# FINGERPRINT FEATURE EXTRACTION AND CLASSIFICATION BY LEARNING THE CHARACTERISTICS OF FINGERPRINT PATTERNS

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**Abstract:** This paper presents a two stage novel technique for fingerprint feature extraction and classification. Fingerprint images are considered as texture patterns and Multi Layer Perceptron (MLP) is proposed as a feature extractor. The same fingerprint patterns are applied as input and output of MLP. The characteristics output is taken from single hidden layer as the properties of the fingerprints. These features are applied as an input to the classifier to classify the features into five broad classes. The preliminary experiments were conducted on small benchmark database and the found results were promising. The results were analyzed and compared with other similar existing techniques.

Key words: *Biometrics, multi layer perceptron, artificial neural networks, fingerprints, feature extraction*

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## 1. Introduction

A wide variety of applications require reliable verification schemes to confirm the identity of an individual. Recognizing humans based on their body characteristics became more and more interesting in emerging technology applications. Traditionally, passwords and ID cards have been used to restrict access to secure systems but these methods can be easily breached and are unreliable. Biometric cannot be borrowed, stolen or forgotten [1].

Due to the increasing demand in security applications, biometrics systems are becoming very important for many real world applications. A biometric system is essentially a pattern-recognition system that recognizes a person based on feature vector derived from a specific physiological or behavioral characteristic that person

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possesses [2]. Generally, a person could be identified based on (a) person's possession (something you possess), e.g. access card to the building; and (b) person's knowledge of a piece of information (something that you know), e.g. login and password associated with it. Another approach is based on identifying physical characteristics of the person based on fingerprints, hand geometry etc. In many civilian and forensic applications, person identification (1:Many) is required rather than verification (1:1) [3].

Fingerprint extraction, classification and matching techniques are computationally expensive and require many resources and robust algorithms. It takes large amount of computational resources for fingerprint recognition. Unlike password or token-based system, a practical biometric system does not make perfect match decisions. The biometric system incorrectly declares the failure of match between the input pattern and a matching pattern in the database. Therefore, there is a need to bridge the gap between the current technology and performance requirements. Some of the major classification techniques are described in this paper.

The fingerprints have been traditionally classified into categories based on the information in the global pattern of ridges. The main purpose of classification of extracted fingerprint features is to reduce the time significantly in matching process. A fingerprint classification system should be invariant to rotation, translation, and elastic distortion of the frictional skin. Based on the current literature, the fingerprints are classified into five major categories: right loop, left loop, arch, tented arch and whorl. Fig. 1 shows the various classes of fingerprint images.


**Fig. 1** *Fingerprint classes based on Henry's classification scheme.*

Novel classifiers based on Support vector machines (SVMs) are comparatively recent techniques and are based on statistical learning theory [4]. SVMs are binary classifiers that work by finding the optimal separating hyperplane in the feature space [5]. Chang and Fan present an alternate fingerprint representation that captures structural information [6]. Chang and Fan claim that all fingerprints can be represented by combinations of these basic types and classification can be performed based on their distribution in the fingerprint. Most of the neural network approaches are using error back-propagation algorithm or self organizing map for classification purposes [7], [8], [9].

A new approach for fingerprint classification, based on the distribution of local features of the fingerprints is described in paper [10]. A typical fingerprint classification approach is based on the extraction of fingerprint singular points and the implementation of rule based classification system.

Hong and Jain [12] also introduced rule-based classification algorithm that uses number of singularities together with the number of recurring ridges found in fingerprint image. Cho presented a classification method [13] that uses only the loop points and classifies the fingerprints based on curvature and orientation of the fingerprint near the loop. Jain and Minut [14] used fingerprint kernel along with the orientation field for classification. Maio and Maltoni [15] presented an idea of structural approach for classification. Senior used hidden Markov models for fingerprint classification [15]. Mitra et al. [17] proposed a fuzzy multilayer perceptron for the classification of fingerprint patterns considering only three classes as output: left loop, right loop and whorl, while the input was given as texture based features along with some directional features. Gabor filter-based fingerprint classification was used by [17]. In correlation-based fingerprint matching, two fingerprint images are superimposed and the correlation between corresponding pixels is computed for different alignments [18].

The paper is organized as follows: Section 2 describes the research methodology technique in details with various sections, Section 3 details the experimental results, Section 4 compares and analyzes the obtained results, and the paper is concluded in Section 5.

## 2. Research Methodology

The proposed technique is divided mainly into two stages: (a) Fingerprint image pre-processing. (b) Fingerprint feature extraction, and classification of extracted features into five classes.

### 2.1 Fingerprint image pre-processing

The quality of the fingerprint image is very poor in most of the cases. It is important to improve the quality of the image using image enhancement techniques. A fingerprint image is applied as an input to the algorithm and the enhanced image obtained will be used for further processing.

Few Steps for rotation of the fingerprint images:

(a) Rotate the fingerprint image around its center,

(b) Each point in the fingerprint image has a distance and angle from the center.

### 2.2 Fingerprint feature extraction and classification

One of the important steps in classifying the features and calculating the similarity is feature extraction. There are few existing techniques for fingerprint feature extraction based on correlation method, gabor filter method, core index technique etc. If the features are not extracted accurately, it is hard to get high-quality classification accuracy. Fingerprint representations are of two types: local and global. Major representations of the local information in fingerprints are based on the entire images. An important property of the ridges in a fingerprint image is that the gray level values on the ridges attain their local maxima along the direction normal to the local ridge orientation.

The algorithm of feature extraction mainly consists of three components: (a) Applying the fingerprint pattern at input and output, (b) learning of the same patterns, (c) taking the output of the hidden layer. The orientation field of a fingerprint image represents the directionality of ridges in the fingerprint image and plays very important role in fingerprint image analysis. The main idea of the auto-associator feature extractor is based on input:hidden:output mapping, where input and outputs are the same patterns.

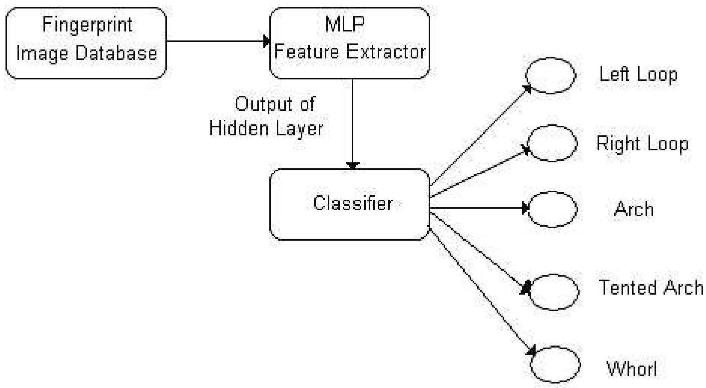


**Fig. 2** *Block diagram of the proposed methodology.*

Fig. 2 shows the block diagram of the proposed methodology. The Multi Layer Perceptron (MLP) learns the same patterns and provides a characteristic through its hidden layer as a feature vector. An auto-associator feature extractor using a single hidden layer feed-forward neural network will be designed. It has $\boldsymbol{n}$ inputs, $\boldsymbol{n}$ outputs and $\boldsymbol{p}$ hidden units. The input and output of the MLP are the same texture patterns and the network will be trained using a supervised learning algorithm. After training is completed, the output of the hidden layer is extracted and taken as a feature vector.

An MLP texture feature classifier is shown in Fig. 3. It has $\boldsymbol{n}$ inputs which is the same as the number of hidden units in an auto-associator feature extractor.

The output of the hidden layer that was obtained from the auto-associator was used as input to the classifier. There were 5 fingerprint classes, so the number of outputs was 5.

# 3. Experimental Results

The objective of these experiments is to illustrate that the proposed fingerprint feature extraction techniques and classification improves the overall efficiency for fingerprint recognition.

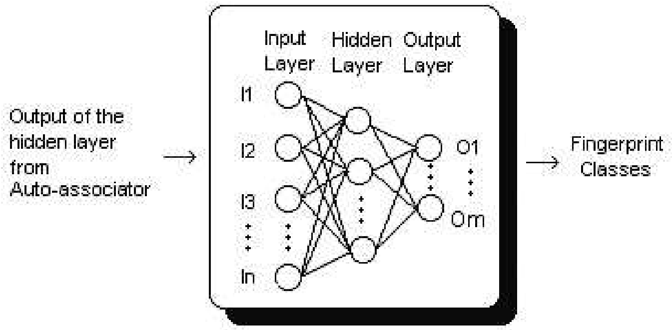


**Fig. 3** *MLP as a fingerprint feature classifier.*

## 3.1 Training of an auto-associator and classifier

The experiments were conducted in two stages, firstly the training of the auto-associator and secondly the training of the classifier. Before training of an auto-associator, it is necessary to provide various parameters to a Multi Layer Perceptron (MLP). The total number of fingerprint images were 800, out of that 600 were randomly selected as training set and remaining as testing set. Tab. I shows the number of images for each class. All the fingerprint images were normalized into 16 X 16 patterns giving 256 as the number of input to the MLP. Fig. 4 shows the normalized fingerprint pattern. In the case of the auto-associator, the same patterns were applied to the output.

**Fig. 4** *Normalized 16 X 16 fingerprint pattern.*

| Left Loop | Right Loop | Arch | Tented Arch | Whorl |
|---|---|---|---|---|
| **124** | **115** | **145** | **134** | **282** |

**Tab. I** *Number of fingerprint images for each class.*

The auto-associator was trained by varying the number of hidden units and iterations to improve feature extraction. It was very important to train the auto-associator properly so that the classification of these features became an easy task. Experiments were conducted by varying number of learning rate and momentum along with the number of hidden units in hidden layer. Optimum results obtained for learning rate ($\eta$) and momentum ($\alpha$) were 0.8 and 0.7 respectively and sigmoid activation function was used. Experiments were conducted using only one hidden layer. The training of the auto-associator was also performed by keeping the number of hidden units constant and varying the number of iterations. For these experiments, number of hidden units was 4 as optimum value.

The classifier was trained after obtaining the output from the hidden layer from the auto-associator. The hidden layer output was given as input to the classifier. The output of the hidden layer of an auto-associator depends upon the number of units in the hidden layer and the number of training pairs. The number of inputs to the classifier is the same as the number of hidden units used to train the auto-associator. The Tab. II shows some of the classification accuracy obtained for training and testing sets. There are two possible types of errors and that prevents to get better classification accuracy, a) Incorrect output neuron is active and all other output neuron including the correct one is inactive, or b) more than one neuron is active or none of the neuron is active.

| **Number of Iterations** | **Classification Accuracy [Training Set]** | **Classification Accuracy [Testing Set]** |
|---|---|---|
| 500 | 82 | 77.5 |
| 1000 | 85.6 | 82.5 |
| 2000 | 88.2 | 84 |
| 3000 | 88.9 | 86.4 |
| 5000 | 89.3 | 88,6 |
| 10000 | 93.6 | 92 |

**Tab. II** *Classification accuracy for training and testing sets.*

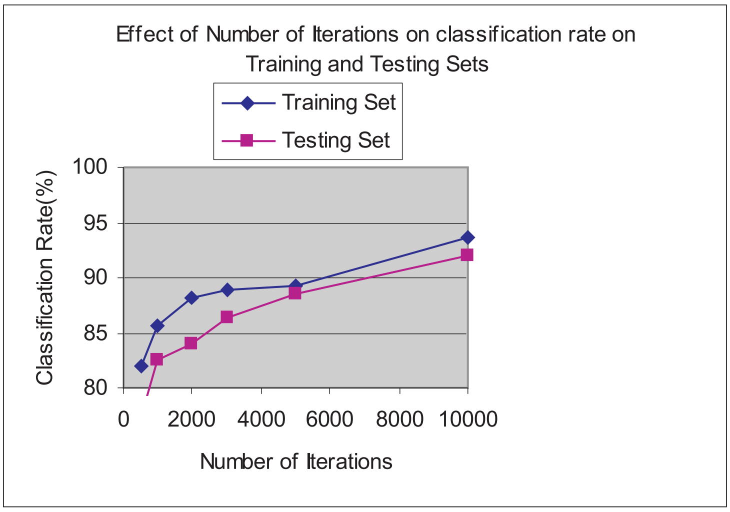


**Fig. 5** *Graphical Representation of Effect of Iterations on Classification Rate.*

# 4. Analysis and Comparison

The objective of these experiments is to illustrate that the proposed fingerprint feature extraction techniques and classification improves the overall efficiency for fingerprint recognition. Number of experiments was conducted to improve the classification accuracy. In these experiments, number of hidden units was varied to obtain better and reduced RMS error. It is difficult to compare the results with other similar techniques as there is no specific fingerprint image database.

The main classification between the patterns of arch and tented arch is challenging. It was seen that few authors combine these two classes as one class and that improves the classification accuracy significantly. In Tab. III, work by Karu and Jain shows the classification accuracy of 91.4%. Some of the classification accuracies are mentioned in the Table below.

| **Author and Year** | **Number of Classes** | **Classification Accuracy** |
|---|---|---|
| Wilson et al. (1992) | 5 | **81%** |
| Jain et al. (1999) | 5 | **90%** |
| Zhang et al. (2002) | 5 | **84%** |
| Yao et al. (2003) | 5 | **90%** |
| Karu and Jain (1996) | 4 | **91.4%** |
| **Senior (2001)** | **4** | **88.5%** |

**Tab. III** *Comparison of some of the fingerprint classification accuracies.*

# 5. Conclusion and Future Work

This paper proposes Multi Layer Perceptron for extracting fingerprint features. Same fingerprint pattern is applied as an input and output of an auto-associator. The output is taken from hidden layer which has specific characteristics for a particular class. These are considered as features and applied to MLP for classification. These features are classified into five classes, such as left loop, right loop, arch, tented arch and whorl. Number of experiments was conducted and very promising results are obtained on small database of 800 fingerprints. Maximum classification accuracy was noted as 92% for testing set and 93.6% for training set. The future work will incorporate the fingerprint matching technique based on fuzzy logic similarity measure and that will significantly reduce the time during identification process.

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