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Biometric Authentication With Finger Vein Images Based On Quadrature Discriminant Analysis

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Abstract: For long ago, biometric authentication has been performed for high-security applications like bank lockers, private places. Here studies made on the physiological attributes of an individual can be represented with his finger print, iris, etc. Among those finger vein identification is a new methodology in the biometric recognition system. Here, finger vein patterns can be used to give authentication to an individual for accessing high-security applications. In this paper, we are going to perform finger vein recognition Quadrature Discriminant analysis method. Finger vein images are subjected to preprocessing steps for making the image more stable for further processing. Then QDA process has been applied, followed by the Minimum Distance Classifier.

Keywords: Biometric recognition, finger vein, QDA, MDC,

I. INTRODUCTION

Nowadays, every smartphone has fingerprint recognition in it. Apart from face and iris, finger vein authentication is mostly available in almost all smart gadgets. But finger vein identification has been introduced in 80’s itself but has not been brought into practice, still, it is a promising technique for the human recognition system [4].

Fig 1. Finger vein scanner

As a first of all procedure finger vein has been extracted with respective device [6]. By this process, ridges of veins are extracted. The output of identification [3] applies primarily to the consistency of retrieval of vein artifacts. Using near-infrared spectroscopy, the normal method is to collect finger vein images. Infrared rays with 760nm have been used and fingers are placed over it; with the light rays passing through tissues of finger patterns of finger veins can be captured and absorbed by deoxygenated hemoglobin the vein[7][8]. Since only the blood vessels consume the rays, the resultant vein picture looks more in-depth than the other finger regions. The direct impact has been shown on feature extraction and matching by this extraction method [5].

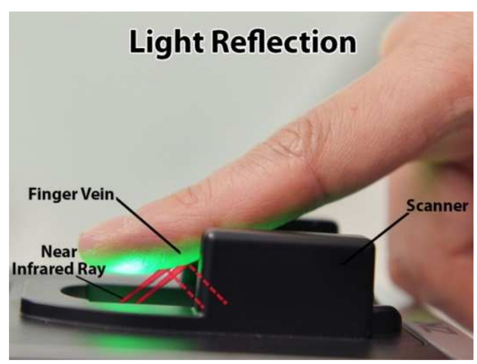

Fig2. Finger vein working procedure

In general, it is known that developing a finger vein recognition device that achieves any degree of efficiency is a great challenge [11][17]. To describe a final configuration used and clarified in this article, numerous extraction methods and variations have been researched for this proposal. This paper also suggests a new form of finger vein pattern identification based on geometric finger vein pattern parameters [15], which is to obtain the maximum and minimum distance values between two lines of finger vein pattern cross-section scans. [9].

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The finger vein pattern [14] used for submission of authentication are stored as an image dataset. An LED light source containing a terminal device has been used to get exact finger vein images with the help of a monochrome charge camera coupled with near-infrared. The LED light with near Infrared has been absorbed by the Hemoglobin present in human blood that makes vein dark and other tissues lighter. The image captured is converted to digital format and stored. Finger vein images have been captured and used for recognition purposes by comparing with database images [10].

II. LITERATURE SURVEY

Faris E. Mohammed et al.(2014) proposed a system for finger vein and iris recognition with 92% detection accuracy. It is using a multimodal biometric recognition and authentication device. The proposed method is a reliable identity and recognition method that is mildly safe and durable. The approach suggested is a novel synthesis of biometric research that can be expanded and developed over time. [6].

D. Ezhilmaran et al. (2015) A thorough analysis of the current techniques of extraction of features and image enhancement algorithms for identification of finger veins is given. The accuracy and robustness of feature extraction techniques are essential in order to achieve a more precise and effective finger vein recognition system. The fuzzy-based approach shown in this paper explains the suitability of vein-based methods on reviews. Future projection of the course will be based on fuzzy and advanced finger veins [1].

Naoto Miura et al.(2017) Describes the methods used for the introduction of authentication based on finger veins for smartphones and other personal electronic gadgets with the help of visible light cameras installed in it. No, these devices are capable of authenticating finger veins with the help of multiple cameras injected in the same device. In a wide range of services, including financial sectors, show the future application with PBI technology [13].

Dr. S. Brindha et al. (2018) Proposed an approach by which obsolete minutiae points are eliminated using a neighborhood removal strategy to increase the device's efficiency. Various considerations, such as the number of intersections in the vein pattern and the pattern around the intersection point, are considered in this biometric method [7]. This intersection point will be taken by the system itself, taking the point of intersection as the mid-point. Thus, the authentication of finger veins by this new approach would ensure a high degree of protection. The proposed reduced feature set approach has high precision and better efficiency [12].

Madhusudhan M V et al. (2019) Presented a novel approach for a finger vein based authentication system. CNN based process has been followed up in this method for recognition. Higher accuracy has been achieved with ResNet-50 by training the system with millions of images as dataset. 250 neuron based hidden layer has been formed with low complexity has been used. For managing overfitting, Optimization and loss functions have been used. 96% accuracy has been achieved with the proposed method [7].

III. METHODOLOGY

Vein images are captured using Near InfraRed light, which compares the contrast of vein and other tissues, which can also be relied on CMOS CCD cameras. Either transmission or reflection tool can be used for the human finger vein recognition system [16].

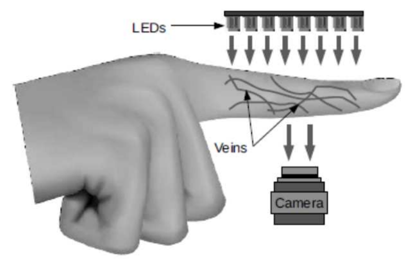

Fig3. Finger vein acquisition using transmitted light.

The finger on which vein has to be captured has been placed between the light source and the camera, as shown in Fig.1a. The light rays passing through the fingers have been captures using an image sensor. The dark pattern has been acquired as vein images as the blood in the vein absorbs NIR light.

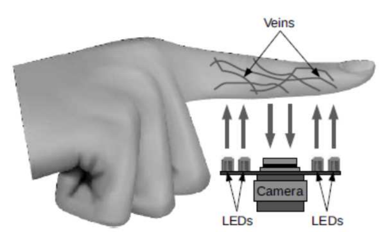

Fig4. Finger vein acquisition using reflected light.

Another method for acquiring finger vein images is through the reflexive approach used to capture fingerprint images and shown in Fig.1b by the image sensors. Light from the light source reaches the finger and are passes through the skin surface. The reflected light shows the fused light image. The difference in reflected light intensity gives the vein pattern of the finger [16]. Less reflection is seen in the vein area since they absorb light and on the rest of the area will show lighter patterns.

A. Step I

Image acquisition: initially, images are acquired with a finger vein image acquisition device. With either two method given above.

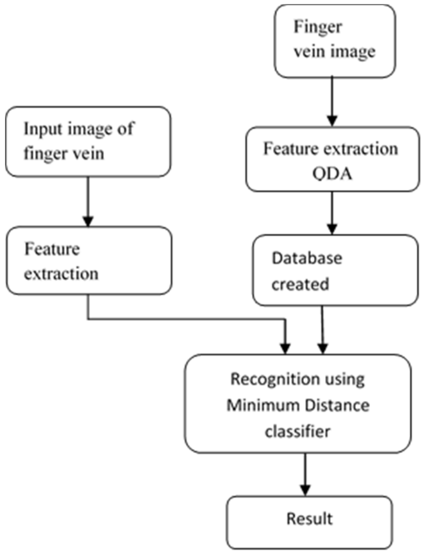

Fig5. Flow diagram of a complete system

Preprocessing: four levels of preprocessing steps are carried out Grayscale conversion, which reduces the data size of the image that makes it more comfortable to work with, then comes image resizing by which all input images given for testing are converted to a uniform size that improves the accuracy of classification, as a final step with median filtering, noise from images are removed.

B. STEP II- QDA for feature extraction

Quadratic Discriminant Analysis (QDA) has been used for the feature extraction process in this work. LDA and QDA show some similar performances with naturally distributed quantities. There is no presumption in QDA process like LDA that gives the same covariance for every class. For quadratic discrimination parameter approximation done with more data and calculation unless Linear Discrimination. When the variation in covariance is shown with low, which makes the process to proceed with Quadratic analysis.

$$F(i = k|j) = \frac{F(i|j = k)F(j=k)}{F(i)} = \frac{F(i|j = k)F(j=k)}{\sum F(i|j = l).F(j=l)_i} \quad (1)$$

And we're going to select class K to maximize this posterior probability.

By using simple probabilistic methods, both LDA and QDA can be derived by which conditional distribution of data can be acquired with $P(I|_{j=k})$ For every class. Using Baye 's law, Predictions will then be achieved for each training set

$$F(i|j = k) = \frac{1}{(2\pi)^{d/2}|\sum_k|^{1/2}} exp\left(-\frac{1}{2}(i - \mu_k)^t \sum k_k^{-1} (i - \mu_k)\right) \quad (2)$$

D is a number of features.

The log of the posterior, according to the model above, is :

$$\log F(j = k|i) = \log P(i|j = k) + \log F(j = k) + Cst$$

$$= -\frac{1}{2}\log\left|\sum x_k\right| - \frac{1}{2}(i - \mu_k)^t \sum k_k^{-1} (i - \mu_k) + log\ F(j = k) + Cst, \quad (3)$$

The constant term Cst corresponds to the denominator F(x) and other constant terms from the Gaussian. The predicted class is the one that maximizes this log-posterior.

Quadrature Discriminant Analysis is one of the algorithms for classifying the discriminant analysis. The QDA probability density function obtained concerning the same covariance matrix is used.

C. STEP III- Minimum Distance Classifier for Classification

The minimum distance classification technique is one of the techniques used to classify the images among the different methods used for image classification. Concerning the nearest area of interest, minimum distance classification classifies images. The mean value for all types of images is determined initially in every data band's minimal distance classification methodology. The initialization of minimum distance is the most important step for classification [18].

The Euclidean distance from each unknown pixel to the average vector for each class is calculated. Both pixels are classified into the nearest area of the class of interest. Index of similarity is referred to as distance in MDC which is similar to maximum similarity. The minimum Distance value between all distances has been chosen with pixel similarity.

Unknown image data has been classified into MDC classes that reduce the distance between multi-feature space and image data. Index of similarity is referred to as distance in MDC, which is similar to maximum similarity. The minimum Distance value between all distances has been chosen with pixel similarity.

The k^{th} class Ω_k is represented by its mean vector m_k and covariance matrix, which can be estimated from the training samples:

$$m_k = \frac{1}{K_k}\sum_{i=1}^{K_k} X_i^{(k)} \qquad (k = 1, \ldots\ldots, C) \qquad (4)$$

and

$$\sum_k = \frac{1}{K_k}\sum_{i=1}^{K_k} X_i^{(k)} \qquad (k = 1, \ldots\ldots, C) \qquad (5)$$

Classification

A given pattern X of an unknown class is classified to Ω_k if its distance to Ω_k is smaller than those to all other classes:

$$x \in \Omega_k if\ Z_M(x, \Omega_k) = min\{Z_M(x, \Omega_i)\ i = 1, \dots \dots, C\}$$

For convenience, the distance$Z_M(x, M_i)$ can be used to replace the distance$Z_M(x, \Omega_i)$. Because only the mean vector of each class is typically used, the classification does not consider how classes are allocated in the function space.

IV. RESULT AND DISCUSSION

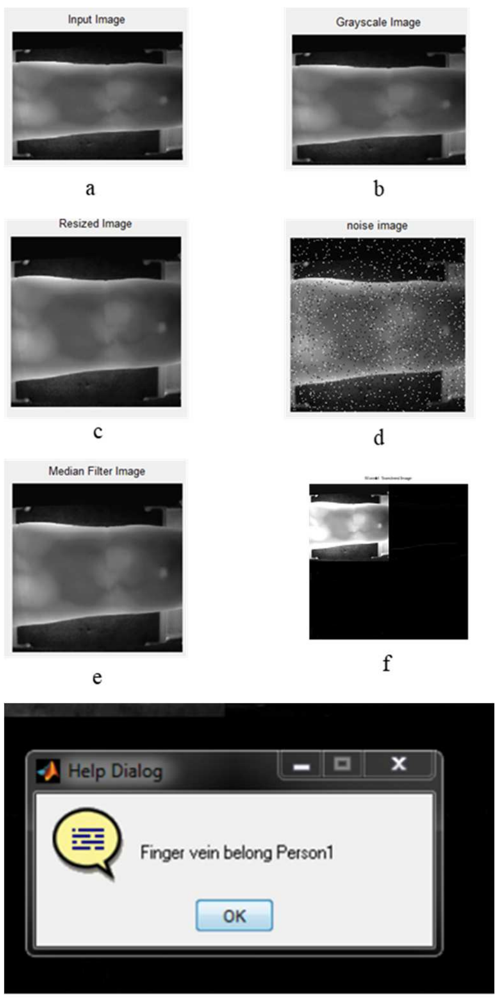

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Figure 6. (a) Input image, (b) Grayscale image, (c) Resized image, (d) Noisy image, (e) Median filtered image, (f) SPHIT decomposition, (g) final recognition

False Acceptance Rate (FAR): FAR refers to the acceptance of images that doesn't match the actual database

$$FAR = \frac{No.of\ images\ accepted\ faultly}{Total\ number\ of\ samples\ in\ the\ database} \tag{6}$$

False Rejection Rate: FRR refers to the rejection of actual matching database

$$FAR = \frac{No.of\ images\ rejected\ faultly}{Total\ number\ of\ samples\ in\ the\ database} \tag{7}$$

Method	Total number of samples	FAR	FRR	Accuracy in %
Knn	1054	5.48	3.36	91.16
MMD	2058	6.32	3.33	90.35
NET	2345	4.52	3.24	92.24
PCA	2154	3.36	2.18	94.46
Proposed	2268	0.75	0.55	98.7

MMD- Maxima minima Distribution

NET-Neighborhood Elimination Technique

PCA- Principle Component Analysis

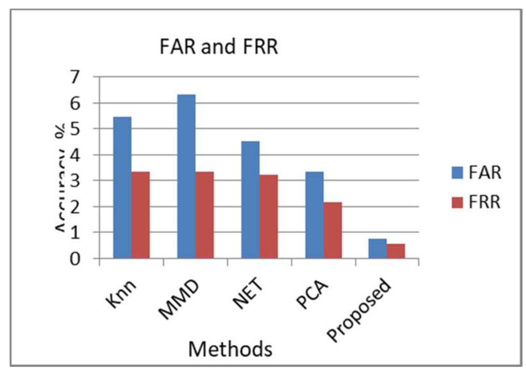

Fig7. FAR and FRR comparison chart of KNN, MMD, NET, PCA, the proposed method

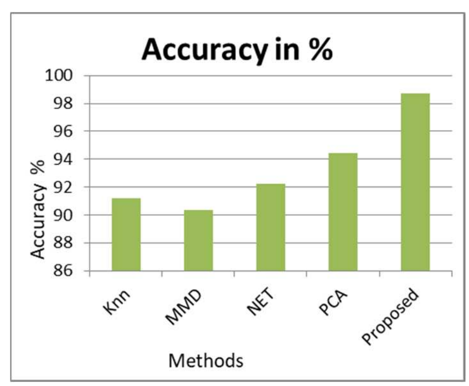

Fig7. Accuracy comparison chart of KNN, MMD, NET, PCA, proposed method

The above figure7 and 8 show the comparison chart of false acceptance rate, false rejection rate, and recognition accuracy with multiple algorithms. This shows low FAR and FRR rate in the proposed system and high accuracy compared to other methods.

V. CONCLUSION

The paper deals with design of a method for finger vein classification with Quadrature Discriminant Analysis and minimum distance classifier. Here input images are subjected to various preprocessing steps for stabilizing images. We perform the grayscale conversion, resizing, and noise removal. Then QDA has been applied for feature extraction. Extracted feature vectors are subjected to classification with a minimum distance classifier. This combination gives 98.7% accurate results of recognition.

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