Hand shape has Sufficient Information for Personal Verification

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ABSTRACT: Needs for automatic personal verification by machine are increasing as security systems become more and more important in order to prevent various crimes of today. We show in this paper that hand shape (outline pattern of a hand image) has enough information for personal verification. We extract 30 features from each hand shape. The effectiveness of each feature is evaluated by calculating variance within classes and variance between classes. We selected 13 features for personal verification based on the statistical analyses. These feature values are fed to a modular type neural network for recognition. Each module in the modular type neural network is a three layered neural network with the back propagation learning algorithm. The performance of the system was examined by using hand image data of 20 persons. We obtained high verification rates with very low misverification rates.

KEYWORDS: hand shape, modular type neural network, personal verification

1 INTRODUCTION

There are increasing needs for personal verification without direct inspection by human eyes, for example, introduction of cash dispenser in a bank, gate control of buildings and rooms, the practical uses of electric account system on Internet, etc. These needs make it more necessary to develop a system for automatic personal verification by machine. So far, various personal verification techniques based on credit cards, keys, or key words have been used in practical systems. But these techniques have common weak points, e.g., forgetting key words, etc. Therefore various personal verification systems using physical characteristics of humans (namely, biometric identification systems) have been developed. Current practical biometric systems use fingerprints [Wegstein 1982] or iris patterns [Rosen 1990] as cues to identify persons. But the use of fingerprints makes users associate crime investigations, and the use of iris patterns forces users to take an unnatural posture and has a hygienic problem. So the development of a biometric personal verification system is needed which does not give users mental and physical loads.

We know that hand shapes are different between persons. But it has not been investigated whether hand shapes have much information for personal verification. It is very adequate for a cue of the purpose because it can be easily used without any physical and mental loads. It gives little mental resistance to us to have our hand shapes registered for personal verification. Data of hand shapes can be easily obtained by just putting our hands on a scanner. If the hand shape is proved to have sufficient information for personal verification, a personal verification system using hand shapes as a cue will be practically realizable.

We have been studying techniques to use hand images of personal verification [Hosaka 1997] [Nagano 1998]. In this paper we propose a personal verification system with hand shapes by utilizing a modular type neural network and image processing techniques.

2 PRE-PROCESSING

Hand images were obtained by using an image scanner (716·573 pixels, 256 gray levels). The position of the top of the middle finger and the orientation of the rightside of the middle finger image were fixed with two guide bars. No other positional restrictions were imposed. An example of original hand images is shown in Fig.1.

The hand part is segmented from an original image by quantizing the gray level of each pixel at an adequate

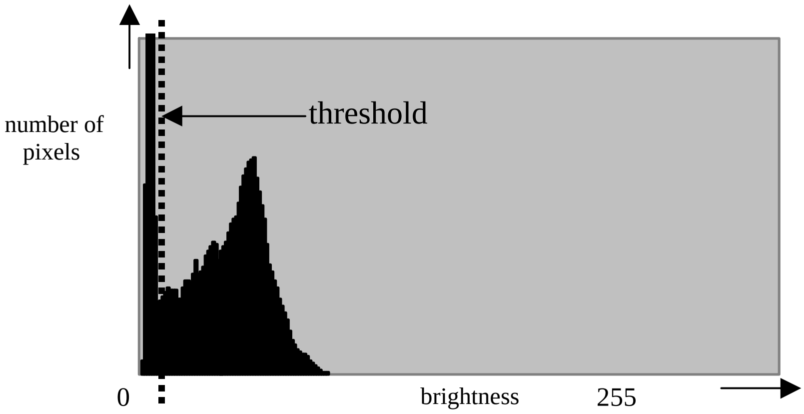

Fig.1. An original hand image Fig.2. Illustration for how to decide the threshold that segments hand part from background

threshold. In order to do this, we, first, construct a histogram of brightness values as shown in Fig.2. The background of hand images has uniformly much lower brightness than that of hand parts. So, the hand part can be successfully segmented by setting the threshold for segmentation at a brightness value between the two neighboring brightnesses which give the maximum difference of pixel numbers as shown in the broken line in Fig.2. After this processing small noise regions are eliminated by finding such regions with the labeling technique. An example of the segmented hand part is shown in Fig.3.

3 FEATURES OF HAND SHAPE

First, 12 feature points of hand shape shown in Fig.4 were intuitively selected. 47 features were defined by using these feature points: e.g. lengths of line segments connecting pairs of feature points, positions of feature points, etc. Then, statistical analyses were made by calculating variance within classes and variance between classes of each feature in order to estimate its effectiveness. 13 features were selected based on the results of the statistical analyses. They are the lengths of 12 line segments and the area of the white part in Fig.4.

Table I. Definition of the 12 feature points

P0	Top of the middle finger
P1	Bottom of the trough between the middle finger and the third finger
P2	Bottom of the trough between the index finger and the middle finger
P3	Bottom of the trough between the third finger and the little finger
P4	Top of the third finger
P5	Top of the index finger
P6	Top of the little finger
P7	Cross point of the right outline of the index finger and the horizontal line crossing P3
P8	Cross point of the left outline of the palm and the bottom horizontal line of the hand part. The bottom horizontal line is defined by the vertical position at which the horizontal width of hand image is equal to 0.9·(length of the middle finger) around the wrist.
P9	Cross point of the right outline of the palm and the bottom horizontal line of the hand part. The bottom horizontal line is defined by the vertical position at which the horizontal width of hand image is equal to 0.9·(length of the middle finger) around the wrist.
P10	Cross point of the vertical line crossing P0 and the horizontal line connecting P8 and P9
P11	Cross point of the left outline of the palm and the line crossing P7 which is orthogonal to the line connecting P2 and P9.

Fig.3. An example of segmented hand part

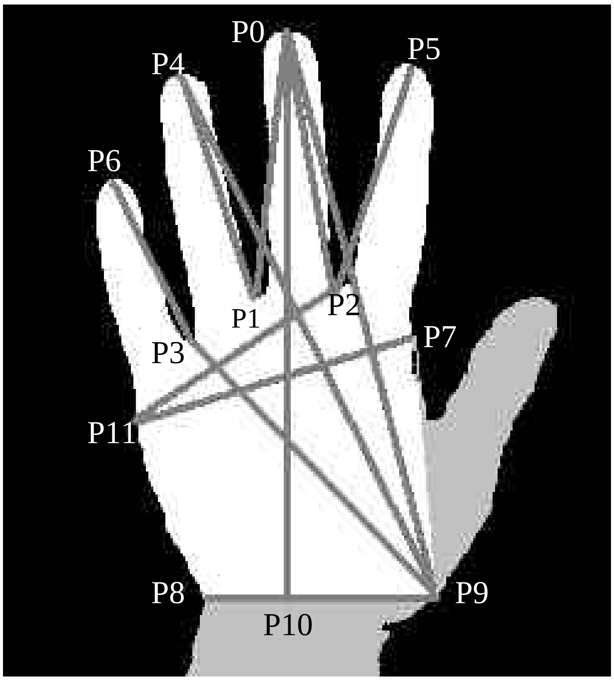

Fig.4. Feature points and features defined by these points

4 A MODULAR NEURAL NETWORK FOR RECOGNITION

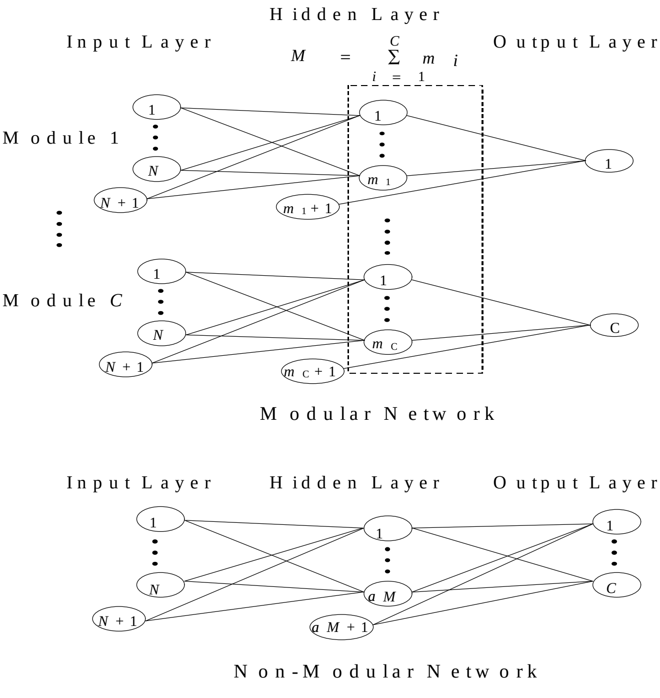

Fig.5. Architectures of the modular network and the non-modular network

We use a modular neural network shown in Fig.5 for recognition. Each module is a three layered neural network with one output unit. The learning algorithm is the usual back–propagation algorithm. Each module in the modular network classifies each class from all the other classes. This type of network has been shown to have better performance than that of the usual layered network (non-modular type) shown also in Fig.5, when the number of classes is large [Ishihara 1998]. Each module we used had 13 input terminals, 5 hidden units and one output unit.

5 EXPERIMENTAL RESULTS AND DISCUSSION

Table II. Verification and misverification rates for test patterns under first criterion

verification rate	misverification rate
99.5%	0.5%

Table III. Verification and misverification rates for test patterns under the second criterion

threshold	verification rate	misverification rate	rejection rate
0.6	96.5%	2.10%	1.40%
0.7	90.0%	1.06%	8.94%
0.8	81.0%	0.52%	18.48%
0.865	72.5%	0.00%	27.50%

We used 300 hand images of 20 persons (15 hand images/person) in order to examine the effectiveness of the features obtained from hand shape and performance of the modular-type neural network. 5 hand images / person were used for training and the rest (10 hand images/person) were used for test. We examined two criteria for correct verification. The fist one is that an input is accepted if the module corresponding the correct person gives the maximum output. Results are shown in Table II. The second criterion is that an input is accepted only if only the module corresponding the correct person exceeds a fixed threshold. Misverification in this case means that one or more wrong modules corresponding wrong person(s) exceed(s) the threshold. All the other cases are classified into "rejection". Results are shown in Table III. Results were dependent on threshold values. We obtained zero misverification rate at the threshold of 0.865. The second criterion is practically more useful than the first one because misverification must be strictly avoided in personal verification for security systems. It can be said that we realized zero misverification rate keeping verification rate relatively high. Correct verification under the second criterion can be obtained by repeating trials again even if the first trial is rejected.

The results proved the effectiveness of hand shape for personal verification. They also shows that the modular-type neural network can be effectively used for this kind of pattern classification problems.

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