Design of Contactless Hand Biometric System With Relative Geometric Parameters

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Abstract

The main concern in contactless biometric system is the position of the hand that may vary relatively to camera. This variation of position result in different parameters of hand geometry captured from the same person, in different time, which is a serious problem in identification process. This paper presents a novel contactless biometric verification system based on relative geometric parameters of the hand, as the biometric feature. A webcam captured color image of the hand, which will be transformed into binary image for segmentation, based on thresholding technique. Binary image was extracted to get nine absolute geometrical sizes. The relative geometric parameters derived from ratios between those geometrical sizes were calculated. Feature extraction was processed by scanning technique. Matching was conducted based on match score, which is the output result by feeding relative geometric parameters to backpropagation-trained artificial neural network. Our design provided accuracy of 87.237%, precision of 85.798%, False Match Rate (FMR) of 14.780%, and False Non Match Rate (FNMR) of 10.747%.

Keyword: biometric system, contactless hand geometry, neural network, backpropagation.

I. Introduction

Biometric system plays an important role in the area of identification and verification application and may replaces conventional identity recognition, such as recognition based on password (knowlegde-based) or ID card (token-based). Such identity recognition can be easily lost, forgotten, shared, stolen and manipulated, thereby decreasing its reliability. Biometrics offers recognition process based on human's biological characteristic, which normally can't be separated from personal existence [1].

There are some characteristics that can be used for biometric recognition, such as face, fingerprint, voice, hand geometry, and many others. One of the main aspect in choosing between those characteristics is the user acceptability. Hand biometric is considered to be the most accepted feature because of its simplicity without unnecessary hassle during the process [2]. Hand geometric system has been commercially installed in hundreds locations around the world, such as Schlage HP3000 Ethernet (Fig. 1).

Most of the hand biometric systems that have been developed use contact platform and pegs (Fig. 1) for positioning the hand when capturing the hand image. This system may cause some problems. First, pegs can deform the shape of the fingers.

Fig. 1. Example of commercial hand biometrics: Schlage HP3000 Ethernet. Adapted from: http://www.datamaticsinc.com

Second, contact-based systems makes people feeling hesitated to use it, because of hygiene issue. The solution for those problems is the contactless-based system.

The contactless hand biometric system has several additional problems need to be solved. Two hand images that taken from the same person in different timing may have different position relatively to the camera. The different position makes the extracted geometrical hand size having different value and the comparison therefore cannot be directly delivered.

This paper describes a design of contactless hand biometric verification system, which can be used to solve the contactless variation position problem by using relative parameter of the geometrical hand size as the pattern recognition reference.

II. MATERIAL AND METHOD

Designed system consists of two modules, enrollment module and verification module, as shown in Fig. 2.

Enrollment Module

This module takes part in enrolling the user to the system. It records five biometric data at the beginning, which will be used as training set data in the Artificial Neural Network (ANN).

Verification Module

This module takes part in verification process, which decides whether a user is using an impostor identity or a genuine identity. The ANN was the verifier that makes decision about this verification result. The verification task is to match two

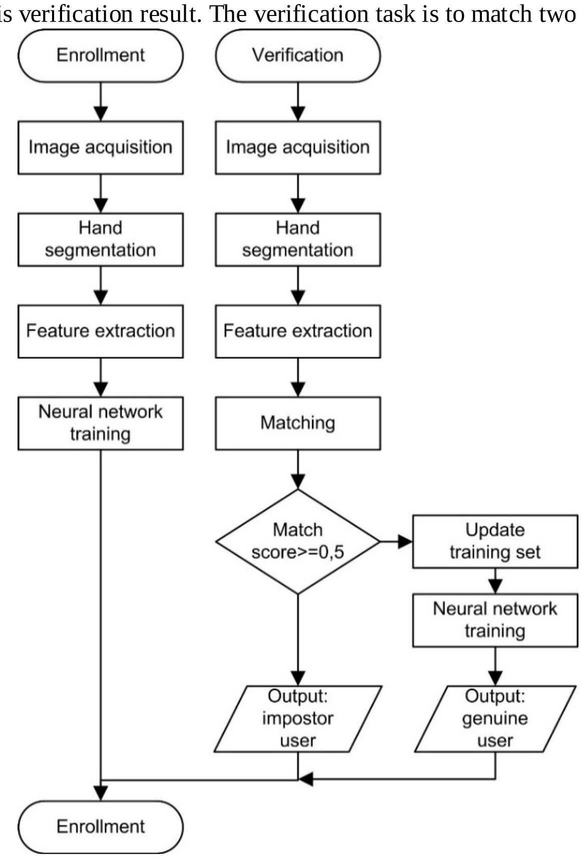

Fig. 2. Proposed biometric system processes diagram

biometric data, user present biometric data and claimed biometric data/biometric reference data, using ANN. The matching result is called match score. If the match score is bigger or equal to 0.5, it is decided as genuine user. If smaller than 0.5, it is decided as impostor user.

Hand geometry size may change in time. So that, the biometric reference data as always updated from the newest accepted biometric data. To take one set of biometric data, camera captures color image of the hand and transforms it into binary image for segmentation. From segmented image, featured will be extracted to get eleven absolute geometrical size (Fig.3).

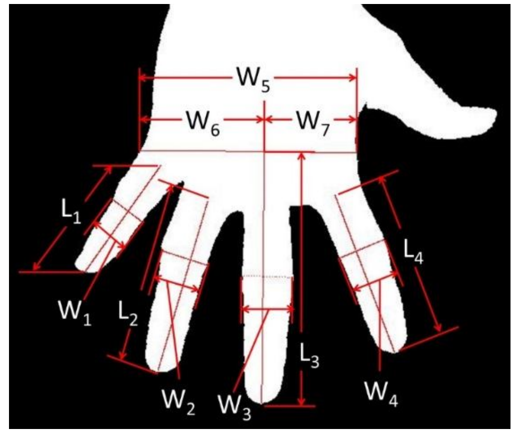

Fig. 3. Measured euclidean distance of hand geometry

The absolute geometrical sizes extracted from two hand images taken contactlessly from the same person in different time will have different value. To overcome this problem, some relative parameters derived from ratios between geometrical sizes are calculated. Those ratios are called relative parameter that can be seen on Table I.

A. Image Acquisition

A webcam is used for image acquisition, with image size of 480x640 pixel. The webcam captures the back side of the hand palm with black background. Hand freely posed witout any contact when the image is captured. But some conditions are applied:

1. The hand palm with all the fingers must be captured.
2. The fingers should not touch each other.
3. The fingers must be in the straightest position.
4. The hand palm must be in the most flat position.

B. Image Segmentation

Thresholding is used to segment the hand region from the background. The segmentation is based on the pixel value using equation (1). With T is the threshold.

$$g(x,y) = \begin{cases} 0, & f(x,y) < T \\ 1, & f(x,y) \geq T \end{cases} \tag{1}$$

The threshold is computed automatically by histogram approach in two steps of processes. First step is to compute the histogram peaks (shown as label μ_1 and μ_2 in Fig. 4) by iterative threshold selection method, as follows [15]:

- $T_{old} = 128$
- Compute $\mu 1$: mean grey level of pixels for which $f(x,y) < T_{old}$
- Compute $\mu 2$: mean grey level of pixels for which $f(x,y) \geq T_{old}$
- $T_{new} = \mu_{1+} \mu_2/2$
- while $T_{new} \neq T_{old}$ do
  - o Compute μ_1
  - o Compute μ_2
  - o $T_{old} = T_{new}$
  - o $T_{new} = \mu_{1+} \mu_2/2$
- end while

Second step is to find final theshold, the local minima between μ_1 and μ_2.

TABLE I
RELATIVE SIZE OF HAND GEOMETRY

No	Relative feature	No	Relative feature
1	$R_1 = L_3 / L_1$	9	$R_9 = W_5 / L_4$
2	$R_2 = L_3 / L_2$	10	$R_{10} = L_3 / W_1$
3	$R_3 = L_3 / L_4$	11	$R_{11} = L_3 / W_2$
4	$R_4 = W_5 / W_1$	12	$R_{12} = L_3 / W_3$
5	$R_5 = W_5 / W_2$	13	$R_{13} = L_3 / W_4$
6	$R_6 = W_5 / L_1$	14	$R_{14} = L_1 / W_1$
7	R7 = W_5 / L_2	15	$R_{15} = L_2 / W_2$
8	$R_8 = W_5 / L_3$	16	$R_{16} = L_3 / W_4$

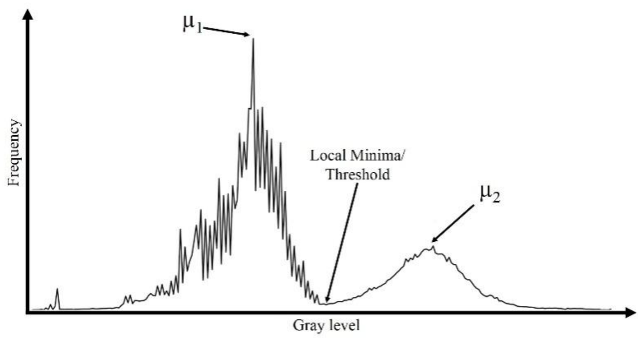

Fig. 4. Segmentation using histogram approach

C. Feature Extraction

Extraction is the process to extract geometrical size that used as biometric feature or biometric data. The absolute geometrical size is calculated as euclidean distance between two pixel coordinate.

The first task of extraction is to rotate the image to make the hand segments be in the same angle when being extracted. The hand segment is rotated so that the middle finger's length axis is parallel with the vertical axis of the image.

After rotating the image, the geometrical size is computed. First, some landmark pixel coordinates must be found by scanning pixel by pixel. Those are x1, x2, until x13 in Fig. 5. This coordinates is used to compute the euclidean distance by pythagoras and trigonometry principles. After all the absolute geometrical sizes are found, those sizes are compared to make ratios as shown in Table I.

D. Artificial Neural Network Training

Every users have their own ANN with different network weights. The weights are adapted with the characteristic of the user hand pattern. The network architecture is feedforward multilayer with one input layer, one hidden layer, and one output layer, as shown in Fig. 6.

ANN must be trained before used in the matching process. Backpropagation is used to train the ANN. The training data are taken from set of data collection from both genuine biometric data and impostor biometric data. The training data taken from impostor user should represent all the impostor user. The training data taken from genuine user just represent the only one user itself. Because of that, ten set of impostor user data and five set of genuine user data are used.

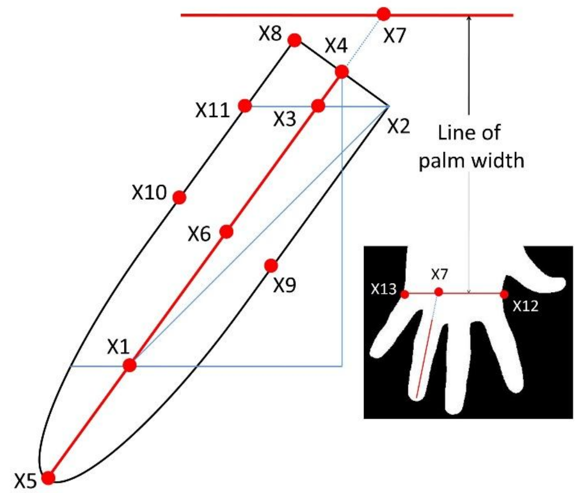

Fig. 5. Approximation of finger measurement

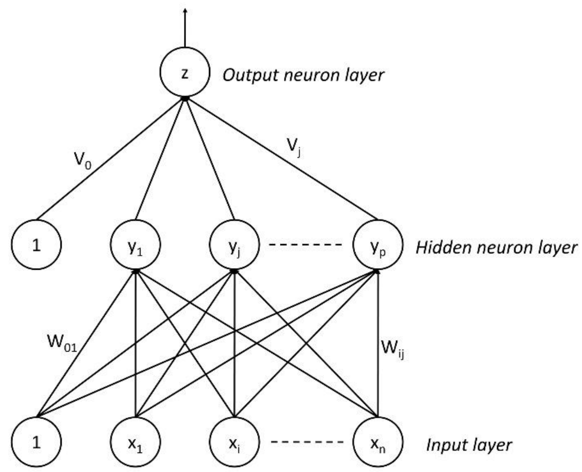

Fig. 6. Artificial neural network used for matching

Hand geometrical size is nonlinear so that the nonlinear activation function should be used. In this system, sigmoid biner is used as ANN activation function. The output is between zero and one. Zero output value represents wrong verification (impostor user) and one output value represents true verification (genuine user).

The training parameters are as follow.

- Total training data set: 15
- Input data: 16
- hidden neuron: 16
- Output neuron: 1
- Learning rate: 0.1
- Mean Square Error (MSE) target : 0.00005

E. Matching

Matching is done based on match score, which is the similarity score between two biometric data. ANN is feed with biometric data and computes the output. If the output is lower than 0.5, verification result is false. If the output is bigger or equal with 0.5, verification result is true.

III. RESULT

Experiment is conducted to know the performance of the designed system by performing verification scenario. Image sample was capture by using a Logitech QuickCam® Pro 9000 for Business with 2 MP of resolution. A 5 watt of lamp was used for controllling illuminance. Both of them is structured as in Fig. 7.

Image sampling consisted of 475 images taken from 20 different person. The number of images taken from each user is various. The hand images were taken with various position of flatness, distance with camera, and closeness of fingers.

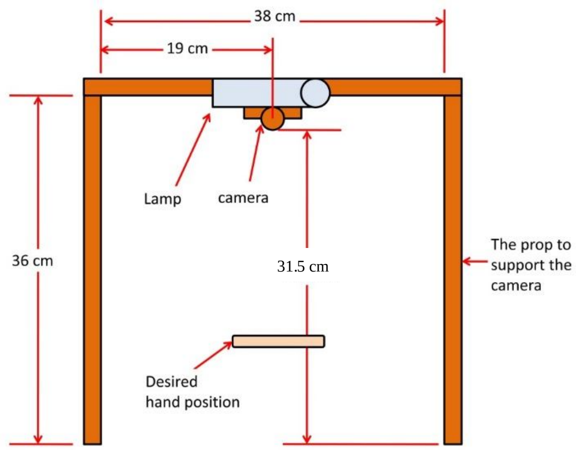

Fig. 7. Testing device

Verification experiment was conducted in two types. They were 375 genuine user verification and 8825 impostor user verification. The experiment was repeated 10 times. The experiment result can be seen in Table II. FP is False Positive, FN is False Negative, TP is True Positive, TN is True Positive, FNMR is False Non Match Rate and FMR is False Match Rate. FP, FN, TP, and TN showed in Table II have been normalized to 100. It is normalized to have equal value of both genuine user verification and impostor user verification.

IV. DISCUSSION

The experiment result shows that the FNMR is 10.747%. It means that if we conduct 100 times of verification, system makes 11 times of false negative or type II error. False negative means that user actually is genuine but system refuses the verification and judges it as impostor. The FNMR is 14.780%. It means that if we conduct 100 times of verification, system makes 15 times of false positive or type I error. False positive means that user is actually impostor but system accepts the verification and judges it as genuine user.

The accuracy rate is 87.237%. It means that system has 12.763% of verification error. 12.763% of verification error means that if we conduct 100 times of verification, system makes 13 times of errors. We don't know the exact errors. We just know it has errors. They can be false negative error or false positive error.

Table II
RESULT OF 10 REPEATED VERIFICATION EXPERIMENT

Para-meters	Minimal	Maximal	Mean	Standard Deviation
FP	14	17	14.78	-
FN	8	15	10.75	-
TP	85	92	89.25	-
TN	83	86	85.22	-
FNMR	8.27%	14.93%	10.75%	2.28%
FMR	13.53%	17.07%	14.78%	1.29%
Accuracy	85.29%	89.10%	87.24%	1.35%
Precision	83.72%	87.15%	85.80%	1.12%

The precision rate is 85.798%. It means that if we have 100 times of true result verification, there are 14 in 100 that should be false verification. The system makes 14 errors.

There are some factors that influence the performance of the system. The system allows a wide range of hand position variations, such as the flatness position variations, distance between hand and camera variations, and fingers position variations. All of these variations have strong contribution in making the difference between geometrical sizes extracted from the same user images.

Proposed segmentation method can't segment the hand and the background image excellently, especially in a bad ilumination environment. The segmentation that wrongly segment the pixels can give contribution to the change of the actual geometrical size. The change of actual geometrical size absolutely decrease the performance of the system.

As a comparison, [3] designs a contact free-hand biometric system for real environment by using a modified webcam. The hand is illuminated by an infra-red light to solve the segmentation problems. It takes approximately 40 wide measures to parameterize each the index, middle, and ring fingers. A Support Vector Machine is used as verifier. A decision level fusion has been used for the final recognition with an EER of 3.4%.

Reference [8] developed a contactless hand biometric system by using 13 measures of absolute geometrical size. Segmentation problem is solved by a nine rule classification to have a boundary walking algorithm. A Support Vector Machine is used as verifier with the result of 92% of accuracy.

Reference [11] uses average width normalization in their contactless hand biometric system. System is tested by data taken from three different public hand database and have 2.5%, 2%; and 1.4% of EER.

V. CONCLUSION

This paper presents a design of contactless hand biometric verification system. The main contribution of this paper is the novel solution using relative parameter of geometrical size to solve the hand position variation problem caused by the contactless platform.

The testing reports an accuracy of 87.237%, precision of 85.798%, *False Match Rate* (FMR) of 14.780%, and *False Non Match Rate* (FNMR) of 10.747%.

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