Finger Vein Authentication Using Enhanced Feature Extraction and SVM Techniques

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ABSTRACT

In today's society, the identity verification is a serious key problem with the rapid development in the domain of computer and network technology. Hence, the necessity for a superior and more consistent methodology for identity authentication becomes more prominent. As biometric identifiers are relatively tough to counterfeit, mislay or share, biometric recognition approach appears to be more effective and reliable than conventional passwords or PINs. Owing to its low forgery risk, consistency and aliveness detection, Finger Vein Recognition (FVR) has emerged to be the most promising and novelist biometric technique. Finger vein pattern is defined as the hypodermic vein structures arbitrarily developing a network of blood vessels underneath the skin of a finger to recognize individuals at a very high level of accuracy. However, it is challenging to extract a more reliable and accurate finger vein pattern due to the random noise, low contrast, illumination variation, image deformation and blur. Not much research has been conducted on effective frequency domain feature extraction techniques, hence, considering the above issues, this research presents an efficient feature extraction approach which employs the Local Directional Pattern (LDP), which is robust in the existence of random noise, ageing effects as well as illumination changes. Support Vector machines (SVM), which is a powerful machine-learning binary classifier, is implemented in order to enhance the recognition performance by classifying finger vein patterns as either imposter or genuine. The experimental results demonstrate that the proposed approach achieved significant performance and better classification accuracy on HKPU database. An accuracy of 97.5% with an Equal Error Rate of 0.81% is achieved indicating superior results over existing techniques.

***Keywords**: Biometric Recognition, Finger Vein, feature extraction, Support vector machines.*

I. INTRODUCTION

Rapid developments of science and information technology lead to a major security issue that needs an immediate solution. Due to the growing demand of user-friendly and stringent personal identification, biometric authentication has become a booming research area for decades. The design of efficient biometric recognition systems is nowadays a challenging and pertinent task for both the scientific and the industrial communities.

Conventional approaches such as passwords, keys, and PINs carry the threats of being forged, stolen, or lost [1]. Hence, it gives rise to an efficient technique

of identity recognition against digital impersonation based on biological features. Hand-based biometrics commonly include fingerprint recognition, finger knuckle print recognition, and palm print recognition. However, all of these features are external to human bodies and hence, are more prone to forgery.

Out of these biometric techniques, finger vein biometric has drawn great attention and gaining popularity. The finger vein authentication system is more efficient and reliable and can solve many difficulties faced by conventional biometrics techniques. From the security and convenience point of view, the finger-vein is a promising biometric pattern as the vein pattern is defined as the vast network of blood vessels underneath the skin of a particular part of a human body [2]. Veins features are unique, robust, stable and largely hidden patterns. In addition, vein patterns are much difficult to be observed, damaged, changed or forged.

In comparison to other biometric features, the finger-vein is more valuable because of these benefits as listed: a) Internal characteristic i.e., it is difficult to forge or replicate finger vein, b) The non-intrusive and contactless acquisition of finger-vein patterns are more convenient and hygienic for the user, and hence, it is more adequate and suitable. c) Living body identification i.e., only vein in the finger of the living person can be captured [3].

Regardless of advantages, there are some challenges that need to be overcome to attain high accuracy and recognition performance. The main challenges are poor lighting, recognition rate and robust feature extraction [4].

A typical finger vein recognition system comprises of four key stages which comprises image acquisition, image preprocessing, feature extraction, and *matching* as shown in Fig.1.

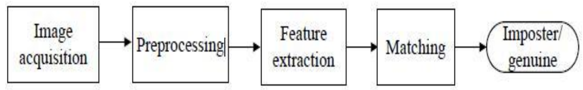

Figure 1. Block diagram of finger vein recognition

It is observed that finger vein recognition is a rigorous and challenging task because of low image contrast, uneven-illumination, image deformation and blur, intensity fluctuations and temperature variations. Therefore, this paper proposes a robust feature extraction technique LDP.

The rest of the paper is structured as follows:

Literature survey is introduced in Section II. Section presents materials and methods for finger ein recognition. Section IV provides experimental results and discussions. Finally, conclusion of this paper is reported in section V.

II. LITERATURE SURVEY

In this section, various finger vein feature extraction and recognition methods reported in the literature are reviewed. Several finger vein feature extraction and classification techniques have been developed in the recent past. A satisfactory level of recognition performance has not yet been achieved. Wu et.al [5] proposed finger vein verification system consisting of image pre-processing and pattern classification. In this work, principal component analysis (PCA) and linear discriminant analysis (LDA) are applied to the image pre-processing as dimension reduction and feature extraction. For pattern classification, this system used an SVM and adaptive neuro-fuzzy inference system (ANFIS). The features are then used in pattern classification and identification. . It is concluded that SVM shows better performance. Souad et al, [6] presented a finger vein recognition system using Support Vector Machine (SVM) based on a supervised training algorithm. Two pre-processing schemes are employed in order to assess the efficiency. Simulation results show that using Gabor filters in pre-processing for codifying the venous network and SVM for the classification can improve the recognition rate when compared to the existing methods but takes extrensive processing time. Lu Yang et.al [7] evaluated the quality of finger vein images using SVM with classifying the finger vein images into two classes namely, high and low quality finger vein images. Kuan-Quan Wang [8] used SVM for classification but they used the Gaussian filter in the preprocessing and the LBPV (Local Binary Pattern Variance) for the feature extraction. This method is not robust to noise, blur and deformation. Yang et.al [9] proposed an efficient method for finger vein recognition based on a personalized best bit map (PBBM). This method is rooted in a local binary pattern based method and then inclined to use the best bits only for matching. PBBM achieves not merely improved performance, but also high robustness and reliability. In addition, PBBM can be used as a general framework for binary pattern based recognition. Sikarwar et al [10] presents finger vein recognition using different types of local directional patterns to achieve best results in terms of classification accuracy. In this paper, different techniques of LDP were analysed to make finger vein recognition reliable. LDP is used to compute the edge response in all eight directions and considering each pixel position. Syarif et.al [11] addressed the limitations of traditional MCM and proposed an integrated Enhanced Maximum Curvature (EMC) method with Histogram of Oriented Gradient (HOG) descriptor for finger vein verification. Unlike MCM, EMC incorporates an enhancement mechanism to extract small vein delineation that is hardly visible in the extracted vein patterns. Next, HOG is applied instead of image binarization to convert a two-dimensional vein image into a one-dimensional feature vector for efficient matching. Experiments show promising verification results for when EMC+HOG+SVM is applied.

Kalaimathi et.al [12] introduced an approach in which the finger vein patterns are pre-processed, features are extracted by applying Gradient boosted feature algorithm technique and labeled using SVM classifier and they are used for authentication purpose. This work is based on Gradient algorithm for feature extraction on all points of gradient of vein, by which the amount of information required for extraction and authentication can be increased. This method is computationally complex and not robust to illumination changes.

Zhou et.al [13] described a new superpixel-based finger vein recognition method in which, two types of effective superpixels, namely stable and discriminative superpixel are developed to represent finger vein image and these superpixels are expected to play different roles in matching stage. Then, the two types of superpixels are combined utilizing a reversible weight-based fusion method in score level. This approach does not take into consideration the consistent directional characteristics of an image.

III. MATERIALS & METHODS

In this paper, a Finger Vein Recognition framework, based on the robust and more efficient feature extraction technique, is proposed that extracts features using the Local Directional Pattern (LDP) technique. The resultant feature vector is applied as an input to the SVM to perform classification of finger vein images as either imposter or genuine. The methodology is described in detail as follows:

A. Image Acquisition

The data utilized in this paper was taken from the publicly available dataset namely Hong Kong Polytechnic University (HKPU) finger vein database This dataset contains 6,264 images obtained from 156 subjects. The finger images were taken in two different sessions. The second session took place at an interval 11 months after the first session. Six image samples of the index and middle fingers of both hands were taken from each subject. Therefore, each subject provided 24 images in one session. All images were in bmp format of 580 * 380 pixel size [14]. For the analysis, a total of 2,580 finger vein images were considered, from which 1,290 were from the first session and 1,290 were from the second session.

B. Image Pre-processing

The Finger vein image data set (training and testing) is pre-processed using image enhancement, normalization, segmentation etc. as the original finger vein image is always low in contrast due to background noise, environment lighting and intensity fluctuations. Therefore, image pre-processing is essential to extract ROI for a more efficient finger vein feature extraction.

C. LDP Feature extraction

Extensive feature dimensions can cause huge computation and the memory cost of the classifier training and classification. However, it is difficult to extract a more accurate finger vein pattern due to the various vein thickness, disparities in illumination, low contrast region, image deformation and existing noise. Feature extraction is the process of converting an input set of images into a set of features. The finger vein feature extraction accuracy is thus adversely affected and the recognition performance of the system is degraded. Conventional feature extraction methods does not take into consideration the consistent directional characteristics and local phase information of an image.

After pre-processing, the essential features are extracted from the finger vein images using the proposed feature extraction technique Local Directional Pattern (LDP) which is insensitive to image deformation, illumination changes, aging effects and random noise.

a) Local Directional Pattern (LDP)

There is a requirement for efficient feature descriptor LDP, which is robust enough to provide consistent representation in the existence of random noise and non-monotonic illumination variation, aging effects, and lighting conditions. This method, based on the known Kirsch kernels, was proposed by Jabid et.al (2010) [10]. A LDP feature is obtained by computing the edge response values in all eight directions at each pixel position and generating a code from the relative strength magnitude. The LDP method assigns an 8-bit binary code to each pixel of an input image. This method results in a histogram and used as 186-dimensional feature vector. This LDP descriptor considers the edge response values in diverse directions instead of pixel intensities, hence offers more consistency in the presence of noise The corresponding LDP histogram is fed as input to SVM in order to perform classification of the testing images. The results of feature extraction are demonstrated in Sec. IV.

D. Support vector machines

A Support Vector Machine (SVM) is a machine learning classifier which, given labelled training data builds an optimal separating hyperplane which categorizes new data instances [6]. A good margin or separating hyperplane is the one where this parting is greater for both the classes. The objective of the SVM is not only to find a separator between the classes but finding the optimum hyper plane. A SVM with radial basis kernel function has been implemented in this paper. The framework of the proposed finger vein recognition approach is as shown in Fig.2

IV. RESULTS & DISCUSSIONS

A. LDP Feature extraction results

The dataset is divided into training set and testing set respectively. For each image, the corresponding LDP histogram is obtained and applied as feature vector. In the end, it is concatenated to obtain an accumulated feature set consisting features of all images. The finger vein images along with their ROI extraction and the corresponding LDP histogram is as shown in fig. 3.

B. Classification results

A binary classifier based on support vector machines was trained to develop a training model which classifies the finger vein images as either imposter or genuine. The classification performance is evaluated on the basis of two parameters- accuracy, and Equal Error Rate (EER). The proposed technique is tested on the HKPU database and SVM is efficiently able to classify the data with overall accuracy of 97.5%, and EER of 0.81%.

It is observed that the proposed approach achieves promising verification results in comparison to the previous approach EMC+HOG+SVM [11].

The LDP feature extraction approach yields remarkable results when SVM is applied as a classifier. Table 1 and Table 2 demonstrates the accuracy and EER of previous and proposed approach based on different size of feature sets.

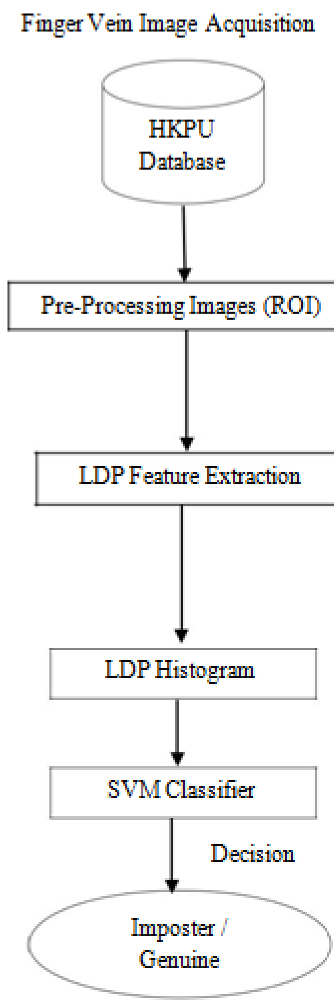

Figure 2. Framework of Proposed approach

Table 1. Accuracy based on different size of feature sets

Features	50	100	All
EMC-SVM [11]	95.28%	95.15%	95%
Proposed	97.75%	97.6%	97.5%

Table 2. Equal Error Rate (EER) based on different size of feature sets

Features	50	100	All
EMC-SVM [11]	0.87%	0.98%	1.06%
Proposed	0.67%	0.73%	0.81%

V. CONCLUSION

A robust feature extraction technique LDP for finger vein recognition is proposed in this paper. This approach is insensitive to illumination variation, image blur and deformation and random noise and satisfactory recognition results were obtained. The recognition performance is evaluated using most widely used machine learning tool i.e. Support Vector Machine to classify the finger vein images as either imposter or genuine. It is observed that the proposed approach has outperformed the EMC-SVM approach by reporting promising recognition results and EER is quite low as well.

Further work can be done to improve the efficiency and security of the system by developing a multimodal approach i.e. combining finger print, finger vein and finger knuckle texture patterns for a more secure user authentication.

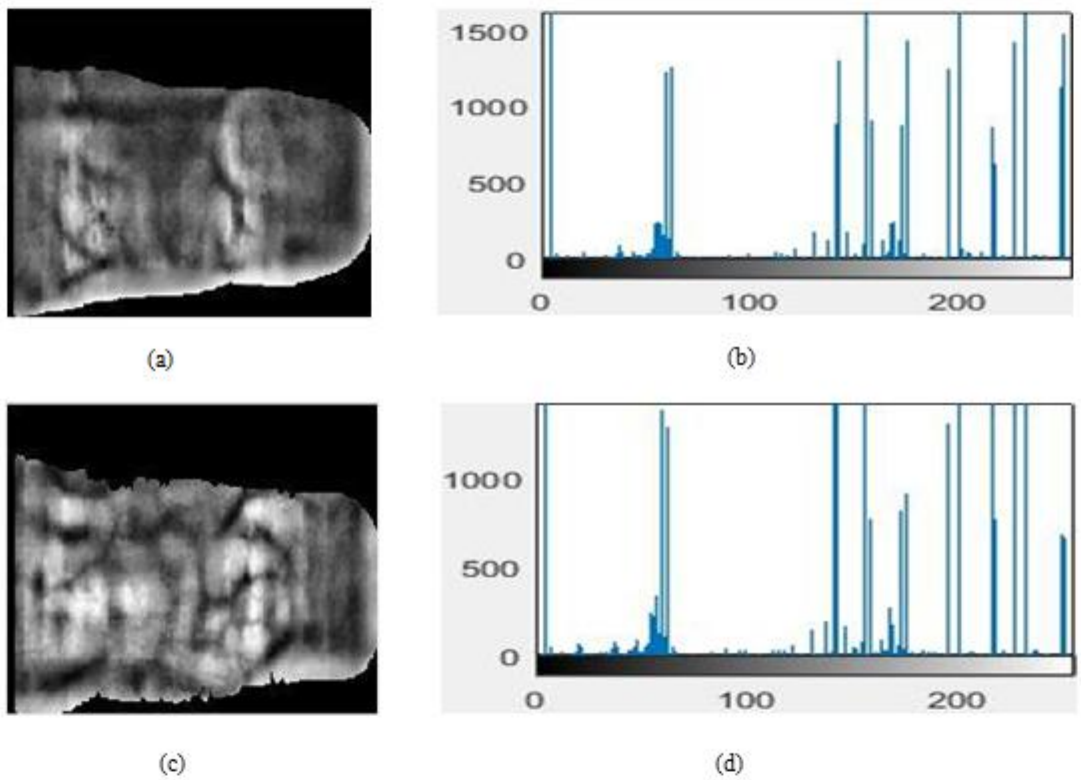

Figure 3. LDP feature extraction results (a) First sample finger vein ROI image (b) LDP Histogram (c) Second sample finger vein ROI image (d) LDP Histogram.

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