Smart Access Control With Finger Vein Authentication And Neural Network

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Abstract: Biometrics systems for identification purposes have been developed for decades. Different methods include fingerprint, face, iris, retina, signature, gait, voice, hand vein, hand/finger geometry, DNA information have been proposed while fingerprint, face, iris and signature are considered as traditional identification methods. Each method has its disadvantages. Fingerprint systems usually have low security because they remain after touching a surface, hence patterns can be copied. Similarly, face and voice patterns can easily be cloned. Iris scanning reflects a light into eyes which make the system unfriendly. Contrasting with other biometrics, vein patterns makes the systems more secure and distinguishable because they are hidden inside the body and the situation of outer skin can not effect on that. This study investigated a Smart Access Control using Finger Vein authentication and Neural Network. Fourteen finger vein images collected from individuals by shining a near-infrared light through fingers. Automated image cropping was implemented. Image processing was done for reducing noise of finger vein images. The patterns of veins were extracted by combining two segmentation methods include: (i) Morphological Operation (ii) Maximum Curvature Points in Image Profiles. After extracting the vein image features, Neural Network was used to get the quality of training and testing. Neural Network was also applied for the purpose of recognizing individuals.

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1. INTRODUCTION

With the rapid growing of information technology, individuals are becoming more and more electronically connected. Therefore, achieving the highly accurate automatic personal identification is becoming more critical. Biometrics that refers to identifying individual based on physiological or behavioural characteristics relies on "something which you are or you do" to make a positive personal identification. They are intended to be unique identifiers which cannot easily be transferred between individuals or copied (Thein, Sein, and Aung 2007).

Personal identification technology has been receiving extensive attention in public security and information security domains (Abiyev and Altunkaya 2007). The authentication tools include key; password; magnetic card are not safe enough because they can easily be stolen or forgotten. To achieve higher security, biometric technology has been applied to a wide range of systems including door control systems, public systems and pc login (Wu and Ye 2009).

Biometric technology is a method that uses inherent physiological or behaviour characteristics to identification purpose. Biometric technology has high reliability and security because biometric features are hard to replicate and stolen. Therefore, the convenience of biometric verification system is becoming significant in daily life (Wu and Ye 2009).

Biometric characteristics consist fingerprint, face, iris, retina, signature, gait, voice, hand vein, hand/finger geometry, DNA information, while fingerprint, face, iris and signature are considered as traditional identification methods (Yin 2008).

Contrasting with other biometric traits, Finger vein recognition is a new biometric identification technology using the fact that different person has a different finger vein pattern. Network of blood vessels under person’s skin are Vein patterns. The idea using vein patterns as a form of biometric technology was first proposed in 1992, while researches only paid attentions to vein authentication in last ten years. Vein patterns are sufficiently different across individuals, and they are stable unaffected by ageing and no significant changed in adults by observing. It is believed that the patterns of blood vein are unique to every individual, even among twins (Yin 2008).

Vein patterns are located inside the body. Therefore, it provides a high level of accuracy due to the uniqueness and complexity of vein patterns of the finger. It is difficult to forge. Epidermis status can not effect on recognition system (Lian, Rui, and Chengbo 2008). Finger vein systems provide user-friendly environment. Therefore, finger vein is a good candidate for biometric recognition system.

A biometric recognition system is a pattern recognition system. During biometric recognition, biometric traits are measured and analysed to perform a person's identity. This paper propose a finger vein authentication system by applying Neural Network, the process of proposed system is explained briefly as follows: Near-infrared rays which are generated by a bank of LEDs (light emitting diodes) penetrate to the finger and are absorbed with the hemoglobin in the blood. The areas (veins) that absorb the rays appear as dark areas in an image taken by a CCD (Charge-coupled device) camera which is located on the opposite side of the finger. Image processing and extraction methods as "Gradient-based threshold" and "Maximum curvature points in an image profile" are performed on taken image to segment and extract the patterns and then extracted features are combined for having better recognition . The Neural Network is applied to evaluating the quality of training and testing. Finally Neural Network is trained and tested to perform personal verification and recognition.

2. BACKGROUND OF STUDY

Biometric laws and regulations are in process and biometric industry standards are being tested. Canadian airports started to use iris scan in 2005 to screen pilots and airport workers. Pilots were initially worried about the possibility that repeated scans would negatively affect their vision but the technology has improved to the point where that is no longer an issue (Sarkar et al. 2010). In 2006, Junichi Hashimoto investigated finger vein authentication, a new biometric method which utilize the vein patterns inside one's fingers for personal identification. Vein patterns are different for each finger and for each person, and as they are hidden underneath the skin's surface, forgery is extremely difficult. These unique aspects of finger vein pattern recognition set it apart from previous forms of biometrics and have led to its adoption by the major Japanese financial institutions as their newest security technology (Hashimoto 2006). In 2006, Yuhang Ding, Dayan Zhuang and Kejun Wang illustrated the theoretical foundation and difficulties of vein recognition, at first. Then, the threshold segmentation method and thinning method of vein image were studied deeply and a new threshold segmentation method and an improved conditional thinning method were proposed. The method of hand vein image feature extraction based on end points and crossing points were studied initially, and the matching method based on distances were used to match vein images (Ding, Zhuang, and Wang 2006). Shi Zhao, Yiding Wang and Yunhong Wang, presented a biometric technique using hand-dorsa to extract vein structures. For conventional algorithm, it is necessary to use high-quality images, which demand high-priced collection devices. The proposed method makes using low-cost devices possible (Zhao, Wang, and Wang 2007). Masaki Watanabe, Toshio Endoh, Morito Shiohara, and Shigeru clarified a biometric authentication using contactless palm vein authentication device which uses blood vessel patterns as a personal identifying factor. Implementation of these contactless identification systems enables applications in public places or in environments where hygiene standards are required, such as in medical applications (Watanabe et al. 2005).

3. FINGER VEIN AUTHENTICATION STEPS

This section explains the proposed system and also the results which obtained from the proposed system. The system is examined on fourteen finger vein images of seven individuals. Here, one of the vein images is considered sample to survey the results.

3.1. IMAGE ACQUISITION

The first step in finger vein authentication system is capturing the image of finger veins. The quality of captured image helps to identify the veins of fingers as well. The images are captured using digital camera with CCD sensor and IR filter which is located on the camera with wavelength 700nm to 1000nm and banks of LEDs. Figure 1 shows a sample of finger vein image as follows.

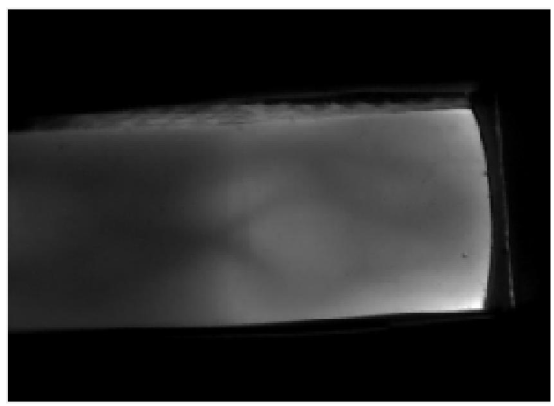


Figure 1. Sample of Finger vein image

3.2. PRE-PROCESSING

The image has been taken by camera has redundant parts which needs to be cropped. The central part of finger vein image can be taken with a command 'imcrop' in Matlab software. Figure2 shows a sample cropping on figure1. This cropping deletes the redundant parts of image and takes only the central part that has the vertical position from 60 to 118 and horizontal position 70 to 200.

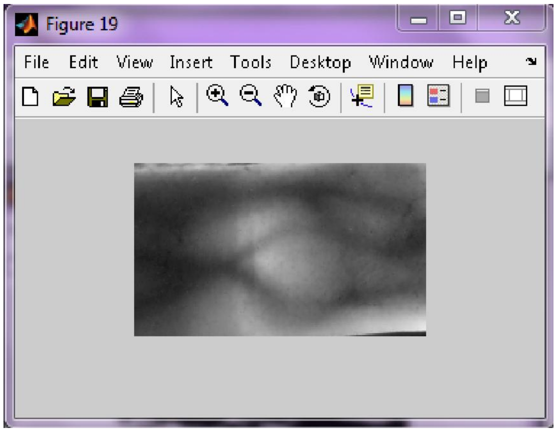


Figure 2. Cropped image

The next step in pre-processing section is reducing the noise of finger vein image to improve the quality. For this purpose, the enhancement functions such as 'filter2', 'medfilt2' are employed. Also, figure 3 shows the image quality after 'filter2' function applying. Figure 4 shows the image quality after 'medfilter2' function applying.

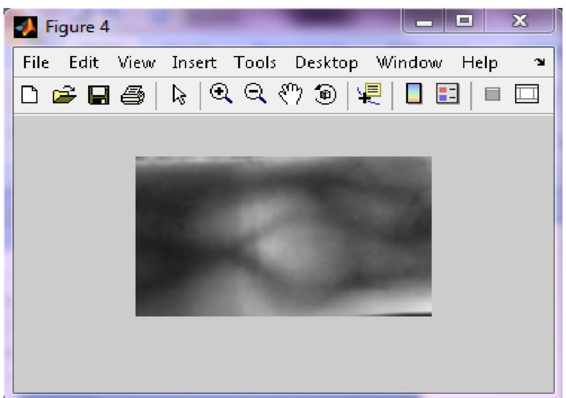


Figure 3. Image quality by after 'filter2' function applying

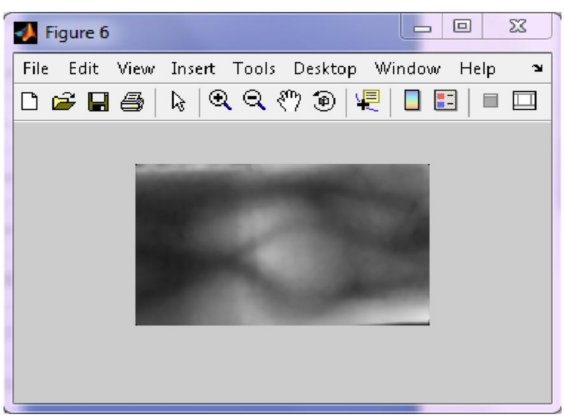


Figure 4.Image quality by after 'medfilter2' function applying

As the final step for image pre-processing, the image contrast can be increased using commands in Matlab such as 'histeq'. Figure 5 shows the image after increasing the contrast. This image is considered as final image in preprocessing step.

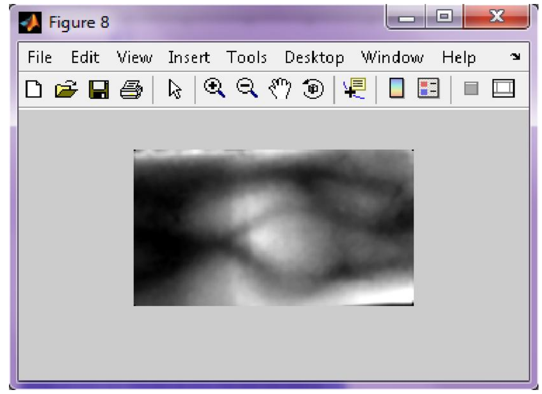


Figure 5. The image after increasing the contrast

3.3. SEGMENTATION AND FEATURE EXTRACTION

In this step, the enhanced finger vein image is segmented and the features are extracted. Since there are different methods for segmentation, two methods of "Gradient-based thresholding using morphological operation" and "Maximum Curvature Points in Image Profiles" which haven't been applied together until now are selected to segment and extract the features.

3.3.1. Gradient-based thresholding using morphological operation

The gradient based methods are popular methods because its efficiency (Green 2002). Therefore, in the paper, gradient based edge detection which apply threshold is considered as the first segmentation method.

In this segmentation, the gradient of image by alpha filter is created. Figure 6 shows the gradient of the finger vein image.

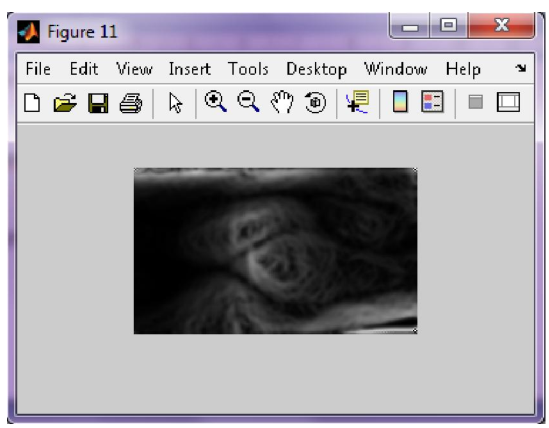


Figure 6. Gradient of the image

The gradient has gradual progress effect from original image colors to target colors by using described alpha in the code. In the next step, iterative thresholding is applied for segmentation. The high gradient values which are more than threshold value in the image fall as edge (Green 2002). Figure 7 shows the edges (vein) have been identified after thresholding.

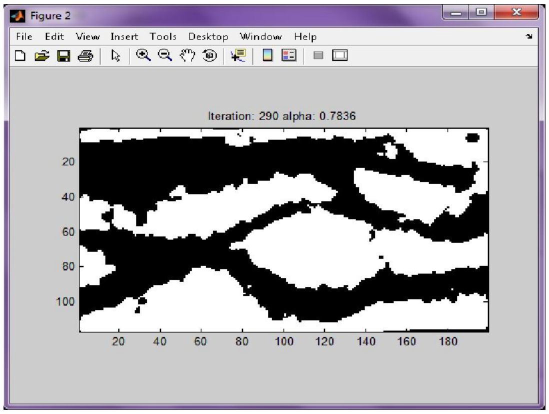


Figure 7. The image after thresholding

In next step morphological operations are used to remove extra pixels, smooth the contour of an image and breaks narrow passages. Since threshold process makes the image binary, therefore morphological operation must be performed on a binary image. Three morphological operations of 'majority', 'opening' and 'bridge' are employed subsequently. The final segmented image is obtained as figure 8.

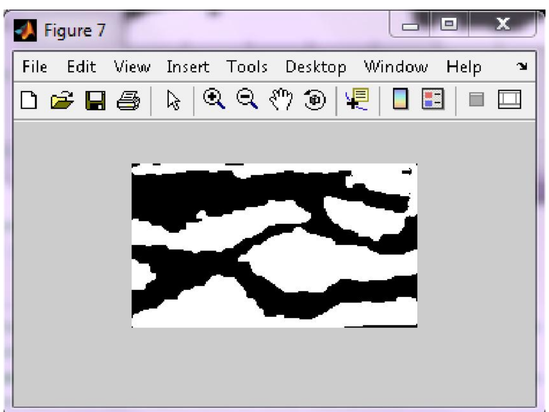


Figure 8.The final segmented image is obtained

3.3.2. Maximum Curvature Points in Image Profiles

The second segmentation method of this system is “Maximum Curvature Points in Image Profiles”. This method checks the curvature of the image profiles in four directions and concentrates only on the centerlines of veins. The positions where the curvatures of a cross-sectional profile are locally maximal define as centerlines of veins. The center points in four directions of vertical, horizontal, oblique1 and oblique2 are combined to obtain the vein patterns. The centerlines obtained from each direction and also the combined centerlines are shown as the following figures. This method is robust against temporal fluctuations in vein width and brightness(Miura, Nagasaka, and Miyatake 2007).

Center points in four directions:

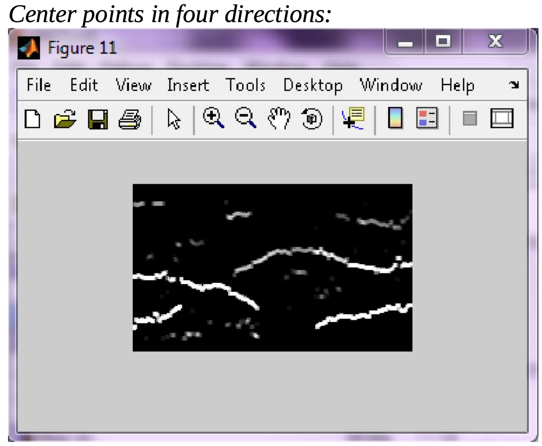


Figure 9. Center points in vertical direction

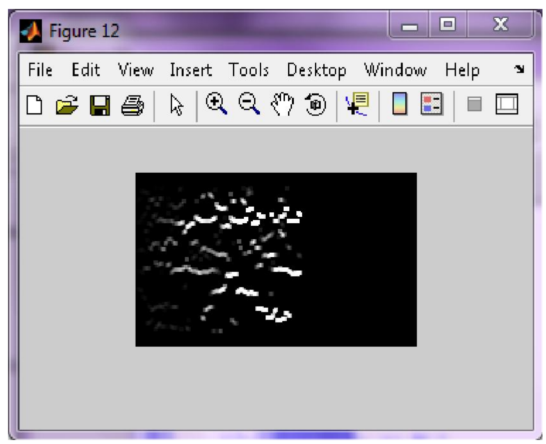


Figure 10.Center points in horizontal direction

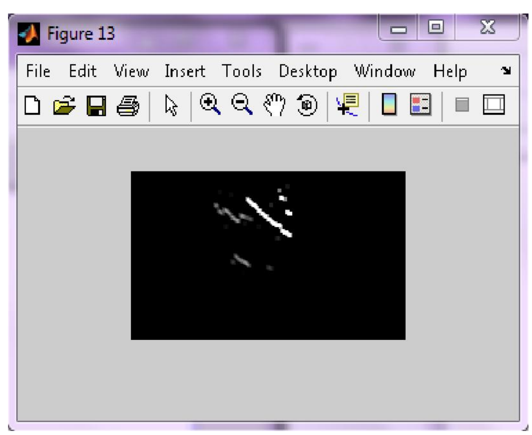


Figure 11.Center points in Oblique1 direction

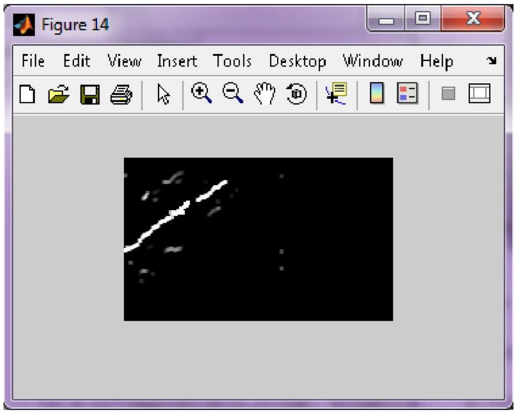


Figure 12.Center points in Oblique2 direction

Combination of Center points in four directions:

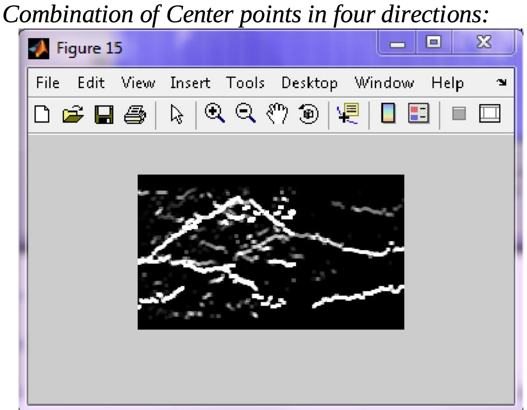


Figure 13.Combining the center points of four directions

After combining the center points in four directions, the noises are removed by 'medfilt2' function in Matlab. Figure 14 shows the result of this filtering.

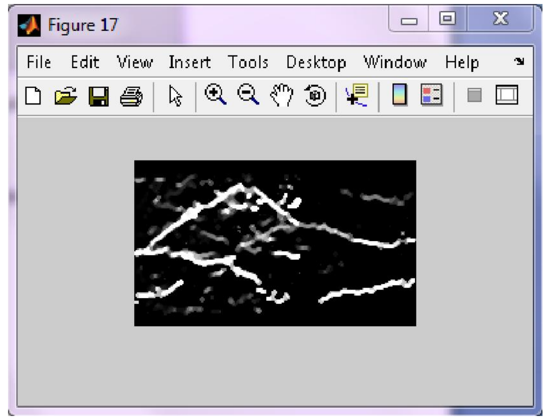


Figure 14. Image after reducing noise

The final veins extraction result is obtained using the second method as shown in figure 14.

After performing two segmentation methods of "Gradient-based thresholding using morphological operation" and "Maximum Curvature Points in Image Profiles ", the features are extracted as the following table.

Table 1. Gathered features of image

	A	B	C	D	E	F	G	H	I	J	K
1											
2		segmentation by morphological operation					segmentation by Maximum curvature points in image profiles				
3		image	sum(~BW2(:))	bwperim(BW2)	bwdist	bwarea(BW2)	CS profile in V direction	CS profile in H direction	CS profile in O1 direction	CS profile in O2 direction	sum(score of curvatures)
4	Afrianto	1	1.29E+04	1.83E+03	6.53E+04	1.05E+04	2.14E+03	1.38E+03	2.99E+02	5.66E+02	3.77E+03
5	Afrianto	1	1.25E+04	1.85E+03	6.24E+04	1.09E+04	2.11E+03	1.36E+03	3.00E+02	5.63E+02	3.73E+03
6	Afrianto	1	1.26E+04	1.81E+03	6.29E+04	1.07E+04	2.14E+03	1.34E+03	2.95E+02	5.58E+02	3.73E+03
7	AlAndra	2	1.05E+04	1.70E+03	4.97E+04	1.28E+04	2.41E+03	1.42E+03	2.67E+02	7.61E+02	4.14E+03
8	AlAndra	2	1.05E+04	1.76E+03	4.88E+04	1.28E+04	2.40E+03	1.40E+03	2.76E+02	7.35E+02	4.13E+03
9	AlAndra	2	1.06E+04	1.68E+03	4.98E+04	1.27E+04	2.43E+03	1.42E+03	2.76E+02	7.59E+02	4.18E+03
10	Aldo	3	1.15E+04	1.75E+03	5.66E+04	1.19E+04	2.72E+03	1.55E+03	3.91E+02	7.62E+02	4.64E+03
11	Aldo	3	1.19E+04	1.73E+03	5.94E+04	1.15E+04	2.69E+03	1.58E+03	4.19E+02	7.38E+02	4.60E+03
12	Aldo	3	1.19E+04	1.73E+03	6.05E+04	1.14E+04	2.70E+03	1.56E+03	3.84E+02	7.60E+02	4.59E+03
13	Fondly	4	1.27E+04	2.06E+03	5.80E+04	1.07E+04	2.57E+03	1.38E+03	3.26E+02	7.80E+02	4.16E+03
14	Fondly	4	1.29E+04	1.98E+03	6.23E+04	1.04E+04	2.57E+03	1.39E+03	3.45E+02	7.74E+02	4.15E+03
15	Fondly	4	1.19E+04	2.02E+03	5.46E+04	1.14E+04	2.57E+03	1.38E+03	3.06E+02	7.31E+02	4.12E+03
16	CunCun	5	8.79E+03	1.68E+03	3.92E+04	1.45E+04	2.46E+03	1.39E+03	3.41E+02	8.21E+02	4.12E+03
17	CunCun	5	9.39E+03	1.65E+03	4.52E+04	1.39E+04	2.45E+03	1.42E+03	3.46E+02	8.04E+02	4.10E+03
18	CunCun	5	8.84E+03	1.68E+03	3.88E+04	1.45E+04	2.50E+03	1.38E+03	3.43E+02	8.42E+02	4.16E+03
19	ChenChihTe	6	6.96E+03	1.52E+03	4.40E+04	1.64E+04	2.22E+03	1.33E+03	2.80E+02	7.35E+02	3.85E+03
20	ChenChihTe	6	1.09E+04	1.91E+03	5.12E+04	1.24E+04	2.22E+03	1.35E+03	2.80E+02	7.52E+02	3.94E+03
21	ChenChihTe	6	9.80E+03	1.84E+03	4.40E+04	1.35E+04	2.19E+03	1.32E+03	2.74E+02	7.16E+02	3.85E+03
22	David	7	1.06E+04	1.66E+03	5.71E+04	1.27E+04	1.78E+03	1.39E+03	3.07E+02	5.25E+02	3.34E+03
23	David	7	1.05E+04	1.65E+03	5.61E+04	1.28E+04	1.77E+03	1.31E+03	2.89E+02	5.41E+02	3.23E+03
24	David	7	1.07E+04	1.67E+03	5.82E+04	1.26E+04	1.82E+03	1.34E+03	2.83E+02	5.64E+02	3.31E+03

3.4. TRAINING AND RECOGNITION USING NEURAL NETWORK

The next step for the proposed finger vein authentication system is training Neural Network using the gathered features of image as table 1 to estimate the quality of training and testing in the model. This assess is performed by comparing the true output and the output of the model. The variance accounted for (VAF) index is usually used for this assessment.

For this purpose, table1 is divided into training and testing tables. Training table includes the first and second records of table1 for each individual as shown in table2.

Table 2. Training table

	A	B	C	D	E	F	G	H	I	J	K
1											
2		segmentation by morphological operation					segmentation by Maximum curvature points in image profiles				
3		image	sum(~BW2(:))	bwperim(BW2)	bwdist	bwarea(BW2)	CS profile in V direction	CS profile in H direction	CS profile in O1 direction	CS profile in O2 direction	sum(score of curvatures)
4	Afrianto	1	1.29E+04	1.83E+03	6.53E+04	1.05E+04	2.14E+03	1.38E+03	2.99E+02	5.66E+02	3.77E+03
5	Afrianto	1	1.25E+04	1.85E+03	6.24E+04	1.09E+04	2.11E+03	1.36E+03	3.00E+02	5.63E+02	3.73E+03
6	AlAndra	2	1.05E+04	1.70E+03	4.97E+04	1.28E+04	2.41E+03	1.42E+03	2.67E+02	7.61E+02	4.14E+03
7	AlAndra	2	1.05E+04	1.76E+03	4.88E+04	1.28E+04	2.40E+03	1.40E+03	2.76E+02	7.35E+02	4.13E+03
8	Aldo	3	1.15E+04	1.75E+03	5.66E+04	1.19E+04	2.72E+03	1.55E+03	3.91E+02	7.62E+02	4.64E+03
9	Aldo	3	1.19E+04	1.73E+03	5.94E+04	1.15E+04	2.69E+03	1.58E+03	4.19E+02	7.38E+02	4.60E+03
10	Fondly	4	1.27E+04	2.06E+03	5.80E+04	1.07E+04	2.57E+03	1.38E+03	3.26E+02	7.80E+02	4.16E+03
11	Fondly	4	1.29E+04	1.98E+03	6.23E+04	1.04E+04	2.57E+03	1.39E+03	3.45E+02	7.74E+02	4.15E+03
12	CunCun	5	8.79E+03	1.68E+03	3.92E+04	1.45E+04	2.46E+03	1.39E+03	3.41E+02	8.21E+02	4.12E+03
13	CunCun	5	9.39E+03	1.65E+03	4.52E+04	1.39E+04	2.45E+03	1.42E+03	3.46E+02	8.04E+02	4.10E+03
14	ChenChihTe	6	6.96E+03	1.52E+03	4.40E+04	1.64E+04	2.22E+03	1.33E+03	2.80E+02	7.35E+02	3.85E+03
15	ChenChihTe	6	1.09E+04	1.91E+03	5.12E+04	1.24E+04	2.22E+03	1.35E+03	2.80E+02	7.52E+02	3.94E+03
16	David	7	1.06E+04	1.66E+03	5.71E+04	1.27E+04	1.78E+03	1.39E+03	3.07E+02	5.25E+02	3.34E+03
17	David	7	1.05E+04	1.65E+03	5.61E+04	1.28E+04	1.77E+03	1.31E+03	2.89E+02	5.41E+02	3.23E+03

Testing table includes the third sample of vein images for each individual as shown in table 3.

Table 3.Testing table

	A	B	C	D	E	F	G	H	I	J	K
1											
2		segmentation by morphological operation					segmentation by Maximum curvature points in image profiles				
3		image	sum(~BW2(:))	bwperim(BW2)	bwdist	bwarea(BW2)	CS profile in V direction	CS profile in H direction	CS profile in O1 direction	CS profile in O2 direction	sum(score of curvatures)
4											
5											
6	Afrianto	1	1.26E+04	1.81E+03	6.29E+04	1.07E+04	2.14E+03	1.34E+03	2.95E+02	5.58E+02	3.73E+03
7	AlAndra	2	1.06E+04	1.68E+03	4.98E+04	1.27E+04	2.43E+03	1.42E+03	2.76E+02	7.59E+02	4.18E+03
8	Aldo	3	1.19E+04	1.73E+03	6.05E+04	1.14E+04	2.70E+03	1.56E+03	3.84E+02	7.60E+02	4.59E+03
9	Fondly	4	1.19E+04	2.02E+03	5.46E+04	1.14E+04	2.57E+03	1.38E+03	3.06E+02	7.31E+02	4.12E+03
10	CunCun	5	8.84E+03	1.68E+03	3.88E+04	1.45E+04	2.50E+03	1.38E+03	3.43E+02	8.42E+02	4.16E+03
11	ChenChihTe	6	9.80E+03	1.84E+03	4.40E+04	1.35E+04	2.19E+03	1.32E+03	2.74E+02	7.16E+02	3.85E+03
12	David	7	1.07E+04	1.67E+03	5.82E+04	1.26E+04	1.82E+03	1.34E+03	2.83E+02	5.64E+02	3.31E+03

Also, another two tables of Trainingoutput and Testingoutput are considered as the following.

Table 4 a) Trainingoutput b) Testingoutput

	A	B
1	Afrianto	1
2	Afrianto	1
3	AlAndra	2
4	AlAndra	2
5	Aldo	3
6	Aldo	3
7	Fondly	4
8	Fondly	4
9	CunCun	5
10	CunCun	5
11	ChenChihTe	6
12	ChenChihTe	6
13	David	7
14	David	7

a

	A	B
1	Afrianto	1
2	AlAndra	2
3	Aldo	3
4	Fondly	4
5	CunCun	5
6	ChenChihTe	6
7	David	7

b

After creating the tables, the Neural Network is trained to assess the quality of training and testing. In training process, the epochs and goal are considered '200000' and '0'. The best run occurred when the performance become close to the goal. After training, as figure 15, the performance becomes '0.183054' from '200000' which is close to the goal '0'.

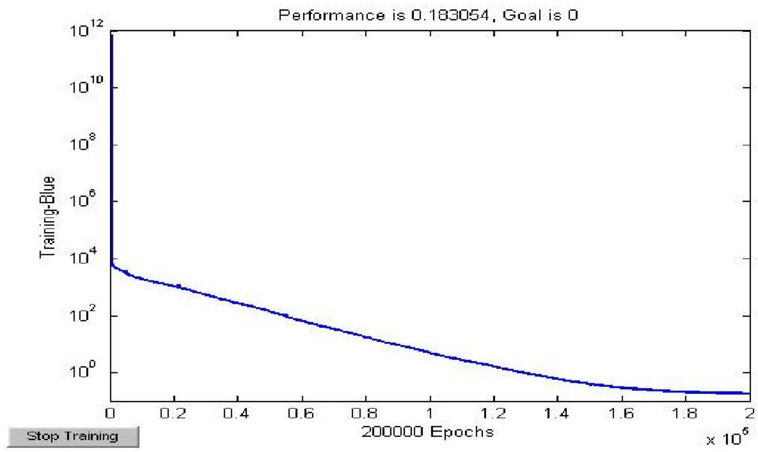
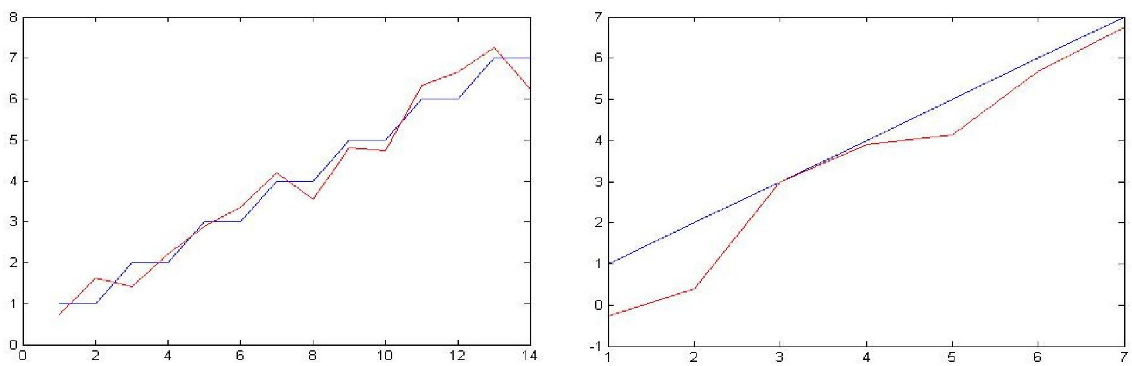


Figure 15.Training process

The results of Neural Network trainig are shown as figure 16. It shows the differences between output and actual output in training and testing.The blue line is output and the red line is actual output.



a b

Figure 16 a) Output and actual output in training b) Output and actual output in testing

The VAF index which obtained at the end of process was 95% for training and 92% for testing as shown in figure 17 .

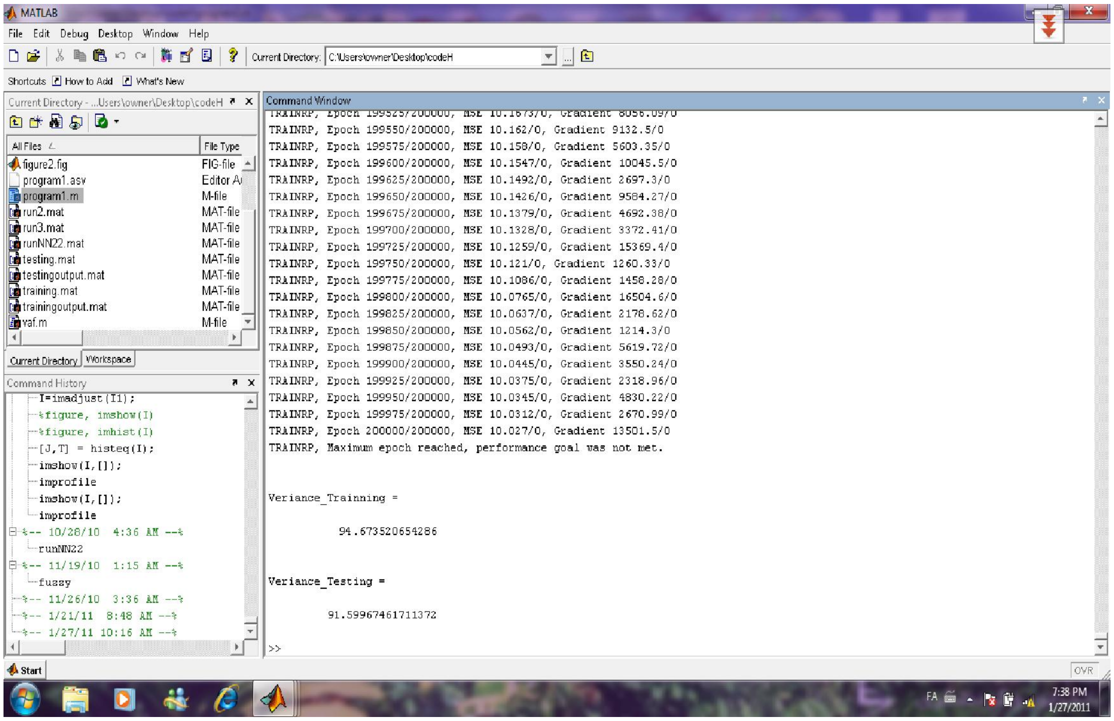
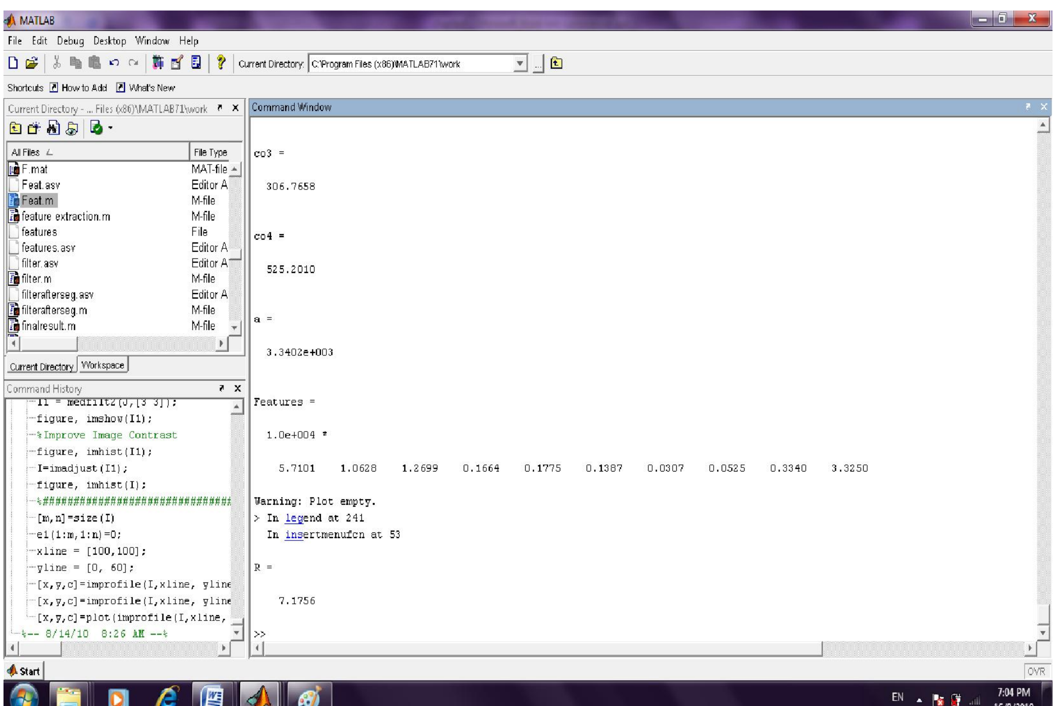


Figure 17. The VAF index for training and testing

In next step, Neural Network is simulated to obtain the result of recognition. It is shown as figure 18.

Figure 18. Simulation result



R=7.1756' shows that the image belongs to the 7th person in the table which was trained as a name of 'David'. Therefore, after achieving R, an individual is recognized and the finger vein authentication is finalized. The finger vein authentication system has been shown as a GUI in Matlab as figure 19.

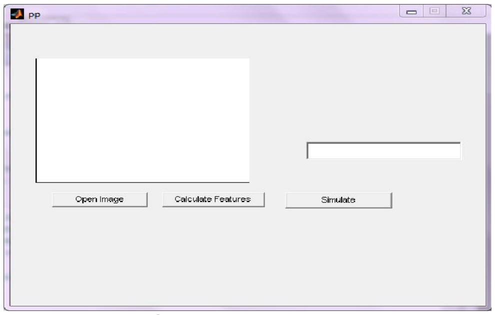


Figure 19. GUI of the system

Also, figure 20 shows the GUI of the system after recognition process. In the GUI, the image and the name of person who belongs to this image is shown as the following.

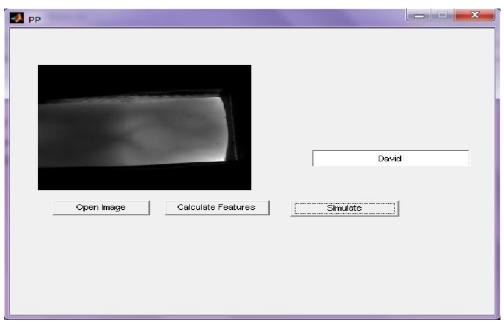


Figure 20. The GUI of the system after recognition process

CONCLUSION

This paper proposed a finger vein authentication system by applying Neural Network. Finger veins patterns and features were extracted using two methods of "Gradient-based threshold" and "Maximum curvature points in image profiles". Then, the obtained features from these two methods were combined to provide precise recognition. Neural Network was employed to train and test the quality of system. Also, it was applied to perform matching and verification. At last, the system showed the name of verified individual in a GUI.

Experimental results of this work show that the system is valid for user authentication purpose even in high security environments, as it was the initial intention given the nature of human finger vein. Results show that the performance of the system is 95% in training and 93% in testing.

Future researches can have improvements on design of image capturing system to take the best quality vein image which has effect on performance and efficiency of the system. Other interesting future line of work are the extension of the proposed system to cope with segmentation and feature extraction tasks which help to precise matching, and also verification and matching tasks in order to enhance individuals verification.

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