International Journal of Applied Sciences & Engineering (IJASE) **2**(1) : April 2014, 13-20

DOI No. 10.5958/2322-0465.2014.01113.7

Personal Verification Through Finger Vein Pattern Recognition Using Support Vector Machine

T. Thilagavathy[1]* and K. Siruba[2]

[1]Embedded System Technologies, K.S.R College of Engineering, Tiruchengode, Tamil Nadu, India.
[2]Department of ECE, K.S.R College of Engineering, Tiruchengode, Tamil Nadu, India.

*Corresponding author : T.Thilagavathy; thilagamahi@gmail.com

ABSTRACT

Biometric based personal verification gains popularity due to the importance of security and privacy protection. The target of this paper was the design and development of a finger vein identification system that could be used by a number of users in an Automated Teller Machine (ATM) environment. Finger vein recognition uses the internal and unique patterns of finger veins to identify individuals at a high level of accuracy. In general, it is identified that it is a great challenge to design a finger vein identification systems that provides a certain level of performance. For this purpose an effective algorithm based on Support Vector Machine (SVM) for finger vein recognition is used. The information of the finger veins extracted based on a Local Binary Pattern (LBP) and Wavelet Transform. Finally, the two score values by the LBP and Wavelet transform is to be combined by the Support Vector Machine (SVM) for image classification. The technique is implemented in MATLAB platform. The Equal Error Rate (EER) and the processing time is reduced when compared to other methods.

***Keywords*:** SVM, LBP, Wavelet transform, Finger vein recognition, ATM, Biometrics.

The problem of truly identifying individuals in our society has become bigger in recent years, due to our complex, mobile and vastly interconnected information society. The most secure way of identifying people is said to be the verification of a concrete entity, naturally belonging to the person: something that he is or that he does. This is what biometrics is: the automated use of physiological or behavioral characteristics to determine or verify identity.

Biometric based personal verification systems are more reliable than password based systems. There are several kinds of biometric recognition systems such as fingerprint (Feifei and Gongping, 2011; Aboalsamh, 2009; Lee, Lee, Kim and Bahn, 2008), face, iris, voice, hand vein (Sathish, 2012), finger vein (Wang, Li and Memik, 2010) etc. All biometric readers work similarly, by comparing the input and the template stored in memory during the process of identification. However, the conventional systems have some problems, in terms of convenience and performance. To overcome those problems, vein patterns such as palm vein and hand vein have been studied. But the size of the devices used for hand vein and vein recognition are too large. So finger vein recognition is preferred in this paper. **Vein recognition** is a fairly recent and advanced technology in the field of biometrics. Finger vein recognition uses pattern-recognition techniques based on images of human finger vein patterns beneath the skin's surface, which can be seen with infrared light illuminators and a camera.

The characteristics (Edgington, 2007) of biometrics depends on the application and some physical characteristics are more secure than others based on the requirements of the application. The finger-vein (Edgington, 2007) is a hopeful biometric for personal identification when considering its security and convenience. The verification process is very fast. The structure of the vein pattern can be captured and subsequently verified based on the light transmission technique. Also, it is difficult to steal internal patterns. Vein pattern recognition technology eliminates the need for PIN numbers, thereby the problems such as loss or theft of cards or passwords can be avoided.

Finger vein patterns are unique (Zhang, Ma and Han, 2006) to each individual. In addition, finger vein patterns remain constant throughout the adult years. Unlike some biometric systems, vein patterns are almost impracticable to forge (Liu, Yin, Wang, Song, and Li, 2010) because they are located beneath the skin's surface. The finger vein ID system is much difficult to fool because it can only authenticate the finger of a living person.

The disadvantages of methodologies for the extraction of finger vein patterns such as repeated line tracking (Miuro, Nagasaka and Miyatake, 2004), Principal component analysis (PCA) (Damavandinejadmonfared *et al.,* 2012), Curvelet (Zhang, Ma and Han, 2006) based extraction etc. are reduced recognition rate because the captured vein images are always not clear. So different methods have to be combined (Park, 2011; CUI and YANG, 2011) to produce more accurate result.

Vein recognition technology is in use or under development for a wide variety of applications that requires very high levels of security including automobile security, end point security, computer and network authentication, hospitals, law enforcement, military facilities and automated teller machines. The system can also be used in banks to effectively manage transactions at bank counters and depositories.

System Description

Finger Vein authentication system matches the vascular pattern in an individual's finger to previously obtained data. The process flow diagram of the project is given in Figure 1. It consists of two stages: Enrollment and verification. The procedures for image acquisition and feature extraction in both stages are similar. The captured image is converted to the acceptable format and preprocessed to enhance the image quality. The processed image was localized (Shahin, Badawi, and Kamel, 2006) to reduce the shadowing problems. In order to localize the finger region from captured images, the masks are used. Then the image is sub-sampled and then the finger vein code was extracted by using the LBP and the wavelet transform.

For enrollment stage after feature extraction the finger vein template database is built and for verification the input finger vein image is compared with the template images.

The processes in each stage were explained in detail in the following sections 2 to 4.

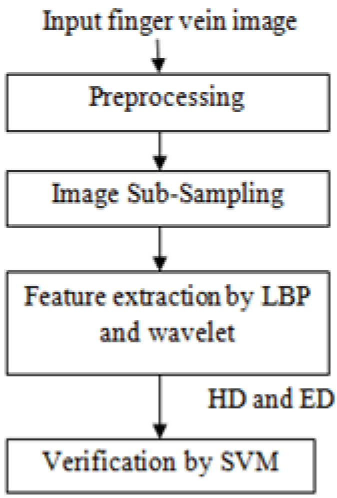

Figure 1: Process flow diagram

Image Acquisition Module

The module used to capture the finger vein image is the Near Infrared (NIR)[7] finger vein sensor based on the principle of light transmission.

To obtain the pattern for the database record and an input image, an individual inserts a finger into an attester terminal containing a near-infrared Light-Emitting Diode (LED) light and a monochrome Charge-Coupled Device (CCD) camera as in figure 2. The hemoglobin in the blood has the property of absorbing near-infrared LED light, so that the vein system appears as a dark pattern of lines which can be captured using the CCD camera.

A near infrared camera used in the system captures the image that flows from a led array from the top of the device through the user's finger to the camera. Because of the near infrared light source the effects to the human as in infrared light can be eliminated.

The amount of light that will be delivered to the sensor will vary according the user's finger thickness.

The camera records the image and the data is digitized, qualified and then sent to a database of registered images.

In the verification stage, the finger is scanned as before and the data is sent to the database for comparison.

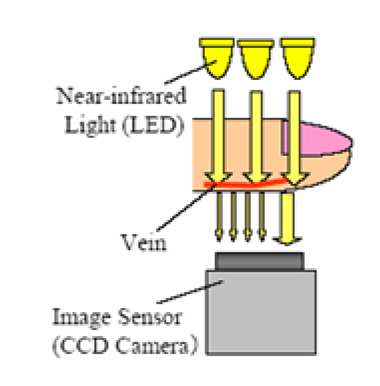

Figure 2: Image Acquisition Module

Image Preprocessing

The preprocessing operation mainly refers to image gray processing, ROI extraction[1](Liu, Yin, Wang, Song, and Li, 2010), size and gray normalization. The original image captured by the device is transformed into an 8-bit gray image based on the gray-scale equation $Y = R * 0.299 + * 0.588 + B * 0.114$, where R, G and B represents the values of red, green, and blue primaries.

As the background of finger vein region might include noise, an edge-detection method used to segment the finger vein region from the gray-scale image. A Sobel operator with a 3×3 mask: It is used for detecting the edges of fingers.

Feature Extraction

To improve the recognition accuracy, global features were extracted by using Wavelet transform (Park, 2011). There are many kinds of Wavelet basis such as Haar, Gabor, Daubechies, etc. Experimental results showed that the EER of finger vein recognition was smallest while using Gabor (Jinfeng Yang *et al.,*) basis for Wavelet transform. Optimal frequency and kernel size of Gabor bases were selected based on the minimum authentication EER (Equal Error Rate) with the training data.

For feature (Yu, Qin, Zhang and Cui, 2009) extraction by wavelet transform, multi-resolution decomposition (Park, 2011) of finger vein region was carried out and then the features were extracted from every sub-region. From that, four sub regions were defined. Then, each sub region was decomposed again and 16 sub regions (two level decomposition) could be obtained. Then, 16 sub regions were decomposed again and obtained 64 sub regions (three- level decomposition. The mean and standard deviations from the 64 sub regions, were measured and obtained 128 features. The number of decomposition level was determined with which minimum EER of finger vein recognition was obtained. Then, the Euclidean Distance (ED) between the extracted feature values and the enrolled ones was calculated. In the previous method (Liu and Song, 2012) the region of interest is to be detected. In the proposed method, a texture descriptor called local binary pattern (LBP) (Nanni *et al.,* 2012; Park, 2011) is utilized as feature extraction technique.

LBP method extracts the finger vein codes in the whole vein region without requiring accurate detection of that region.

The LBP (Park, 2011) is defined as an ordered set of binary values determined by comparing the gray values of a center pixel and the eight neighborhood pixels around the center, the LBP operator extracts a finger vein binary code of M × N × 8 bits, M × N is the size of the image as in figure 3. The binary sequence on the 3 × 3 block is defined clockwise from the top-left.

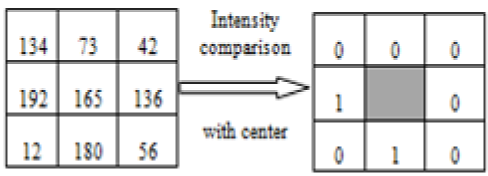

Figure 3: The LBP operator

The hamming distance (HD) is calculated using equation (2) to measure dissimilarities between two binary patterns.

$$HD = \frac{\|LBPCodeA \otimes LBPCodeB\|}{Code\ Length} \tag{2}$$

Where —” is a Boolean Exclusive-OR operator between the two binary patterns. The LBP feature of image in the database and the input image is denoted by LBPCodeA and LBPCodeB respectively.

Personalized Best Bit Map

In general, many samples can be captured from an individual, and the corresponding LBP Codes can be acquired through the extraction of LBP features from each sample.

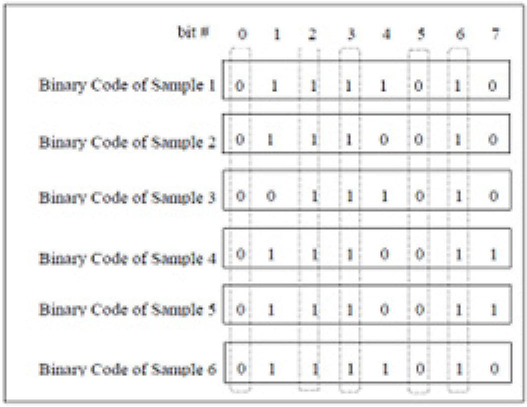

Figure 4: Example Binary code samples

When investigating these LBP Codes of samples from the same finger vein, the values of the bits in same location of LBP Codes have different behavior. The values of some bits are either 1's or 0's; the values of some bits may have majority of 1's or 0's; the values of some bits interlace 1's and 0's.

Example of LBP Binary Codes of six samples from a certain individual is shown in figure 4. Actually, the values of bit6, bit5, bit3, bit2, bit0 are very consistent i.e., the values are mostly 1's, the values of bit7 are primarily 0's, and bit4 has the values interlaced between 1's and 0's.

If a bit has different value, it is considered as a noisy bit, which may have a negative effect on recognition performance. These consistent bits can be acquired through samples from same individual, record their values and locations in LBP Code (Damavandinejadmonfared *et al.,* 2012).

By doing this, when verifying a test sample, the values of bits are just compared at the same location as consistent bits. This may provide better performance in recognition and time consumption than comparing all bits.

Image classification - Support Vector Machine (SVM)

Support vector machine is used as a recognition algorithm to combine the extracted features by LBP and wavelet transform.

A set of input data is given as an input to the SVM linear classifier. For every given input it predicts, which of two possible classes produces the output. Given a set of training samples, each mentioned as belonging to one of two categories, an SVM training algorithm developes a model that assigns new samples into one category or the other.

The two distance values (Hamming Distance (HD) and Euclidean Distance(ED)) calculated by LBP and wavelet transform were used as the input values of the SVM.

The output value of the SVM is represented by a continuous (Park, 2011) value. A value that is close to 1 represents an authorized user and a value that is close to ”1 represents an imposter.

Experimental Results

The experiment was simulated in MATLAB R2009a. When measuring for the same user, the HD and ED was close to 0 and when for imposter users, the HD and ED was close to 1.

Based on these values the SVM produces the result that displays the corresponding image which is the equivalent image in the database for the input vein image. The result of the vein recognition with the proposed method is shown in figure 6. This provides the approximate vein image for the given input and

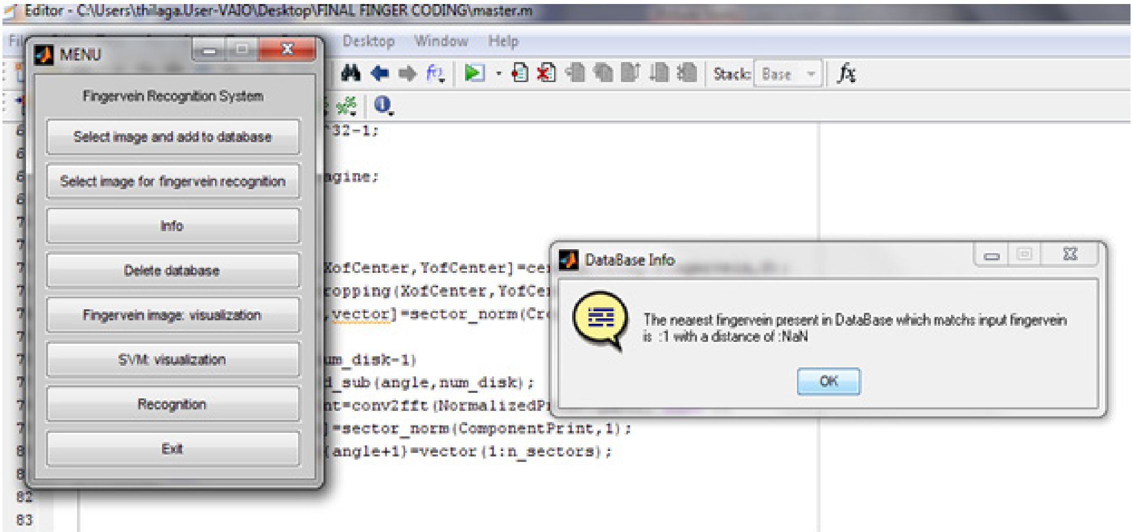

Figure 6 : Simulation result of the proposed method

the message which indicates that the image has the value nearer to the acceptable distance value (NAN in figure 6) which indicates the authorized person. The processed image can also be visualized at the time of recognition process.

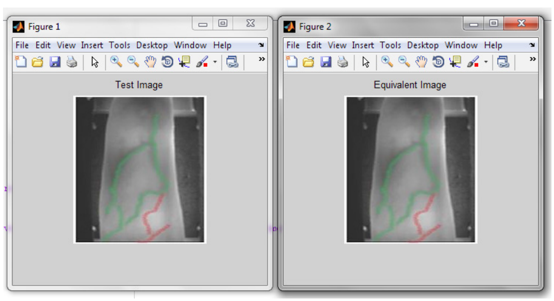

Figure 7: Simulation result for the given input vein image

The database consists of train and test images for the SVM. By selecting the recognition option from the menu the test image (left image in figure 7) can be given as input and then the given input test image and its equivalent image (right image in figure 7) from the train database will be displayed as in figure 7. When the recognition is successful further processes in ATM transaction will be continued.

When the input image of unregistered user was found it displays the error message as in figure 8 so that the unknown persons cannot access the account.

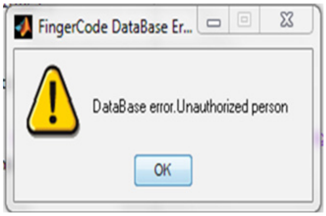

Figure 8: Error message for unauthorized user

Recognition performance of the biometric methods is measured based on the EER. EER is the rate at which the false acceptance and false rejection rate are equal. For better accuracy EER (Luo *et al.,* 2010) value should be low. From the survey (Park, 2011) the EER of the SVM based recognition with LBP and wavelet features is less when compared to other methods such as fractal (Liu and Shangling Song, 2012), Repeated Line Tracking (RLT), Curvelet based, FPGA (Khalil-Hani and Eng, 2011) based recognition.

From the experimental results using the proposed method for 100 images of 10 fingers the EER of the proposed method is calculated as 0.01%. From the observation, EER of the recognition process using proposed method is less and thus the proposed method provides better accuracy.

Conclusion

Finger vein authentication technology offers contactless (Liu, Yin, Wang, Song, and Li, 2010) authentication and provides a hygienic solution, thus promoting a high-level of user acceptance. From the experiments in MATLAB recognition using SVM provides a better result in terms of accuracy and processing time. Vein print is extremely difficult to forge and therefore contributes to a high level of security, because the technology extracts the patterns by infrared absorption of hemoglobin flow through veins internal to the body. Vein recognition systems are smaller in size. Because of the security considerations and the portability the system is suitable for ATM authentication process.

References

G Sathish *et al.,* 2012, "Personal Authentication System using Hand Vein Biometric", *International Journal of Computer Technology and Applications*, **3**(1):383-391.

Jinfeng Yang *et al.,* "Finger-Vein Recognition Based on Gabor Features", available at www.intechopen.com.

Kang Ryoung Park, 2011, "Finger vein recognition by combining global and local feature based on SVM", Computing and Informatics, **30**.

Loris Nanni *et al.,* 2012, "Survey on LBP based texture descriptors for image classification", Expert Systems with Applications, **39**:3634–3641.

M.Khalil-Hani and P.C.Eng, 2011, "Personal verification using finger vein biometrics in FPGA based system-on-chip", 7th International Conference on Electrical and Electronics Engineering.

Feifei CUI and Gongping YANG, 2011, "Score level fusion of fingerprint and finger vein recognition", *Journal of Computational Information Systems*.

D.Wang, J.Li and G.Memik, 2010, “User identification based on finger vein patterns for consumer electronic devices”, IEEE Transactions on Consumer Electronics, **56**(2).

Z.Liu, Y.Yin, H.Wang, S.Song, and Q.Li, 2010, “Finger vein recognition with manifold learning”, *Journal of Network and Computer Applications*, **33**(3).

Hao Luo *et al.,* 2010, “Survey of vein recognition techniques”, *Information Technology Journal* **9**(6): 1142-1149.

Hatim A Aboalsamh, 2009, “Vein and fingerprint biometrics authentication – Future trends”, *International Journal of Computer and Communications*, **3**.

Cheng-Bo Yu, Hua-Feng Qin, Lian Zhang, Yan-Zhe Cui, 2009, “Finger-vein image recognition combining modified hausdorff distance with minutiae feature matching”, *Journal of Biomedical Sci. and Engineering*, 261-272.

H.Lee, S.Lee, T.Kim and Hyokyung Bahn, 2008, “Secure user identification for consumer electronic devices”, *IEEE Transactions on Consumer Electronics*, **54**(4).

Ben Edgington, 2007, “Introducing Hitachi’s Finger Vein Technology”, A White Paper.

M.Shahin, Ahmed Badawi, and M.Kamel, 2006, “Biometric authentication using fast correlation of near infrared hand vein patterns”, *International Journal of Biological and Life Sciences*.

P.Corcoran and A.Cucos, 2005, “Techniques for securing multimedia content in consumer electronic devices using biometric signatures”, *IEEE Transactions on Consumer Electronics*, **51**(2).

Naoto Miuro, Akio Nagasaka and Takafumi Miyatake, 2004, “Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification”, *Machine Vision and Applications*.

Masaki Watanabe, “Palm vein authentication”, 1Fujitsu Laboratories Ltd., Research Center for Image Processing and Biometrics Technologies, Tiburon Enterprises LLC.

Sepehr Damavandinejadmonfared *et al.,* 2012, “Finger Vein Recognition using PCA-based Methods”, World Academy of Science, Engineering and Technology **66**.

Xianjing Meng, Gongping Yang, Yilong Yin and Rongyang Xiao, 2012, “Finger vein recognition based on Local directional code” *sensors* pp. 14937-14952.

Z. Zhang, Siliang Ma and Xiao Han, 2006, “Multiscale feature extraction of finger vein patterns based on curvelets sand local interconnection structure neural network”, *IEEE*.

Zhi Liu and Shangling Song, 2012, “An embedded finger vein recognition system for mobile devices”, *IEEE Transactions on Consumer Electronics*, **58**(2).