

A Neural Network Based approach for Fingerprint recognition system

Avinash Kumar Jha¹, Supriya Narasimham¹, Sudheer Sreedhara Krishna², V.P. Mahadevan Pillai²

*avinash_jha41@yahoo.com

1. Vellore Institute of Technology, Vellore 632014

2. University of Kerala, Thiruvananthapuram

Abstract: A simple neural network based approach has been developed for fingerprint recognition. The fingerprint were taken using optical scanners and further processed using neural network. The system uses candidate score, ideal weight model score and recognition quotient for recognition of the pattern. The algorithm is based on winner takes all.

I. Introduction:

Biometrics comprises methods for uniquely recognizing humans based upon one or more intrinsic physical or behavioral traits. Fingerprint identification is one of the most well-known and publicized biometrics. Because of their uniqueness and consistency over a century, more recently becoming automated due to advancements in computing capabilities. Fingerprint identification is popular because of the inherent ease in acquisition, the numerous sources (ten fingers) available for collection. A fingerprint usually appears as a series of dark lines that represent the high, peaking portion of the friction ridge skin, while the valleys between these ridges appears as white space and are the low, shallow portion of the friction ridge skin.

A neural network is an information processing system. It consists of massive simple processing units with a high degree of interconnection between each unit. The processing units work cooperatively with each other and achieve massive parallel distributed processing. The design and function of neural networks simulate some functionality of biological brains and neural systems. The advantages of neural networks are their adaptive-learning, self-organization and fault-tolerance capabilities. For these outstanding capabilities, neural networks are used for pattern recognition applications. Some of the best neural models are back-propagation, high-order nets, time-delay neural networks and recurrent nets.

A neural network based approach is well suited for fingerprint recognition because of several reasons. First, fingerprints form a very specific class of patterns with very peculiar flavor and statistical characteristics [1]. Thus the corresponding pattern recognition problems seem well confined and constrained, perhaps even more so than in other pattern recognition problems, such as the recognition of handwritten characters, where neural networks have already been applied with reasonable success. Second, neural networks could avoid some of the pitfalls inherent to other more conventional approaches. It has been known for over a century [2] that pairs of fingerprint images can be matched by human operators on the basis of minutia and/or ridge orientations. Indeed, it is this strategy based on minutia detection and matching that has been adopted in most of the previous attempts to find automated solutions. The minutia-based approach has two obvious weaknesses: it is sensitive to noise and computationally expensive since it is essentially a graph matching problem. Third, neural networks are robust, adaptive, and trainable from examples. This is particularly important since fingerprint images can include several different sources of deformation and noise

ranging from the fingers and their positioning on the collection device.

In this paper, a simplified neural approach to recognition of optical or visual fingerprint is presented .

II. Method

II. Fingerprint acquisition

Optical imaging is used to acquire the fingerprint. The top layer of the sensor, where the finger is placed, is known as the touch surface. Beneath this layer is a light-emitting phosphor layer which illuminates the surface of the finger. The light reflected from the finger passes through the phosphor layer to an array of solid state pixels (a charge-coupled device) which captures a visual image of the fingerprint.

III. Learning Mechanism

In the employed system, a highly simplified architecture of artificial neural networks is used. In the used method, fingerprints are taught to the network in a supervised manner. A print is presented to the system and is assigned a particular label. Several variant patterns of the same print are taught to the network under the same label. Hence the network learns various possible variations of a single print and becomes adaptive in nature. During the training process, the input to the neural network is the input matrix M defined as follows:

If $I(i, j) = 1$ Then $M(i, j) = 1$

Else:

If $I(i, j) = 0$ Then $M(i, j) = -1$ (1.1)

In the current method of learning, each candidate character taught to the network possesses a corresponding weight matrix. For the kth fingerprint sample to be taught to the network, the weight matrix is denoted by W_k . As learning of the system progresses, it is this weight matrix that is updated. At the commencement of teaching (supervised training), this matrix is initialized to zero. Whenever a fingerprint sample is to be taught to the network, an input pattern representing that fingerprint is submitted to the network. The network is then instructed to identify this pattern as, say, the kth finger in a knowledge base of fingerprints. That means that the pattern is assigned a label k. In accordance with this, the weight matrix W_k is updated .

$$\begin{aligned} & \text{for all } i=1 \text{ to } x \\ & \{ \\ & \quad \text{for all } j=1 \text{ to } y \\ & \quad \{ \\ & \quad \quad W_k(i, j) = W_k(i, j) + M(i, j) \\ & \quad \} \\ & \} \end{aligned} \quad (1.2)$$

Here x and y are the dimensions of the matrix W_k (and M). We can notice certain peculiarities in such a weight matrix, like,

1. The matrix-elements with higher (positive) values are the ones which stand for the most commonly occurring image-pixels.
2. The elements with lesser or negative values stand for pixels which appear less frequently in the images.

The weights may represent the importance or priority of a parameter, which in the instant case is the occurrence of a particular pixel in a character pattern. It can be seen that the weights of the most frequent pixels are higher and usually positive and those of the

uncommon ones are lower and often negative. The matrix therefore assigns importance to pixels on the basis of their frequency of occurrence in the pattern. In other words, highly probable pixels are assigned higher priority while the less-frequent ones are penalized. However, all labeled patterns are treated without bias, so as to include impartial adaptation in the system.

IV. Recognition System

A network is constructed with each node trained to recognize a particular finger print .The weight matrix is updated for each of node . when a fingerprint is produced for recognition ,the input is fed to every node and tested for match .Decision is taken in favor of a stored fingerprint depending on the Candidate Score, Ideal Weight-Model Score and Recognition Quotient (Q).

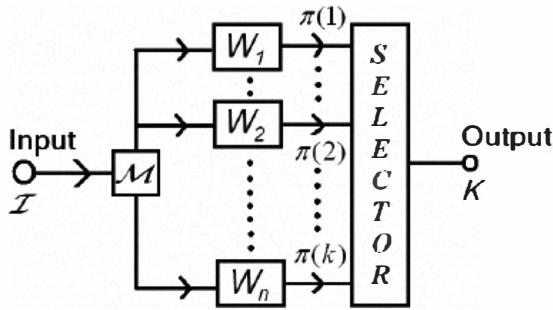


Fig.1 Block Diagram of the network.

IV.a Candidate Score This statistic is a product of corresponding elements of the weight matrix W_k of the k th learnt pattern and an input pattern I as its candidate. It is formulated using the as follows:

$$\psi(k) = \sum_{i=1}^x \sum_{j=1}^y W_k(i, j) * I(i, j) \quad (1.3)$$

Unlike in the training process where M was the processed input matrix, in the recognition process, the binary image matrix I is directly fed to the system for recognition.

IV.b Ideal Weight-Model Score (μ):

This statistic simply gives the sum total of all the positive elements of the weight matrix of a learnt pattern. It may be formulated as follows

$$\begin{aligned} & \text{for } i=1 \text{ to } x \\ & \{ \\ & \quad \text{for } j=1 \text{ to } y \\ & \quad \{ \\ & \quad \quad \text{if } W_k(i, j) > 0 \text{ then} \\ & \quad \quad \{ \\ & \quad \quad \quad \mu(k) = \mu(k) + W_k(i, j) \\ & \quad \quad \} \\ & \quad \} \end{aligned} \quad (1.4)$$

IV.c Recognition Quotient (Q): This statistic gives a measure of how well the recognition system identifies an input pattern as a matching candidate for one of its many learnt patterns. It is simply given by:

$$Q(k) = \frac{\psi(k)}{\mu(k)} \quad (1.5)$$

The greater the value of Q , the more confidence does the system bestow on the input pattern as being similar to a pattern already known to it. The classification of input patterns now follows the following trivial procedure:

1. For an input candidate pattern I , calculate the recognition quotient ($Q(k)$) for each learnt pattern k .
2. Determine the value of k for which $Q(k)$ has the maximum value.

3. Too low maximum value of $Q(k)$ (a threshold obtained after multiple trials) indicates poor recognition. In such a case:

Conclude that the candidate pattern does not exist within the knowledge base

OR

Teach the candidate pattern to the network till a satisfactory value of $Q(k)$ is obtained

4. Conditionally, identify the input candidate pattern as being akin to the k th learnt pattern or proceed with the training for better performance

V. Result and discussion

The proposed neural network had been simulated using MATLAB .

Three finger prints shown in fig.2.a ,fig.2b, and fig.2.c were taken and to train three nodes of the network. Different variation of each print was used to train the nodes and hence updated weight matrix were obtained. The threshold was obtained as 0.635.

Two trials were performed, in the first trial a distorted version of fingerprint as in fig 2.a was taken as input(fig.2.d) while in the second trial a new fingerprint shown in fig.2.e was fed to the system as input

The recognition quotient for the first trial corresponding to first second and third node were 0.937 ,0.456 ,and 0.345 respectively. In case of second trial it was found as 0.543,0.399 and 0.434 respectively thus in second trial no match is found while in first decision is taken in favor of first fingerprint. Hence the system was found to be efficient in

comparing and matching the input pattern with the stored patterns.



Fig.2.a



Fig.2.b



Fig.2.c



Fig.2.d



Fig.2.e

VI. Conclusion. A simple and efficient neural network based fingerprint recognition system has been proposed and tested with simulation .

The system is found to have good performance in comparing and matching the test pattern with already stored patterns. System is adaptive and gives satisfactory

results in case of slight variation in the same fingerprint due to cut or burn etc.

The system threshold was found to be 0.635 which can be further improved on training.

For same fingerprint the recognition quotient is as high as 0.937 while for different prints it is lower than 0.5 hence the system provides well distinction in case of different prints.

VII References

1. L. E. Cun, Y., et al., *Handwritten digit recognition with a back propagation*

network. Neural Information Processing Systems, Vol. 2,

pp. 396-404.

2. Moenssens, . *Fingerprint Techniques*. Chilton Book Company, Radnor,

3. Alexander J. Faaborg, *Using Neural Networks to Create an Adaptive Character Recognition System*, March 2002

4. E. W. Brown, *Character Recognition by Feature Point Extraction*, unpublished paper authored at Northeastern University, 1992