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신경회로망을 이용한 지문인식방법에 관한 연구

A Study on the Fingerprint Recognition Method using Neural Networks

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요 약

본 논문에서 제안한 특징 벡터 추출방법의 기본 아이디어는 융선 패턴의 지역 방위에 따라 그레이-스케일 영상의 융선을 따라가면서 융선의 방향성을 추출하는 것이다. 융선을 따라가는 시작점은 그레이-스케일 영상을 일정한 격자로 나누어서 격자안의 중심점으로 결정한다. 그 다음에 융선을 따라가면서 여러방향의 방향성 특징 벡터를 추출하고, 추출된 방향성 특징 벡터를 4방향성 특징 벡터로 라벨링한다. 실험은 4개의 지문에서 구성한 124개의 특징 패턴을 가지고 하였으며, 하나의 지문은 31개의 특징패턴으로 구성하였다. 그 결과 학습된 지문을 인식하는 능력이 매우 우수함을 보여주었다.

ABSTRACT

The basic idea of the above mentioned method is to track the ridge lines on the gray-scale image, by "sailing" according to the local orientation of the ridge pattern. A set of starting points are determined by superimposing a grid on the gray-scale image. A labeling strategy is adopted to examine each ridge line only once and locate the intersections between ridge lines. After the direction feature vectors are consisted of vectors by four direction labeling. Matching method used in this paper is four direction feature vectors based matching. The experiment are used total 124 feature patterns of four fingerprints, and One fingerprint image is consisted of 31 feature patterns. The results is presented excellent recognition capability of learned fingerprint images.

Key words : Fingerprint Recognition, Neural Networks

1. INTRODUCTION

In this paper, a fingerprint identification method using neural networks and the direction feature vectors based on the directional image extracted from gray-scale fingerprint image is proposed. In this paper proposed, where the direction feature vectors are extracted directly from the gray-scale image without binari- zation and thinning

The basic idea of the above mentioned method is to track the ridge lines on the gray-scale image, by "sailing" according to the local orientation of the ridge pattern. A set of starting points is determined by superimposing a grid on the gray-scale image ; for each starting point, the algorithm keeps following the ridge lines until they terminate or intersect other ridge lines (direction detection). A labeling strategy is adopted to examine each ridge line only once and locate the intersections between ridge lines. After the direction feature vectors are consisted of vectors by four direction labeling. Matching method used in this paper is four direction feature vectors based matching. In this paper is proposed the use of Neural Networks(NN) in fingerprint matching.

In section 2, discusses multilayered Neural Networks(NN) used experimental. In section 3, which discusses the direction feature vectors detection algorithm. In section 4, discusses Four Direction Labeling and Pattern Detection. In section 5, discusses the result of fingerprint matching. Finally, in Section 6 some conclusions are drawn.

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2. Neural Networks

2.1 Learning and Structure of Multilayered Neural Networks

Multilayered neural networks were used as basic structure for the applications discussed here. Fig. 1 shows multilayered neural networks[3],[5 - 8].

The back propagation training algorithm allows experiential acquisition of input/output mapping knowledge within multilayered neural networks. Fig. 2 illustrates the flowchart of the error back propagation training algorithm for a basic two layer network as in Fig. 1 [5 - 8].

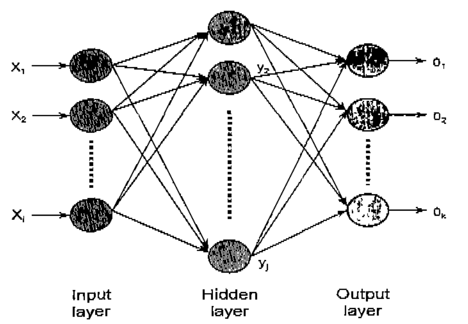


Fig. 1 Multilayered neural networks

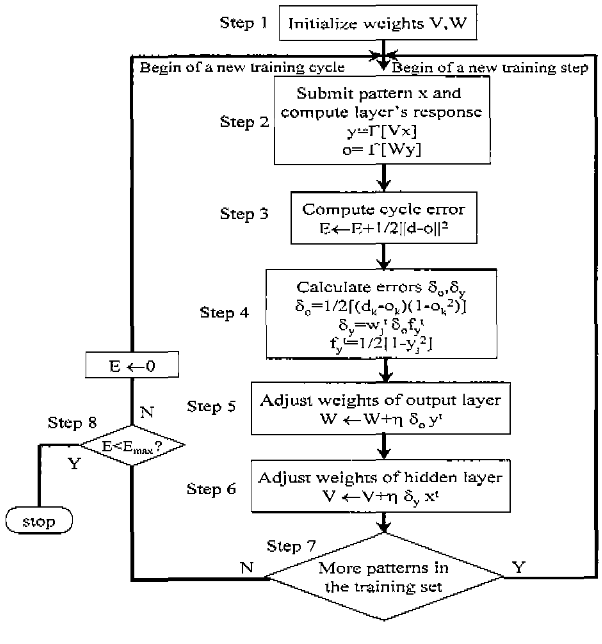


Fig. 2 Error back propagation training algorithm

Given are P training pairs, $\{x_1, d_1, x_2, d_2, \cdots, x_p, d_p\}$, where x_i is $(i\times1)$, d_i is $(K\times1)$, and $i=1,2,\cdots,P$. The operator Γ is a nonlinear diagonal operator with diagonal elements being identical activation functions. The learning begins with the feedforward recall phase(step 2). After a single pattern vector x is submitted at the input, the layers' responses y and o are computed in this phase. Then, the error signal computation phase(step 4) follows. Note that the error signal vector must be determined in the output layer first, and then it is propagated toward the network input nodes. The weights are subsequently adjusted within the matrix W, V in step 5, 6. Note that the cumulative cycle error of input to output mapping is computed in step 3 as a sum over all continuous output errors in the entire training set. The final error value for the entire training cycle is calculated after each completed pass through the training set $\{x_1, x_2, \cdots, x_p\}$. The learning procedure stops when the final error value below the upper bound, E_{max} is obtained as shown in step 8.

Also, weight adjustment use momentum method in this paper as shown Fig. 3. The purpose of the momentum method is to accelerate the convergence the error back propagation learning algorithm. This is usually done according to the formula (2.2).

$$\Delta w(t) = -\eta\frac{\partial E}{\partial w(t)} + \alpha\Delta w(t-1) \qquad (2.2)$$

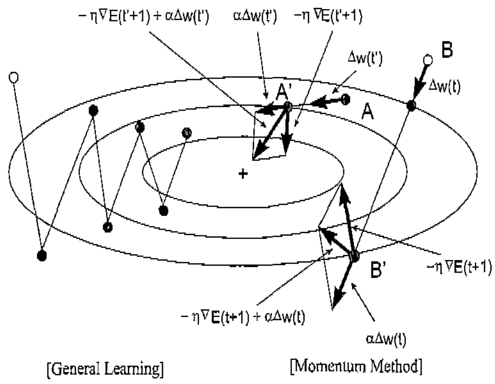


Fig. 3 Illustration of adding the momentum term in error back propagation training for a two-dimensional case

where the arguments t and t-1 are used to indicate the current and the most recent training step, respectively, and alpha is a user-selected positive momentum constant. Fig. 3 illustrates the momentum term heuristics and provides the justification for its use. Let us initiate the gradient descent procedure at point A'. The consecutive derivatives $\partial E/\partial w_1$ and $\partial E/\partial w_2$ at training points A', A'', $\cdots$, are of the same sign. Obviously, combining the gradient components of several adjacent steps would result in convergence speed-up. After starting the gradient descent procedure at B', the two derivatives $\partial E/\partial w_1$ and $\partial E/\partial w_2$, initially negative at B', both alter their signs at B'', The figure indicates that the negative gradient does not provide an efficient direction of weight adjustment because the desired displacement from B'' should be more toward the minimum M, or move the weight vector along the valley rather than across it.

2.2 Multilayered Neural Networks used Experimental

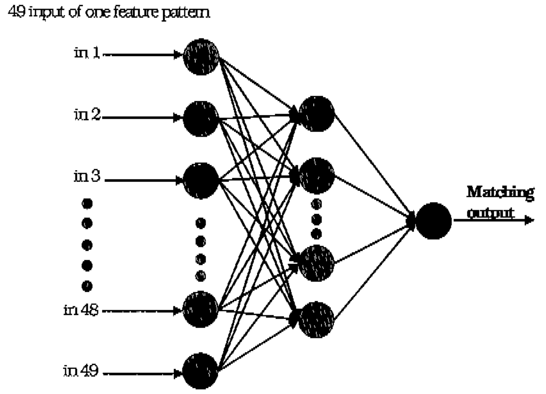


Fig. 4 Multilayer neural networks used for matching system

The proposed neural networks has the capability of excellent pattern identification. The number of input node neurons is fifty including bias, hidden node is fourteen, output node is one. The used algorithm is error back propagation algorithm in general multilayer neural networks. The proposed neural networks were learned until error become 0.01.

3. Direction Feature Vector Detection

Let I be an a×b gray-scale image with gl gray levels, and gray(i,j) be the gray level of pixel (i,j) of I, i = 1,....a, j = 1,...b. Let z = S(i,j) be the discrete surface corresponding to the image I: S(i,j) = gray(i,j), i = 1,...a, j = 1,...b. By associating bright pixels with gray levels near to 0 and dark pixels with gray levels near to gl-1, the fingerprint ridge lines (appearing dark in I) correspond to surface ridges, and the spaces between the ridge lines (appearing bright in I) correspond to surface ravines(Fig.5)

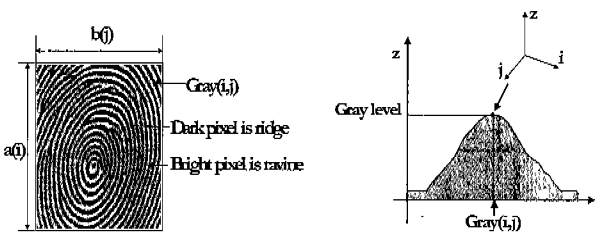


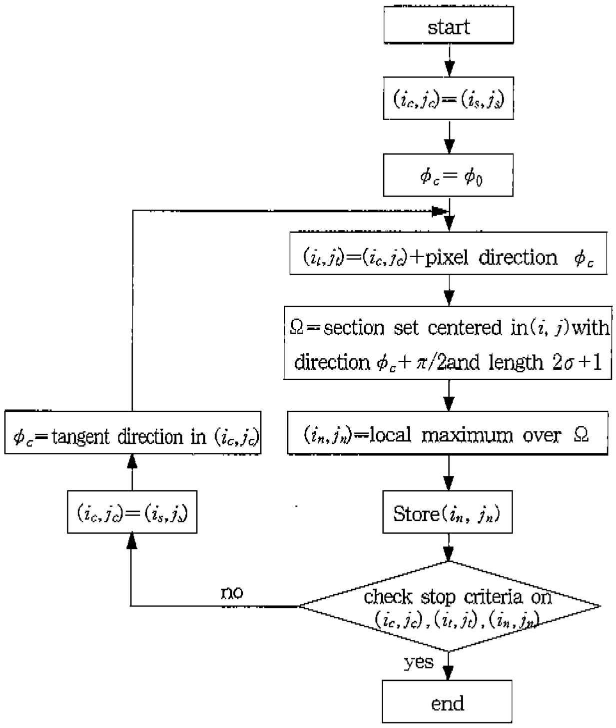
Fig. 5 a×b gray-scale fingerprint image

From a mathematical point of view, a ridge line is defined as a set of points which are local maxima along one direction. The ridge-line extraction algorithm attempts to locate, at each step, a local maximum relative to a section orthogonal to the ridge direction. By connecting the consecutive maxima, a polygonal approximation of the ridge line can be obtained

Let (i_s, j_s) be a local maximum of a ridge line of I, and φ_0 be the direction of the tangent to the ridge-line in (i_s, j_s); a pseudo-code version of the ridge-line following algorithm is :

4. Four Direction Labeling and Pattern Detection

I shall begin with four direction labeling. This algorithm steps, a various direction feature vectors of 360° are changed four direction labeling. In principle, each vector is computed 'simply by determining conditional ; using an angle value of the direction feature vector. Fig. 6 show the coordinates which are



four direction labeling. Labeling of coordinates, 0° = direct1, 45° = direct2, 90° = direct3, 135° = direct4. The direct1 is the direction feature vectors of 0° ~ 22.4° or 157.5° ~180° . The direct2 is the direction feature vectors of 22.5° ~67.4° . The direct3 is the direction feature vectors of 67.5° ~112.4° . The direct4 is the direction feature vectors of 112.5° ~ 157.4° .

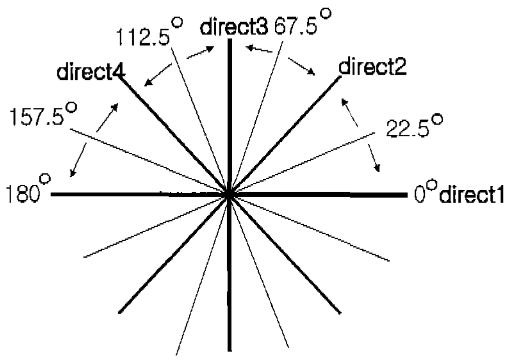


Fig. 6 Four direction labeling coordinates

In this explained, making fingerprint feature pattern of four direction labeling. A fingerprint image is divided on blocks the size of 15×15 pixels. At each block is labeling. Let 128×128 fingerprint image is consisted of 49 blocks. At each blocks, the direction vector is expressed label value(Fig. 7). All the blocks are consisted of label values. Therefore, a fingerprint image is built up of feature vector pattern using 49 direction label value.

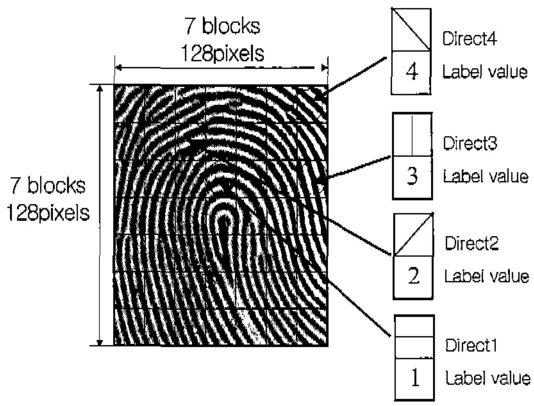


Fig. 7 A fingerprint image is divided on blocks the size of 15×15 pixels.(128×128 Image, At each blocks, show label value)

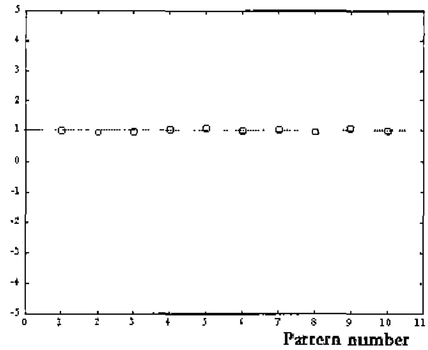
5. Experimental Results

In experimental, preference step1, four fingerprint images are detected as various direction feature vectors, and step2, a various direction feature vectors are changed Four direction feature vectors, and step3, the direction feature vectors are labeling, and step4, registered for matching system(neural networks) labeling each fingerprint images for number; in experimental, whorl registered to number1, arch registered to number2, right loop registered to number3, left loop registered to number4. Step5, Matching experi- mental using label feature patterns of each fingerprints. Fig. 8 shows matching results. As shows experimental results is presented very good capability.

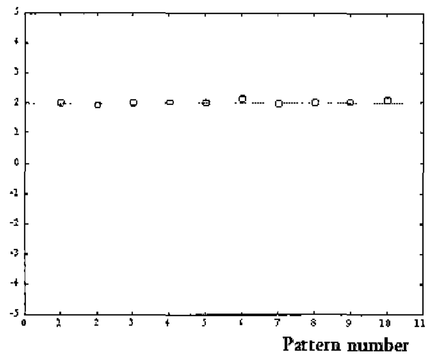
Input patterns using in experiment shows table 1.

Table 1

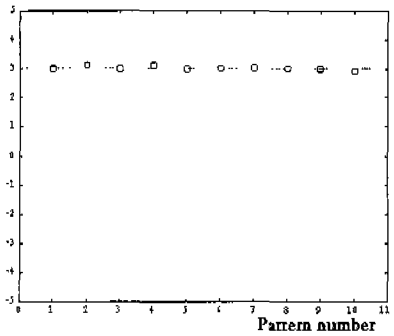
Fingerprint \ Input number	1	2	3	4	5	6	7	8	9	10
Whorl(number 1)	3°	5°	7°	-3°	-9°	11°	15°	-15°	-7°	13°
Arch(number 2)	-9°	-13°	5°	3°	7°	-15°	-11°	-3°	-1°	9°
Right loop(number 3)	1°	9°	7°	11°	3°	-3°	13°	-13°	15°	-9°
Left loop(number 4)	-15°	-7°	-9°	-3°	-5°	13°	5°	7°	-11°	3°



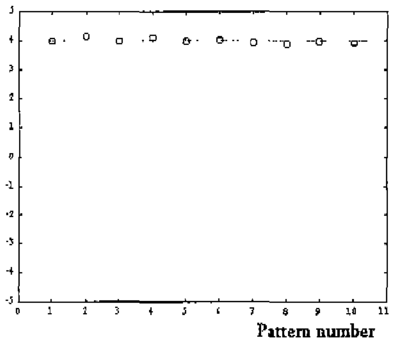
(a) Whorl is number 1



(b) Arch is number 2



(c) Right loop is number 3



(d) Left loop is number 4

Fig. 8 Results for feature pattern matching

6. Conclusion

In this paper we have presented approach to automatic the direction feature vectors detection, which detects the ridge line directly in gray scale images.

In spite of a greater conceptual complexity, we have shown that our technique has less computational complexity than the complexity of the techniques which require binarization and thinning. And a various direction feature vectors are changed four direction feature vectors. In this paper used matching method is four direction feature vectors based matching.

This four direction feature vectors consist feature patterns in fingerprint images. This feature patterns were used for identif- ication of individuals inputed multilayer Neural Networks (NN) which has capability of excellent pattern identification.

In experimental results is presented very good capability. In the future work, in order to reduce error rate mistaken identification, have to continue research, and apply actual automatic systems for fingerprint comparison.

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