Finger Print Based Gender Classification Using Neural Network Model Approach

Bhuvaneswari C Melinamath [1], Mulla Rahesha Y [2]

[1] S.S.D.G.C.T's Sanjay Ghodawat Group Of Institutions,Atigre, melinamath.bc@sginstitute.in
[2]S.S.D.G.C.T's Sanjay Ghodawat Group of Institutions, Atigre, mulla.ry@sginstitute.in

ABSTRACT

Identification of Gender using fingerprint applying neural network is proposed here. Finding the owner of finger print in criminal scene is advantageous. Theoretically, if the quantity of the male and female fingerprints in a database is equivalent, then the identification of a fingerprint on that database would be two times faster. Most of the method is based on ridge density. The proposed neural network method showed good result. However, ANN method is sensitive to the location of the fingerprint area where ridge density is determined.

Key Words: RTVTR, MM, OCM, GFM, DWT.

1. INTRODUCTION

Fingerprint is one of the well-known biometric techniques capable of identifying an individual. In the modern electronic era, system security is a major concern as a large amount of data is easily exchanged through computer networks. Obtaining positive identification is a vital.

An automatic fingerprint identification system is widely needed. It plays important role in forensic and civilian applications. Minutiae extraction forms an important step in fingerprint verification system. Fingerprint recognition is still challenging and important pattern recognition Problem. As fingerprints get increasingly embedded into various systems such as cell phones, it becomes highly important to analyze the impact of biometrics on the overall integrity of the system.

2. LITERATURE SURVEY

Lot of work is going in biometric recognition and privacy concern, security is still challenging [1]. Many researchers have used different technique Techniques [2], [6], [7], [8] [9], [10]. Pallavi et al. Proposed a A Novel method for Gender classification using 2D Discrete Wavelet Transform and Singular Value Decomposition. S. S. Gornale et al proposed technique for Gender Classification Using Spatial and Frequency Domain Analysis [3]. Rijo Jackson Tom and T. Arulkumaran proposed a method Gender Classification Using 2D Discrete Wavelet Transforms and Principal Component Analysis [4]. Sudha Ponnarasi et.al. Proposed a method for Gender Classification System Derived from Fingerprint Minutiae Extraction [5].

3. PPROPOSED METHODOLOGY

Module 1: Registration

In registration module we will use the left thumb print of a user. Biometric Device, device **eBioscan-C1** is used for taking input from user shown in figure 1.

Name: **eBioscan-C1,** Form Factor: Desktop**,** Package Dimensions: 8.9*8.9*3.9, Item Model Number: HFDUOB, Power Source: USB. OperatingSystem: Windows, Linux, Android.

Fig 1. eBioscan-c1

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Module 2: Preprocessing

The obtained input (Fingerprint) from the database goes through various stages like segmentation, normalization, orientation estimation, ridge frequency estimation,   binarization and thinning.

Segmentation:
Segmentation is the segregation of front regions in the image from the background regions. Subsequently, segmentation is utilized to evacuate the foundation regions, which encourages the reliable extraction of minutiae.

$$V(p) = \frac{1}{W^2}\sum_{i=0}^{W-1}\sum_{j=0}^{W-1}(I(j,i) - S(k))^2 \rightarrow (1)$$

where V(p)is the variance for the block I (k,j)is the gray level value at pixel (j,i) and S(k) is the mean gray level value for the block k. The result after segmentation is shown below in figure 2.

Fig. 2. Segmentation

Normalization: It is used to minimize varying range of the gray scale between ridges and valleys of the image in order to facilitate the processing of the following stages.

Normalization can remove the influences of sensor noise and gray-level deformation. Normalized gray value is given in following equation 2.

$$N(j,i) = \begin{cases} M_0 + \sqrt{\frac{V_0(I(j,i)-M)^2}{V}} \; if\ I(j,i) > M, \\ M_0 - \sqrt{\frac{V_0(I(j,i)-M)^2}{V}} \; otherwise, \end{cases} \rightarrow (2)$$

the gray-level value of pixel (j, i) considered as I (j, i),and the size of fingerprint image is m x n, M and V are the estimated mean and variance of input fingerprint image, respectively, and gray-level value at pixel (j, i) is given as N (j, i)., where M0, and V0 are the expected mean and variance values, respectively. Normalization process will not change ridge and valley structure but useful in pixel-wise operation.

Binarization: A grey level image is converted to a binary image with the help of **p**rocess of binarization. It minimize the noise between the ridges and valleys in a fingerprint image, and improves the extraction of minutiae. The binarization looks at the grey level value of each pixel of the improved image, and, if the value is greater than the global threshold, then the pixel value is set to a binary value one; otherwise, it is set to zero. The output after binarization in shown in figure 3,

Ridge frequency estimation: The image is first divided into small blocks and the gray scale values of the pixel in each block along a directional orthogonal to the local ridge orientation are plotted as per equation 3.

$$F(i,j) = \frac{1}{S(i,j)} \rightarrow (3)$$

Thinning: It makes the image crisper by reducing the binary valued image regions to lines that approximate the skeleton of the region.

Thinning cleans the image so that only reduced data needs to be proceed in the next image processing stage. Input after thinning is shown is shown in figure 4. All steps in finger processing are shown in figure 5.

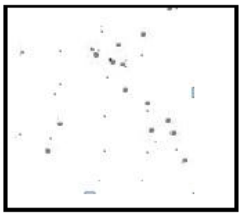

Fig. 3. Binarization

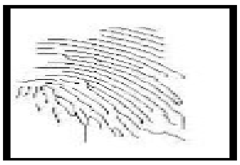

Fig. 4. Thinning Image

Fig. 5. Preprocessing stages in finger processing

First image is the original image which is captured from ebioscan-C1 device. Second image is segmented image, here separating the front region in the image from the background image is performed. This is input to the next image. Third image is, image orientation, in this image ridge count valley thickness, can be calculated, also image can be adjusted using transformation and rotation. Fourth image is Binarization, convert the gray scale image into binary image having either 0 or 1 last image is thinning. Thinning cleans the image so that only reduced data needs to be proceed in the next image processing stage.

Module 3: Feature Extraction

Feature extraction play a vital role in machine learning and pre-processing step for pattern recognition. In the Proposed method, non-zero singular values obtained from the SVD of fingerprint and the energy of all DWT sub-bands image are used as features for the classification of gender.

The separation of images into different frequency ranges allows the isolation of the frequency components introduced by “intrinsic deformations” or “extrinsic factors” into certain sub-bands. This method results in separating small changes in an image of high frequency sub-band images

To improve the performance of fingerprint gender classification more, the biometric features like the ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, ridge count asymmetry, minutiae map(MM) orientation colinearity maps(OCM), Gabor Feature maps(GFM) and orientation map (OM) for pattern type, 2D wavelet transform (DWT),features are extracted.

Module 4:- Neural Network Training

In Module 4 all the combined vectors within the database will then be allowed to pass for unsupervised training mode. It uses clustering with neural network technique within the combined vector database. It generates the clusters with unsupervised learning attempts of neural network model. The neural network model uses similarity measures or minimum distance for the entire combined vectors database.

Artificial Neural Networks (ANN) The ANN is called a “black box” due to the complexity of the ANN architectures. ANN has its advantages that include high affordability to the noise data with low error rate, and the continuously advancing and optimization of various network training, pruning, and rule extraction algorithms.

Naive Bayes algorithm [11]

The Naive Bayes Classifier technique is based on Bayesian theorem and is particularly suited when the number of inputs is high. Regardless of its effortlessness, Naive Bayes can regularly beat more modern characterization techniques.

Naive Bayes Classification is better understood by below example figure 6. As indicated, the objects can be classified as either GREEN or RED. Our task is to characterize new cases as they arrive, i.e., choose to which class label they have a belong, in light of the presently leaving objects. Since there are twice as many MALE objects as RED, it is reasonable to believe that a new case (which hasn't been observed yet) is twice as likely to have membership GREEN rather than RED. In the Bayesian analysis, this belief is known as the prior probability. Prior probabilities are based on previous experience, in this case the percentage of GREEN and RED objects, and often used to predict outcomes before they actually happen.

Prior probability for Male α Number of Male object / Total number of objects

Prior probability for Female α Number of Female object / Total number of objects

Since there is a total of 60 objects, 40 of which are GREEN and 20 RED, our prior probabilities for class

Membership are: *Prior probability for Green α 40/60 and Prior probability for Red α 20/60.*

Having formulated our prior probability, we are now ready to classify a new object (WHITE circle) shown in figure 7. Since the objects are well clustered, it is reasonable to assume that the more GREEN (or RED) objects in the vicinity of X, the more likely that the new cases belong to that particular color. To quantify this probability, we draw a circle around X which envelops a number (to be picked from the earlier) of focuses independent of their class names. Then we calculate the number of points in the circle belonging to each class label. From this we calculate the likelihood.

Likelihood of X given GREEN α Number of GREEN in the vicinity of X / Total number of GREEN cases.

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Likelihood of X given RED α Number of RED in the vicinity of X/ Total number of RED cases.

From the representation above, obviously Likelihood of X given GREEN is smaller than Likelihood of X given RED, since the circle envelops 1 GREEN object and 3 RED ones. Thus:

Probability of X given GREEN α 1/40
Probability of X given RED α 3/20

Posterior probability of X being GREEN α Prior probability of GREEN * Likelihood of X given GREEN
P(X, Green) =4/6 * 1/40 = 1/60
Posterior probability of X being RED α Prior probability of RED * Likelihood of X given RED
P(X, RED) =2/6 * 3/20 = 1/20

Finally, we classify X as RED since its class membership achieves the largest posterior probability using naïve Bayes algorithm.

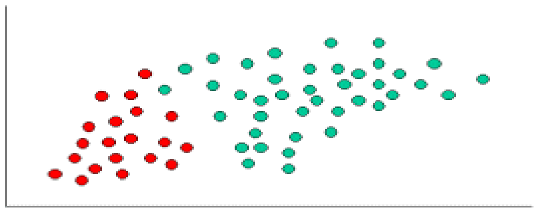

Fig.6. Cluster of Green and Red

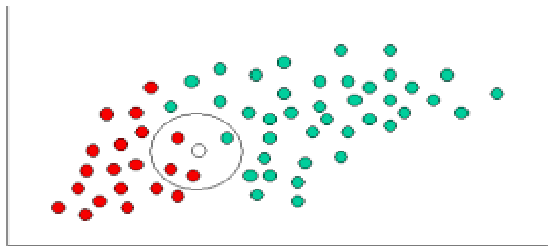

Fig.7. Cluster of Green, Red and white

4. Conclusion

Fingerprints give a unique identification and fingerprint most acceptable and reliable evidence. Most of the traditional methods used in identification of gender gave the satisfactory results. Better accuracy can be achieved by using combination of techniques like. Clarity of Image, Frequency domain analysis, singular value deco-position techniques etc.

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