Handprint Identification Using Fuzzy Inference

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Abstract

In this paper, a personal identification system based on handprint features is presented. This system utilizes a CCD(Couple Charged Device) digital camera to capture a handprint image. Three different features are extracted from the image, which are WLIP(Wide Integrated Profile), VWILP(Variation of WLIP), and FW(Finger Width). The similarity for each of the first two features and the dissimilarity for the third feature between two handprint images are measured using correlation functions and the Euclidean distance, respectively.

Finally, the identification is accomplished by a fuzzy inference engine based on these similarity/dissimilarity measures.

The experimental results indicate that the proposed method has demonstrated good performance in both identification rate and speed.

Keywords: wide line integrate profile, variation of wide line integrate profile, fuzzy inference engine, similarity measure, dissimilarity measure.

1. Introduction

The need to identify people is as old as humankind. In today's complex society, the demand for an efficient and reliable security system has tremendously enhanced the importance of an automatic personal identification system [1-10]. There are many security systems in place in areas ranging from business, banking, health care, education, and government. Yet finding satisfactory methods of identifying an individual can be difficult. Some methods are easy to fool, some are too expensive, and others are felt to be inconvenient or too intrusive.

Biometric identification is an enhancing technology to cope with these difficulties, which is an automated method of verifying or recognizing the identity of a person on the basis of some physiological characteristic, like a fingerprint, handprint, voice, or iris pattern. Unlike pass cards, codes, and keys, which identify things, biometric recognition technology identifies people and is much more resistant than conventional security measures.

Of all biometric techniques, biometric hand recognition is the least expensive and the most user acceptable. The hand identification problem has been addressed by several researchers in the past [11-15]. Zhang and Shu present datum points invariance and line feature matching for palmprint verification [13]. WLIP (Wide Line Integrated Profile) extracted from finger crease pattern has been used in the identification system proposed by Joshi and et al.[15]. Boles and Chu use Hough transform to detect the extracted major lines on the palm. Kung, Lin, and Fang [16] have used a decision-based neural network to recognize palm images.

The objective of this paper is to find some effective features on the hand image and propose a personal identification system utilizing these features. The block diagram of the proposed identification system is shown in Figure 1.

In section 2, we introduce the features we adopt and the algorithms for finding these features. Section 3 deals with similarity/dissimilarity measure of each feature from two hand images, and a fuzzy inference engine described in section 4 makes a binary choice of either accepting or rejecting the person's claim to accomplish the verification. Section 5 presents experimental results. Section 6 is conclusion.

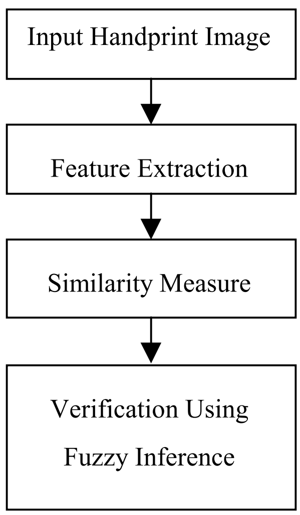

Figure 1. Block diagram of the proposed identification system

2. Feature Extraction

The handprint image can be captured from a digital camera for later retrieval or analysis. The benefit of using digital camera is the high quality of image capturing. If the image quality of handprint is good then the system verification rate will be higher. So, in this paper, A digital camera is employed to capture handprint image. A hand is simply placed on a platform for image capturing and analysis.

Figure 2. A finger image and it's middle axis and reference rectangles.

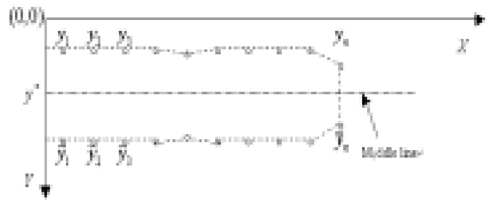

Figure 3. Boundary points with their y-coordinates and the middle axis of the finger in Figure 2.

There are many kinds of significant characteristics on a hand image like size, geometry shape, ratio of the length of finger to the length of hand, the major lines, and the finger creases. The performance of an identification system is highly related to what features are utilized.

In the proposed system, three features are taken into account, which are described as follows:

(1) WLIP[15](Wide Line Integrated Profile):

WLIP is presented by Joshi and et. al. PL which is a sequence of gray values computed along the length of a finger(the middle finger is taken in the proposed system) from the hand image. For the purpose of accuracy, our WLIP is modified to be several gray-level sequences instead of one single sequence, and every gray-level sequence is a series of the mean of gray values which is the vertical projection of the crease pattern in some reference rectangles, which is the sampling range of WLIP features. To locate these reference rectangles, we need to find the middle line of the finger image. According, the size of the rectangles, and the distance between every two adjacent rectangles, we may simply locate these rectangles as shown in Figure 2.

To compute the middle axis of the finger, we find out some points from the boundary of the finger. As in Figure 3, sequences $y_1, y_2, \ldots, y_n$ and $\bar{y}_1, \bar{y}_2, \ldots, \bar{y}_n$ denote the y-coordinates of some points on the upper boundary and the lower boundary of finger, respectively. The mean of the y-coordinates of these points is evaluated and denoted by y^* (see Equation 1), and the middle axis is then defined as the horizontal line passing through the point $(0, y^*)$.

$$y^* = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i + \bar{y}_i}{2} \tag{1}$$

(2) VWLIP(Variation of WLIP):

The second feature we extract is VWLIP. The VWLIP is the variation of WLIP, which is a sequence of averages of every α consecutive elements in WLIP, where α is a parameter.

$$dw_i = \frac{\sum_{j=i}^{i+\alpha-1} d_j}{\alpha} \tag{2}$$

As in Figure 4, $w_1, w_2, \ldots, w_n$ denote a WLIP sequence, and the $d_1, d_2, \ldots, d_n$ is the sequence of differences between every two adjacent elements in WLIP. The elements of VWLIP can be defined using Equation 2, where the parameter α determines how smooth the VWLIP is. In this paper, we set α = 10.

(3) FW(Finger Width):

Shape information from hands is an effective feature to distinguish one person from another, but it need a complicated representation to keep track of the whole contour of the pattern. Besides, it is highly affected by the rotation and tempts to accumulate errors in comparison. The third feature adopted in our system is a sequence of widths, which is also computed along the length of the finger. This feature involves some shape information from the finger, but is simpler than the shape feature described by the contour of the finger, and thus can be evaluated in lower computational time.

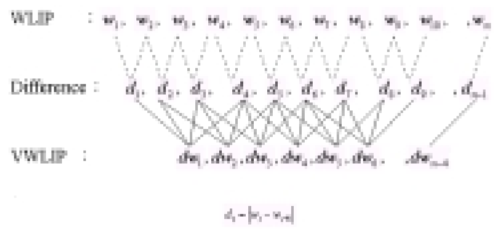

Figure 4. VWLIP feature extracting.

3. Similarity/ Dissimilarity Measure

In this section, we will measure the similarity/dissimilarity for the features extracted in the previous section. The correlation function is utilized to measure similarity between two WLIP features and similarity between two VWLIP features. And the dissimilarity of two FW patterns is computed using a distance function.

Let $X=(X_1, X_2, \ldots, X_n)$ be a template pattern and $Y=(Y_1, Y_2, \ldots, Y_n)$ be an input pattern, then their similarity is measured using the correlation function as follows:

$$C(X,Y,a,b) = \frac{\sum_{i=1}^{N}(X_i - \bar{X})(Y(a,b)_i - \overline{Y(a,b)})}{\sqrt{\sum_{i=1}^{N}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{N}(Y(a,b)_i - \overline{Y(a,b)})^2}} \tag{3}$$

where C(X, Y, a, b) means the correlation between the template and the input pattern with displacement (a, b), N is the size of the template pattern, $\bar{X}$ denote the mean of X, Y(a, b,) denotes the input pattern with displacement α units in the vertical direction and b units in the horizontal direction, and $\overline{Y(a,b)}$ denotes the mean of Y(a, b). It is obviously that the range of C(X, Y, a, b) is [-1,1] and If X and Y(a, b) are identical, then C(X, Y, a, b) = 1.

Let X_W denote the WLIP feature of the template pattern, Y_W denote the WLIP feature of the input pattern and $Y(a,b)_W$ denote the WLIP feature of the input pattern with displacement (a, b), where (a, b)∈R, and R=(-I, I)×(-J, J) is the range of allowable displacement. Then the maximal value of $C(X_w, Y_w, a, b)$ is defined as the correlation value of X_w and Y_w, denoted by $C(X_w, Y_w)$, see Equation 4. Meanwhile, the displacement (m, k) which makes correlation value between template and input pattern maximal, can also be found as shown in Equation 5.

$$C_W(X,Y) = \max_{(a,b)\in R} C(X_W, Y_W, a, b) \quad (4)$$

$$(m,k) = \arg(\max_{(a,b)\in R} C(X_W, Y_W, a, b)) \quad (5)$$

Why do we have to consider displacement when computing correlation value of two features? Because the geometrical constrains are not adhered, it causes two finger crease images from the same person are possibly not alignment. Thus, we consider all allowable displacement of the input pattern, and find out the one having the maximal correlation value with the template pattern.

The correlation value of VWLIP is simply computed according to displacement (m, k) which was obtained in the step of evaluating correlation value of WLIP. Let X_{vw} denote the VWLIP feature of the template pattern and Y_{vw} denote the VWLIP feature of the input pattern. The correlation value for VWLIPs of two patterns is $C_{vw}(X, Y)=C(X_{vw}, Y_{vw}, m, k)$.

The FW(finger width) feature described in section 2 is also an useful information to increase correct matching rate. Let X_{FW} denote the FW feature of the template pattern and Y_{FW} denote the FW feature of the pattern, then the dissimilarity for FWs of two patterns is computed using the distance function $D(X_{FW}, Y_{FW})$ as shown in Equation 6, in which k is displacement acquired from Equation 5.

$$D(X_{FW}, Y_{FW}) = \frac{1}{n}\sum_{i=1}^{n} \left| X_{FW}[i+k] - Y_{FW}[i] \right| \quad (6)$$

4.Verification Using Fuzzy Inference

Using similarity/dissimilarity measure as described in section 3, we obtain two correlation values and one distance value computed while comparing two finger patterns. To achieve a verification result, the system has to analyze these values. In this paper, fuzzy inference is utilized to accomplish verification. A fuzzy inference is a collection of fuzzy IF-THEN rules. Statement 1 shows an example of fuzzy IF-THEN rules.

IF x is A and y is B THEN z is C (1)

The statement following IF is the IF-part of fuzzy rule, and the THEN-part is the statement following THEN. The operation of fuzzy inference is shown in the following:

Step1. Elements are input into fuzzy inference system, and the membership value of the IF-part for each rule is computed.

Step2. The fuzzy set describing the membership for the THEN-part for each rule is computed according to the membership value of the IF-part.

Step3. Using the union operator in the fuzzy sets obtained in Step2, we can get the final fuzzy set. Finally, the output result is computed using a Defuzzification method.

There are two steps to construct fuzzy inference system for handprint verification:

Step1: Build fuzzy sets for the IF-part

Three measures, C_W, C_{VW} , and D_{FW} obtained by the work done in section 3 are converted into fuzzy sets. For C_W, there are three level of fuzzy sets built, they are CL, CM, and CH which mean that the levels of similarity in C_W is low, median, and high, respectively. Similarity, VL, VM, and VH are fuzzy sets for C_{VW}, and FL, FM, and FH are fuzzy sets for D_{FW}. For these fuzzy sets, their membership functions are defined in Figure 5.

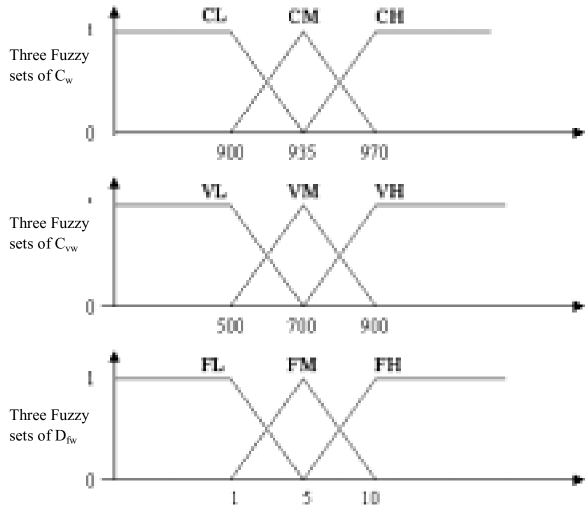

Figure 5. Fuzzy sets for three inputs.

Step2: Build Fuzzy rules

There are three input of this system, and three fuzzy sets for each input. So, there are 27 different permutations of fuzzy sets in IF-part of fuzzy rule. Therefore, there are 7 different fuzzy sets C_0, C_1, …, C_6 in THEN-part which are shown in Figure 6, All fuzzy rules are shown in Figure 7.

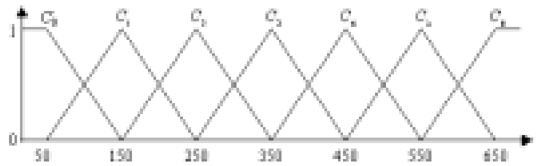

Figure 6. Fuzzy sets of IF-part

5.Experimental Results

In our experiments, a 1152×864 24-bits handprint image is captured from a Kodak DC210 digital camera, and we translated into a grayscale image. The medius part of the image is clip by PhotoShop 5.0 software. The algorithms this paper proposed were tested on an experimental setup to obtain statistics on false rejection rate (FRR) and false acceptance rate (FAR). We totally gathering 108 handprint images from 27 individuals, 4 images from each person. The first two images of each person are set to be training samples, and the last two are test samples. We use training samples to modify system parameters on the chance of better verification rates, and FAR and FRR are the experimental results based on the test samples. The best 5 parameter sets, FAR, and FRR base on the test samples are listed in Table 1. The parameter *dy* is the height of the reference rectangle

If	**CL**	AND	**VL**	AND	**FH**	THEN	$\mathbf{C_0}$
If	**CL**	AND	**VL**	AND	**FM**	THEN	$\mathbf{C_1}$
If	**CL**	AND	**VM**	AND	**FH**	THEN	$\mathbf{C_1}$
If	**CM**	AND	**VL**	AND	**FH**	THEN	$\mathbf{C_1}$
If	**CL**	AND	**VL**	AND	**FL**	THEN	$\mathbf{C_2}$
If	**CL**	AND	**VM**	AND	**FM**	THEN	$\mathbf{C_2}$
If	**CL**	AND	**VH**	AND	**FH**	THEN	$\mathbf{C_2}$
If	**CM**	AND	**VL**	AND	**FM**	THEN	$\mathbf{C_2}$
If	**CM**	AND	**VM**	AND	**FH**	THEN	$\mathbf{C_2}$
If	**CH**	AND	**VL**	AND	**FH**	THEN	$\mathbf{C_2}$
If	**CL**	AND	**VM**	AND	**FL**	THEN	$\mathbf{C_3}$
If	**CL**	AND	**VH**	AND	**FM**	THEN	$\mathbf{C_3}$
If	**CM**	AND	**VL**	AND	**FL**	THEN	$\mathbf{C_3}$
If	**CM**	AND	**VM**	AND	**FM**	THEN	$\mathbf{C_3}$
If	**CM**	AND	**VH**	AND	**FH**	THEN	$\mathbf{C_3}$
If	**CH**	AND	**VL**	AND	**FM**	THEN	$\mathbf{C_3}$
If	**CH**	AND	**VM**	AND	**FH**	THEN	$\mathbf{C_3}$
If	**CL**	AND	**VH**	AND	**FL**	THEN	$\mathbf{C_4}$
If	**CM**	AND	**VM**	AND	**FL**	THEN	$\mathbf{C_4}$
If	**CM**	AND	**VH**	AND	**FM**	THEN	$\mathbf{C_4}$
If	**CH**	AND	**VL**	AND	**FL**	THEN	$\mathbf{C_4}$
If	**CH**	AND	**VM**	AND	**FM**	THEN	$\mathbf{C_4}$
If	**CH**	AND	**VH**	AND	**FH**	THEN	$\mathbf{C_4}$
If	**CM**	AND	**VH**	AND	**FL**	THEN	$\mathbf{C_5}$
If	**CH**	AND	**VM**	AND	**FL**	THEN	$\mathbf{C_5}$
If	**CH**	AND	**VH**	AND	**FM**	THEN	$\mathbf{C_5}$
If	**CH**	AND	**VH**	AND	**FL**	THEN	$\mathbf{C_6}$

Figure 7. Fuzzy rules for handprint identification system.

described in section 2. The parameter WNum is the size of gray-level sequences for each WLIP feature. The parameter YDist is the distance of any two gray-level sequences in the Y-direction. The parameter YMove is the maximal displacement in the Y-direction for the WLIP feature of the input pattern.

6.Conclusion

We have presented a handprint identification system on the basis of three features extracted from the image of middle finger, which are WLIP (Wide Line Integrated Profile), VWLIP(Variation of WLIP), and FW(Finger Width). The correlation function is utilized for similarity measure between two WLIP features and between two VWLIP features as well. The dissimilarity between two FW features is measured using the distance function. All of theses three measures are then converted into fuzzy sets, which represent degrees of similarity. Finally, the identification is accomplished by means of a fuzzy engine.

The experimental results show that our system has some advantages, such as:

(a). Low cost competition: it need only about 120 k bytes per hand data.
(b). High speed in identification: it takes less than 1 second to verify an identity.
(c). High successful identification rate: the FRR(false rejection rate) and FAR(false acceptance rate) are 0.997% and 0%, respectively, and
(d). High user acceptance: it is a non-intrusive technology.
(e). Ease of use: it can run on a personal computer.

However, There is space for improvement of the system such as taking a second finger into account to achieve more precise identification results.

dy	WNum	YDist	YMove	FRR	FAR
51	5	25	1	0.997%	0%
51	5	25	11	1.104%	0%
51	5	25	21	1.14%	0%
51	5	25	31	1.14%	0%
51	5	25	41	1.14%	0%

Table 1. The best 5 parameters and the corresponding FRR and FAR.

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