EFFICIENT INTEGRATED MODEL FOR FEATURE DESCRIPTOR AND TEXTURE CLASSIFIER USING WDOLBP HISTOGRAM FORHAND-DORSA VEIN RECOGNITION SYSTEM

C. PREMAVATHI
Part-Time Ph.D Scholar, Periyar University, Salem, Tamil Nadu, India,
Assistant Professor, Department of Computer Science,
Navarasam Arts and Science College for Women,
Arachalur, Tamil Nadu, India

Dr. P. THANGARAJ
Professor and Head,
Dept. of Computer Science and Engineering,
Bannari Amman Institute of Technology,
Sathyamangalam, Tamil Nadu, India

Abstract

　　Hand-dorsa Vein Recognition System is a biometric authentication system using inherent physiological characteristics to enable identification of individuals. In this paper a new integrated framework has been proposed to specify the features of hand vein images and identify the individual images with classification method. The framework consists of three primary components called Feature Extraction, Dimensionality Reduction, and Texture Classification and each have sub components. The feature extraction component is based on Weber Differential Orientation Local Binary Pattern (WDOLBP) where as the feature reduction is based on Principal Component Analysis (PCA) and the texture classification component is based on nearest neighbour classification. For each pixel of the input image, WDOLBP descriptor is computed with two features called differential Orientation (DO) and Local Binary Pattern (LBP). By combining DO and LBP features (called WDOLBP feature) per pixel, the feature vector is represented in a histogram, which is called WDOLBP histogram. Feature reduction component is required to reduce the dimensionality of feature images in a histogram. In this work, PCA is suggested to reduce the features of images which then can be used in Classification. The final component is a classifier is based nearest neighbour classification method. The proposed method is evaluated on a NCUT Dataset contains 2040 images from Prof. Yiding Wang, North China University of technology (NCUT) (Wang et al, 2010). Similarity measures of various classification methods such as Chi-square, Cityblock, Euclidean, Chebychev and Minkowski are computed and compared for the better performance. The experimental results show that the proposed integrated framework performs better than other feature representation.

Keywords: *Weber Local Binary Pattern, Pattern Recognition, Feature Descriptor, Feature Rduction, Classification*

Introduction

Authenticated security access system has becoming emerging requirement of every system or organization. Biometric recognition of hand vein features has attracted significant attention in the research community recently. Special infrared devices are used to capture the hand vein images for biometric analysis. As the captured image contains a large noisy and unwanted data, pre-processing methods such as image filtering, normalizations are required to shape the image data which are then applied for further biometric analysis. Hand vein biometric recognition system requires the components such image acquisition, image pre-processing, feature descriptor, feature reduction and classification. Feature descriptor is a model to represent the characteristics of images. Primary purpose of this paper is to represent the hand vein images in a feature descriptor and classify them for a biometric authenticated system. Feature descriptors can be categorized into sparse descriptor [2] and dense descriptor. Sparse descriptor detects the interesting points in the images and then samples local patches and describes its invariant features and dense descriptor extracts local features pixel by pixel over the input images [5]. Scale Invariant Feature Transform (SIFT) and Histogram of Oriented Gradient (HOG) are based on sparse descriptor where as Gabor Wavelet and Local Binary Pattern (LBP) are based on dense descriptor. Recently Chen et al [2] proposed a robust local descriptor, called the Weber Local Descriptor (WLD). In this scheme, the image patterns based on human perception is represented by original intensity and change of intensity in stimulus (such as sound, lighting).

WLD descriptor consists of two components: differential excitation and orientation. It is inspired by Weber's Law, which is a psychological law [3]. Differential excitation component of Weber Local Descriptor (WLD) is computed based on the ratio between relative intensity differences of a current pixel against its neighbours and the intensity of the current pixel. Differential orientation components in WLD is computer based on gradient orientation of given pixel. In this paper we propose a new integrated framework feature descriptor WDOLBP consists of two components called WLD differential Orientation and Local Binary Pattern (LBP). The differential Orientation extracts perception features by Weber's law, while the LBP (Local Binary Pattern) can describe local features of images. Local micro patterns corresponding to bright/dark spot, edges and flat areas are computed by LBP patterns. These two image components are computed for an image and the resultant statistical value is represented in a single histogram called WDOLBP histogram. In the feature reduction phase, the combined histogram form of image statistics is reduced with Principal Component Analysis (PCA). Nearest neighbour classification is applied to find the authenticated images for bio metric system.

The rest of the paper is organized as follows: in section 2 the proposed frame work and its components are explained. Data base features, experimental results and

performance evaluations are given in section 3 and conclusions are given under section 4.

Proposed Framework

A new framework is proposed and depicted in fig 1, which contains the component such as feature descriptor, feature reduction and classification.
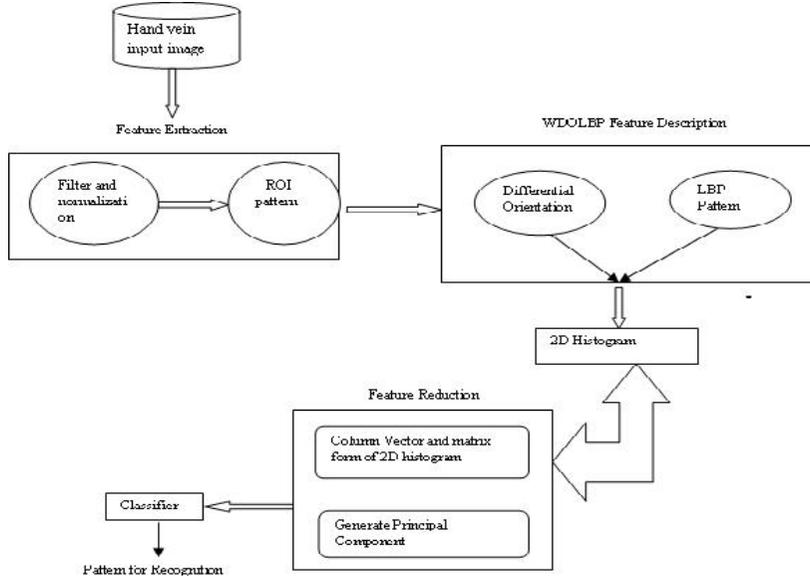

Fig. 1: A framework for feature descriptor and classification for hand vein recognition

Region of Interest (ROI) Extraction

Hand vein images are captured and filtered for noise reduction. The information contains the vein patterns are most vital part for our computation. The specific regions of interest are needed to be extracted from the whole images. The detail procedure on extraction of ROI has been described in [1] [8].

In this work, the centroid is considered as the centre to extract the ROI. The centroid (x_0, y_0) of vein image $f(x, y)$ can be calculated as shown in (1, 2). The image coverage area is larger than the back of the hand as shown in Figure 2. In this work, the image centroid was identified to extract the ROI. Let (x_0, y_0) be the centroid of vein image $f(x, y)$ then

$$x_0 = \frac{\sum_{i,j} i \times f(i, j)}{\sum_{i,j} f(i, j)} \quad (1) \qquad y_0 = \frac{\sum_{i,j} j \times f(i, j)}{\sum_{i,j} f(i, j)} \quad (2)$$

After finding the image centroid the image cropping is subsequently performed to yield a sub-image of 360×360 pixels. Figure 2 (a) shows a back of the hand vein image captured with a resolution of 640 by 480. Figure 2 (b) and (c) respectively show the centroid and ROI of an image.
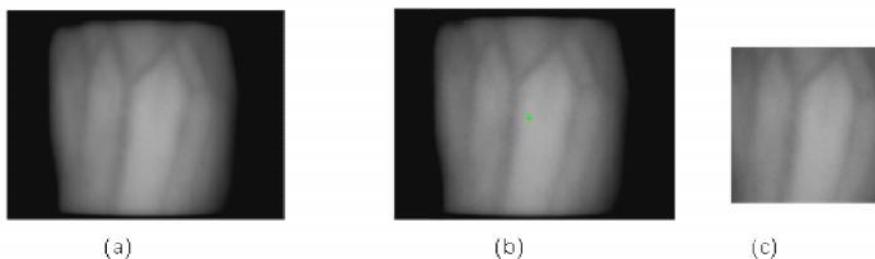
Fig. 2: (a) Back of hand vein image (b) Centroid (c) ROI

Weber Differential Orientation Local Binary Pattern (WDOLBP) Image Descritor

WDOLBP image descriptor consists of two components called Differential Orientation and Local Binary Pattern (LBP). For a given image, the pattern value of each pixel is computed through LBP operator and intensity of each pixel is computed by differential Orientation model. Images from these two components are combined to construct a model based on histogram.

Weber's Law

Ernst Weber, an experimental psychologist in the 19th century, observed that the ratio of the increment threshold to the background intensity is a constant [3]. This relationship, known since as Weber's Law, can be expressed as:

$\Delta I / I = k$

where ΔI represents the increment threshold ; I represents the initial stimulus intensity and k signifies that the proportion on the left side of the equation remains constant despite variations in the I term. The fraction $\Delta I/I$ is known as the Weber fraction. Weber's Law, more simply stated, says that the size of a just noticeable difference (i.e., ΔI) is a constant proportion of the original stimulus value.

Differential Orientation (DO)

Differential Orientation is one of the subcomponents of Weber Local Descriptor (WLD). It is based on the fact that human perception of a pattern depends not only on the change of a stimulus (such as sound, lighting) but also on the original intensity of the stimulus. The orientation component of WLD is the gradient orientation of pixel, which is computed as: for a 3 x 3 patch of image

X_1	X_2	X_3
X_4	X_c	X_5
X_6	X_7	X_8

$) = \arctan (——$

where $\theta(x_c)$: differential orientation. From the above equations, it is clear that LBP makes full use of the nine pixel while Orientation operator only utilizes four pixels

Thus orientation component is calculated as the ratio of difference between the neighboring pixels.

Local Binary Pattern (LBP)

LBP labels the pixels of an image by considering neighbourhood of each pixel and convert the result by a binary sequence. In LBP, the surface textures can be described by two measures: local spatial patterns and gray scale contrast. Each pixel of images can be processed into binary number by comparing 3 x 3 neighbour pixel with its centre value. The histogram of these 2^8 = 256 different labels can then be used as a texture descriptor. Basic operation of LBP operator is illustrated in figure 3. For each pixel in an image, its value is compared with all the neighbouring pixel values. The result of each comparison is coded as binary 1 if the center pixel value is smaller and binary 0 otherwise. The binary bits are then grouped in the clockwise direction starting from the top left pixel, and the arranged binary string is converted to a decimal number as the final LBP result for the center pixel.
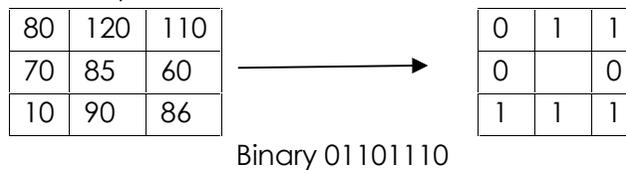
80	120	110
70	85	60
10	90	86

$\longrightarrow$

0	1	1
0		0
1	1	1

Binary 01101110

Fig. 3: Example of basic LBP Operator

The LBP operator can be extended to neighbourhoods of different sizes[6]. For circular neighbourhoods, the pixel values can be interpolated to allow any radius and number of pixels in the neighbourhoods. With $LBP_{P,R}$ denoting P sampling points on a circle with a radius of R, some examples of the circular neighbourhoods are shown in Figure 4.
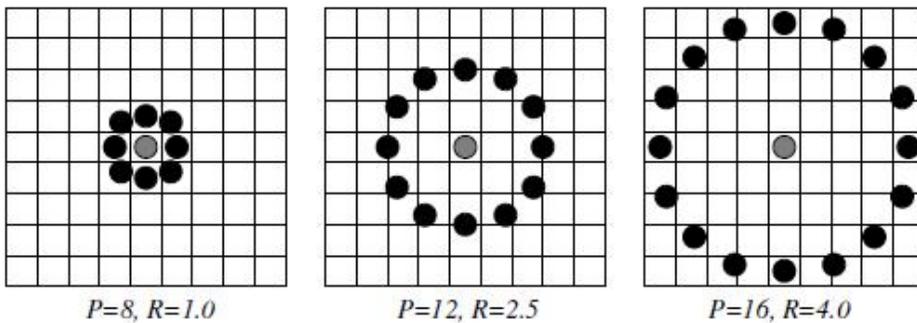

P=8, R=1.0   P=12, R=2.5   P=16, R=4.0

Fig. 4: Circular neighbourhoods for LBP

Another extension to the original operator is the definition of so-called uniform patterns, which can be used to reduce the length of the feature vector and implement a simple rotation-invariant descriptor. To remove the effect of image rotation resulting in different binary patterns to be generated, each LBP is rotated to a position that acts

as the common reference for all rotated versions of the binary patterns, and this involves the use of the rotation invariant LBP operator, $LBP_{P,R}^{u2}$ defined

$$LBP_{P,R}^{u2}(x,y) = \begin{cases} I(LBP_{P,R}(x,y)) & U(LBP_{P,R}) \le 2, I(z) \in [0,(P-1)P+1] \\ (P-1)P+2 & \text{otherwise} \end{cases} \tag{4}$$

Where

P	:	Number of Sampling Points
R	:	Radius of the Circle
I	:	Index function
(x,y)	:	Spatial coordinate in an Image
U	:	Uniform pattern operator

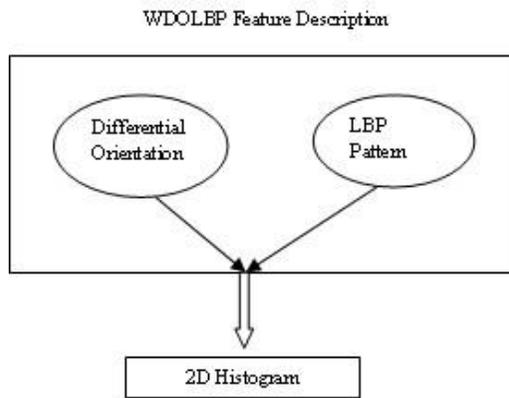## WDOLBP 2-D Histogram

Figure 5: WDOLBP Descriptor

WDOLBP consists of two components: Differential Orientation and LBP. For or a given image, the pattern value of each pixel is computed by these two components. The image is then combined to construct a histogram diagram {WDOLBP(s,t)}, (s = 1,.....,S, t = 1,.....,T) of the original image. The size of this 2D histogram is $T \times S$, where S is the number of intervals of ξ, T is the total number of LBP's patterns. In this 2D histogram, each column represents a pattern t of LBP, and each row corresponds to a differential orientation interval. Thus, the value of each cell {WDOLBP(s,t)} corresponds to the frequency of the certain differential excitation interval 1_s and the LBP pattern t. Figure 5 shows the steps in WDOLBP descriptor calculation (Liu et al 2012).

To enhance the discriminality, the 2D histogram WDOLBP(s,t) is further encoded into 1D histogram H. Each row of 2D histogram is used to form a 1D histogram H(s),(s = 1,.....,S). Each sub-histogram H(s) corresponds to the differential excitation interval l_s. 1D histogram $H = \{H_s\}, s = 1,.., S$ is obtained by concatenating the S sub-histograms.

Feature Reduction

The WDOLBP histogram obtained from previous phase contains large dimensions or features. A simple feature reduction procedure called Principal Component Analysis (PCA) is used to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables. It performs a linear mapping of the data to

a lower-dimensional space. PCA identifies the subspace of image represented in a histogram and decorrelates the pixel value. The reduced dimensionality features are considered as image data for classification. It reduces the time and storage space required. Removal of multi-collinearity improves the performance of the machine learning model. It becomes easier to visualize the data when reduced to very low dimensions such as 2D or 3D.

The steps of the transformation are: The basic histogram is transformed into matrix representation. Covariance matrix V is calculated and the corresponding eigen values are computed. This is the subspace of the feature vector. Thus, the feature vectors given as input to PCA have been reduced to the number of eigen veins needed for performing pattern matching. This number can range from 3 to number of eigen veins itself.

WDOLBP Histogram for Texture Classification

In this section, WLBD histogram of feature representation is taken for the nearest neighbour classification. The aim of this phase is to construct a classifier model for classification. The NCUT left dorsal hand dataset and right dorsal hand dataset are considered for input data base. For a given image I1 and I2, the WDOLBP histograms H1 and H2 were obtained. Similarity between two images are evaluated by different measure calculations such as Chebychev, Chi square, city block, Euclidean and Minkowski, and different performance are evaluated.

Experimental Result

In this proposed work, the NCUT dorsal hand vein database is used to experiment the performance. A database of 2040 images from Prof. Yiding Wang, North China University of technology (NCUT) (Wang et al, 2010) has obtained and used in this research work.

A dataset of 2040 hand vein images are captured with a resolution of 640 × 480, called North China University of Technology hand-dorsa vein dataset or NCUT dataset. In detail, 10 right and 10 left back of the hand vein images were captured from all 102 subjects, aged from 18 to 29, of which 50 were male while 52 were female.

In the classification model, K fold cross-validation (Kohavi Ron, 1995) is applied. The 10 samples of 102 subjects are divided into 5 equal parts. The classification model is trained on 4 set of dataset and tested on the remaining one part. Average error rate of different execution of algorithms is considered as generalization error. The performance of the framework of the proposed work is evaluated with quantifiable measurement. A minimum distance classifier is used to classify the test image data to classes. Similarity between histogram is measured by finding distances. The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity. The following distance measures used to identify the distance between two histograms. The recognition rate is given by the equation

$$\text{recogntion rate} = \frac{\text{the number of recognized images}}{\text{the number of testing images}}$$

Table 1 shows the recognition rate of various nearest neighbour classification algorithm. The Chi – Square classification have high recognition rate.

Table 1: Recognition rate for NCUT hand vein database – left & right hand images

Distance Measure		Chi - Square		Cityblock		Euclidean		Minkowski		Chebychev	
		Left	Right	Left	Right	Left	Left	Left	Right	Left	Right
K Fold Cross Validation	Testing Images	Recognition Rate (%)									
K=1	204	95.59	95.2	87.75	93.63	73.04	69.12	80.88	77.45	71.07	72.06
K=2	204	95.2	96.08	93.63	95.59	75.49	75.49	75.49	80.88	72.06	71.07
K=3	204	95.59	99.51	96.08	95.59	73.04	87.75	73.04	80.88	71.07	71.07
K=4	204	96.57	98.53	96.08	96.08	79.41	73.04	79.41	80.88	72.06	71.07
K=5	204	96.08	99.51	95.59	95.59	75.49	77.45	73.04	77.45	71.07	84.31
Avg. Recognition Rate		**95.74**	**97.33**	**93.39**	**95.22**	**75.25**	**76.35**	**77.21**	**80.02**	**71.46**	**73.91**

Table 2 shows the comparisons of various pattern representation method with different distance measure algorithm. The result shows that, the performance rate for feature descriptor contains WDOLBP (DO & LBP) with PCA is high.

Table 2: Feature Descriptor Comparison – NCUT hand vein database

Distance Measure	Chi - Square		Cityblock		Euclidean		Minkowski		Chebychev	
	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Feature Descriptors	Recognition Rate (%)									
LBP	90.68	92.25	87.35	90.88	80.39	84.71	74.80	79.71	76.54	50.80
WDOLBP	94.79	96.07	93.32	92.05	79.21	50.80	68.03	39.20	74.80	46.70
HOG	94.70	96.27	91.82	93.82	88.92	91.86	86.96	89.50	75.25	71.07
WDOLBP with PCA	**95.74**	**97.33**	**93.39**	**95.22**	**75.25**	**76.35**	**77.21**	**80.02**	**71.46**	**73.91**

An accuracy of classification is given as a percentage of correct classifications. Performance of the classifier is evaluated with biometric evaluation schemes like FAR and FRR, ROC curve, and error rate. The biometric authentication system compares enrolled biometric data with identity of a person he claims. The matching is closer then the match score is higher. If the match score exceeds a given threshold then the person authenticating is accepted. If the threshold is set too high, genuine users will be rejected. If it is set too low, impostors will be authenticated. The system will generate two types of errors called FRR and FAR.

$$\text{False Acceptance Rate} = \frac{\text{False Positive}}{\text{False Positive} + \text{True Negative}}$$

Flase rejection rate = 1- False acceptance rate

True acceptance rate (TAR) and True rejection rate is given by the Equation as follows.

$$\text{True acceptance rate} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

True rejection rate=1-True acceptance rate

Both FAR and FRR depend on threshold. A higher threshold will generally reduce FAR, but at the expense of increased FRR, and vice versa. The threshold affects FRR and FAR. At a low threshold, FRR will be low and FAR will be high. When the threshold is increased more genuine users will be rejected and less impostors will be accepted. At some point FRR and FAR will be equal. The value of the FAR and FRR at this point is the EER. The EER tells about what the FAR and FRR will be at any other threshold. Sensitivity is also called as True Acceptance Rate, or the Recall rate measures the proportion of actual positives which are correctly identified. Fig 6 shows the performance of classifier with FAR and FRR.
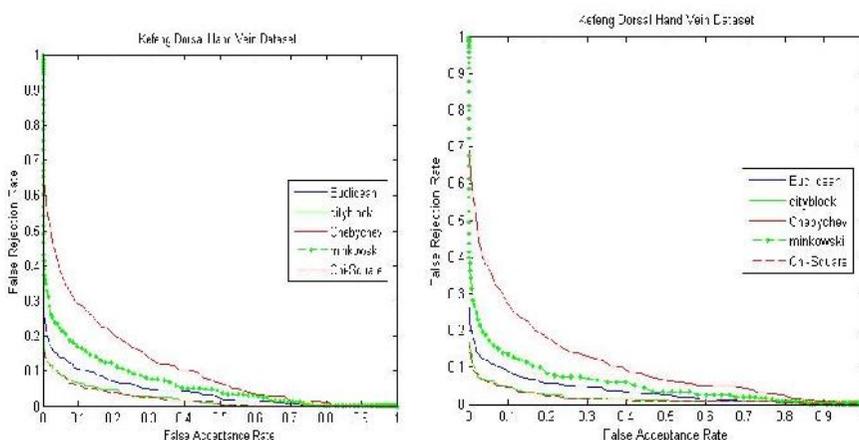

Fig 6: FAR and FRR for left and Right Hand Vein Dataset

Accuracy of classifier is evaluated by ROC (Receiver Operating Characteristic**).** In a ROC curve the true positive rate (Sensitivity) is plotted in function of the false positive rate (100-Specificity) for different cut-off points of a parameter. In fig 7 ROC curve for the classifier chi-square passes through the upper left corner (100% sensitivity, 100% specificity). Therefore the closer the ROC curve is to the upper left corner, the higher the overall accuracy of the test. Receiver operating characteristic (ROC) curve plots parametrically the FPR (i.e. imposter attempts is accepted) on the x-axis, against the corresponding True positive rate (TPR) (i.e. genuine attempts accepted) on the y-axis as a function of the decision threshold. It is threshold independent allowing performance comparison of different systems under similar conditions, or of a single system under differing conditions. It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in

specificity). The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test. A Detection error trade-off (DET) curve (Martin et al., 1997) plots error rates on both axes, giving uniform action to both types of error. The DET curves can be used to plot matching error rates FRR against FAR.
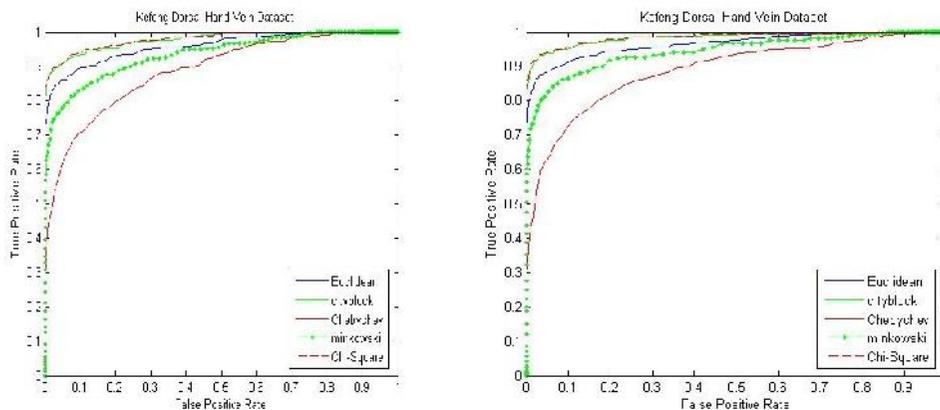

Fig. 7: ROC for left and Right Hand Vein Dataset

Table 3: Equal error rate for NCUT hand vein dataset left hand images

Distance Measure	Left	Right
	Equal Error Rate	
Chi-Square	0.07	0.10
Cityblock	0.08	0.07
Euclidean	0.11	0.09
Minkowski	0.15	0.13
Chebychev	0.20	0.19

Table 3 gives the EER obtained from NCUT hand vein dataset left & right hand images. It shows that Chi-square approach works in a very robust way in comparison to other methods.

Conclusion

In this paper, a framework for biometric classification system using dorsal hand vein patterns is proposed with fusion of the components such Feature Descriptor, Feature reduction and Pattern Identification. Feature Descriptor is constructed by combining the benefits of WLD differential orientation and LBP feature. This method uses various distance measures such as Chi-square, Cityblock, Euclidean, and Minkowski as similarity measure between training and testing images. The experimental results show that Chisquare distance measure outperforms other distance measures with the recognition rate of 98.72% for NCUT Dataset. Also the results are examined with state-of- art algorithms LBP and WDOLBP, the proposed work outperforms the existing methods.

References

1. Ajay Kumar, and K. Venkata Prathyusha, "Personal Authentication Using Hand Vein Triangulation and Knuckle Shape", IEEE Transactions on Image Processing, Vol. 18, No. 9, Sep. 2009, pp. 2127-2136.

2. Jing Li, Nigel M, A comprehensive review of local features for Computer Vision, Neurocomputing, 71 (2008), 1771-1778

3. A.K. Jain, Fundamentals of Digital Signal Processing. Englewood Cliffs, NJ: Prentice-Hall, 1989.

4. C. L. Lin, K. C. Fan and F. D. Chou, "A novel approach to palmprint verification utilizing finger-webs as datum points," Image and Vision Computing.

5. WLD: A Robust Local Image Descriptor Jie Chen, Member, IEEE, Shiguang Shan, Member, IEEE, Chu He, Guoying Zhao, Matti Pietikäinen, Senior Member, IEEE, Xilin Chen, Senior Member, IEEE, Wen Gao, Fellow, IEEE, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2009, TPAMI-2008-09-0620

6. M. Pietika, A. Hadid, "Face recognition with local binary patterns," in Proc. 8th European Conference on Computer Vision, ser. Lecture Notes in Computer Science, vol. 3021. Springer, 2004, pp. 469–481

7. T. Ojala, M. Pietika¨inen, and D. Harwood, "A comparative study of texture measures with classification based on feature distributions," Pattern Recognition, vol. 29, no. 1, pp. 51–59, 1996.

8. Chen, J, Shan, S & Chu, H 2010, 'WLD: a robust local image descriptor', IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, no. 9, pp. 1705–[9]

9. Déniz, O, Bueno, G, Salido, J & De la Torre, F 2011, 'Face recognition using histograms of oriented gradients', Pattern Recognition Letters, vol.32, no.12, pp. 1598-1603.

10. Fan, KC & Lin, CL 2004,'Biometric Verification Using Thermal Images of Palm-Dorsa Vein Patterns', IEEE Transaction on Circuits & System for Video Technology, vol.14, no. 2, pp. 199 - 213

11. Gonzalez R & Woods RE 2002, 'Digital Image Processing', Addison-Wesley, 2nd edition.

12. Huang, D, Tang, Y, Wang, Y & Chen, L 2012, 'Hand Vein Recognition based on Oriented Gradient Maps and Local Feature Matching', Proceedings of the 11th Asian Conference on Computer Vision: Springer Berlin Heidelberg, pp. 430 - 444.

13. Hui-Xing, J & Yu-Jin Z 2007, 'Fast human detection by boosting histograms of oriented gradients', Proceedings of 4th International IEEE Conference on Image and Graphics (ICIG) , pp. 683-688.

14. Newell, A, J & Griffin, L, D 2011, 'Multiscale histogram of oriented gradient descriptors for robust character recognition', Proceedings of International in Document Analysis and Recognition (ICDAR), pp. 1085-1089.

15. Shahin, M, Badawi, A & Kamel, M 2007, 'Biometric Authentication Using Fast Correlation of Near Infrared Hand Vein Patterns', International Journal of Biomedical Science, vol. 2, no. 3, pp. 141-148.