Finger Vein Recognition using Integrated Response of Texture Features

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***Abstract*— The finger vein recognition system is a secure anda reliable system with the advantage of robustness against malicious attacks. It is more convenient to operate this biometric feature than other biometric features such as facial and iris recognition system. The paper proposes a unique technique to find the local and the global features using Integrated Responses of Texture (IRT) features from finger veins which improves the overall accuracy of the system and is invariant to rotations. The segmentation of region of interest at different resolution levels makes the system highly efficient. The lower resolution data gives the overall global features and the higher resolution data gives the distinct local features. The complete feature set is descriptive in nature and reduces the Equal Error Rate to 0.523%. The Multi-Support Vector Machine (Multi-SVM) is used to classify and match the obtained results. The experimental results indicate that the system is highly accurate with an accuracy of 94%.**

***Keywords*— Pyramid Levels; Local Binary Pattern; Integrated Responses; Multi- SVM**

I. INTRODUCTION

The finger vein recognition system is a very innovative system that has been evolved through the various biometric identification techniques such as fingerprint pattern, voice recognition, iris recognition, and identification using different facial features, hand and body gestures [1]. It is easier to operate and harder to fool unlike the complex iris systems, high resolution fake facial patterns or false recordings. Therefore, there is a requirement of a system with a higher accuracy in the field of finger vein recognition systems. The extraction of prominent features for recognition is always a complex task. Therefore, an effective feature extraction method is required for increasing the accuracy of the system.

Commonly used methods for extracting features are based on segmented finger vein network including the repeated line tracking method [2], the mean curvature [3], the maximum curvature point method [4], the Gabor filter [5] in which the information such as geometric shape, topological structure are obtained from the segmented network of blood vessel [2 -7]. The segmentation of an image maximally depends upon the quality of the captured images which needs to be taken care of while creating the database. To improve the vein extraction, a technique which covers the local and global features by segmenting the images in the different pyramid levels based on Gray, Texture and Orientation [8] with a personalizedfeature set has been used with the less prominent features. A comparative study on pyramid levels of Texture using Local Line Binary Pattern, Local Binary Pattern, pyramid levels of Gray and Orientation Gradients [8] stated the advantages of LBP in comparison to LLBP in extracting the finger vein pattern. Pattern Extraction techniques using texture and matching with the correlation coefficient [9] has been used in which sobel detector, enhancement filter with binarization has been applied. Although various finger vein extraction techniques have been used, there is still a requirement for a more promising feature extraction technique which is less complex, accurate and efficient.

Thus, an effective feature extraction technique termed as Integrated Responses of Texture using Local Binary Pattern is proposed in which different resolution levels of Texture using LBP is concatenated to form a complete set of features which describes the local and the global features more prominently. In the proposed method, when finger of a human being is inserted, it is being illuminated by the near-infrared Light Emitting Diode (LED) and the images of the veins are captured through a charge- coupled camera. When the near IR (infrared) radiations falls on the finger, the hemoglobin present in the blood of the vein absorbs the radiation and gives a dark pattern due to absorption. These digital images are recorded and form the database for the system. The blood vessels can only be seen in living human beings therefore can't be forged when a person is dead. The structure of vessel is unique to everyone and can't be copied easily. In the proposed system, the Local Binary Pattern Operator in texture at various resolution levels is analyzed to improve the accuracy of the system. Integrated Responses of Texture (IRT) using Local Binary Pattern proves that IRT is a better substitute with a more descriptive feature vector with a smaller vector size.

In this paper, Section II presents the block diagram of the proposed model, Section III discusses the extraction of ROI and features based on the Local Binary Pattern. This section also includes the measure of Similarity as well as Matching from Multi-SVM. The experimental results are shown in Section IV. Section V concludes the paper.

II. PROPOSED MODEL

The block diagram of the proposed method is shown in the Fig.1 and each block is explained in the section III of the paper.

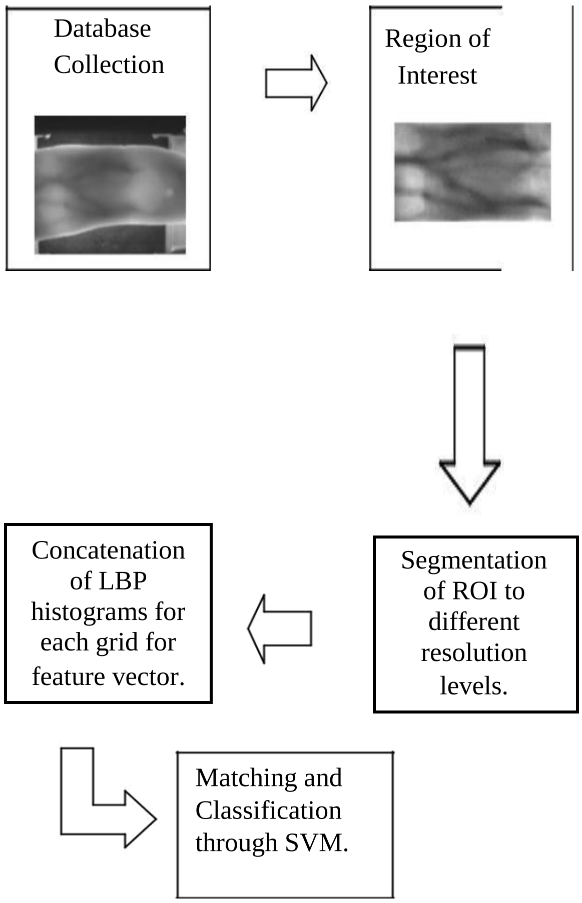

Fig. 1: Block Diagram of the Proposed Method

III. PROPOSED METHOD

A. Database Collection:

Data acquisition involves collection of im ages to form a database from the human beings. The images are used from the database (SDUMLA-HMT) of 6 finger vein images of 106 individuals with a total of 3,816 images of 320 x 240 pixel and stored in 'bmp' format [10]. However, the proposed method is only tested on selected 17 individuals in which 6 samples from each of index, middle and ring finger per hand (6 x 6 x 17 = 612 images) is taken which constitutes a database of 612 images in total for ease of processing.
A sample is shown as in Fig. 2:

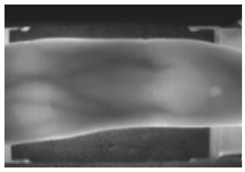

Fig 2: Acquired Image from the Database

B. Pre-Processing and Region of Interest:

To make images of finger vein invariant to rotations, the rotation correction is used. The boundaries of the images are highlighted and edge points are found out. The finger vein image is processed by using CLAHE (Contrast-limited Adaptive Histogram Equalization) technique and the image is normalized and the required ROI is extracted. This technique works on good as well as poor samples and extract the region of interest for rotated images as well. The Fig. 3 illustrates the extraction of Region of Interest and the processed ROI with normalization.

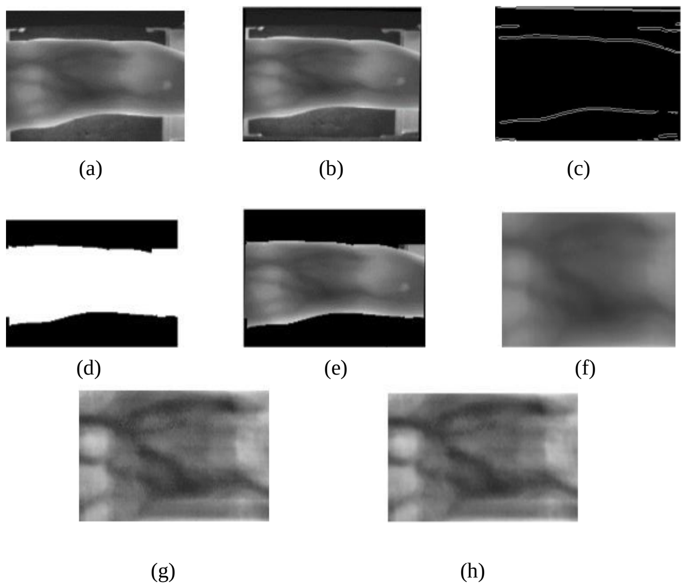

Fig.3: (a) Image from Database, (b) Rotation corrected original image withtheta (in degree) = -1.12, (c) Edged Image, (d) Finger Vein Region, (e) Masked ROI, (f) Region Of Interest, (g) Extracted ROI with CLAHE, (h) Normalized Image.

C. Feature Extraction:

Local Binary Pattern has gained attention as a typical feature descriptor in finger vein recognition [8]. It has turned to outperform various other features therefore it is used as a base feature and it is relatively simple. A n LBP can be described as an ordered set of binary values determined by comparing all the gray values of a center pixel with its 3 x 3 -neighborhood pixels. All binary codes can be concatenated together.

Local Binary Pattern (LBP) is uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice-versa when the bit pattern is traversed circularly. For computing LBP bins, these uniform patterns are used to get separate bin for each uniform pattern and to label all the non-uniform patterns with a single bin. For example, in a circle of radius 1, if 8 neighborhood sampling points are taken then there will be total of 256 patterns, out of whic h 58 are uniform and gives 59 different bin. Fig. 4 shows the LBP operator with sample, difference and threshold values.

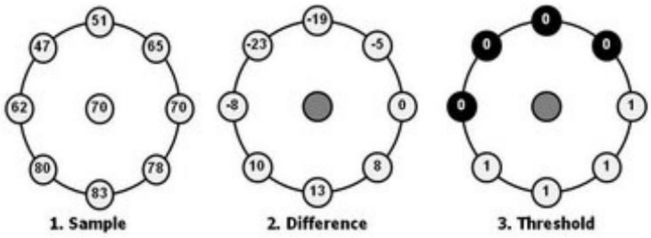

Fig. 4: Local Binary Operator

In the proposed method, the ROI is a segmented into grids of different levels and uniform LBP (Local Binary Pattern) of each grid cell is found and again the concatenation of all the LBP histograms of grids at each level will give the IRT (Integrated Responses of Texture). The given set of features is invariant to rotation [8]:

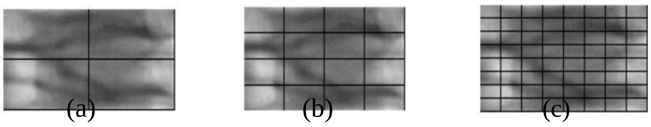

Fig. 5: Pyramid Resolution (a) Level 1, (b) Level 2, (c) Level 3

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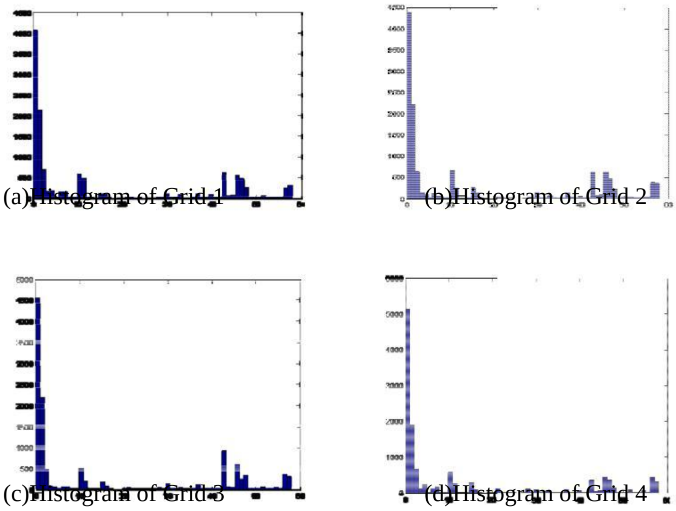

Fig. 6: LBP histograms for each grid

The concatenated histogram of all grid levels is as shown in Fig. 7:

IV. Experimental Results

The samples of 612 images of finger vein with sample of 3 fingers per hand of a human in which 6 images each from index, middle and ring is taken from 17 selected individuals from the database of 3,816 images of 106 individuals [9]. The ROC curve i.e. Receiver Operational Characteristic Curve is shown in the Fig. 8 in which the FAR Vs GAR is plotted and the EER comes out to be 0.5 %.

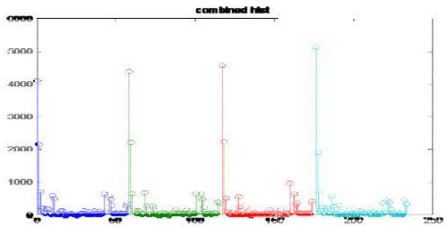

Fig. 7: Concatenated Histogram of all grid levels

The Region of Interest of the normalized and processed image is segmented into Grids based on different pyramidal resolution levels. Level 1 indicate the four grids. Level 2 indicate 16 grids and Level 3 indicates the 64 grids. Different Pyramid Resolution Levels are shown in Fig. 5; (a) ,(b) and (c) respectively. For Level 1, i.e Fig. 5 (a), the LBP histograms of each of the four grid s are taken; Fig. 6, and all the histograms are concatenated to form a single histogram as shown in Fig. 7. Similarly, at level 2 and level 3, the ROI is segmented into grids of 16 and 64 respectively and LBP Histograms for each grid is calculated. The concatenation of each grid at their individual re solution level is further integrated to form a complete feature vector in which lower levels gives the global features and higher level gives the more localized feature. The complete feature vector describes all the neighbourhood details of the images.

D. Similarity Measure:

The obtained Feature vector of i mages is used to find the similarity index. The similarity measure is found using Chi Square Distance method:
The value of the test statistic is:

where x and y are feature vector of two images for which the similarity index is to be found.
X_i and y_i are the corresponding elements of feature vector.

E. Matching:

The matching of finger vein images are performed using Multi-SVM Classifier in which the complete database is divided into Training and Testing sets and features are extracted from both the sets along with the Testing and Training Labels as well as their Sample List. The database is divided into 432 images in Training set and 180 images in Testing set with zero overlapping. The classification Accuracy is 94% as shown in Table I.

Table I: Classification Accuracy on Multi-SVM

Classifier	Training Set	Testing Set	Accuracy
Multi-SVM	432 samples	180 samples	94%

It is seen from Table II that the EER goes on decreasing with the increasing number of samples. Therefore a bigger database will eventually give the smaller EER. The plot of EER at different number of samples is as shown in Fig. 10 suggest that the accuracy of the system increases with the increasing number of samples. It is due to the fact that prior knowledge is increased when the numbers of samples are increased.

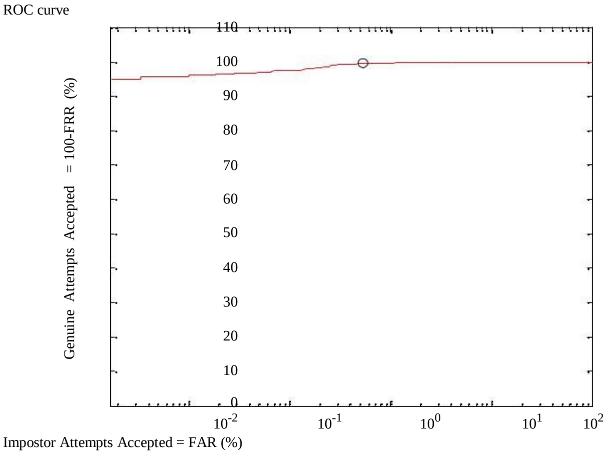

Fig. 8: ROC curve

The graph between False Acceptance Ratio (FAR) and False Rejection Ratio (FRR), Fig. 9 meets at the threshold of 0.5 which equivalently shows the value of Equal Error Rate (EER) as 0.5 %.

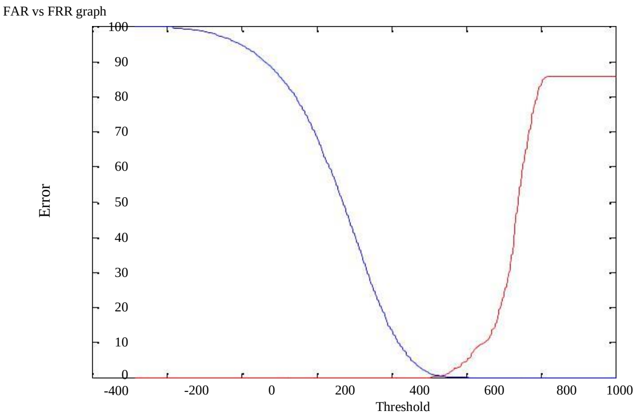

Fig. 9: FAR Vs FRR graph

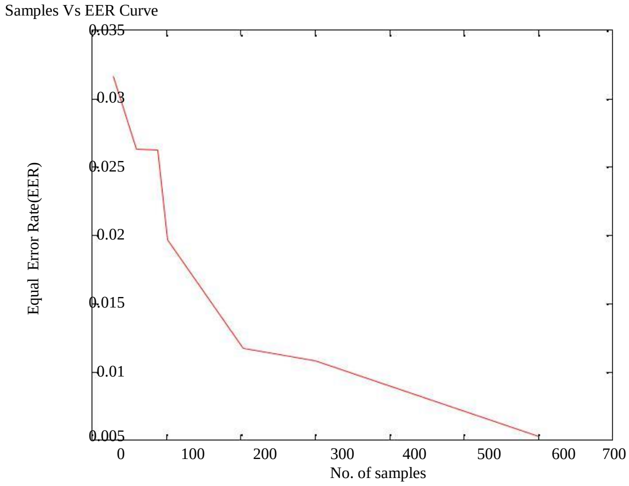

Fig. 10: Performance at different number of samples

V. CONCLUSION

The Integrated Responses of Texture (IRT) using Local Binary Pattern is proposed in this paper in order to extract the prominent and descriptive features for improving the accuracy of the system. To make system invariant to rotations, rotation correction techniques have been used along with CLAHE (Contrast-limited Adaptive Histogram Equalization) and normalization. The segmentation of Region of Interest at different resolution levels gives the both global and local features which reduces the Equal Error Rate to 0.523%. The multi-SVM classifies the data and matches the result with an accuracy of 94% when tested on a dataset of 612 finger vein images.

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