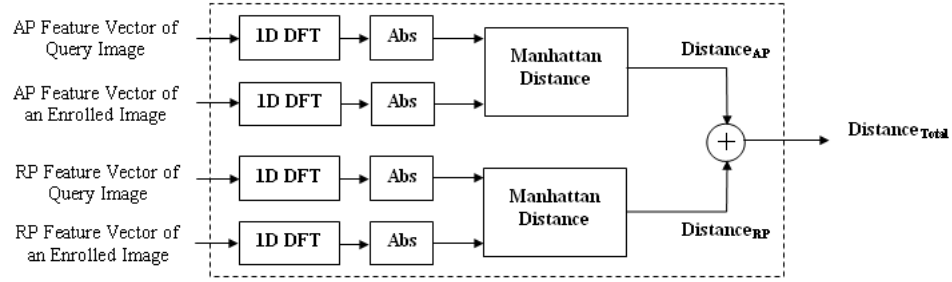


Fig. 5. Overview of the decision making stage.

Table 1. Results for identifying query images in the proposed system.

Rotation Degree	5	10	15	30	45	90	180	270	Mean
Accuracy (percent)	100	97.5	97.5	95	100	100	100	100	98.75

5 Conclusion

In this paper, a novel human identification system based on retina images was introduced. To identify a retina image, after normalizing it in a preprocessing step, the blood vessels' pattern was extracted from the retina image and a morphological thinning process is applied on the extracted pattern. Two feature vectors were extracted from the thinned pattern using angular and radial partitioning. To match the query image with the database, the feature vectors were analyzed using 1D discrete Fourier transform. The similarity between feature vectors was measured by Manhattan distance. The performance of the proposed system was evaluated using a database containing 360 images from 40 objects. Experimental results demonstrated an average true accuracy rate equal to 98.75 percent for the proposed system. Simplicity, low computational complexity, robustness against rotation, scaling and translation and high accuracy ration of the proposed approach, make it attractive for secure human identification systems and real-time applications. Further research will study the performance of the proposed identification approach against different geometric and non-geometric distortions and attacks.

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