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Review

Artificial neural network based classification technique for minutiae verification

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ABSTRACT

The theory behind the fingerprint verification based on minutiae matching, was in detail studied. The performance of the developed system was evaluated on database with 2 fingerprints from 20 different people. The test showed that the system and algorithm is fully capable of distinguishing the related fingerprints apart from the non-related fingerprints. The system has proved to be robust towards translation, rotation and/or missing minutiae between the matched fingerprints. Future work can be improved by applying the fingerprint classification and recognition for more damaged and noisy fingerprint image database. System performance could be determined for database of more than 1000 images.

Keywords: Minutiae, artificial neural network, classification, fingerprint.

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INTRODUCTION

The observations showed that the fingerprints offer more secure and reliable person identification than keys, passwords or id-cards can provide. With decreasing cost of fingerprint readers and cheap increasing computer power, automatic fingerprint recognition gives an efficient and inexpensive alternative to ordinary solutions in person identification (Karu and Jain, 1996; Zhou and Gu, 2004; Daugman, 2010; Eshera and Fu, 2004; Jain et al., 1997). Examples such as mobile phones and computers equipped with fingerprint sensing devices for fingerprint based password protection are being produced to replace ordinary password protection methods. Another limitation is that this paper only takes into consideration the so called one-to-one matching method, otherwise called verification (Driscoll et al., 1991; Hong et al., 1998). This means that the comparison is performed only once and that is between template [the pre-stored fingerprint(s) on a safe place in the system] and fingerprint of the person to confirm that his identity is the same as the templates. Although, there are a number of finger print classification and recognition algorithms that work well in constrained environments (Maltoni et al., 2003; O'Gorman and Nickerson, 1988, 2009; Kwon et al., 2011), fingerprint classification and recognition is still an open and very challenging problem in real world applications. The complexity and uncertainty found in fingerprint based classification and recognition are wide in range. This leads us into difficult situation in learning, teaching and practicing the system for appropriate recognition. The Data Mining techniques are an appropriate algorithm to model the range of uncertainties found in fingerprint classification and recognition systems. Many approaches were developed for the fingerprint verification algorithm. They are model based, structure based, and frequency based and syntactic. The model-based fingerprint classification technique uses the locations of singular points (core and delta) to classify a fingerprint into the five classes (O'Gorman and Nickerson, 2009). In the structure-based approach, the estimated orientation field in a fingerprint image is used to classify the fingerprint into one of the five classes (Kwon et al., 2011). A syntactic approach uses the formal grammar to represent and classify fingerprints. The variable sized minutiae based mechanism does not lend itself to indexing mechanisms. Typical graph based (Haykin, 2009) and point pattern based approaches to match the minutiae

from two fingerprints need to align the unregistered minutiae patterns of different sizes which makes them computationally expensive. Correlation based techniques (Reed and Marks, 1999) match the global patterns of the ridges and valleys to determine if the ridges align. The global approach to fingerprint is typically used for indexing and does not offer a very good individual discrimination. Further, the indexing efficiency of the existing global representation is poor due to small number of categories that can be effectively identified and a highly skewed distribution of the population, in each category. The local texture analysis technique is used where the finger print area of interest is tessellated with respect to the core point categories that can be effectively identified and a highly skewed distribution of the population, in each category. The local texture analysis technique, is used where the finger print area of interest is tessellated with respect to the core point (Chang et al., 2007).

The paper is organized as follows: In feature extraction and new approach section, the details on enhanced model for fingerprint classification and recognition are given and the neural network approach for classification is described. The simulation results are discussed in feature extraction section with the concluding remarks in the conclusion.

FEATURE EXTRACTION AND NEW APPROACH

Extracting minutiae from the skeleton of the fingerprint requires a method that is able to distinguish and categorize the different shapes and types of minutiae. This is a classification problem and can be solved by constructing and training a neural network which work as a classifier. Neural network is a nonlinear mapping system whose structure is loosely based on principles of the real brain. The whole network is built up with simple processing units and structures. The neurons are structured in layers, and connections are drawn only from the previous layer to the next one. A typical structure of this type of the neural network can be seen.

A back-propagation is one of many different learning algorithms that can be applied for neural network training and has been used in this paper. Training data is divided into three different pattern classes: termination, bifurcation and no minutiae. The neural network output layer consists of three neurons, each representing one class of the training data. By training the neural network so it activates the right neuron corresponding to the pattern class, the classification of the input patterns can be achieved. Size of the training data is chosen to 5 × 5 windows. The 3 × 3 window does not view much information and the 7 × 7 window show to much information which is unnecessary. Example on how the different sizes of the window results on the training patterns are shown in Figure 1. The size of the window is

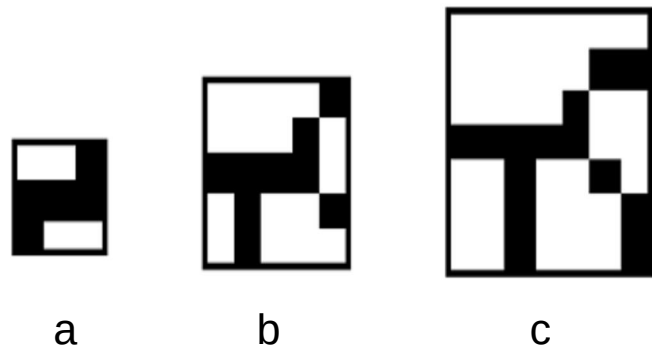

Figure 1. Different window sizes for the training data. a) 3 × 3; b) 5 × 5; c) 7 × 7.

deliberately odd so there is exactly one pixel in the center.

A total of 23 different fingerprint skeletons have been used to collect the necessary patterns for the three classes. A total of 1951 different patterns have been gathered. The different classes had 84 termination patterns, 388 bifurcation patterns and 1479 no minutiae patterns. Selection of the patterns was carefully done so the different minutiae types are found in the center. Even patterns with minutiae slightly off center are classified as no minutiae to avoid false classification towards that particular minutiae type nearby. To find an optimal size and shape of the neural network for good realization, training test on various nets was conducted. To measure how fast the different neural networks learns a total error in each epoch has been calculate. The convergence of this error reveals how fast and good each neural network is. The error function that has been used is:

$$\text{Esse} = \frac{1}{2p}\sum_{i=1}^{P}\overline{e_i^T}\,e_i^T \qquad (1)$$

where e_i is the error vector of the particular pattern i in the training data set and P is total number of patterns in the training data set. This function is called sum of squared errors (SSE) and is normalized with size of the training set. Three neural networks were tested, two with single hidden layer and one with two hidden layers. The single hidden layers had 50 and 60 neurons respectively and two hidden layers had 25 neurons each. All neural networks were trained for 5000 epochs and then how fast and low the error falls were compared. A graph with the error function calculated for each neural network is shown in Figure 2. The"hl1 50" denotes one hidden layer with 50 neurons, "hl1 60" denotes one hidden layer with 60 neurons and "hl2 2525" denotes neural network with two hidden layers with 25 neuron in each layer. It can be clearly seen that the neural network with two hidden layers converges fastest and lowest. The two single

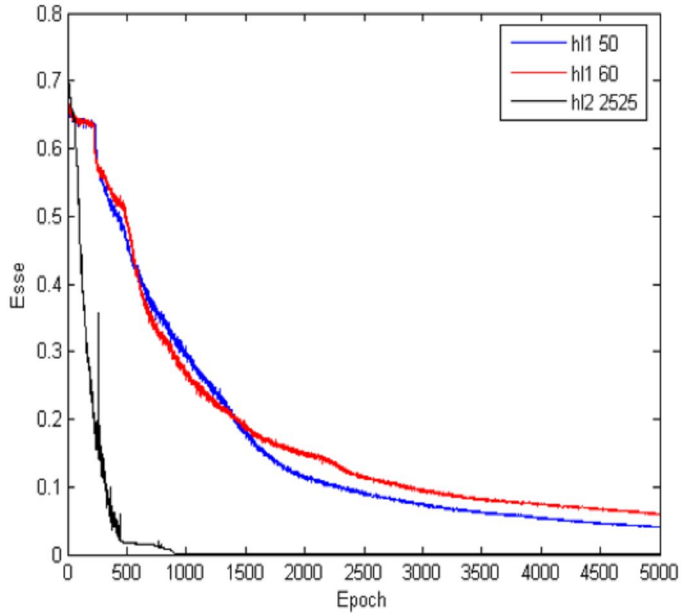

Figure 2. The SSE error functions normalized with size of training data for three different neural networks. The"hl1 50" denotes one hidden layer with 50 neurons, "hl1 60" denotes one hidden layer with 60 neurons and"hl2 2525" denotes neural network with two hidden layers with 25 neuron in each layer.

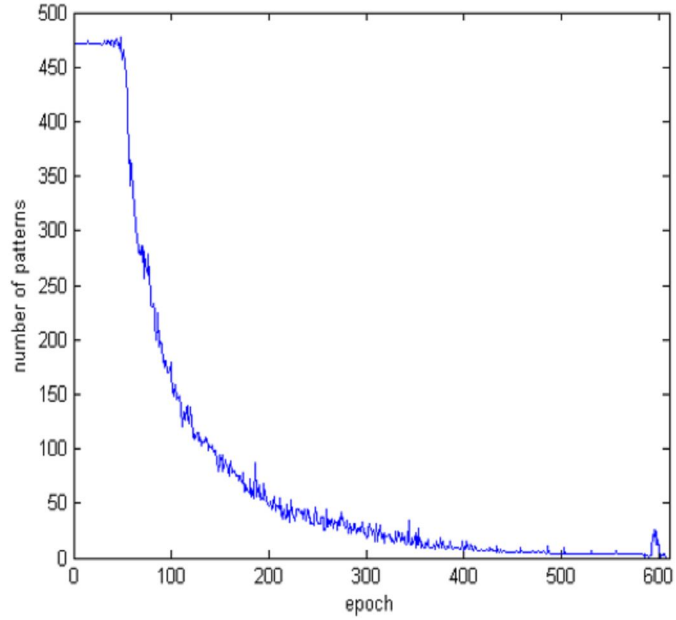

Figure 3. MAXNET error function indicates how many patterns are left to be learned by the neural network. Error is 0 after 610 epochs.

hidden layered are about the same. The interesting thing is to see how much improvement the extra hidden layer does.

The problem with two hidden layered neural network is that it can be easily over-trained; therefore training should not be longer than necessary. A so called MAXNET has been added on the output of the neural network. What MAXNET does is that it compares the three outputs from the neural network. The output from the neuron that has the biggest value is taken as the activated neuron. So the input pattern to the neural network is classified to the class that is represented by activated neuron in the output layer. The error function of the MAXNET under the training of the neural network indicates how many patterns are left to be learned. When MAXNET error is 0, all patterns have been learned by the neural network, the training can now be stopped to avoid possible over-training. An error function of the MAXNET can be seen in Figure 3 for the two hidden layered neural network. The trained neural network has 25 neurons in each hidden layer. It took 610 epochs to learn all the patterns in the training set.

Finally, the extraction of the minutiae from the fingerprint's skeleton is done by sliding the 5 × 5 window though the image. Each portion is then presented to the trained neural network which classifies it into one of the three classes. If the data sent to the neural network is a minutia coordinates (x, y) of the pixel in the picture are stored in a vector. The coordinates (x, y) represents the middle pixel in the window corresponding to the global coordinates in the picture.

To speed up and make things easier in the extraction of the minutiae, an assumption is made. The portions of data that are viewed by the neural network are only those who have a black pixel in the middle. Since the minutiae are made only from the thinned lines, there is no need to examine data where lines are off center in the data portion. This assumption gives three very good improvements:

1. A skeleton image has only about 30% of the black pixels. This means that 70% of the data portions are not examined by the neural network. This gives very fast and accurate minutiae extractions since the window can be slide pixel-by-pixel through the image.
2. Since lines are centered in the data portions, the patterns where lines are off centered does not needs to be included in the training set. The training set is much smaller than it needs to be.
3. Because the middle pixel in the data portion is always black, it does not give any new information to the neural network. Therefore, the middle pixel can be discarded from the input to the neural network and the input vector is made smaller.

EXPERIMENTAL RESULTS

In the previous part, the diverse parts of the fingerprint verification system have been in depth explained. In this part, the performance evaluation of the developed

Table 1. Results for the matching of the identical fingerprint.

Parameter	Min	Max	Average
Ems	5.9720	41.0103	19.0690
Matched minutiae [%]	52.3810	93.4783	81.1289

Table 2. Results for the matching of the identical fingerprint.

Parameter	Min	Max	Average
Ems	0	80.3645	43.7337
Matched minutiae [%]	2.1739	50.9804	31.7193

system is in detail described and the experimental results are presented. A database was assembled from pre-stored fingerprints in FVC2002/Db1 (Karu and Jain, 1996). Two fingerprints from 20 different people of good quality with varying rotation and translation were collected into the database. This database was then used to evaluate the performance of the fingerprint verification system. The matching is divided into two groups; examination of the identical fingerprints and examination of the non-identical fingerprints. The data of interest is the percentage of matched minutiae and mean squared error. Table 1 shows the results for the matching of the identical fingerprint only. The values are the minimum, maximum and average of percentage matched minutiae and mean squared error. Table 1 shows the results for the matching of the identical fingerprint only. The values are the minimum, maximum and average of percentage matched minutiae and mean squared error.

The results for the matching of the non-identical fingerprints can be found in Table 2. It is obvious that the two groups are mainly separated in the amount of matched minutiae given in percent.

To get a better view on how the two groups are separated, the data is plotted in the matched minutiae vs. mean squared error plane. The plotted data is viewed in Figure 4. The two groups are more of less forming clusters around the calculated average values.

It can be seen that the cluster of the non-identical examples are somewhat directed. The smaller number of matched minutiae is, the smaller the Ems gets. While with increasing number of matched minutiae, the Ems gets bigger. This is because the smaller number of matched minutiae offers better chance to be found closer to each other.

CONCLUSION

The goal of this paper is to develop a complete system for fingerprint verification through extracting and matching minutiae. A neural network is trained using the back-propagation algorithm and will work as a classifier

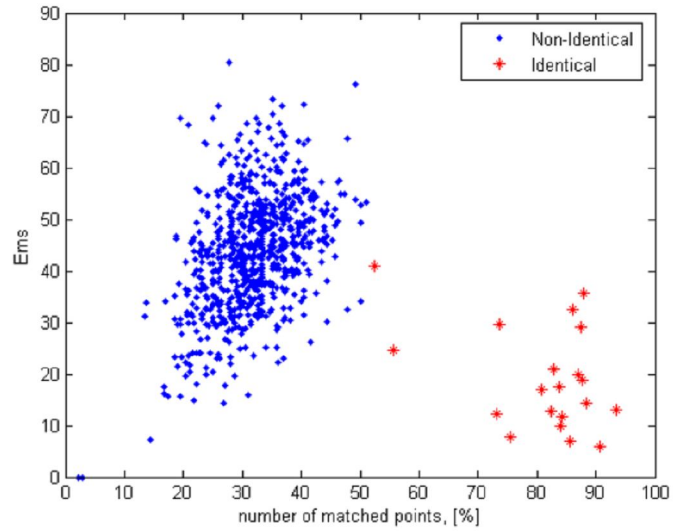

Figure 4. Position of the examined fingerprint pairs for the two groups, plotted in the matched minutiae vs. mean squared error plane. The matched minutiae are given in the percentage.

to locate various minutiae. To achieve good minutiae extraction in fingerprints with varying quality, preprocessing in form of binarization and skeletonization is first applied on fingerprints before they are evaluated by the neural network. Extracted minutiae are then considered as a 2D point pattern problem and an efficient algorithm is used to determine the number of matching points between two point patterns. Performance of the developed system is evaluated on a database with fingerprints from different people and experimental results are presented.

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