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Fingerprint Classification and Matching Using Self Organizing Feature Map

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ABSTRACT:- *Fingerprints are one of the basic and most popularly used form of biometric identification. Fingerprints of every person is unique and inalterable. However fingerprint images get demoted and affected due to changes in skin and other conditions. Two fingerprints can never be same due to presence of many variations during their formation. But, since the fingerprints are separated from the same genes, they are not totally random patterns either. Traditionally we are using whorl, left loop, right loop, arch and tented arch for extraction and matching minutiae. We are able to perform the identification and verification operation on the fingerprint successfully and efficiently. But to reduce the run time complexity and increase the performance we have used the classification technique using neural network technique.*
This paper presents an idea on neural network technique for the classification of images. The paper is based on Self Organizing Map (SOM) algorithm. In this paper we are going to find out the orientation field of each pixel masking the minutiae points, detection of core points and using SOM finding out the class of input vector taking from sample space.

Keywords:- *Fingerprint Classification, Fingerprint enhancement, SOM.*

I. INTRODUCTION

Fingerprint's application as a biometric is viable because of its uniqueness and permanence. It is the reproduction of the friction ridges present on the inner surface of a fingertip obtained from the impression on a touched surface. Fingerprint contains unique and abnormal points or discontinuities on ridges and furrows and is called as Minutia.

Fingerprints are the most widely used parameter for personal identification amongst all biometrics. Fingerprint identification [9] is commonly employed in forensic science to aid criminal investigations etc. Minutiae points are the local ridge discontinuities, which are of two types: ridge endings and bifurcations. A good quality image has around 40 to 100 minutiae. It is these minutiae points which are used for determining uniqueness of a fingerprint. Automated fingerprint recognition and self authentication systems can be categorized

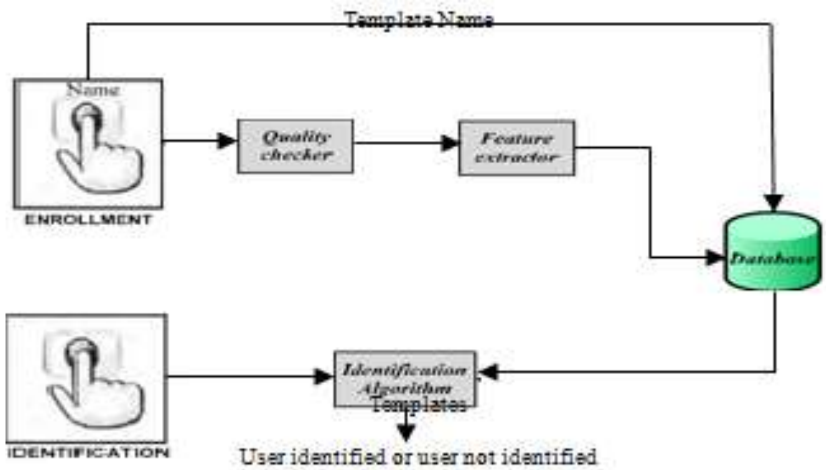


Fig.1: Typical diagram of the fingerprint enrollment and identification processes.

As verification or identification systems. The verification process either accepts or rejects the user's identity by matching against an existing fingerprint database (Fig.1).

It has been estimated that on an average each fingerprint has about 70 minutiae and can be categorized into six features which is shown in Fig. 2–

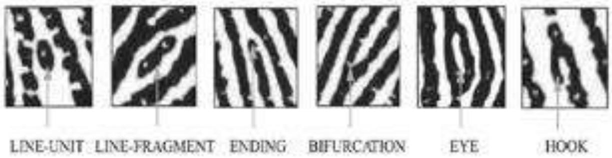


Fig. 2: Basic features of fingerprint

II. FINGERPRINTS FORMATION

Finger ridge configurations remains same throughout the life until and unless the person faces any accidents such as cuts and bruises on the fingertips. These characteristics makes fingerprints an alluring biometric identifier. The phenotype is particularly determined by the mutual action of a specific genotype and an environment. Different parts of an individual's phenotype are Physical appearance and fingerprints. Fingerprint formation is similar to that of angiogenesis process. The fingerprint general characteristics emerge on the fingertip as the differentiation of the skin begins. The differentiation process is triggered by the growth in size of the volar pads on the palms, fingers, soles, and toes. The fingertip cells grow in a microenvironment that is different from finger to finger. The differentiation process of the cells is amplified by a small difference in microenvironment Due to the presence of variations during the formation of fingerprints it would be practically impossible for any two fingerprints to be exactly same. But, because fingerprints are differentiated from the same genes, they are not totally random patterns either.

III. METHODOLOGY

Fingerprint Classification:

A person's identification requires the comparison of her/his fingerprint with all the fingerprints present in the database, which may be very large in large scale use (several million fingerprints). A familiar strategy, to decrease the number of alterations during the process of fingerprint retrieval and, hence, to enhance the response time of the fingerprint identification process, is to separate these fingerprint data into some predefined classes. Fingerprint classification [2] assigns each fingerprint to a class in an accordant and secure way, so that an unknown fingerprint which is to be searched is only compared with the subset of fingerprints in that database close to the same class. Fingerprint matching is performed according to the fingerprint micro-features, such as bifurcations (minutiae) and ridge terminations. Fingerprint classification is mostly based on macro-features, like global ridge structure. All the classification schemes presently used by police agencies is based on Henry's classification scheme.

Five classes (Tented arch, Arch, Left loop and Right loop and Whorl), shown in Fig.3, are mainly used by fingerprint classification techniques [3]. In reality ,distribution of fingerprints are not uniform in between these five classes: the proportions have been calculated as 3.7%, 2.9%, 33.8%, 31.7% and 27.9% for Arch, Tented arch, Left loop, Right loop and Whorl, respectively (Refer to Fig.4).

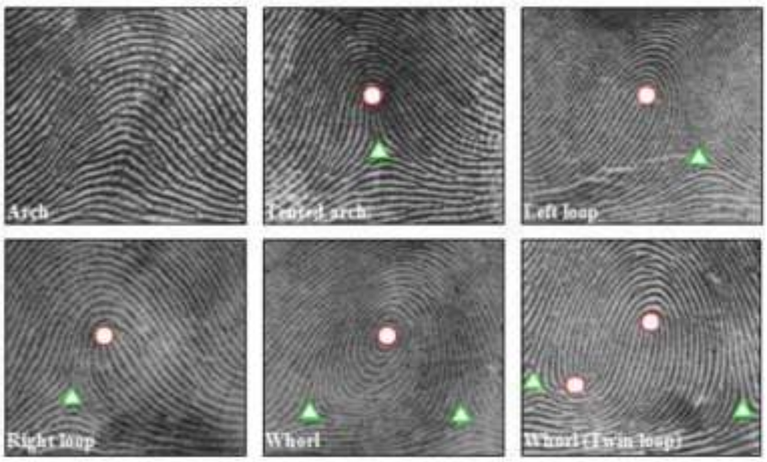


Fig. 3: Global feature with core and delta

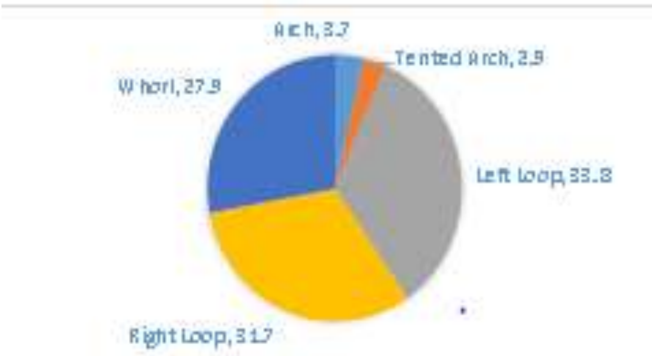


Fig. 4: Occurrence of Fingerprint Class in percentage

Fingerprint classification isn't limited to the above concept. Further levels of classifications [4] lie as local features. Level 2 defines local features like (Fig. 5):

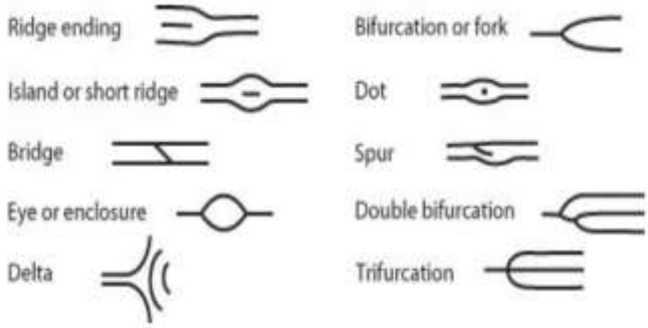


Fig. 5: Level 2 (local features) for fingerprint classification.

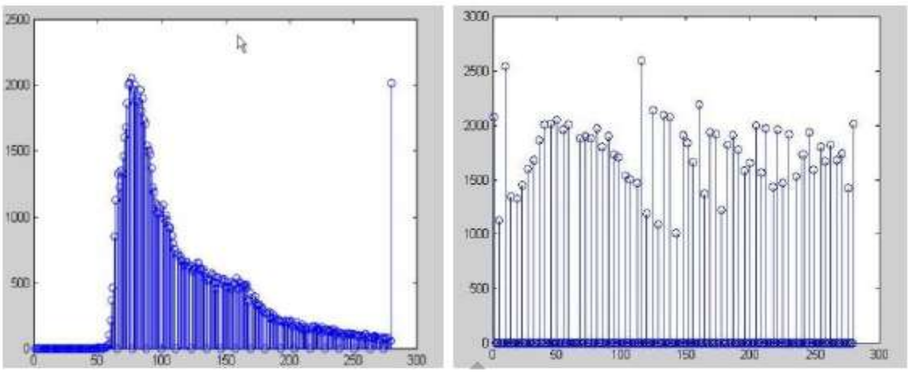
IV. FINGERPRINT ENHANCEMENT

Fingerprint Image enhancement is performed to improve the quality of image and to make it better for further operations. Fingerprint images from different sources are void of contrast and clarity [6]. Therefore, image enhancement is quite necessary. It enhances the contrast between furrows and ridges and inter connect the false broken points of the ridges due to lack of ink or bad quality of the sensor input.

Under the image enhancement step of Histogram Equalization, the Fast Fourier Transformation raises the quality and nature of the input image and Binarization process transforms the grey scale image to binary image. Then image segmentation is done to extract a Region of Interest.

1. Histogram Equalization:

Histogram equalization is a technique used to improve the global contrast of an image by adjusting and also studying its intensity distribution on a histogram. It results in areas of lower local contrast to obtain a higher contrast without having any effect on the global contrast. Histogram equalization achieves this by effectively spreading out the most frequently occurring intensity values. In Fig. 6 (a) we can see the original histogram of a fingerprint image , similarly from Fig.6 (b) it's clear that the histogram occupies all the range from 0 to 255 after the histogram equalization and the visualization effect is also enhanced.



(a) (b)

Fig.6: (a) Original histogram, (b) Histogram after equalization

2. Fast Fourier Transformation:

In this method the image is subdivided into small processing blocks of32 x 32 pixels and then Fourier transform is performed.

$$F(u,v) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) * \exp\{-j2\pi * (\frac{ux}{M} + \frac{vy}{N})\}$$

For u=0, 1, 2……. 31 and v=0, 1, 2…… 31.

We multiply the magnitude with the FFT of block to improve a specific block by its dominant frequency values.

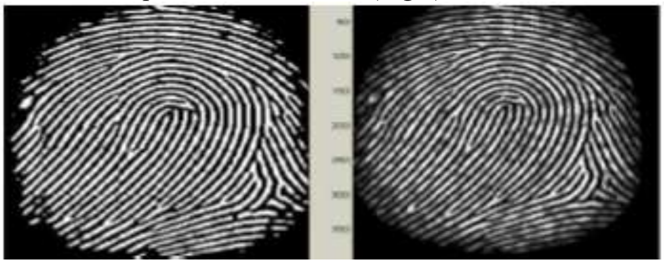
$$g(x,y) = F^{-1}\{F(u,v) * |F(u,v)|^k\}$$

The k in equation (2) is an experimentally determined constant, where we choose k=0.45 to calculate.

3. Binarization:

Image Binarization is a process used to transform an 8-bit Gray image to a 1-bit image having thevalue-1 for furrows and value-0 for ridges [8]. After the operation, ridges and furrows in the fingerprint are represented in black and white color respectively.

A locally adaptive Binarization method is carried out to binarize a fingerprint image. In this step, the image is broken into (16 x 16) pixel blocks. The value of the pixel is then assigned 1, if the value of that pixel is greater than the average intensity value of the pixel's current block (Fig.7).



(a) (b)

Fig. 7: (a) Binarize Image after FFT, (b) Image before Binarization

4. Thinning:

In this process the redundant pixels of ridges are eliminated till the ridges are reduced to just a single pixel wide. This is obtained by using the MATLAB's in-built morphological thinning function [11].

Bwmorph (binaryImage,'thin', Inf)

// bwmorph function does the thinning operation

The thinned image is then filtered, using MATLAB's three morphological functions to delete some H breaks, spikes and isolated points (Fig.8).

Bwmorph (binaryImage, 'hbreak', k)

Bwmorph binaryImage, 'spur', k)

Bwmorph (binaryImage, 'clean', k)

Ridge Thinning is to excludethe redundant pixels of ridges until the ridges are just single pixel wide. This method is bid out which uses the in-built Morphological thinning function of MATLAB.

The thinned ridge map is filtered by using other three Morphological operations to exclude some H breaks, spike and isolated points.

(a) (b)

Fig. 8: (a) Image before, (b) Image after thinning

5. Block Direction Estimation:

For the region of interest to be extracted, two steps are used:

First step is the Block direction estimation followed by ROI extraction by Morphological methods.

Here the fingerprint image is distinguished into 16 x 16 pixels (W x W)size blocks after that block direction of each block is estimated according to the following algorithm:

I. The gradient values are calculated along the direction x-axis (g_x) and y-axis(g_y) for each and every pixel of the block.In this task two Sobel filters are involved.

II. For each block, by using the following formula we can have the Least Square approximation of block direction for all the pixels in each block.

$$tan2\beta = \frac{2\sum\sum(g_x * g_y)}{\sum\sum(g_x^2 - g_y^2)}$$

After finishing the estimation of each block direction, the blocks without having any significant information on furrows and ridges are expelled based on the following equation:

$$E = {\{2\sum\sum(g_x * g_y) + \sum\sum(g_x^2 - g_y^2)\}}\Big/{W * W * \sum\sum(g_x^2 + g_y^2)}$$

For every block, if the certainty level E is under the threshold, then that block is considered as background block. The direction map of the binarize image is shown in the following figure (Fig. 9).

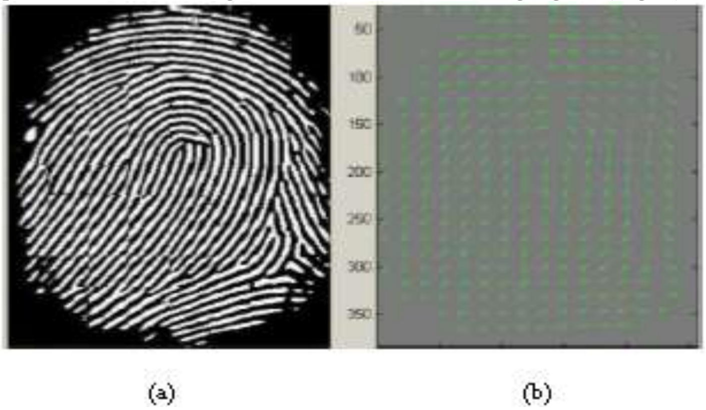


Fig.9:a) Binarize Image, (b) Direction map of image

6. Morphological Operations:

ROI extraction is performed using two Morphological operations known as OPEN and CLOSE. The OPEN operation enlarges images and removes peaks introduced by the background noise. The 'CLOSE' operation shrinks images and removes small cavities.

7. Image Segmentation:

After image enhancement is done the next process is fingerprint image segmentation. Basically, only a Region of Interest (ROI) is used to recognizeevery fingerprint image. The image region without effective ridges and furrows is first eliminated since it only holds background data.

Fig. 10 shows the final Region of Interest of the fingerprint which is nothing but the bound area after subtracting the closed area from opened area. Then several out of the bound area like the leftmost, rightmost, uppermost and bottommost blocks are discarded.

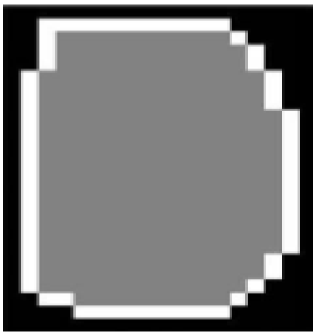


Fig. 10: Final ROI

8. Core Point Extraction:

One most important step before classification is the core point extraction which otherwise can be stated as the automatic detection of the core point of the fingerprint [8]. This step is important because a reference point is needed in order to accurately compare two fingerprints. Here we are using the algorithm that uses the block directional map to find the core, which is the topmost point on the innermost upward recurring ridge, by comparing the slopes of block directions. After the core point is determined, both the block directional image and the corresponding certainty matrix are translated so that the core of the fingerprint coincides with the center of the image. Then both matrices, namely the block directional image and certainty matrix are scanned in row-major order to form the block directional feature vector that will be used in classification.

V. SELF ORGANIZING MAP

Till now only the supervised training techniques were taken into consideration, in which for each input pattern there is a target output pattern, and the required outputs are produced.

Now moving to unsupervised training, in which the training data form their own classifications without any external help. For this the presumption will be the membership of a class is outlined by the input patterns which shares familiar features, and those features will be identified by the network across the wide range of input patterns.

Not all but one particularly engrossing class of unsupervised system is designed upon competitive learning, in which there is competition among output neurons to get activated, but only one gets activated at one time. This activated neuron is known as winner-takes all neuron or exclusively the winning neuron. Such bout can be catalyzed by having lateral constraint connections (negative feedback paths) in between neurons. As a result neurons are compelled to organize themselves. For unambiguous reasons, such type of network is known as Self-Organizing Map (SOM) [12].

1. Components of SOM:

There are four major building blocks involved in self organizing process:

Initialization: Small random values are assigned to all connection weights.

Competition: For every pattern inputted, the neurons reckon their own values of different function that furnishes the basis for a bout. The picky neuron with smallest value of the discern function is declared as the triumphant.

Cooperation: The winning neuron arbitrates the spatial position of topological abut of excited neurons, thereby giving the basis for collaboration among the neighboring neurons.

Adaptation: The individual values of excited neurons get diminished their discriminant function with respect to the input pattern by suitable acclimatization of cohort connection weights, so that subsequent application of akin input pattern with respect to the response of winning neuron is enhanced.

Kohonen Networks:Here we will focus on a particular nature of SOM known as a Kohonen Network. The feed-forward structure of SOM is arranged in rows and columns with a single computational layer [1].

In the input layer each single neuron is totally connected to all the source nodes as shown in Fig.11.

In the computational layer a one dimensional map will have a single row or a single column.

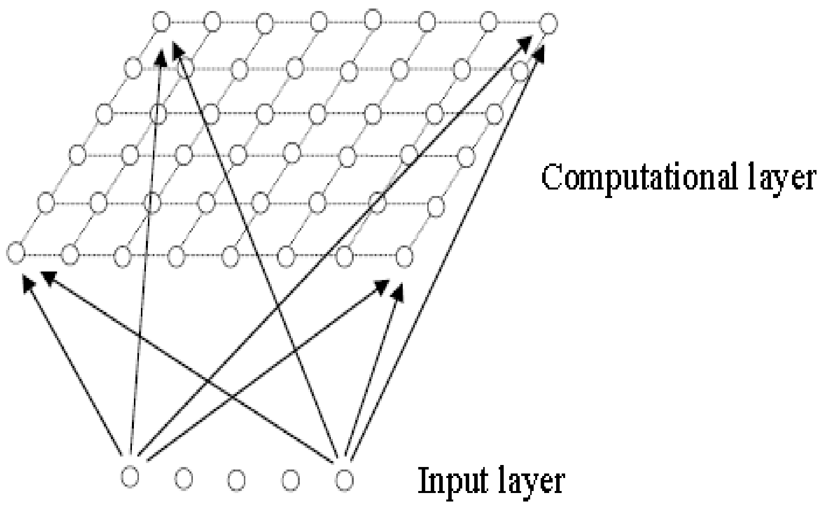


Fig. 11: Brief architecture of a Kohonen network

2. Network Topology and Operation of Original SOM:

The SOM is a unique neural network that accepts n-dimensional input vectors and maps them to a lower dimensional, usually 2-D, output plane. The topology for a typical SOM network is shown in fig.12 [5].It has n input nodes and m by n output nodes, each output node j in the SOM network has a connection from each input node i, where w_{ij} being the connection weight between them.

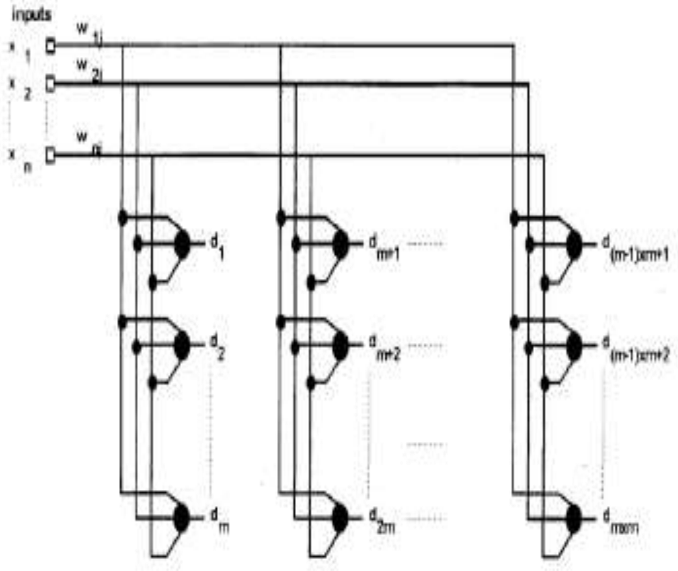


Fig. 12: Network Topology of SOM

There are two phases of operation in SOM: the training phase and the classification phase. Classification is simple after the training phase has been completed successfully. The network finds an output node such that the Euclidean distance between the current input vector and the weight set connecting the input nodes to this output node is minimum. This node is called the winner and the weights of the neighboring output nodes of the winner are updated so that the new weight set is closer to the current input vector. This procedure is applied repeatedly for all input vectors until weights are stabilized. The choice of the neighborhood function, the learning rate and the termination criteria are all problem dependent. The training steps of the original SOM are as follows:

- Assign small random values to weights w_{ij}
- Choose a vector x from the sample space and apply it as input
- Find the winning output node d_{win} by the following criterion.

  $d_{win} = \min\{|x - w_j|\}$

Where RHS denotes the Euclidean norm and w_j is the weight vector that connects input nodes to output node j.

- Theweight vectors should be adjusted in accordance to the following formula:

$$w_{ij}(t+1) = w_{ij}(t) + n(t)\left[x_i(t) - w_{ij}(t)\right]N(j,t)$$

Where w_{ij} *is* the ith component of the weight vector and N (j, t) is known as the neighborhood function.

- Repeat steps 2-4 until no eloquent alteration occur in the weights.

The learning rate n (t) is a function of time that is kept large at the onset of the training and decreased gradually as learning proceeds. The neighborhood function N (j, t) is a window centered on the winning unit d_{win} found in step 3whose radius decreases with time. Neighborhood function determines the degree that an output neuron j participates in training [10]. This function is chosen such that the magnitude of weight change decays with increase of the distance of the neuron to the winner. This distance is calculated using the topology defined on the output layer of the network. Neighborhood function is usually chosen as rectangular, 2-D Gaussian or Mexican hat windows. After training is completed classification is a matter of applying step-3 for the vector to be classified. The winning output node determines the class of the applied input vector. In this way all the fingerprints in the database are assigned a class number.

V. CONCLUSION

This paper presents an idea about the classification of one of the most important biometrics, fingerprint with application of neural network technique. This work includes classification of the various fingerprint images taken from a sample space using Self Organizing Map (SOM) algorithm. Using these approaches we are successfully able to reduce the run time of identification and verification operation of images. We conclude from our work that SOM algorithm can be used for large scale of verification and identification operation efficiently and with less time complexity.

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