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Fingerprint Authentication Using Back-Propagation Algorithm

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Abstract: The objective of this research is to incorporate finger print authentication with the widely used PIN authentication scheme currently used for online transactions, to achieve a foolproof system. A complete minutiae extraction scheme for automatic fingerprint recognition systems with intelligent method is presented. A critical step is to reliably extract minutiae from the fingerprint images and process with artificial neural network method. Fingerprint images are rarely of perfect quality. They may be degraded and corrupted due to variations in skin and impression conditions. So, fingerprint minutiae enhancement techniques are employed prior to minutiae extraction to obtain a more reliable estimation of minutiae locations. In the first stage, image normalization and orientation field of the fingerprint are calculated. The local orientation of the ridges serves as the parameter for the next processing stages. Details of the adaptive morphological filtering used for ridge extraction and background noise elimination are described. Minutiae patterns of the scanned and stored fingerprints are then compared and evaluation results are obtained by processing through supervised artificial neural network. Greater security is achieved with PIN authentication.

Key words: Fingerprint, minutiae, artificial neural network, supervised method, back-propagation algorithm, authentication, ridge extraction

INTRODUCTION

Fingerprint image databases are characterized by their larger size. Distortions are very common in fingerprint images due to elasticity of the skin. Commonly used methods for taking fingerprint impressions involve applying uniform ink on the finger and rolling the finger on the study. Over-inked areas of finger, which create smudgy areas in the images. Breaks in ridges, created by under-inked areas, The elastic nature of the skin can cause positional shifting and the non-cooperative attitude of criminals also leads to smearing in parts of the fingerprint images. Although inkless methods for taking fingerprint impressions are now available, these methods also suffer from the positional shifting caused by the skin elasticity (Donahue and Rokhlin, 1992; Douglas Hung, 1993; Ratha *et al*., 1995, 1996; Maio and Maltoni, 1996). Thus a substantial amount of research reported in the literature on fingerprint identification is devoted to image enhancement techniques (Achermann and Bunke, 1997; Ariyaeeinia and Sivakumaran, 1997). The problems associated with fingerprint identification are very complex and an inappropriate representation scheme can make it intractable. For the purpose of automating the process of fingerprint identification, a suitable representation of fingerprints is essential.

Retention of the discriminating power of each fingerprint at several levels of resolution. Easy computability, Amenable to automated matching algorithms, stable and invariant to noise and distortions, efficient and compact representation. But these representations do not guarantee exact matching because of the presence of noise or availability of a partial image. Hence high-level structural features, which can uniquely represent a fingerprint, are extracted from the image for the purpose of representation and matching. Some of these features are described below (Maio and Maltoni, 1997; Hong *et al*., 1998a, b; Lee and Wang, 1999; Jain *et al*., 1997; Lumini *et al*., 1999; Alessandro and Zsolt, 1999; Jain *et al*., 1999).

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Fig. 1: Common types of fingerprints

Fig. 2: Common line types

Structural features of fingerprint images: Some fingerprint images are shown in Fig. 1. Fingerprint images can be considered as a weakly ordered texture with oriented texture pattern. The black portions of the fingerprint image are called 'ridges' and the space in between 2 ridges is called a 'valley's. These ridges and valleys are flowing in a constant local direction. A close observation of fingerprint reveals that these ridges and valleys exhibit anomalies of various kinds such as ridge bifurcations, ridge endings, short ridges, ridge crossovers etc. Ridge bifurcation is the point where a ridge splits itself into two ridges. Ridge ending is the termination point of a ridge. Eighteen different features have been obtained (Tico *et al*., 2001; Bailly-Bailli'ere *et al*., 2003; Albrecht, 2003).

Some of these features are shown in Fig. 2. Collectively, these features are called 'minutiae' in fingerprint literature. Even, though there are 18 different types, only 2 types of Minutiae are considered for matching. They are ridge ending and ridge bifurcation. More complex features can be expressed as a combination of these 2 basic features. An enclosure can be a collection of two bifurcations and a short ridge can be a pair of ridge endings. In a good quality rolled fingerprint image, there are 70-80 minutiae points and in a latent fingerprint the number of minutiae is about 20-30. In addition to these features, there exist some other high level features. They are referred as 'singular points' and 'ridge density'. A singular point depicts the orientation of fingerprint ridges in a local region (Fig. 3). Ridge density is the number of ridges in between 2 singular points. Two types of singular points in fingerprint images are very popular in the literature (Alterman, 2003; American National Standards Istitute, 2003; Antonelli *et al*., 2005). These are core and delta points. These are very useful for fingerprint classification. The core and delta points are present in a fingerprint image. The core point in a fingerprint image is the point where the ridges take a maximum turn (i.e., maximum angle of curvature) in a local neighborhood around that point. It is the top most point on the innermost ridge of a fingerprint. A delta point refers to a location where 3 or more ridges form a diamond shaped region. It is the tri-radial point with three ridges radiating from it.

Common types of fingerprints: Fingerprint patterns are divided into three main groups consisting of: Arches, Loops and Whorls. Approximately 5% of all fingerprints are Arches, 30% are Whorls and 65% are Loops.

Common line types (shapes) found in fingerprints: Fingerprint patterns (Balidissera *et al*., 2005; Allen *et al*., 2005; Bergman, 2005) are made up of

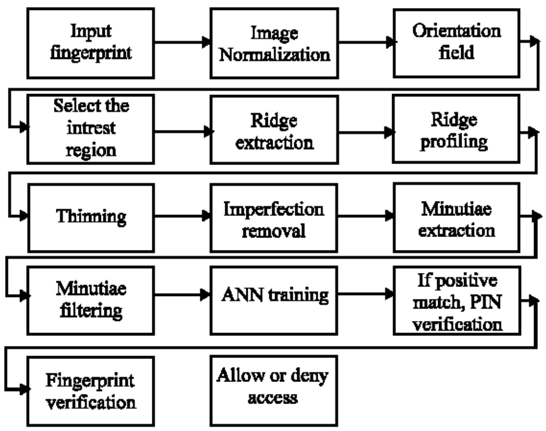

Fig. 3: Flow for fingerprint recognition

'line-types' (shapes), which determine the general classification characteristics of the print (i.e., Arch, Loop or Whorl). The 'Pattern Area', is a term used to describe the center area of a print, which contains many of the line-types previously described. This area and its contents determine the classification of the print (i.e., Arch, Loop, Whorl, etc.). The following are typical of the most common line-types found in prints.

Schematic diagram: The sequence of fingerprint authentication is given in the form of schematic diagram (Fig. 3).

ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network (ANN) is a mathematical way of simulating the capability of human brain. The category of supervised method requires inputs and target outputs.

The Back-Propagation Algorithm (BPA) is a supervised method that uses steepest-descent method to reach global minima. The flowchart for the BPA is given in Fig. 4. The number of layers and number of nodes in each layer is decided. The connections between nodes are initialized with random weights. A pattern from the training set is presented in the input layer of the network and the error is calculated in the output layer. The error is propagated backwards towards the input layer and the weights are updated. This procedure is repeated for all the training patterns.

At the end of iteration, test patterns are presented to ANN and the classification performance of ANN (Hirosey *et al*., 1991) is evaluated. Further training of ANN is continued till the desired classification performance is reached.

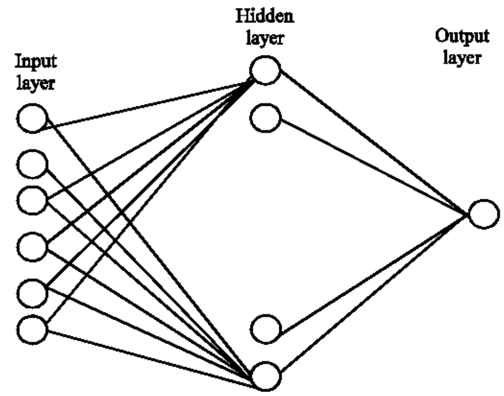

Fig. 4: Back propagation network

Steps involved

Forward propagation: The output of each node in the successive layers is calculated.

$$O(\text{output of a node}) = 1/(1+\exp(-\Sigma w_{ij}\, x_i)) \quad (1)$$

The error E(p) of a pattern number p is calculated

$$E(p) = (1/2)\ \Sigma(d(p) - o(p))^2 \quad (2)$$

Reverse propagation: The error δ for the nodes in the output layer is calculated

$$\delta(\text{output layer}) = o(1-o)(d-o) \quad (3)$$

The new weights between output layer and hidden layer are updated

$$W(n+1) = W(n) + \eta\ \delta(\text{output layer})\ o(\text{hidden layer}) \quad (4)$$

The error δ for the nodes in the hidden layer is calculated

$$\delta(\text{hidden layer}) = o(1-o)\ \Sigma\delta(\text{output layer})\ W(\text{updated weights between hidden and output layer}) \quad (5)$$

The weights between hidden and input layer are updated.

$$W(n+1) = W(n) + \eta\delta(\text{hidden layer})\ o(\text{input layer}) \quad (6)$$

The above steps complete one weight updation. The remaining training patterns are presented and Eq. 1-6 are followed which form one iteration. The training of the network is stopped once the desired Mean Squared Error (MSE) is reached as given below

$$E(MSE) = \Sigma E(p) \tag{7}$$

The final updated weights are saved for testing the fingerprint.

IMPLEMENTATION

Step 1: The fingerprint image is obtained using fingerprint scanner which is a flatbed scanner with 600 DPI.

Step 2: The image is preprocessed using various preprocessing technique like median filtering which is one of the preprocessing technique.

Step 3: The edges of the image are found. The edges of the image are found using edge operators also known as sobel or canning operators.

Step 4: Find the location of '1' in the thinned image. The number '1' basically tries to represent valley or ridge.

Step 5: To start with skip uniformly 10 columns on the left hand side, 10 columns on the right side, 10 rows on the top and 10 rows from the bottom.

Step 6: Take a 3*3 window in the picture with the 1's as the starting point.

Step 7: Find the absolute difference between center pixel and the neighborhood. Sum the differences and verify whether the values are 1, 2, 3 ,4 ,5 ,6.

Step 8: Divide the values by a factor of 2.

Step 9: If the value is 1 or 3 then find the angle at which the ridge is moving.

Step 10: Note down the coordinates, angle and the calculated value.

Step 11: Scan through the entire image.

Step 12: Create a zero matrix.

Step 13: Once the values are obtained, mark different portions of the zero matrixes with two different values, based on whether it is 1 or 3 obtained in the step 10.

Step 14: Store the values obtained in the database against the person's detail like name, PIN.

Step 15: For different persons, the number of minutiae and the branching points will be different.

Step 16: If a proper match takes place, then the PIN number is compared. Subsequently, an access can be given for the system.

RESULTS

The fingerprint has been scanned with standard fingerprint scanner with required resolution. As there can be some imperfection in the capture of fingerprint due to lighting condition as well as dirt in the fingerprint, enhancement has been done followed by thinning, minutiae points have been shown in Fig. 5.

Fig. 5: Outputs of the fingerprint processed images

CONCLUSION

The reliability of any automatic fingerprint recognition system strongly relies on the precision obtained in the minutiae extraction process. This research has combined many methods to build a minutia extractor and a minutia matcher. The combination of multiple methods comes from a wide investigation. The following concepts have been used: Segmentation using Morphological operations, minutia marking by specially considering the triple branch counting, minutia unification by decomposing a branch into three terminations and matching in the unified x-y coordinate system after a 2-step transformation; have been implemented, in order to increase the precision of the minutiae localization process, reducing consequently the generation of spurious inserted minutiae a back-propagation algorithms has been implemented for obtaining higer accuracy. The research has been implemented using Matlab 7. The research requires further improvement by employing different types of neural network.

REFERENCES

Achermann, B., X. Jiang and H. Bunke, 1997. Face recognition using range images. In: Proc. Int. Conf. Virtual Sys. Multimedia, pp: 126-136.

Albrecht, A., 2003. Privacy best practices in deployment of biometric systems, BIOVISION: Roadmap to Successful Deployments from the User and System Integrator Perspsective, Final report IST-2001-38236.

Alessandro Farina, Zsolt M. Kovacs-Vajna and Alberto Leone, 1999. Fingerprint minutiae extraction from skeletonized binary images. Pattern Recog., 32 (4): 877-889.

Allen, R., P. Sankar and S. Prabhakar, 2005. Fingerprint Identification Technology. In: Biometric Systems: Technology, Design and Performance Evaluation, Wayman, J.L., A.K. Jain, D. Maltoni and D. Maio, (Eds.). London: Springer-Verlag, 2: 21-61.

Alterman, A., 2003. A piece of yourself. Ethical issues in biometric identification. Ethics Inform. Technol., 5: 139-150.

American National Standards Institute, 2002. Information technology-BioAPI Specification (Version 1.1) (formerly ANSI INCITS 358-2002). New York, USA: American National Standards Institute.

American National Standards Institute, 2003. Biometric Information Management and Security for the Financial Services Industry: ANSI X9.84-2003. New York, USA: American National Standards Institute.

Antonelli, A., R. Cappelli, D. Maio and D. Maltoni, 2005. A new approach to fake finger detection based on skin distortion, in Proceedings of International Conference on Biometrics 2006 (ICB), Zhang, D. and A. Jain (Eds.), 3832: 221-228.

Ariyaeeinia, A. and P. Sivakumaran, 1997. Comparison of VQ and DTW classifiers for speaker verification. In: Proc. Eur. Conf. Security and Detection (ECOS), pp: 142-146.

Bailly-Bailli´ere, E., S. Bengio and F. Bimbot *et al*., 2003. The BANCA database and evaluation protocol. In: Proc. 4th Int. Conf. Audio- and Video-Based Biometric Person Authentication (AVBPA), Kittler, J. and M. Nixon, (Eds.), LNCS, 2688: 625-638.

Baldisserra, D., A. Franco, D. Maio and D. Maltoni, 2005. Fake fingerprint detection by odor analysis. In: Proc. Int. Conf. Biometrics 2006 (ICB), Zhang, D. and A. Jain (Eds.), 3832: 265-272.

Bergman, C., 2005. Multi-biometric match-on-card alliance formed. Biometric Technol. Today, 13 (5): 6.

Donahue, M.J.and S.I. Rokhlin, 1992. On the use of level curves in image analysis. Image Understanding, 57: 652-655.

Douglas Hung, D.C., 1993. Enhancement and feature purification of fingerprint images. Pattern Recog., 26 (11): 1661-1671.

Hirose, Y., K. Yamshita and S. Hijiya, 1991. Back-propagation algorithm which varies the number of hidden units. Neural Networks, 4 (1): 61-66.

Hong, L., Y. Wan and A. Jain, 1998. Fingerprint Image Enhancement: Algorithm and Performance Evaluation. IEEE Trans. Pattern Analysis and Machine Intelligence, 20 (8): 777-789.

Hong, L., Y. Wan and A.K. Jain, 1998. Fingerprint Image Enhancement: Algorithms and performance Evaluation. IEEE. Trans. PAMI., 20 (8): 777-789.

Jain, A., L. Hong and R. Bolle, 1997. On-Line Fingerprint Verification. IEEE. Trans. Pattern Anal. Machine Intell., 19 (4): 302-314.

Jain, L.C., U. Halici, I. Hayashi, S.B. Lee and S.Tsutsui, 1999. Intelligent biometric techniques in fingerprint and face recognition. The CRC Press.

Lee, C.J. and S.D. Wang, 1999. Fingerprint feature extraction using Gabor filters. Elec. Lett., 35 (4): 288-290.

Lumini, A., D. Maio and D. Maltoni, 1999. Inexact Graph Matching for Fingerprint Classification, Machine GRAPHICS and VISION, Special issue on Graph Transformations in Pattern Generation and CAD, 8 (2): 231-248.

Maio, D. and D. Maltoni, 1996. A Structural Approach to Fingerprint Classification. In: Proceedings 13th ICPR, Vienna.

Maio, D. and D. Maltoni, 1997. Direct gray-scale minutiae detection in fingerprints. IEEE. Trans. Pattern Anal. Machine Intell., 19 (1): 27-40.

Ratha, N., K. Karu, S. Chen and A. Jain, 1996. A Real Time Matching System for Large Fingerprint Databases. IEEE. Trans. Pattern Analysis and Machine Intelligence, 18 (8): 799-813.

Ratha, N., S. Chen and A.K. Jain, 1995. Adaptive Flow Orientation Based Feature Extraction in Fingerprint Images. Pattern Recognition, 28: 1657-1672.

Tico, M., P. Kuosmanen and J. Saarinen, 2001. Wavelet domain features for fingerprint recognition. Elec. Lett., 37 (1): 21-22.