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A New approach for fingerprint recognition using Earth Mover's Distance

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Abstract: Fingerprint recognition has been widely used in information security, personal identification etc. for its uniqueness and invariance. Efficient features extraction from input image is one of the important components of the fingerprint image recognition. Till now various algorithm have been proposed by many researchers. Out of the two widely followed approaches for fingerprint recognition, the minutia-based technique represents the fingerprints by its local features like terminations and bifurcations. This approach has been intensively studied and is also the backbone of the current available fingerprint recognition products. In this paper, we developed a fingerprint recognition concept, which uses the regular texture regions of fingerprint image that can be successfully represented by co-occurrence matrices. We first extract the features based on certain characteristics of the co-occurrence matrix. Simultaneously, the histogram of each image with certain bins and texture features is also extracted. These histogram values obtained for both the existing finger prints and the fingerprint to be tested are fed to the EMD (Earth mover's distance technique) algorithm to measure the distances. These measures with a certain threshold value are used for the matching. Experimental results show that our approach is very efficient in recognizing both poor quality images and variants of the same image.

Key words: Fingerprints, Gabor filter, EMD, gray level co-occurrence matrix (GLCM)

I. INRODUCTION

A fingerprint-based biometric system [8] is essentially a pattern recognition system that recognizes a person by determining the authenticity of his/her fingerprint. Depending on the application context, a fingerprint-based biometric system may be called either a verification system or an identification system. A verification system authenticates a person's identity by comparing the captured fingerprints with his/her own biometric template(s) pre-stored in the system. It conducts one-to-one comparison to determine whether the identity claimed by the individual is true. On the other hand, an identification system recognizes an individual by searching the entire template database for a match [1, 4]. It conducts one-to-many comparisons to establish the identity of the individual. Till now lots of research works have been done. The structure of the rest of this paper is as follows. In section 2, we make a thorough survey of the research work done so far on finger print recognition and identification. In section 3 we discuss on the methodology used. We discuss on image enhancement using Gabor filter in section 4, which is used by us in our approach. Section 5 contains an outline of the GLCM and the different gray-level co-occurrence features introduced by various researchers at different points of time. Out of these we select and use 9 co-occurrences which we found to be very much suitable. In section 6, the EMD is presented for the completeness of the work. We present the experiments carried out and the results obtained there in. Also, we justify the selection of 9 features for our purpose through some illustrations. Finally, we present the materials consulted for the compilation of this piece of work as references.

II. LITERATURE SURVEY

Many approaches to automatic fingerprint recognition have been presented in the literature and the research on this topic is still very active. The approaches are mostly based on two main features in a fingerprint:

a) Global ridge and furrow structures that form special patterns in the central region of the fingerprint.
b) Local ridge and furrow minute details.

Usually, a fingerprint is classified based on the first type of features and is uniquely identified based on the second type of features (ridge endings and bifurcations, also know a as minutiae). One advantage of this framework is that the ridge structures can be global features, and therefore can often be reliably extracted from images even in the presence of hard noise. Based on our survey related to fingerprint classification, it has been cleared that most of the existing technology are aimed to classify the fingerprint database based on the minutiae sets, singular points and other techniques. Many systems detect minutiae point as fingerprint features and these points are used for matching [6, 7]. Minutiae extraction is very difficult if the quality of image is poor. In [3] the concept of gray level co-occurrence matrices to extract texture features of the image was introduced and has been used in several other papers [2, 10, 14]. In paper [14], they have introduced a new framework for fingerprint image classification using 12 gray level co-occurrence features of the image and they had shown 99.02% classification accuracy and also the elements under classification being perfectly correct. Also they had provided a comparative study of their work with other existing works. In this paper, we have also used texture features using gray level co-occurrence matrices and used EMD for the first time as a measure of the minimal distance between two fingerprint images for matching. Here we are using texture features, which is more efficient than the minutiae extraction for low quality images in the sense that for such images it is difficult to predict the exact number of minutiae.

III. METHODOLOGY

In the proposed system, we have used FVC2000, FVC2002 and FVC2004 fingerprint database where fingerprint images had been taken from different sensor.

Sizes of different image database are different. So first of we have to resize it to a constant size and then we have applied Gabor filter [12] to enhance fingerprint image. After enhancing the fingerprint image we have taken nine texture features of the image using gray level co-occurrence matrixes. Then we have stored these features into system DB as template file. Simultaneously we have extracted the histogram of each image with respect to nine bins and then it is stored into another template of the system DB. During testing phase we extracted the nine texture features and histogram value (with respect to nine bins) and fed to the EMD function. There we have calculated the how much minimum image dissimilarity value occurred between testing image and existing image. After that we have found out the matching value of testing image. If the matching value is greater than threshold then we can easily say that the claimed is verified.

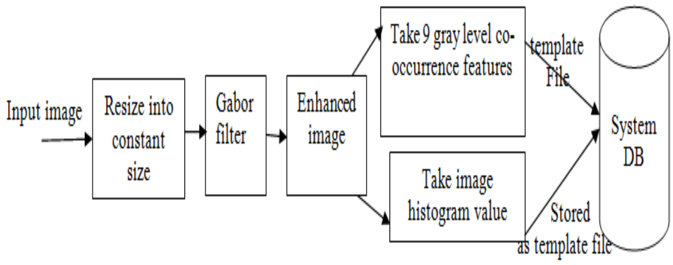

Figure.1 block diagram of the proposed system

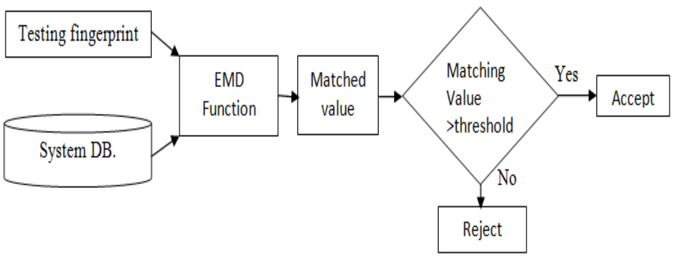

Figure.2 block diagram of proposed system

IV. IMAGE ENHANCEMENT USING GABOR FILTER

The robustness of the recognition system depends on its ability to enhance poor quality images. Majority of the techniques are based on the local ridge orientation and frequency. The ridges and valleys in a small local neighbored hood have well defined local frequency and local orientation properties. A set of band pass filters can remove the understand noise and preserve true ridge structures. Fingerprint enhancement methods based on the Gabor filter have been widely used to facilitate various fingerprint application such as fingerprint matching and fingerprint classification. Because Gabor filter have both frequency selective and orientation selective properties and also have optimal joint resolution in both spatial and frequency domains. Gabor filters are used to remove the noise and preserve true-valley structures. One of the most useful characteristic of fingerprint image is that they have well defined local ridge orientation and ridge frequency. So, the enhancement algorithm takes advantage of this regularity of spatial structure by applying Gabor filters which are tuned to match the local ridge orientation and ridge frequency around each pixel. The Gabor filter is applied to each pixel location in the image. Therefore, the filter enhances the ridge oriented in the direction of the local orientation, and decreases anything oriented differently. Hence, the filter increases the contrast between the foreground ridges and the background, which can efficiently reduce the noise. So, the two-dimensional Gabor filter can be depicted as

$$g(x,y)=\exp[-\frac{1}{2}(\bar{x}^2/\sigma_x^2+\bar{y}^2/\sigma_y^2)].$$

$$\exp(2\pi j\omega\bar{x})/2\pi\sigma_x\sigma_y$$

$$\bar{x}=x\cos\theta+y\sin\theta$$

$$\bar{y}=-x\sin\theta+y\cos\theta$$

The commonly used even symmetric two-dimensional Gabor filter can be expressed as:

$$g(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp[-(\bar{x}^2/\sigma_x^2+\bar{y}^2/\sigma_y^2)/2].$$

$$\cos(2\pi\omega\bar{x})$$

Where θ ($\theta\in[0,\pi]$) defines the orientation of Gabor filter. σ_x and σ_y is the standard deviation of elliptical Gaussian along x and y axes respectively. ω be the radian frequency.

V. GRAY LEVEL CO-OCCURRENCE MATRICES (GLCM's)

The GLCM's was firstly introduced by Haralick [3]. A gray level co-occurrence matrix is essentially a 2D histogram in which (i, j) th element is the frequency of event i co-occurs with the event j. In paper [10, 14] researchers also have provide a details description of GLCM and some textural features of gray level image. Suppose, an image, which to be analyzed is rectangular and has N_x columns and N_y rows. Suppose that the gray levels appearing at each pixel is quantized to N_g levels. Let $p(i,j)$ be the (i, j)th entry in a normalized GLCM. The mean and standard deviations for the rows and columns of the matrix are

$$\mu_x=\sum_i\sum_j i.p(i,j),\quad \mu_y=\sum_i\sum_j j.p(i,j),$$

$$\sigma_x=\sum_i\sum_j(i-\mu_x)^2.p(i,j) \quad ,$$

$$\sigma_y=\sum_i\sum_j\left(j-\mu_y\right)^2.p(i,j)$$

The following gray levels co-occurrence features are as follows.

i. ***Energy:*** $f_1=\sum_i\sum_j p(i,j)^2$

ii. ***Contrast:*** $f_2=\sum_{n=0}^{N_g-1}n^2\{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}p(i,j)\,|\,|i-j|=n\}$

iii. ***Correlation:*** $f_3=\dfrac{\sum_i\sum_j(ij)p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$

iv. ***Homogeneity:*** $f_4 = \sum_i \sum_j \left(\frac{p(i,j)}{1+(i-j)^2} \right)$

v. ***Entropy:*** $f_5 = -\sum_i \sum_j p(i,j) \log(p(i,j))$

vi. ***Maximum probability:*** $f_6 = \underset{i,j}{Max}\, p(i,j)$

vii. ***Autocorrelation:*** $f_7 = \sum_i \sum_j (ij)\, p(i,j)$

viii. ***Cluster shade:*** $f_8 = \sum_i \sum_j (i + j - \mu_x - \mu_y)^3 p(i,j)$

ix. ***Cluster prominence:*** $f_9 = \sum_i \sum_j (i + j - \mu_x - \mu_y)^4 p(i,j)$

x. ***Dissimilarity:*** $f_{10} = \sum_i \sum_j |i - j| . p(i,j)$

xi. ***Mean:*** $f_{11} = \frac{\sum_i \sum_j p(i,j)}{m \times n}$

Where m and n are the number of rows and columns respectively in p

If we define $T = \sum_i \sum_j p(i,j)$,

we got 4 others features [14] as follows.

Xii. $f_{12} = \frac{\sum_i \sum_j \frac{p(i,j)}{j^2}}{T}$

Xiii. $f_{12} = \frac{\sum_i \sum_j j^2 p(i,j)}{T}$

Xiv. $f_{14} = \frac{\sum_i \left(\sum_j p(i,j) \right)^2}{T}$

Xv. $f_{15} = \frac{\sum_j \left(\sum_i p(i,j) \right)^2}{T}$

VI. EARTH MOVER'S DISTANCE (EMD)

Linear optimization method to find a solution to the transportation problem is used in EMD. It can allow partial matching of two distributions. It is more robust than histogram matching techniques. To compare distributions with the same overall mass, the EMD is a true metric. Given two distributions, it is often useful to depict a quantitative measure of their dissimilarity, with the intent of approximating perceptual dissimilarity. This is particularly important in image retrieval applications. This is used in understanding of texture discrimination. Defining a distance between two distributions requires first a notion of distance between the basic features that are aggregated into the distributions. This distance is known as ground distance. In paper [9], for image retrieval, they have used this distance measure to compare two signatures in texture space. The transportation problem is in the class NP but has a solution as a linear optimization problem. It deals with finding the minimal cost that is to be paid to transport objects from specified sources to destinations. It can be applied to signatures with different sizes, which leads to better storage utilization. A signature $\{s_j = (m_j, w_{m_j})\}$, on the other hand, represents a set of feature clusters. Each cluster is represented by its mean (or mode) m_j, and by the fraction w_{m_j} of pixels that belong to that cluster. The integer subscript j ranges from one to a value that varies with the complexity of the particular image. While j is simply an integer, the representative m_j is a d-dimensional vector.

The ground distance between two single perceptual features can often be found by psychophysical experiments. Here they computed the distance one features space to another features space where the ground distances can be perceptually better defined. For example given two distributions, one can be seen as a mass of earth property spread in space, the other as a collection of holes in that same space. Then, the EMD measures the least amount of work needed to fill the holes with earth. Here, a unit of work corresponds to transporting a unit of earth by a unit of ground distance. Computing the EMD is based on a solution to the well-known transportation problem. For example, suppose that several suppliers, each with a given amount of goods, are required to supply several consumers, each with a given limited capacity. For each supplier-consumer pair (see for instance [9]), the cost of transporting a single unit of goods is given. The transportation problem is then to find a least-expensive flow of goods from the suppliers to the consumers that satisfy the consumers' demand. In this way Signature matching can be naturally cast as a transportation problem by defining one signature as the supplier and the other as the consumer, and by setting the cost for a supplier-consumer pair to equal the ground distance between an element in the first signature and an element in the second. Intuitively, the solution is then the minimum amount of "work" required transforming one signature into the other.

This can be formalized as the following linear programming problem: Let $P = \{(p_1, w_{p_1}), ...(p_m, w_{p_m})\}$ be the first signature with m clusters, where p_i is the cluster representative and w_{p_i} is the weight of the cluster; $Q = \{(q_1, w_{q_1}), ...(q_n, w_{q_n})\}$ the second signature with n clusters; $D = [d_{ij}]$ the ground distance matrix where d_{ij} is the ground distance between clusters p_i and q_j. We want to find a flow $F = [f_{ij}]$, with f_{ij} the flow between p_i and q_j, that minimizes the overall cost

$$work(P,Q,F) = \sum_{i=1}^{m} \sum_{j=1}^{n} d_{ij} f_{ij}$$

Subject to following constraint:

$$f_{ij} \geq 0 \qquad 1 \leq i \leq m, 1 \leq j \leq n \qquad (1)$$

$$\sum_{j=1}^{n} f_{ij} \leq w_{pi} \qquad 1 \leq i \leq m \qquad (2)$$

$$\sum_{j=1}^{m} f_{ij} \leq w_{qj} \qquad 1 \leq j \leq n \qquad (3)$$

$$\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} = \min\left(\sum_{i=1}^{m} w_{pi}, \sum_{j=1}^{n} w_{qj} \right) \quad (4)$$

Constraint (1) allows moving "supplies" from P to Q and not vice versa. Constraint (2) limits the amount of supplies that can be sent by the clusters in P to their weights. Constraint (3) limits the clusters in Q to receive no more supplies than their weight; and constraint (4) forces to move the maximum amount of supplies possible. They have called this amount as the total flow. Once the transportation problem is solved, and they also have found the optimal flow F, the earth mover's distance is defined as

$$EMD(P,Q) = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} d_{ij} f_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} f_{ij}}$$

The normalization factor is the total weight of the smaller signature, because of constraint (4). Till now our discussion about EMD related to Rubner paper [9]. So basically they have used same features space in both distribution and weight may be either equal or different. For image retrieval they were trying to find the dissimilarity between two images using histogram weight where two images are belongs to different category. We use this concept to find the dissimilarity between fingerprint images where images are same category (only fingerprint image).Here, instead of using feature spaces we have used directly texture features of fingerprint image. Texture features of same fingerprint with different impression is more likely same. But in different image is confidently different. Because we have nine texture features of fingerprint image. Nine texture features and histogram with nine bins together can differs the one image to another and according to this different/dissimilarity we can easily recognize the fingerprint id either it is exist or not in the database.

VII. EXPERIMENT AND ANALYSIS

In this experiment we have used FVC2000, FVC2002, and FVC2004 [15, 16, 17] database where for each individual fingerprint there are 8 impressions exist. Fingerprint verification competition is organized by D. Maio, D. Maltoni, R. Cappelli from Biometric System Laboratory (University of Bologna), J.L.Wayman from the U.S. National Biometric Test Center (San Jose State University) and A.K. Jain from Pattern Recognition and image processing Laboratory of Michigan State University. Finger matching is very difficult job. Till now most probably fingerprint identification technique are based on minutiae matching. But minutiae extraction is not efficient for low quality images. Figures 3 to 5 are poor quality fingerprint images. In this case it is difficult to find out the exact number of minutiae. Latest study of fingerprint identification [5, 11, 13] focus on the global features of the fingerprint images and same way in our study, we focus on the texture features of the fingerprint images. During testing or matching phase, texture features and histogram of claimed fingerprint is extracted and compared with earlier store features using EMD technique.EMD techniques calculate the distance between the claimed fingerprint feature with stored features. Then we have calculated matching value of the claimed id. According to our strong observation we provide a threshold value which measures existence of claimed id. In our experiment we got the best result by using 9 texture features and histogram value of each image. In this case minimum distance between same image and different impression (i.e. it looks like different in non-trained eye but it belongs to same fingerprint) is more likely same.

Figure.3

Figure.4

Figure.5

Figure.6

Figure.7

Figure.8

In Fig.6 and Fig.7, images are belongs to the same fingerprint but they are in different impression and the difference between these two fingerprint is .000661. But the difference between Fig.7 and Fig.8 (they are belongs to different image but looking same in non-trained eye) is 3.889991.In our experiment we got the minimum dissimilarity value between two image impression but they are in same fingerprint varies from 0.0 to less than 1.0. In this case, minimum dissimilarity value also depend on the how many number of texture features we consider. First of all using nine texture features we found best matching accuracy where threshold value 92(in a sense matching accuracy is 92). Instead of using first nine features if use first six texture features of fingerprint image, then we have to fixed threshold value as 85. But here we found some problem. For some cases, if the fingerprint image does not exist in the fingerprint database but it shows that it is exist in the database. So, six features are not good enough for fingerprint authentication purpose. So we need to increase the number of texture feature of the fingerprint image.

According to our experiment, if we use more than nine features (i.e. 12 or 14 features) image to image dissimilarity value is high. In this case we have to increase the threshold value. Here we found some another problem; images which are exist in the database, but it shows that it is not exist in the database. That means two images belongs to same fingerprint but different impression and if we totally delete the one impression of same image and trying to identify either it is exist or not. In this situation we got bad results. So according to our study nine features are best to authenticate fingerprint id. In FVC20002 database, every fingerprint image has 8 impressions. Suppose if we store only six image impression features into database and trying to find out another two image impression is exist or not. For nine feature case we got good result. Its shows that it is exist in the database. Actually, here we got the minimum dissimilarity value lying between 0.0 and 1.0 (more likely same).

VIII. CONCLUSION

In this paper we have provided the step by step procedure to recognize the fingerprint identity and we have got good results Because in paper [14] researcher's got 99.02% classification accuracy using texture features of fingerprint images. Same way we have used nine texture features. Here, we got 90 to 99% matching accuracy. But one hindrance is still there in our research work; that is if the capacity of database is high; time required to linear optimization procedure is high. This occurs due to EMD technique, which is based on linear optimization method. To reduce the time complexity one needs to replace EMD by a more efficient technique where we need not use the linear optimization method.

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