

Fingerprint Recognition using Neural Network based Hybrid Approach

Mayur Nagin Dongre
M. Tech. Scholar
Embedded System and VLSI Design
Acropolis Institute of Technology and Research
Indore (India)
mdongre222@gmail.com

Abstract – This paper presents a neural network (NN) architecture for a system of recognition of people through the biometric measurement of the fingerprint. In this system, a database of the fingerprint image is processed by means of morphological operations. The inputs to the neural network architecture are the processed fingerprint images and the output is the number of the person identified. This work proposes the hybridization of DWT (Discrete Wavelet Transform) and LBP (Local Binary Pattern) features of the images to train the neural network. The classification accuracy obtained with the hybrid approach on the images is 85% with 60:40 ratio of training and testing respectively.

Keywords – DWT, LBP, Morphological Operations, Neural Network.

I. INTRODUCTION

Knowing how to determine the identity of a person automatically is always a problem. In a world that is becoming increasingly interconnected, it is more than necessary to recognize users in order to give them access to a building or to allow them to use specific resources, etc. It is therefore urgent to have automatic and reliable authentication systems in order to be able to combat fraud and to meet the very high requirements in various fields ranging from crossing international border crossings to accessing personal information [1]. In addition, passwords and identity cards cannot provide vital authentication functions such as non-repudiation and detection of multiple registrations. For example, users can easily deny the use of a service by claiming that their password was stolen or guessed. Individuals can also hide their true identity by presenting duplicates of falsified identity documents [2].

As a result it becomes increasingly clear that these mechanisms are not sufficient to reliably determine the identity of a person and that a stronger mechanism for identification based on something you are, Namely biometrics, is more than necessary.

Biometrics is thus an alternative to the old modes of identification. It involves identifying a person based on their physical or behavioural characteristics [3]. Face, fingerprints and iris are examples of physical characteristics. Voice, writing, rhythm of typing on a keyboard are behavioural characteristics. These characteristics, whether innate like fingerprints or acquired as signature, are attached to each individual and therefore do not suffer from the weaknesses of methods based on knowledge or possession [4].

Biometric systems based on a single modality are called unified modal systems [5]. Although some of these systems [6] have led to considerable improvements in terms of reliability and accuracy, they suffer from problems in the learning phase, due mainly to the non-universality of biometric characteristics, Exposure to biometric impersonation, and inadequate accuracy of noisy data [7].

Fingerprint recognition is a complex pattern recognition problem. It is difficult to design accurate algorithms capable of extracting salient features and matching them in a robust way, especially in poor quality fingerprint images and when low-cost acquisition devices with small area are adopted. There is a popular misconception that automatic fingerprint recognition is a fully solved problem since it was one of the first applications of machine pattern recognition [8]. On the contrary, fingerprint recognition is still a challenging and important pattern recognition problem. The real challenge is matching fingerprints affected by [9]:

1. High displacement/or rotation which results in smaller overlap between template and query fingerprints (this case can be treated as similar to matching partial fingerprints).
2. Non-linear distortion caused by the finger plasticity.
3. Different pressure and skin condition.
4. Feature extraction errors which may result in spurious or missing features.

In a common style, this will be a difficulty to know and differentiate the types of fingerprint. By using NN toolbox, we able to assign an input pattern or train the network. This ability of the network is to recognize the data features that were extracted from the image with a little difference.

A good biometric is characterized by use of a feature which is highly unique so that the chance of any two people having the same characteristic will be minimal, stable – so that the feature does not change over time, and be easily captured – in order to provide convenience to the user, and prevent misrepresentation of the feature.

Current system has many drawbacks in terms of recognition rate that they cannot recognize the fingerprint in the worst cases, and these drawbacks are directly depends upon the feature extraction technique used. This motivate us to use DWT as feature extraction technique which perform better as compare with the other approaches and to make a system by using that feature extraction technique which is more efficient as compare with the current scenario.

It is believed that fingerprint is unique to individuals. They remain unchanged throughout at least a certain period during the adult life of an individual. Fingerprints possess all of the following properties:

- Universality, which means the characteristic should be present in all individuals.
- Uniqueness, as the characteristic has to be unique to each individual.
- Permanence: its resistance to aging.
- Measurability: how easy is to acquire image or signal from the individual.
- Performance: how good it is at recognizing and identifying individuals.
- Acceptability: the population must be willing to provide the characteristic.
- Circumvention: how easily can it be forged?

For instance, iris based methods, which are the most reliable, require more expensive acquisition systems than fingerprint recognition systems. Face and voice characteristics are easier to acquire than fingerprints, but they are not so reliable. Overall, fingerprint recognition based systems are well balanced in terms of cost and performance [10].

The main aim of this paper is to develop fingerprint recognition system using 4 level Haar Discrete Wavelet Transform (DWT), Local Binary Pattern and back-propagation neural network. The database for this research work contains 10 classes of

fingerprint images and every class has 5 images. The fingerprint image goes through the pre-processing and the feature vectors are stored in the database and is used for classification.

II. PROPOSED METHODOLOGY

Figure 1 shows the basic block diagram for proposed fingerprint recognition system. It consists of two modules; training and test. Rest of the methodology is explained as follows:

A. Pre-Processing

Each input image goes through pre-processing stage where the following operations are performed:

Morphological Operations:

There are two basic operations in morphology, which are called dilation and erosion.

The dilation of I by B is denoted by $I \oplus B$ and it is defined as:

$$I \oplus B = \{c \mid c = i + b, \text{ where } i \in I, b \in B\} \quad (1)$$

To complete the dilation operation, B should be translated to the every image pixel and the union of the result should be taken as an overall result. Therefore, to be precise, translation of a set should be defined to shift the structuring element to a specific image point.

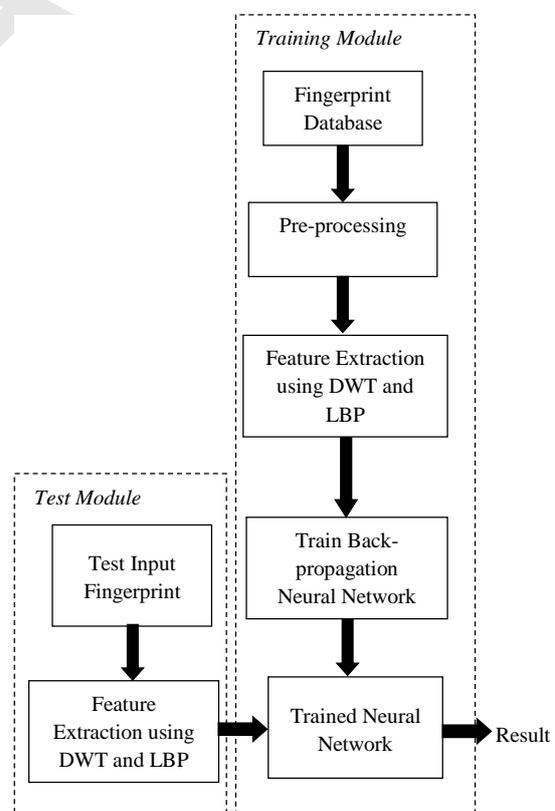


Figure 1: Flow diagram of proposed work

The translation of set B by t is defined as follows:

$$B_t = \{c \mid c = b + t, \forall b \in B\} \quad (2)$$

Dilation operation is defined as follows:

$$Dil(I, B) = \bigcup_{t \in I} I \oplus B_t \quad (3)$$

In the same sense, erosion and erosion operations are defined as in Equations (3), (5) respectively.

$$I \ominus B = \{c \mid c = i - b, i \in I, b \in B\} \quad (4)$$

$$Ero(I, B) = \bigcap_{t \in I} I \ominus B_t \quad (5)$$

By using the primitive operations, several morphological operations can be defined. The two basic compound functions that could be constructed by using dilation and erosion are opening and closing respectively. The opening could be defined as dilating an image after eroding. The closing could be defined as eroding and image after dilating.

The opening of a set I by structuring element B is defined as:

$$I \circ B = (I \ominus B) \oplus B \quad (6)$$

Similarly, the closing of a set I by structuring element B is defined as:

$$I \cdot B = (I \oplus B) \ominus B \quad (7)$$

Finally isolate objects in image reading line wise (left to right in each line).

B. Feature Extraction

DWT

The wavelet transform is established on the basis of a signal decomposition by wavelets whose expansion and translation parameters are continuous variables.

In addition, while dealing out with the digital signals, a discretization of the parameters a and b is necessary. Consequently, the integral of wavelet transform expressing the conservation of energy is also discretized, which raises the question of the conditions under which the approximation of this integral will be applicable [11].

It is necessary to give a rule on the discretization of the steps of dilation and translation of the wavelets. As long as this rule is followed, the preservation of all signal information can be ensured, allowing a numerically applicable expression of the inverse transform as a discrete wavelet series.

We can choose to sample the signal using the wavelet “like a microscope”: since the size of the wavelet varies according to the dilation, the conservation of the same time sampling step is redundant and useless.

At low frequencies, many wavelets would be used to represent little information, so the theoretical transform is redundant. Likewise, since the

frequency band covered by the wavelet is wider at high frequencies, less wavelets will be needed to represent this band.

Morlet proposed to create bases of functions built on the following model [11]:

$$\psi_{j,k}(t) = a_0^{-\frac{j}{2}} \psi(a_0^{-j}t - kb_0) \quad (8)$$

With, $a_0 > 1$ and $b_0 > 0$ fixed and $j, k \in Z$

This discretization assigns values to the scale a on a logarithmic scale with proportional translation parameters:

$$a = a_0^j \text{ and } b = kb_0 a_0^j \quad (9)$$

A range of commonly used scales is the dyadic range, $a_0 = 2$ and $b_0 = 1$. We thus obtain families consisting of functions of the form:

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}} \psi(2^{-j}t - k) \quad (10)$$

However, one very often finds in the literature, a dyadic WT where only the scale parameter is sampled according to a dyadic sequence $[2^j] j \in Z$, and the parameter b remains a continuous variable. Such a transform, for a signal $x(t)$, can be written as:

$$DWT(2^j, b) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{+\infty} x(t) \psi^* \left(\frac{t-b}{2^j} \right) dt \quad (11)$$

Local Binary Pattern (LBP)

Given a central pixel in the image, a pattern code is computed by comparing it with its neighbours:

$$LBP_{P,R} = \sum_{p=0}^{P-1} S(g_p - g_c) 2^p \quad (12)$$

$$S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (13)$$

Where g_c is the gray value of the central pixel, g_p is the value of its neighbours, P is the total number of involved neighbours and R is the radius of the neighbourhood. Suppose the coordinate of g_c is $(0, 0)$, then the coordinates of g_p are $(R * \cos(2\pi p/P), R * \sin(2\pi p/P))$. Figure 2 gives examples of circularly symmetric neighbour sets for different configurations of (P, R) . The gray values of neighbours that are not in the center of grids can be estimated by interpolation [12].

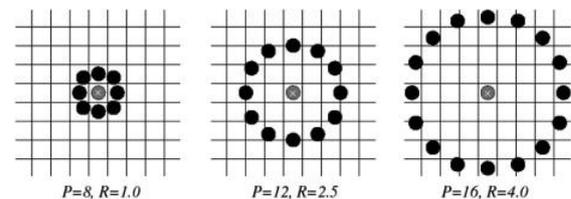


Figure 2: Circularly symmetric neighbour sets for different (P, R)

Suppose the texture image is of size $N \times M$. After identifying the LBP pattern of each pixel (i, j) , a histogram is built to represent the whole texture image:

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$$H(k) = \sum_{i=1}^N \sum_{j=1}^M f(LBP_{P,R}(i, j, k)), k \in [0, K] \quad (14)$$

$$f(x, y) = \begin{cases} 1, & x = y \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

Where K is the maximal LBP pattern value.

The U value of an LBP pattern is defined as the number of spatial transitions (bitwise 0/1 changes) in that pattern [12]:

$$U(LBP_{P,R}) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \quad (16)$$

For example, the LBP pattern 00000000 has a U value of 0 and 01000000 has a U value of 2. The uniform LBP patterns refer to the patterns which have limited transition or discontinuities ($U \leq 2$) in the circular binary presentation. It was verified that only those “uniform” patterns are fundamental patterns of local image texture. In practice, the mapping from $LBP_{P,R}$ to $LBP_{P,R}^{u2}$ (superscript “u2” means that the uniform patterns have a U value of at most 2), which has $P * (P - 1) + 3$ distinct output values, is implemented with a lookup table of 2^P elements. The dissimilarity of sample and model histograms is a test of goodness-of-fit, which could be measured with a nonparametric statistic test.

These feature vectors are classified using the Neural Network classifier.

C. Classification using Neural Network

Among the different architectures of artificial neural networks we adopted for this study the Multi Layer Perceptrons (MLPs) [13]. MLPs are most commonly used in supervised learning approaches, that is, when an association between two types of data, representing network input and output respectively, must be learned. In an MLP artificial neurons are organized in layers. Neurons belonging to the same layer are not connected to each other. Each neuron receives its inputs from the previous layer and transmits the result of its treatment to the next layer. The two extreme layers correspond to the layer that receives the data (input layer), and the layer that provides the result of the performed processing (output layer). The intermediate layers are called hidden layers, their number is variable. The connectivity between the successive layers is total and each connection is weighted by a weight.

Let $y = f(x)$ be a function with $x \in R^D$ and $x \in R^D$ and let $H_i, i = 1, \dots, N$ a set of basic functions.

The function f can be written in the form [13]:

$$y = f(x) = \hat{f}(x) + r(x) \quad (17)$$

Where $r(x)$ is the residue.

The function $f(x)$ can be approximated by $\hat{f}(x)$ given by the form (18)

$$y \approx \hat{f}(x) = \sum_{i=1}^N w_i h_i(x) \quad (18)$$

The goal is to minimize the error by adjusting the w_i settings appropriately. A possible choice for the approximation error is the L_2 standard of the residual function $r(x)$ is defined as:

$$(\|r(x)\|_{L_2})^2 = \int r(x)^2 dx \quad (19)$$

Approximation of functions by RBF networks The output of an RBF network is given by following equation:

$$\hat{y} = \hat{f}(x) = \sum_{i=1}^N a_i \phi_i(x, \mu_i, \sigma_i) \quad (20)$$

Using the above equation (3.4), the function $\hat{f}(x)$ can be written as:

$$y = \sum_{i=1}^N a_i \phi_i(x, \mu_i, \sigma_i) + r(x) = \hat{y} + r(x) \quad (21)$$

The error can be minimized by appropriately adjusting the weights a_i , centres μ_i and the widths σ_i .

When the function $f(x)$ is unknown, and having a set of couples outputs $(x_i, y_i), i = 1 \dots n$, the RBF network can be built and it can be learn it to follow the function $f(x)$.

Learning this network is an optimization problem to choose the values of centres, weights and widths to minimize criterion:

$$J^2(\mu, \sigma, a) = \sum_{i=1}^n \|y_i - \hat{y}\|^2_i \quad (22)$$

Let E_k represents the mean squared error and the definition is as follows:

$$E_k = \frac{1}{2} \sum_{i=1}^n (\hat{y}_i - y_i)^2 \quad (23)$$

III. SIMULATION AND RESULTS

The performance of proposed algorithms has been studied by means of MATLAB simulation.

Confusion Matrix

	1	2	3	4	5	6	7	8	9	10	
1	3 7.5%	0 0.0%	0 0.0%	1 2.5%	0 0.0%	1 2.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	60.0%
2	0 0.0%	2 5.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100.0%
3	0 0.0%	1 2.5%	4 10.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	80.0%
4	1 2.5%	0 0.0%	0 0.0%	3 7.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	75.0%
5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	4 10.0%	0 0.0%	0 0.0%	1 2.5%	0 0.0%	0 0.0%	80.0%
6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	3 7.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100.0%
7	0 0.0%	1 2.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	4 10.0%	0 0.0%	0 0.0%	0 0.0%	80.0%
8	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	3 7.5%	0 0.0%	0 0.0%	100.0%
9	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	4 10.0%	0 0.0%	100.0%
10	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	4 10.0%	100.0%
	75.0%	50.0%	100%	75.0%	100%	75.0%	100%	75.0%	100%	100%	85.0%
	25.0%	50.0%	0.0%	25.0%	0.0%	25.0%	0.0%	25.0%	0.0%	0.0%	15.0%
	1	2	3	4	5	6	7	8	9	10	

Figure 3: Confusion matrix plot

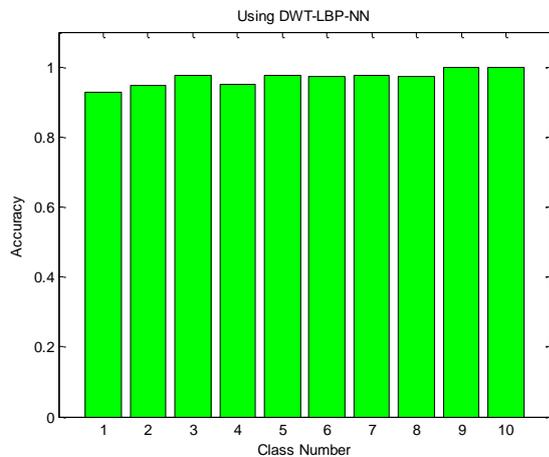


Figure 4: Accuracy graph for proposed approach

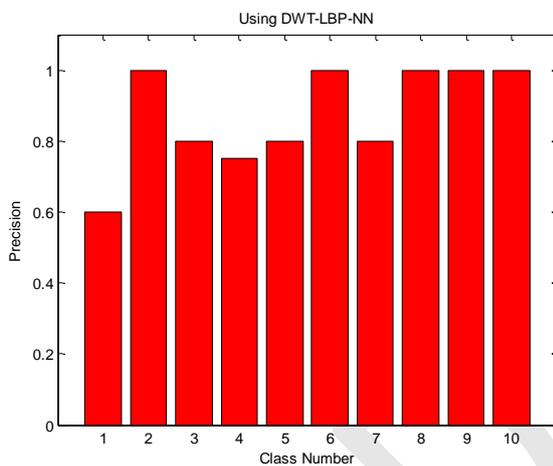


Figure 5: Precision graph for proposed approach

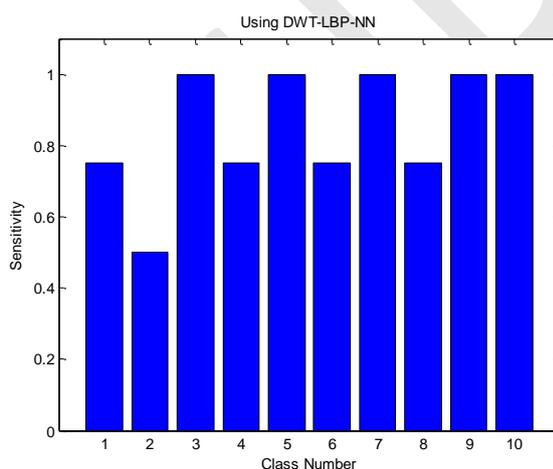


Figure 6: Sensitivity graph for proposed approach

IV. CONCLUSION

Fingerprint recognition is in constant technological evolution, it is widely used in many official and commercial fields for identification applications. The main purpose of fingerprint recognition method

is to compare user data with the reference data which will be obtained via an external sensor in order to prove the identity of the person subjected to the tests and possibly to authorize it or not to access a secured item.

The recognition of fingerprint is currently one of the most accurate biometric techniques and explicitly used in registration of the AADHAR card in India. In a fingerprint recognition system, pre-processing plays a very important role. The raw image is processed with morphological operations. Further hybrid features (DWT+LBP) are used with neural network classifier and the achieved accuracy is 85%. It is interesting to see the fingerprint feature extraction in future, fingerprint images obtained in less controlled environments, for example, under different lighting conditions.

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