

# A Modified SOM-Based RBFN for Rotation Invariant Clear and Occluded Fingerprint Recognition

Sumana Kundu and Goutam Sarker

**Abstract** In this paper, a modified radial basis function network (RBFN) based on self-organization mapping (SOM) has been designed and developed for rotation invariant clear as well as occluded fingerprint recognition. The SOM-based RBFN learns different fingerprint images and performs subsequent rotation invariant recognition of clear and occluded images. The system is efficient, effective, and fast. Also, the performance evaluation of the system is substantially moderate.

**Keywords** SOM · RBFN · BP learning · Occlusion · Holdout method · Accuracy · Precision · Recall · F-score

## 1 Introduction

Fingerprint recognition is one of the vital biometrics methods that has been widely used in various applications because of its reliability and accuracy in the process of recognizing and verifying a person identity.

Most of the fingerprint recognition methods are based on feature (minutiae) extraction and minutiae matching [1, 2]. In [3], a fingerprint identification technology was represented by minutiae feature extraction using back propagation (BP) algorithm.

A three-rate hybrid Kohonen neural network (TRHKNN) was proposed in [4] for distorted fingerprint image processing in conditions of wide variation in degree of distortion. This proposed TRHKNN is capable to identify the distorted image of fingerprint and restore the undistorted image of fingerprint.

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A fingerprint classification method was proposed based on self-organizing maps (SOM) in [5]. The concept of “certainty” was introduced and used in the modified algorithms, and the size of the network was increased.

In our previous works [6, 7], we have developed a RBFN with Optimal Clustering Algorithm (OCA), and in [8], we have developed a RBFN with Heuristic-Based Clustering (HBC) for clear and occluded location invariant fingerprint recognition. However, these systems are not adapted to recognize rotation invariant fingerprints excepting  $90^\circ$  and  $180^\circ$  rotation.

In the present paper, a self-organizing mapping-based modified RBFN is used for clear and occluded rotation invariant fingerprint identification.

## 2 Theory of the Operation

In this approach, a feature mapping network that is self-organization network [5, 9] with Kohonen’s learning is used to form groups of the preprocessed input data set which are taken as input of the radial basis function network (RBFN). The SOM can construct the two-dimensional feature map (here, we use  $15 \times 15$  feature map) from which the number of clusters can be figured out directly. It forms groups of different qualities of fingerprints of each person and angle (person-angle). The mean “ $\mu$ ” and standard deviation “ $\sigma$ ” of each cluster formed by SOM with approximated normal distribution output function are used for each basis unit of RBFN. Then, BP Learning Algorithm is presented which classifies the “person fingerprint-angle” into “person fingerprint.” In the output layer, using BP learning, we get the optimal weights. Here, we set the number of inputs equals to the number of fingerprint images present in the training database, while the number of outputs sets to the number of classes and the number of hidden units is equal to the number of cluster formed by SOM based on qualities of fingerprints of each “person-angle.” Hence, the modified RBFN with BP network classifier is used for fingerprint identification.

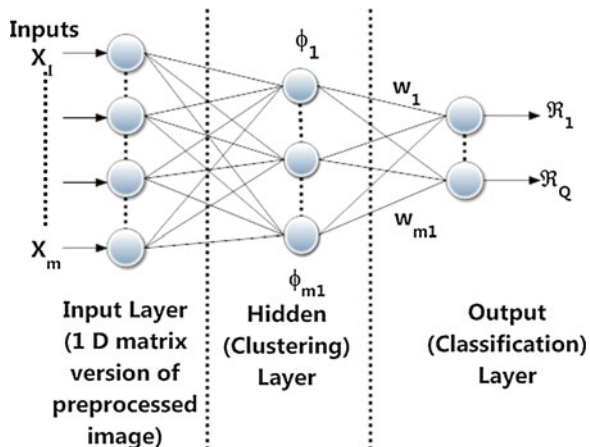
### 2.1 Preprocessing

The finger print images of training and test database have to be preprocessed before learning and recognition. The different steps in preprocessing are as follows:

1. Conversion of RGB fingerprints images to grayscale images.
2. Removal of noise from images.
3. Deblurring of the images.
4. Background elimination.
5. Conversion of grayscale images into binary images.
6. Image normalization.
7. Conversion of binary images into 1D matrix.

This set is the input to the self-organizing network.

**Fig. 1** Modified RBFN architecture



## 2.2 Radial Basis Function Network (RBFN)

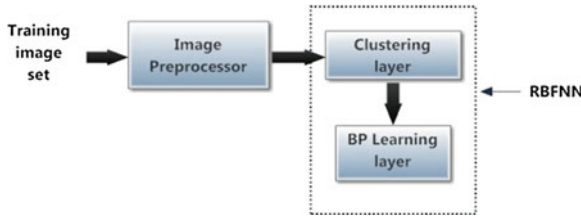
The RBFN of Fig. 1, [6–8, 10, 11], consists of three layers, namely an input layer for fingerprint pattern presentation, a hidden (clustering) layer containing “basis units,” and an output (classification) layer. The clustering outputs (mean  $\mu$ , standard deviation  $\sigma$ , and corresponding approximated normal distribution output functions) are used in “basis units” of RBFN. Thus, SOM is the first phase learning, and using BP learning [6–8, 12, 13], we get the optimal weights in the BP network, which is the second phase of learning. The hidden layer uses neurons with RBF activation functions describing local receptors. Then, output node is used to combine linearly the outputs of the hidden neurons. Here, “m” denotes the number of inputs while “Q” denotes the number of outputs.

## 2.3 Identification Learning

The training database contains finger prints of 4 different people. For each person’s finger print, 5 different qualities of finger prints and also 3 different angular ( $0^\circ$ ,  $90^\circ$ , and  $180^\circ$ ) finger prints are there. After preprocessing, all the finger print images are fed as input to SOM network. When the SOM-based RBFN network has learned all the different qualities of fingerprints of all the angles ( $0^\circ$ ,  $90^\circ$ , and  $180^\circ$ ) for all the different persons, the network is ready for recognition of learned fingerprint images (refer to Figs. 2 and 3).



**Fig. 2** Set of few training fingerprint images for recognition



**Fig. 3** Block diagram of learning identification

## 2.4 Identification with Test Image

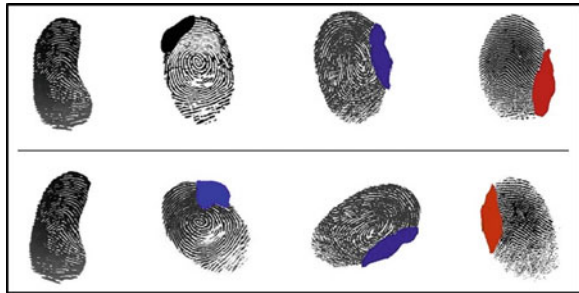
The labeled test image set consists of 4 different person's (same as training data set) clear and occluded finger prints of various different angles, and the qualities are different with respect to training set. It also contains some unknown fingerprints of various qualities and angles. The test image from the test image set is fed as input to the preprocessor. The preprocessed pattern is fed as input to the previously trained BP network. If any of the 4 outputs of the network is active high, then the corresponding finger print is identified or recognized.

If the test fingerprints are different angular fingerprints other than ( $0^\circ$ ,  $90^\circ$ , and  $180^\circ$ ), then we calculate the angle of rotation and rotate that corresponding fingerprint by this angle and then fed this rotated fingerprint to the previously trained BP network. In this case also, if any of the 4 outputs of the network is active high, then the corresponding finger print is identified or recognized (refer to Figs. 4 and 5).

**Fig. 4** Set of few clear test images with or without rotation



**Fig. 5** Set of few occluded test images with or without rotation



### 3 Result and Performance Analysis

We have used the training and test data set for fingerprints samples from FVC database (<http://www.advancedsourcecode.com/fingerprintdatabase.asp>).

#### 3.1 Classifier's Performance Evaluation

We use holdout method [14] to evaluate the performance of the classifier (refer Tables 1 and 2; Figs. 2, 4, and 5).

From Fig. 6 mentioned confusion matrix, if there are only two classes (say X and Y), then the accuracy, precision, recall, and F-score are defined as follows:

$$\text{Accuracy} = \frac{a + d}{a + b + c + d} * 100 \quad (1)$$

$$\text{Precision} = \frac{a}{a + b} \quad (2)$$

$$\text{Recall} = \frac{a}{a + c} \quad (3)$$

**Table 1** Accuracy of the classifier (Holdout method) and fingerprint learning time (seconds)

Type of the fingerprint	Learning time (in seconds)			
	Accuracy (%)	Training time	Performance evaluation time <sup>a</sup>	Total (learning) time
Single clear fingerprints	96.29	90.17	0.17	90.34
Single occluded fingerprints	93.33	90.17	0.17	90.34
Single clear and rotated fingerprints	90.00	90.17	0.18	90.35
Single occluded and rotated fingerprints	85.00	90.17	0.17	90.34

<sup>a</sup> We take 10 test samples from test data set of fingerprints to find out performance evaluation time

**Table 2** Precision of the classifier (Holdout method)

Type of the fingerprint	Person 1	Person 2	Person 3	Person 4	Unknown person
Clear fingerprints	1	1	0.90	1	0.92
Occluded fingerprints	1	1	0.93	0.84	0.91
Clear rotated fingerprints	1	1	1	0.78	0.75
Occluded rotated fingerprints	1	1	0.78	1	0.63

		Actual Class	
		X	Y
Predicted Class	X	a	b
	Y	c	d

**Fig. 6** Confusion matrix (2 class)

$$F\text{-score} = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}} \quad (4)$$

### 3.1.1 Experimental Results

The proposed system was made to learn on a computer with Intel Core 2 Duo E8400, 3.00 GHz processor with 4 GB RAM and Windows 7 32-bit Operating System.

From Table 1, we find the *accuracy* of the classifier with holdout method. From Tables 2, 3, and 4, *precision*, *recall*, and *F-score* metrics for different clear, occluded, rotated fingerprints clarify the performance of each class. Again in Table 1, the proposed approach shows overall low performance evaluation time (<0.02 s for each fingerprint) for the standard test data set. Hence, the proposed approach shows improvement in terms of accuracy and learning as well as

**Table 3** Recall of the classifier (Holdout method)

Type of the fingerprint	Person 1	Person 2	Person 3	Person 4	Unknown person
Clear fingerprints	0.93	1	1	1	0.89
Occluded fingerprints	0.96	0.96	1	1	0.74
Clear rotated fingerprints	0.88	1	1	0.88	0.75
Occluded rotated fingerprints	0.63	1	0.88	0.88	0.88

**Table 4** F-score of the classifier (Holdout method)

Type of the fingerprint	Person 1	Person 2	Person 3	Person 4	Unknown person
Clear fingerprints	0.96	1	0.95	1	0.90
Occluded fingerprints	0.98	0.98	0.96	0.91	0.82
Clear rotated fingerprints	0.94	1	1	0.83	0.75
Occluded rotated fingerprints	0.77	1	0.83	0.94	0.73

performance evaluation time which is comparably appreciable than the present existing systems [1–5] mentioned in the Sect. 1. So, the main contribution of this paper is to perform accurate fingerprint identification.

## 4 Conclusion

A self-organizing mapping (SOM)-based modified RBFN has been designed and developed for fingerprint recognition. This system is able to identify rotation invariant clear as well as occluded finger prints. The performance measurement in terms of accuracy, precision, recall, and F-score with holdout method is moderately high for fingerprint images. Also, the learning as well as performance evaluation time is moderately low for different types of fingerprints. Due to the application of our new SOM-based RBFN, the present system is efficient, effective, and faster compared to any other conventional fingerprint identification technique.

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