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Fingerprint Matching through Back Propagation Neural Network

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Abstract

Objectives: This paper is focused with original features used in fingerprint matching founded on back propagation neural network. For finding the features in the images, it can be improved using filtering techniques as isotropic and anisotropic. Isotropic can protect features on the input images but can barely progress the dominance of the images. But on the contrary, anisotropic filtering can successfully eliminate noise from the image just when a consistent point of reference is provided. **Methods and Analysis:** The filters commonly used namely median filter, gabor filter along with anisotropic filters are used for filtering the noises under direct gray scale enhancement .Whereas for an input image, the narrow ridge direction is predictable and the region of interest is positioned. The uniqueness of a fingerprint is exclusively determined by the local ridge characteristics and their relationships. The ridges and valleys in a fingerprint alternate, flowing in a local constant direction. The two most prominent local ridge characteristics are: 1) ridge ending and, 2) ridge bifurcation. A ridge ending is defined as the point where a ridge ends rapidly. A ridge bifurcation is defined as the point where a ridge forks or diverges into branch ridges. Collectively, these features are called *minutiae.* Minutiae points are extracted during the enrollment process and then for each authentication. In a fingerprint, they correspond to either a ridge ending or a bifurcation. Minutiae are major features of a fingerprint using which comparisons of one print with another can be made. After finding the minutiae points the filters reducing image noises, smoothing, removing some forms of misfocus and motion blur, is in the front step of image processing. Filtering is also used for preserving the true ridge and valley structures. **Findings:** The digital results of these features are practically feeded as input of the neural network using median filter, gabor filter, anisotropic filter for training function. For fingerprint identification the confirmation part of the system identifies the fingerprint based training show of the network. **Novelty and Improvement:** To finish the new outcome reveals that the number of accepted sample rate of the proposed method using the three filters which is far better than the existing fingerprint verification system using artificial neural network

Keywords: Anisotropic Filter, Artificial Neural Network, Back Propagation Algorithm, Gabor Filter, Median Filter

1. Introduction

Biometric recognition refers to the use of distinctive physiological (fingerprint, face, retina, hand geometry, iris etc.) and behavioral (voice, gait, signature etc.) characteristics, called biometric identifiers or simply biometrics. Biometrics has come to occupy an increasingly important role in human identification due primarily to their universality and uniqueness.[1] As a result of this evolution, a new breed of techniques and methods for user identity recognition and verification has appeared based on the biometric features that are unique to each individual. A reliable identification system is a critical component in several applications that contribute their services specifically to genuine users. Examples of such applications include physical access control to a secure facility, e-commerce, access to computer networks, attendance mark etc. Traditional methods of establishing a person's

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identity include knowledge-based (e.g., passwords) and token-based (e.g., ID cards) mechanisms. These representations of the identity can easily be lost, shared or stolen as stated by Jain A.K.[2] Therefore, they are not sufficient for identity verification in the modern day world. The use of fingerprints for identification purposes has a long history and, along with other biometric identification systems, is becoming increasingly prevalent. With this increased use, however, has come the need for placing the technique on a firmer scientific foundation.

Fingerprint individually is more difficult to quantify than, say, that of DNA profiles or iris patterns, because the latter are normally available in complete form and lend themselves to a standard representation. There has as yet been no definitive study on the statistical uniqueness of fingerprints.

In this paper a comparative study is made by using median, gabor and anisotropic filters. The False Acceptance Rate (FAR) and Rejection Rate (FRR) can be calculated for three diverse filters. The images of different filters is filters is shown in Figure 1.

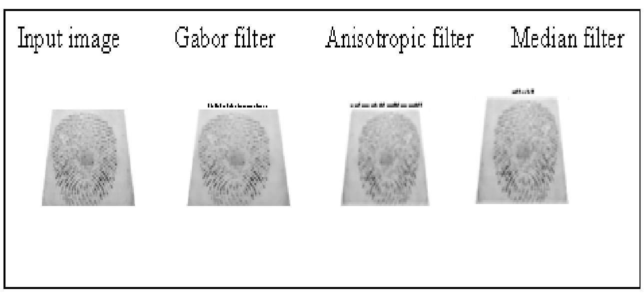


Figure 1. Images of Several filters.

Artificial neural networks are currently one of the most frequently used classifiers for fingerprint categorization systems. Further researchers have come out with a neural network categorization system and feature of blood cells.[3] On the other hand, quite a few works use feed-forward neural network to classify feature vectors consisting of 64 wavelet coefficients. The outcome from this system is not very remarkable due to the restrictions of the feature set. Furthermore, Mohamed and Nyongesa described the fuzzy-network classifier used to classify fingerprints based on singularity features.[4] The features used comprise the number of core and delta points, the orientation of core points, the comparative location of core and delta points and the total direction of the orientation field.

2. Fingerprint

A fingerprint is the feature pattern of one finger (Figure 2). Every individual has his own fingerprints with the continuing individuality. A fingerprint is combination of various ridges and valleys. Fingerprints are not identified clearly by their ridges and valleys, but by Minutia, which are some unusual points on the ridges.[5]

Figure 2. Fingerprint image.

3. Minutiae

The most perceptible structural attribute of a fingerprint is the prototype of interleaved ridges and valleys that over and over again run in parallel at local level. The other important features called minutiae is recognized to ridge discontinuities. Most minutiae can be individuated by their clip. Such as bridge are like "H", bifurcation like "Y" etc. The extracted minutiae points can be shown in Figure 3.

Figure 3. Minutiae Points.

4. Filtering Techniques

4.1 Median Filter

Median filter, the most prominently used impulse noise removing filter, provides better removal of impulse noise from corrupted images by replacing the individual pixels of the image, as the name suggests by the median value of the gray level. The median of a set of values is such that half of its values in the set are below the median value and half of them are above it and so it is the most acceptable value than any other image statistics value for replacing the impulse corrupted pixel of a noisy image for if there is an impulse in the set chosen to determine the median it will strictly lie at the ends of the set and the chance of identifying an impulse as a median to replace the image pixel is very less. A commonly used non-linear operator is the median, a special type of low-pass filter. The median filter takes an area of an image (3x3, 5x5, 7x7, etc.), sorts out all the pixel values in that area, and replaces the center pixel with the median value. The median filter does not require convolution. (If the neighborhood under consideration contains an even number of pixels, the averages of the two middle pixel values are used.) The best known order-statistics filter is the *median filter,* which replaces the value of a pixel by the median of the gray levels in the neighborhood of that pixel.

The original value of the pixel is included in the computation of the median. Median filters are quite popular because, for certain types of random noise they provide excellent noise reduction capabilities, with considerably less blurring than linear smoothing filters of similar size. The median filter is effective for removing impulse noise such as "salt and pepper noise" which is random occurrences of black and white pixels. The median filtered image is shown in Figure 4.

123	127	150	120	100
119	115	134	120	121
111	120	122	125	180
111	120	145	100	200
110	120	120	130	150
		121		

Figure 4. The median filtered image.

The sorted pixel values of the shaded area are: (100, 115, 119, 120, 121, 122, 125, 134 and 145), providing a median value of 122 in the output image.

Algorithm for median filter

The main steps of the algorithm include:

1. Image Acquisition.
2. Histogram equalization.
3. Apply the Median Filtering on gray-scale image and eliminate the noises by replacing the Centre pixel.
4. Get a Median Filtered quality Gray-scale image.

a) b)

Figure 5. a) Fingerprint Image b) Median Filtered Image.

4.2 Gabor Filter

Gabor filters have both frequency selective and orientation selective properties. Gabor filters can remove noise and preserve the true ridge and valley structures thus showing good performance. Gabor filters have been applied to the problem of fingerprint image enhancement. Gabor filters are band-pass filters with adjustable frequency, orientation, and bandwidth parameters.

A gabor function is a sinusoidal waveform that is modulated by a rotated gaussian envelope, and has the following form in the spatial domain:

$$G(x, y, \theta, \sigma) = exp\left\{\frac{x'2 + y'2}{2\sigma 2}\right\}\cos(2\pi f x') \tag{1.1}$$

$$x' = x\cos\theta - y\sin\theta\,,\; y' = x\sin\theta - y\cos\theta \tag{1.2}$$

Where *f* is the sinusoidal frequency along the direction s is the standard deviation of the Gaussian envelope. Here the filter frequency to the average ridge frequency *(1/K)*, where *K* is the inter-ridge average distances. The normalized fingerprint is then convolved with a bank of filters tuned with the dominant orientation in each *WxW* image block. Orientation field is obtained by the mean square orientation estimation algorithm

Step 1: Normalization: An input fingerprint image is normalized and it has a pre-specified mean and variance.

Step 2: Local orientation prediction: The orientation fingerprint is anticipated from the normalized input fingerprint image.

Step 3: Local frequency prediction: The frequency fingerprint is calculated from the normalized input fingerprint and the predicted orientation image.

Step 4: Region mask estimation: The region mask is obtained by classifying each block in the normalized input fingerprint image into a recoverable or a unrecoverable block.

Step 5: Filtering: A bank of Gabor filters which is tuned to local ridge orientation and ridge frequency is useful to the ridge and furrow pixels in the normalized input fingerprint image to achieve an improved fingerprint image.

4.3 Anisotropic Filtering

Anisotropic filtering is to use the local intensity orientation to control the shape of the filter. It is essentially adapting the filter shape to the local features (local intensity orientation) of the fingerprint image. The filter kernel applied to each point is defined as following:

$$G\theta\{x,y\} = \left\{exp\left(\frac{-(u-mean)^2}{2\sigma 2}\right)\right\} 1\sqrt{2\pi\sigma 2}exp\left\{\frac{-(v-mean)^2}{2\sigma 2}\frac{1}{\sqrt{2\pi\sigma 2}}\right\} \quad (1.3)$$

$$u = x\cos\theta - y\sin\theta, \quad (1.4)$$
$$v = x\sin\theta + y\cos\theta v = x\sin\theta + y\cos\theta$$

The shape of the kernel is controlled through mean and σ. This formula which is a modulation of a gaussian and it is derived, behaves as a pass-band filter in the given direction. By modifying the filter with a scale

c=-2 as follows:

$$h_\theta = c^* g_\sigma(x,y) \quad (1.5)$$

For certain directions, these filters are represented by images represented in Figure 6.

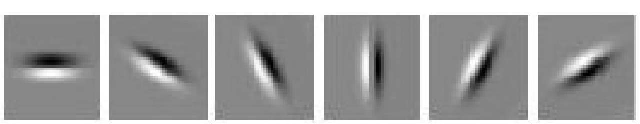


Figure 6. Controlling anisotropy in different directions.

Yang projected the structure-adaptive anisotropic filtering. This method adopts a limited intensity direction and an anisotropic measure of level contours to arrange the shape and level of the filter kernel. In this paper improvement to the structure-adaptive anisotropic filter in the space domain is proposed.[8] Since there is an vital need for filling this gap, the work is focused on achieving this objective. As before mentioned the indispensable idea of the enhancement is to apply the median filter for pixels bounded by an anisotropic elliptical kernel. In anisotropic filtering the Corner strength measure x_0 is extremely inclined by noise. This results in an erroneous inference of space constants $\sigma_1^2(x0)$ and $\sigma_2^2(x0)$. These variables in turn deal with the shape of the filter kernel. Derivatives-based approach for oriented pattern direction estimation falls short to produce accurate approximation for noisy images. The normalization factor β controls how realistically the corners and junctions can be conserved throughout the filtering procedure. Therefore, it is a significant factor and the selection of β considerably has an effect on the filter performance. The structure-adaptive filter is directional and regulates the shape of the kernel in accordance to image anisotropic local features. At the same time the results obtained by this method causes to blurring in processed image. This is because of the linearity of its filtering function. The structure-adaptive anisotropic filter operates on a pixels neighborhood of a constant size and furthermore, the size is not based on local features of input image.

5. Artificial Neural Network

An Artificial Neural Network (ANN) is an information exemption model, expectant by the technique of the biological neural systems, such as the brain and the course of action of information. An ANN is configured for a open purpose, such as pattern identification or data categorization. The objective of ANN is arrived at by means of a learning process. There are three different layers (input, hidden and output) in the network. In order to train the network, an algorithm is used such as back propagation.

Afsar *et al.*, projected a Gabor filter related technique to improve the input fingerprint image.[9] Whereas it has some short comings. It is somewhat superior computational cost as well as it consumes a whole lot of time, which is generally consider as not very effective. A prevalent problem of the MGF is that it does not give reliable and accurate results when image regions are impure with deep noises. Chaur-Chin Chen and Yaw-Yi Wang have come out with an Automatic Fingerprint Identification System (AFIS) with the help of fingerprint classification and minutiae pattern matching.[10] Needless to say that the method developed has some disadvantages. For example it is used for very small database and only slight rotations and translations from one fingerprint to another may be present. On the other hand Rashid and Hossain, projected a method of fingerprint identification system using back propagation algorithm. Even this method suffers from a few limitations. This method could not get rid of false minutiae which have to be rejected to get better results.

6. Algorithm Back Propagation

1. Set the input layer's values ($a^{(1)}$) to the t-th training example x(t).Perform a feed forward pass (Figure 7), computing the activations ($z^{(2)}$, $a^{(2)}$, $z^{(3)}$,$a^{(3)}$) for layers 2 and 3. To add a+1 term to ensure that the vectors of activations for layers a(1) and a(2) also include the bias unit. In MATLAB, if a-1 is a column vector, adding one corresponds to a-1 = [1 ; a-1].
2. For each output unit k in layer 3 (the output layer), set

$$\delta_k^{(3)} = \left(a_k^{(3)} - y_k\right)$$

where $y_k \epsilon \{0,1\}$ indicates whether the current training example belongs to class k (y_k =1), or if it belongs to a different class (y_k = 0).

3. For the hidden layer l = 2, set

$$\delta^{(2)} = (\Theta^{(2)})^T \delta^{(3)}.* g'\left(z^{(2)}\right)$$

4. Accumulate the gradient skip or remove δ_0^2 ,removing δ_0^2corresponds to delta_ 2 = *delta_2(2:end)*.

$$\Delta^{(l)} = \Delta^{(l)} + \delta^{(l+1)}\left(a^{(l)}\right)^T$$

5. Obtain the (unregularized) gradient for the neural network cost function by dividing the accumulated gradients by$\frac{1}{m}$:

$$\frac{\partial}{\partial \Theta_{ij}^{(l)}} J(\Theta) = D_{ij}^{(l)} = \frac{1}{m}\Delta_{ij}^{(l)}$$

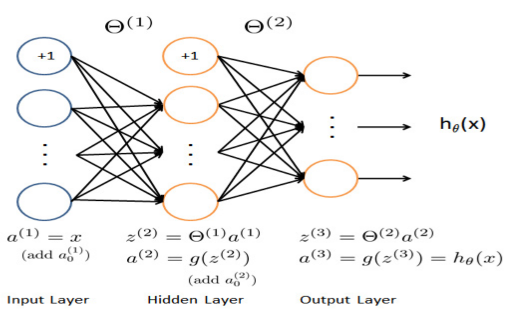


Figure 7. Neural Network Model.

The implementation of back propagation algorithm is as follows. Given a training example (x^t, y^t), and first run a forward pass to compute all the activations throughout the network, including the output value of the hypothesis h(x). Then, for each node j in layer l, compute an "error term"δ_j^ithat measures how much that node was responsible "for any errors in the output.

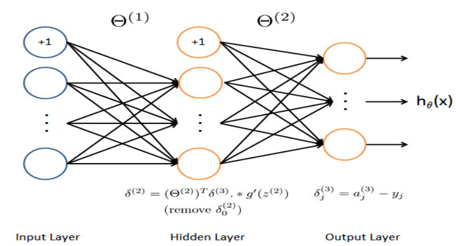


Figure 8. Back propagation network.

For an output node, it is used to directly measure the difference between the network's activation and the true target value, and use that to define $\delta_j 3$ (since layer 3 is the output layer). For the hidden units, compute $\delta_j i$ based on a weighted average of the error terms of the nodes in layer (l + 1).

In detail, here is the back propagation algorithm (also depicted in Figure 8) implement Steps 1 to 4 in a loop that processes one example at a time. Concretely, implement a for-loop for t = 1: m and place steps 1-4 below inside the for-loop, with the t^{th} iteration performing the calculation on the t^{th} training example ($x^{(t)}$,$y^{(t)}$). Step 5 will divide the accumulated gradients by m to obtain the gradients for the neural network cost function.

The performance assessment protocol used in FVC2004 is used separately in these median gabor and anisotropic experiments. The performance indicators of fingerprint verification such as False Acceptance Rate (FAR). This value is the rate that an imposter fingerprint is erroneously acknowledged as a genuine claim. It is equivalent to the probability that an illegal person is incorrectly accepted as official person. Further False Reject Rate (FRR), .which is the rate that a authentic fingerprint is mistakenly redundant as an imposter claims, equivalent to the probability that the system does not sense an approved person. Equal Error Rate (EER), is the rate at which both admit and decline rates are indistinguishable. The EER is used as a performance pointer. Genuine acceptance rate (GAR), which is the rate that a genuine fingerprint is correctly accepted as genuine.

The GAR, FAR and FRR are defined as follows:

$$\text{GAR} = \frac{\text{Number of accepted genuine finger}}{\text{Total number of genuine finger}} * 100$$

$$\text{FAR} = \frac{\text{Number of accepted imposter finger}}{\text{Total number of imposter finger}} * 100$$

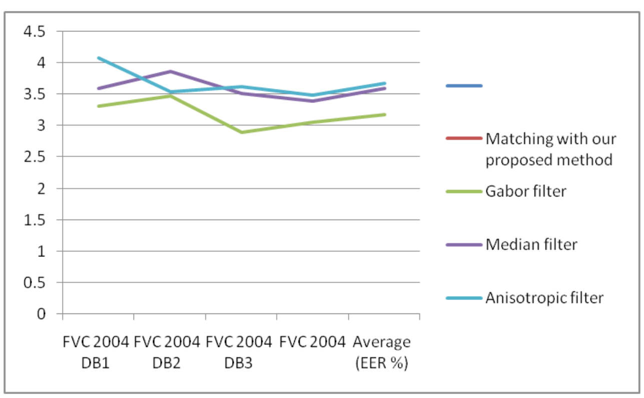
$$\text{FRR} = \frac{\text{Number of rejected genuine finger}}{\text{Total number of genuine finger}} * 100$$

Database	FVC 2004 DB1	FVC 2004 DB2	FVC 2004 DB3	FVC 2004 DB4	Average (EER %)
Matching with our proposed method					
Gabor filter	3.32	3.48	2.89	3.06	3.18
Median filter	3.59	3.87	3.52	3.39	3.59
Anisotropic filter	4.08	3.55	3.63	3.49	3.68

Equal Error Rate

Proposed method with the supervised Back Propagation Neural Network (BPNN) over the four databases, using the comparison of the Equal Error Rate EER (%).

Table 1. EER Value calculation



From the above results that the Equal Error Rate (EER), False Reject Rate (FRR) and False Accept Rate (FAR) are computed on the four databases of FVC 2004 . The accepted fingerprint match (genuine) and rejected fingerprint match (impostor) were also performed. For genuine fingerprint match, each test fingerprint of each person was compared with the template fingerprint of the same person. For impostor fingerprint match, the test fingerprint of each person was compared with the template fingerprint of other persons The average EER (%) values of Back Propagation Neural Network (BPNN) match over four databases with the three different filters was found with the proposed method. Further the results reveal an improvement in performance since the best average EER (%)of matching with gabor filter is 3.18%.

7. Conclusion

In this paper, an improved feature for fingerprint matching using artificial neural networks is proposed. The proposed algorithm basically uses moment features invariant to scale, position and rotation to increase the matching accuracy. It further pursues an enhanced performance by using the alignment and rotation after a difficult reliable recognition of a reference point. By having invariant characteristics in the proposed algorithm has resulted in a significantly improved performance for input images under a variety of conditions. The working out speed of the proposed algorithm is also much superior to other similar algorithms. For very low quality and sternly unclear images as those in FVC2004 Databases, the proposed algorithm still shows better performance than others.

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