

A Novel Hybrid FLANN-PSO Technique for Real Time Fingerprint Classification

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ABSTRACT

In this paper we are presenting a Particle swarm optimized functional link neural network for classifying a collection of real time fingerprints in the field of biometric recognition. From the collected fingerprints the feature vectors are extracted as a collection of different angle oriented features using the Gabor filter bank. The classes of the fingerprints are assigned as per the Henry System. For classification a novel FLANN-PSO algorithm is used and tested for accuracy through different parameters and different angular features of the fingerprints. In this work we have obtained an accuracy of 98% for real time collected fingerprint images. It has been compared with other classifiers and the results obtained of this work in terms of accuracy and MSE value has shown appreciable improvement over the other algorithms.

Keywords: Particle swarm optimization, angular features, parameters, Henry system

Introduction

A fingerprint can be classified and recognized by its local features like (ridge bifurcation and termination) and global features or singular points like (left loop, right loop, whorl, arch and tented arch) based on the complexity of the attributes. But when a distorted fingerprint needs classification, the local feature information as alignment match process fails to identify the process with accuracy. For this type of distorted and noisy fingerprints we need to analyze its detailed global features described by the Henry System^{11,12}. The global features e.g. LL, RL, W, A and TA are Henry's classification present in each and every individual human beings in this world and are unique for the person as shown in fig.1.

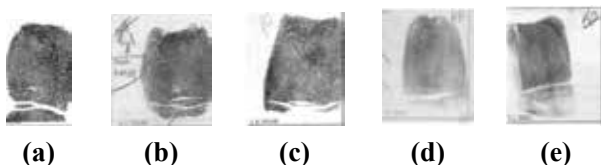


Fig. 1: Five fingerprint classes from NIST-9 database (a) right loop (b) left loop (c) whorl (d) arch (e) tented arch

In this paper we have extracted the unique global features of the noisy distorted fingerprints collected from NIST-9 database images, by using Filter bank

approach^{12,13}. The features are collected in terms of feature vectors of each individual fingerprints and stored in a feature sheet and further classification is tested using a novel Particle swarm optimized FLANN. The Functional link ANN [1] is an excellent classifier. Here we have used PSO as an optimizer to optimize the weight parameters of the network for faster convergence with least mean square error values.

Motivation:

- To makeover the complexity and linearity of multilayer as well as single layer neural network, the FLANN architecture is suggested.^{1,2}
- Here the primary advantage of the PSO based encoding technique is in its capacity to decrease trapped status in local optima and increase the classification accuracy as well as the training speed.^{2,3}

Accomplishment of this work:

In this work

- First the real time fingerprint images are collected from different persons and the respective features are extracted by filter bank method and stored in an excel sheet as a Real time database.

- The feature database is then passed to a FLANN-PSO hybrid network for classification.
- Here we have obtained a classification accuracy of 98% with a best cost value in terms of MSE as 0.009. The total execution time for the process is calculated to be 681.9 seconds.
- Finally the results are compared with other existing algorithms^{12,14,15}, which shows that it is a better classifier than other existing algorithms.

Real time Database Collection and Feature Extraction: Classification of fingerprints is basically tested on standard database e.g. NIST 9. But in this work we have focused on generating a real time database of fingerprint samples. Here we have collected a group of 50 fingerprint sample images from 10 students of Silicon Institute of Technology, Bhubaneswar. The images are captured through fingerprint sensors and stored in a memory. So a total of 50 fingerprints consisting of all 5 classes of fingerprints originates the database for further processing task.

Feature Extraction: It is a process of extracting the minute details present in each and every individual class of fingerprints and makes each one identical. The groups of fingerprints are assigned to a particular class if the majority details are similar in both the samples. In order to assign a particular class to each one of the fingerprints, here the feature extraction step is done. During feature extraction the following steps are carried out as given in fig.2.

- Feature vector creation
- Normalization and Segmentation of fingerprint image
- Orientation field estimation
- Core point estimation
- Circular region formation
- Mean and Variance calculation for each of the sectors

Gabor filtering by 2-D convolution for 0, 45, 90, 135 degrees angles keeping a constant frequency,

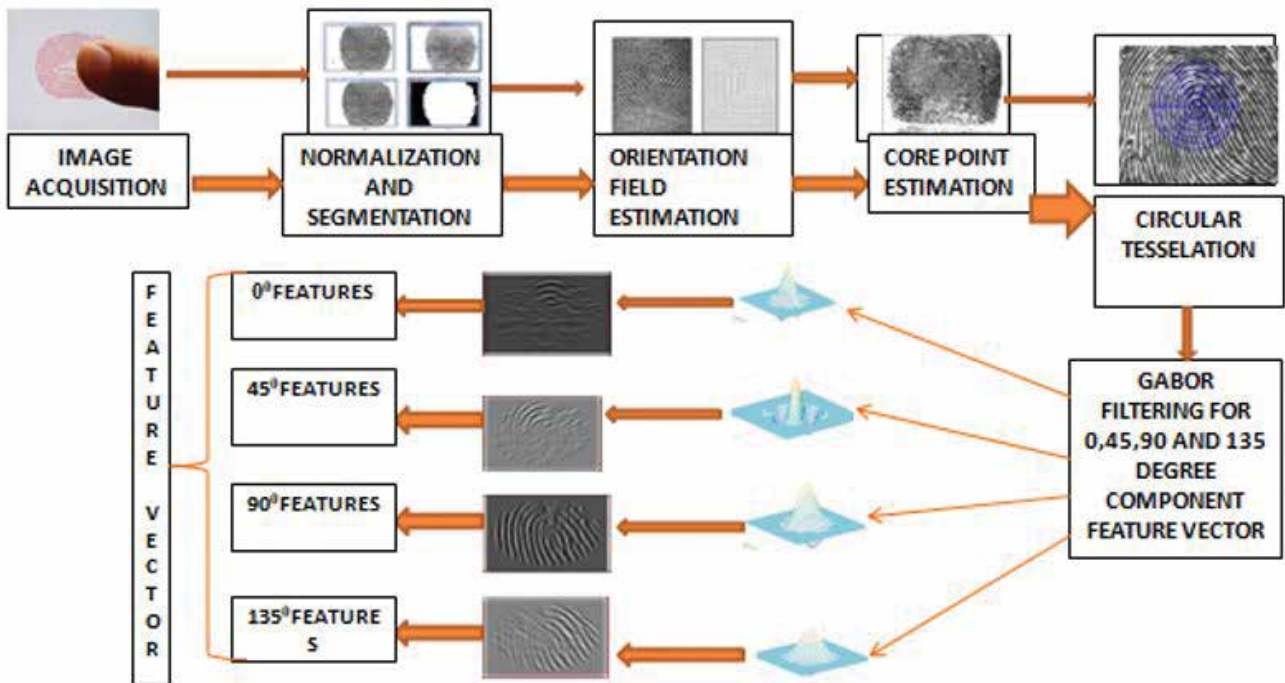


Fig. 2: Feature Extraction process

- separate the decision boundary to indicate the input class.

FLANN Architecture: Here FLANN is used as a single layer network as an alternative approach to the complexities of the multilayer NNs to handle classification problem. The classification of fingerprints is highly non-linear in nature [1, 4 and 5]. FLANN architecture basically consists of two major components like, a neural network and linear mapping for expansion of our input feature vector.

Let our input vector before expansion is $r(i)$, $1 < i < d$, where the elements of $r(i)$ can be written as $r_n(i)$, $1 < n < N$, where N represents the total expansion points if input. The expansion of input pattern is,

$$x_1(i) = r(i), x_2(i) = f_1(r(i)), \dots, x_N(i) = f_N(r(i)) \dots (1)$$

Where, $r(i)$, $1 < i < d$, and d represents the features.

After expansion, it is fed to our network for training. Here the process of learning the network i.e. supervised learning creates problem in classification approach to generate the perfect class boundaries^{8,9}. During pattern classification, our input pattern is assigned to one of the predefined classes. Let the input is a collection of input feature vectors x consisting of N elements as $x_1, x_2, \dots, \dots, x_N$. These elements show the measurement of selected feature vector used for classification. Our classifier is used to

FLANN as a Classifier: Here we have used the trigonometric expansion model, where each element of the input feature vector before expansion can be represented as, $r(i)$, $1 < i < I$ where each element $r(i)$ can be represented as $r_n(i)$, $1 < n < N$, where N = number of expanded points for each input element. In our case, $N=11$ and I = represents the total number of features in the feature vector. The expansion can be represented as,

$$x_1(i) = r(i), x_2(i) = \cos\Pi(r(i)), x_3 = \sin\Pi(r(i)), x_4(i) = \cos3\Pi(r(i)), \dots, x_{11}(i) = \sin9\Pi(r(i)) \dots (2)$$

where, $r(i)$, $1 < i, d$, d is the set of features in the data set.

Then the random weights chosen from the range $[-1,1]$ are multiplied to the output and then added to produce the actual output of the network as given in fig.6^[1]. For comparison the specified desired output is taken into consideration and the corresponding difference is the calculated error and is used to modify the weight in each path q , which can be expressed as,

$$\Delta W_j(k) = \mu \times x_f(k) \times e(k) \dots (3)$$

where, $x_f(k)$ is the functionally expanded input at k^{th} iteration.

For q number of patterns, the change in weight is

$$\overline{\Delta W_j(k)} = \frac{1}{q} \sum_{i=1}^q \Delta W_j^i(k) \dots (4)$$

The weight updation is done by,

$$W_j(k+1) = W_j(k) + \Delta W_j(k) \dots (5)$$

Where, $W_j(k)$ is the j^{th} weight at the k^{th} iteration.

By taking $y(k)$ as the desired output of the network, and $\hat{y}(k)$ as the actual output of the network, the error $e(k)$ can be calculated as,

$$e(k) = y(k) - \hat{y}(k) \dots (6)$$

where,

$$\hat{y}(k) = \sum_{j=1}^J x_f_j(k) \cdot w_j(k) \dots (7)$$

and x_f_j represents the expansion of input.

Reviews of Particle Swarm Optimization (PSO):

Particle swarm optimization follows the population based algorithm that optimizes the objective function³. Here the solution is based on particles^{3,4}, which imitates bird’s flocking and are allowed to fly freely in the search space. In this process each and every particle are allowed to update their respective position and velocity for the whole population. The steps followed during the process are:

- **Initialization of Particles:** Here the particles are allowed to set their velocity and position randomly within a specific range.
- **Velocity Update:** During this, it follows a specific rule to update the velocities of particles in each iteration.

$$\vec{v}_i \leftarrow w \cdot \vec{v}_i + c_1 \cdot R_1 \cdot (\vec{p}_{i,best} - \vec{p}_i) + c_2 \cdot R_2 \cdot (\vec{g}_{best} - \vec{p}_i) \dots (8)$$

where,

\vec{p}_i and \vec{v}_i are position and velocity of particle i , $\vec{p}_{i,best}$ and \vec{g}_{best} represents the position and best object values, w is used to control the particle flying and R_1 and R_2 are random variables taken in the range $[0,1]$, c_1 and c_2 are used to control the weights of the terms.

- **Position Update:** Here the position of the particles are updated during the iterations as per the following rule,
- $$\vec{p}_i \leftarrow \vec{p}_i + \vec{v}_i \dots (9)$$

- **Memory Update:** It makes the update of $\vec{p}_{i,best}$ and \vec{g}_{best} when condition is met.

$$\begin{aligned} \vec{p}_{i,best} &\leftarrow \vec{p}_i \text{ if } f(\vec{p}_i) > f(\vec{p}_{i,best}), \\ \vec{g}_{best} &\leftarrow \vec{p}_i \text{ if } f(\vec{p}_i) > f(\vec{g}_{best}) \end{aligned} \dots (10)$$

Where $f(\vec{x})$ represents the objective function.

- **Termination Criteria:** Here step 2 to step 4 is repeated until the condition specified is achieved. After termination, the corresponding \vec{g}_{best} and $f(\vec{g}_{best})$ are identified as solutions.

Proposed fingerprint classification method: The proposed algorithm is based on multichannel Gabor filter bank method, which is tuned in different angle orientations [6,7]. This part of our work forms the extracted feature for classification. Then the features are passed to the FLANN-PSO hybrid classifier for classification.

Feature Vector Creation: In each component image as shown in fig.3, a neighborhood of ridges and furrows in the orientation field those follow the path similar to the filter direction show large variations are considered. Here the global structures are useful features which can be properly captured by the standard deviation of the values [8, 9 and 10]. So the standard deviation of each sectors collectively considered as the feature vector. The feature vector is extracted as given in the following method.

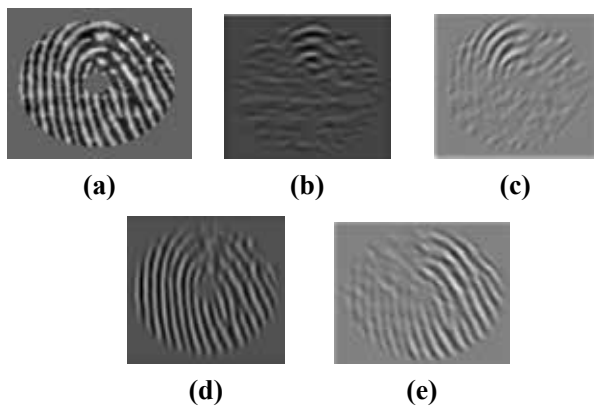


Fig. 3: (a) Normalized image (b) component image 0° (c) component image 45° (d) Component image 90° (e) component image 135°

Let $C_{i\theta}(x, y)$ be the component image corresponding to direction θ for sector S_i . For $i = 0, 1, 2, \dots, 36$ and $\theta \in [0^\circ, 45^\circ, 90^\circ, 135^\circ]$, a feature is the standard deviation $F_{i\theta}$ is defined as:

$$F_{i\theta} = \sqrt{\sum_{k_i} (C_{i\theta}(x, y) - M_{i\theta})^2} \quad \dots(11)$$

where k_i is the number of pixels in S_i and $M_{i\theta}$ is the mean pixel intensity in $C_{i\theta}(x, y)$. So we have a 152 dimensional feature vector.

Here the features associated with 0 degree component image is collected as saved as feature vector for 0 degree orientation and similarly the features are collected from 45 degree, 90 degree and 135 degree respectively and stored in excel sheets to represent the feature vectors with respect to different angle orientations.

Classification using FLANN-PSO Hybrid algorithm: This work uses PSO as an optimizer to update the weight

parameters of FLANN classifier as shown in fig.6. The steps involved during this process are:

- Initially a fixed number of habitats are generated, where each habitat carries the respective weights and bias of the network.
- The best fit value in terms of MSE is calculated. Here the goal is to minimize the error with respect to the desired and the estimated output of the classifier.
- To satisfy the optimization criteria, various operations like Initialization of weights, position and velocity update, memory update are performed and once the condition is satisfied it is terminated to find the best solution in terms of optimization.
- Then the network with high fitness (solution parameters) are passed to the next generation and repeated until the desired goal is achieved as given in fig.4.

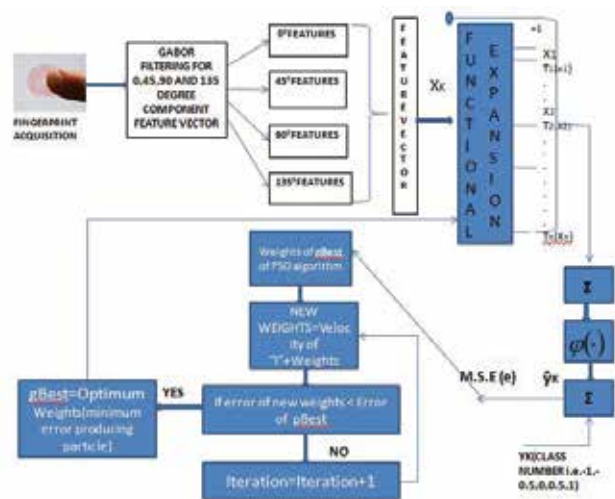


Fig. 4: Structure of the proposed FLANN-PSO hybrid method

Experimental Results: Selected degraded fingerprint images from the created and extracted real time database are feature extracted using filter bank approach and the feature excel sheet is created consisting of 152 features of each fingerprint image. The extracted features of 50 fingerprint images in excel format are used for training and testing of the network. Both the training and test sets of feature vectors are of all the classes starting from class1 to class5. Each class is represented in the excel sheet in terms of five values between 1 to -1 i.e. (-1, -0.5, 0, 0.5, 1) to represent the five classes respectively. The algorithm is tested by taking the C_1 and C_2 parameters

(the cognitive and social parameters) as a fixed value i.e. 2. The population is taken as 1000. It is tested for better performance for different iteration levels like 500, 1000, 2000, 3000 and 5000 respectively. The test confusion matrix and the best cost graph are collected for analysis purpose. During the feature extraction stage a 152 dimensional feature vector is extracted by collectively considering four angle orientations (0, 45, 90 and 135 degrees) respectively. Here each angle orientation vector provides 38 no. of features and finally it forms 152

features for the whole fingerprint. The angular feature vector is tested in the network for (0, 45, 90 and 135 degrees) respectively and finally the whole feature vector is tested for accuracy. From the output graph as shown in fig. and table.1,it is clear that by providing the total feature vector as input to the network, it is providing best classification accuracy of 98% than other angular feature vectors and the best cost value for this is 0.009. The best cost graphs and the confusion matrix are shown in the fig.5 below.

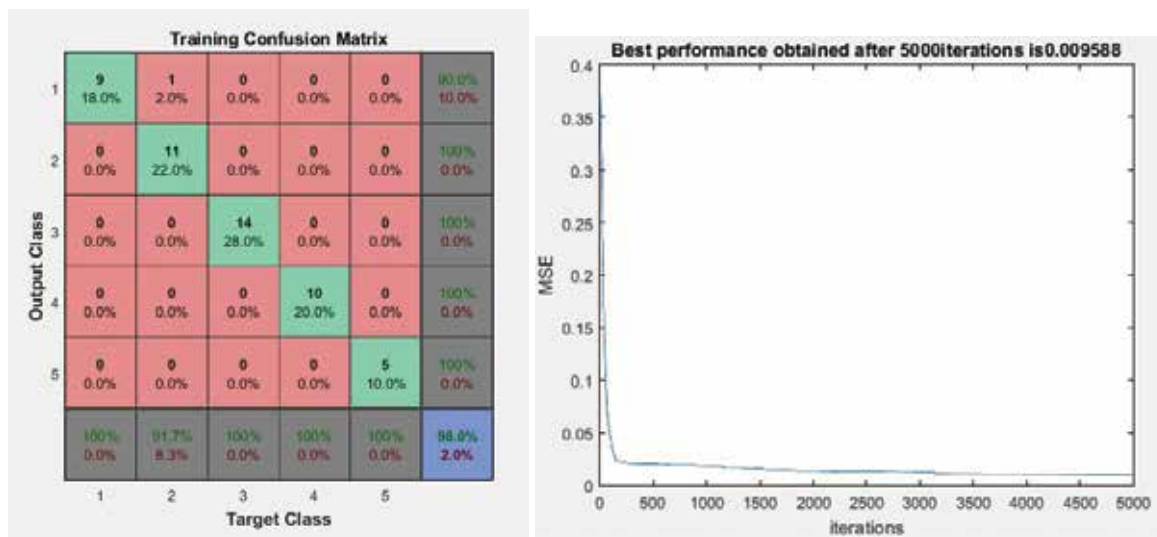


Fig. 5: The Confusion matrix and best cost graph for total feature vector

Here we are reflecting the classification performance in various parameters like Confusion matrix, Best cost graph and total execution time. The confusion matrix consists of 6 rows and 6 columns, where each row represents the predicted class and column represents the actual class as output of the classifier. The diagonal elements of the confusion matrix represent the correct classification percentage of the respective class. The other element in the matrix other than diagonal elements represents the misclassification percentage. In the fig.5, the 6×6 confusion matrix represents the overall result, where the first five rows and five columns represent the predicted and actual class of the classifier. The 6th row and 6th column represent the total classification accuracy of the respective class. The last element in the diagonal array shows the overall classification accuracy of the classifier. The 1×1 element of the matrix represent the classification result of the fingerprint that belongs to class 1(right loop) as per the Henry system and is classified in the same class in percentage i.e. 18% where as the other elements in the first row i.e. (1×2, 1×3 ... 1×5) show the misclassification percentage. The 1×6 position of the matrix shows the true classification of class1 (right loop) i.e. 90% and 10% error of misclassification. Similarly the other rows and columns reflect the different classification and error percentage in green and red color digits respectively. The best results are obtained as a mean square error value of 0.009 for 5000 iterations of the network. Its execution time is about 681.9 seconds.

Performance Comparison

Table 1: Performance comparisons of different classification algorithms

Reference Paper	R.Capelli. et. Al(1999)	A.K Jain et.al(1999)	A.Senior et.al(2001)	J.Hu et. Al(2010)	This Work
Classification Method	Image Partition Method	KNN method	HMM + DT method	SVM + GP	FLANN + PSO
Classification Accuracy	93.68%	92.1%	93.37%	93.6%	98%

Table 1 shows the different classification accuracy of fingerprints using different classifier algorithms. As given in the table, R. Capelli et. al. (1999) have adopted Image Partition method to classify the fingerprints into five classes and has got the classification accuracy of 93.68%¹⁴, A.K Jain et. al. also experimented the classification process using KNN and NN and have reached at the accuracy of 92.1%¹². A. Senior et. al. [2001] have adopted the classification using HMM+DT+PCASYS method and could able to classify at 93.37%¹⁵, where as J. Hu et. al. [2010] has tested the classification using SVM+GP method to classify the fingerprints with 93.6% accuracy. Our proposed method is robust enough to classify the fingerprints into five classes with an accuracy of 98% for real time fingerprint database.

Conclusion

In this paper, the real time classification of fingerprints into five broad classes is successfully carried out. During feature extraction the Gabor filter bank play a major role for extracting the vital significant features of the respective fingerprints and then the proposed hybrid FLANN-PSO classifier is able to classify it into five classes. Here we have classified the fingerprints for each angular component feature vector for 0, 45, 90 and 135 degree. Then the classification is also performed considering the whole feature vector consisting of all angle component features. From the results it is seen that the classifier is producing best result of 98% accuracy with a total execution time of 681.9 seconds. The best cost value for this result is 0.009588. The improvement in execution time may be taken up as a future research work considering other attributes.

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