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ON THE PRINCIPAL COMPONENT BASED FINGERPRINT CLASSIFICATION USING DIRECTIONAL IMAGES

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Abstract — This study presents a method for fingerprint recognition based on principal component analysis (PCA) and point patterns (minutae) obtained from the directional histograms of a fingerprint. We first employ Principal Component Analysis (PCA) method to compress fingerprint data. The compressed data are then used for directional image representation. After the compressed data are obtained, the process continues with directional image formation, directional image block representation, and fingerprint matching, respectively. Our method determines the direction of each pixel, process the images in blocks and uses directional histograms, thus removes the need for thinning. The method gives the same performance as that of the uncompressed data, but reduces computation. Furthermore, the parts of the system that successfully use artificial neural networks (ANN) are mentioned.

1. INTRODUCTION

Fingerprint is a unique property for each person and does not change during the person's lifetime. This makes fingerprint matching one of the most reliable methods for personal identification [2,3,4,12]. There has been a growing interest in automated analysis of fingerprints with the improved preprocessing and recognition algorithms. Automating fingerprint identification enabled its use in other applications such as criminal identification, access control, financial security, etc.

Most common fingerprint classification methods [1,2,3,4,12] are based on point patterns that are called ridge endings and bifurcations (minutiae) in fingerprints. As a result of coarse level classification of point patterns, Wirbel (whorl and twin loop) and Lasso (arch, tented arch, right and left loop) can be defined [2]. Thus, once these point patterns are extracted, they can be used to find out similarity (distance) between fingerprint patterns.

In this study, we present an automated method for coarse fingerprint classification that first removes the compress information and then, determines the point patterns using directional images and directional histograms. In the first stage, Principal Component Analysis (PCA) method is applied. This method removes the necessity for thinning and reduces the computation time. Then, the features are extracted by directional images. Finally, point patterns are matched for classification. The experimental results are shown for the compressed and uncompressed fingerprint examples.

2. IMAGE FORMATION

Various methods are used to acquire fingerprints. They may roughly be classified into two classes: the inked and inkless impression methods [2,4]. The conventional inked method captures the inked impression of fingerprint from a layer of ink. The finger is rolled from one side of nail to the other side over the inked slab. Then, the finger is rolled over on a piece of paper. Thus, these steps are necessary before digitization. The drawbacks of inked method can be summarized as ink blotches, smudges which hinder segmentation. Inkless method improves these drawbacks. Inkless fingerprint scanners are now available which are capable of directly acquiring fingerprints in digital form. But poor contrast and loss of ridge details remain a problem for both methods.

In this study, we use various acquired inked and inkless fingerprint samples. In the experiments, inkless samples are digitized using a Cannon Powershot 600 CCD camera to obtain M x N images.

3. DIMENSION REDUCTION BY PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal component analysis (PCA) [5,6] is a linear, orthogonal transformation of the observed data (variables with *superficial dimension* n) to independent factors (variables with *intrinsic dimension* m) that are really needed to describe data. The n observed variables are represented as a function of m independent principal components where m n and often m n.

We assumed that a random vector $x= [x_1,x_2,\ldots x_n]^T$ with covariance $C=E\{x.x^T\}$(with zero mean). The transformed feature vector, $y = W.x$, is computed where W defines the projection and is an orthonormal basis (eigenvector matrix):

$$W.C = D.W^T \qquad (1)$$

where the diagonal matrix D consists of eigenvalues (variances) with decreasing order.

The projection of x is the reconstruction of x :

$$\mathrm{proj}(x) = W^T.y=W^T.W.x \qquad (2)$$

The maximization of the projection variance is equivalent to minimization of the mean square reconstruction error. For example, the eigenvalues $e_1,e_2,e_3,\ldots..e_m,e_{m+1},\ldots..e_n$ can be divided into two partitions: the largest eigenvalues $e_1,e_2,e_3,\ldots..e_m$ and the smallest eigenvalues $e_{m+1},\ldots..e_n$. If we only use the largest eigenvalues for reconstruction with variance of 95% and neglecting the smallest ones, we introduce a reconstruction error of 5%.

4. DISTORTION REDUCING BY CLIPPING

In this phase, we preprocess the compressed gray-level fingerprint image to reduce distortion and enhance contrast. First, we adaptively clip the compressed fingerprint image, then compare and make an interpolation between the clipped and original compressed data. The clipping is as follows: the average intensity value v is computed at each pixel in a 5 x 5 neighborhood. If the pixel value is less than v, then the pixel value is zero; otherwise, the pixel value remains unchanged. For enhancement, we interpolate the clipped image and the fingerprint image to produce an M x N preprocessed image P.

5. DIRECTIONAL IMAGE REPRESENTATION

From the preprocessed image P, we compute an M x N directional image V that defines the orientations of point patterns. We compute the directions at each pixel P(i,j) by sliding the 5 x 5 mask over P where c is the center pixel P(i,j) [3,4,7,8,9]. The direction D(i,j) at the point (i,j) is defined as follows:

$$D(i,j) = \min_m \Sigma \, [\, V(i,j) - V(i_m, j_m) \,] \qquad (3)$$

where m is the number of pixels which defines the dimension of block [3,4]. For each block, we quantize the dominant direction to 0, 1, 2, or 3, which represent 0°, 90°, 45°, and 135°, respectively [4]. Thus, we obtain a reduced directional image S with the new dimension (M/q) x (N/q) (q=5). As a result, reducing the size of image decreases computation complexity.

6. POINT PATTERNS

Using the reduced directional image S, we determine the point patterns. Let (i,j) denote a pixel on the S, and PP(i,j) matrix denotes the neighbors (eq. 4).

$$\mathrm{PP}(i,j) = \begin{bmatrix} S(i-1,j-1) & S(i-1,j) & S(i-1,j+1) \\ S(i,j-1) & S(i,j) & S(i,j+1) \\ S(i+1,j-1) & S(i+1,j) & S(i+1,j+1) \end{bmatrix} \qquad (4)$$

The directions defined by PP(i,j) matrix is then employed to decide the kind of pattern points [4,2,7,9]. The following example denotes the heuristics of the algorithm: if S(i,j) and S(i-1,j+1) are in the same local direction, S(i+1,j-1) will also be in the same direction. This rule is used to detect ridge endings. On the other hand, if there is continuation from S(i,j) to S(i-1,j+1) and S(i+1,j+1), this rule is used to detect ridge bifurcations. Hence, database of the point patterns is formed.

7. MATCHING

In this study, we use a simple matrix-based matching approach on the pattern points based on euclidian distance (eqn. 5). A simple form of it between x and y vectors can be defined as follows:

$$d = \sqrt{(x - y)^2} \tag{5}$$

Direction matrix representation is derived for each fingerprint pattern as explained previously. Then, these matrices are classified according to the minimum distance to the original fingerprint matrix. Whole ridge endings of the data are matched to each ridge endings of the database one by one, and the same is repeated for ridge bifurcations. The matrix based measure results in the best fit on the basis of similarity.

8. EXPERIMENTAL RESULTS

We have tested our fingerprint system on two sets of fingerprint images that are captured with inkless and inked impression methods. The first set contains 16 inked fingerprint samples. The other one contains 15 inkless samples [3,4]. The size of this images is 256x256. When this fingerprint images were captured, no restrictions on the position and orientation of fingers were imposed. The captured fingerprint images vary in quality. Most of the fingerprint images in these databases are of reasonably good quality. Inked method have worse result than inkless method. Inked fingerprint images suffer from ink blotches and smudges.

In this study, we report some initial classification results on fingerprint matching, for the cases of with and without PCA application. Without using PCA method in the preprocessing stage, we achieve 87% success rate in the classification of inkless samples. When we use PCA method, we obtain a data compression rate of 50% without any reconstruction error, a compression rate of 12.5% with an error of less than 5%. This gives us the same success rate as before. Thus, the PCA method reduces memory requirement of the system and computation time for classification.

9. CONCLUSION

We introduce a fast and memory efficient fingerprint classification technique. Our method reduces processing time by compressing the data and removing the need for thinning and processing images in blocks. Our method increases resolution by determining directions for each individual and uses directional histograms to detect point patterns. Our method outperforms similar featured-based fingerprint classification algorithms [9].

10. FUTURE WORK

ANN provides a unique characteristics and advantages for the fingerprint applications [2,14]. A very important feature of these networks is their adaptive nature, where "learning by samples" replaces conventional "programming" in solving problems.

Owing to the large number of interconnections between their basic processing units, neural networks are error –tolerant, and can deal with noisy data. Thus, ANN can be successfully employed in fingerprint enhancement applications using sufficient amount of training data. ANN architecture encodes information in a parallel fashion. This inherent parallelism makes it easy to extract the principal components of the heterogenous components of the input at the output. It is possible to make use of ANN in principal component extraction [15].
Finally, at the stage of fingerprint pattern classification, ANN will also be an efficient tool [14].
In this study, we propose a small scale security system example, therefore we do not use large amount of fingerprint samples that does not give a chance to build a satisfactory training set. But we later plan to employ ANN in the other applications.

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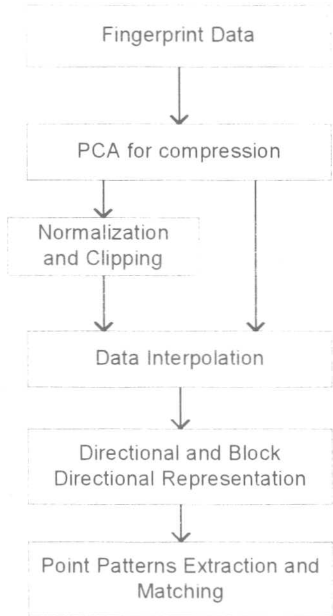

Figure.1. Block diagram of fingerprint recognition algorithm

Figure.2. Point patterns a) Ridge endings b) Ridge bifurcations

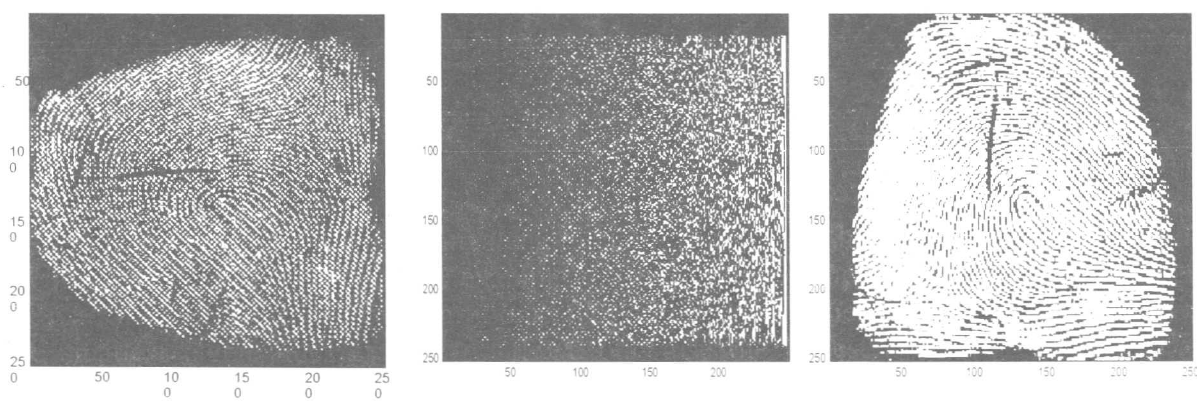

Figure.3. A fingerprint example a) Raw data b) PCA transformation data
c) Reconstructed and flipped data