Performance Analysis Based Comparison of Different Feature Extraction Methods using SVM and Authentication of Finger Vein Images

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Abstract:- **Finger vein is a promising biometric pattern for personal identification and authentication in terms of its security and convenience when compared to other biometrics. In this project, we compare different feature extraction techniques based on their performance. First the input image is pre-processed and then feature extracted. The methodologies like Gray Level Co- occurrence Matrix (GLCM), Haar wavelet, Curvelet, Local Binary Pattern (LBP) are used for feature extraction of finger vein images. These methods are compared using performance evaluation metrics like FAR (false acceptance rate), FRR (false rejection rate), Recognition rate, accuracy and time with the help of multi SVM (Support Vector Machine) classifier and later matching is done using Euclidean distance. The result shows better accuracy for Haar and LBP, less computation time for LBP and better recognition rate for Haar when compared.**

Keywords: Authentication, Euclidean distance, Feature extraction methods, Finger vein, Multi SVM Classifier Performance metrics, Pre-processing.

I.INTRODUCTION

Biometric technology refers to a pattern recognition system which depends on physical or behavioral features for the person identification. Many biometric systems exist today by using fingerprint, face, iris, voice, palm print, signature, etc. Finger print is a popular trait for recognition but the scanner scans only a section of the finger, so it is susceptible to error also they aren't that private because we leave fingerprints almost everywhere, it can be easily spoofed. [12] It is sensitive to dirt, cuts, marks, wet and age. Finger vein is a new member of biometric family. Finger vein patterns are blood vessel present underneath the covering of a finger, so it is different for every individual even for twins. [2][13] The permanence and uniqueness of finger vein is high. Individuality of finger vein compared to other biometric traits [1] are:

- The vein pattern is difficult to forge or steal, because the vein is hidden inside the body and it is invisible to the human eye.
- The non-invasive capture of finger-vein ensures the convenience for the user, so it is more acceptable.
- Finger-vein pattern can only be taken from a live body.
- It ensures higher performance and spoofing resistance as finger veins can't be duplicated because they do not depart any trace during the authentication process.

- It is protected by skin, so it has less damage also it is least affected by any weather or health conditions.
- The patterns of vein need only low image resolution.

Usually the finger vein images are captured using near-infrared rays (NIR) produced by the LEDs (light emitting diodes) which penetrate through the finger and gets absorbed by the haemoglobin in the blood. The areas at which the rays are absorbed (i.e. Veins), appears as dark in an image taken by a CCD (Charged Coupled Device) camera. Image processing can then construct a finger vein pattern from the camera image. The obtained pattern is digitized and stored as a template in a compressed form as biometric authentication data. [2] Here, the input image is pre-processed and feature extracted, then performance evaluation metrics are compared with the help of the classifier for different extraction methods used. Then matching is done, for authentication.

II. LITERATURE REVIEW

P. Mohanaiah et al [3] proposed the application of GLCM to extract second order statistical texture features of the images. The results showed that texture features have high accuracy, less computation time and reduced image compression time. V Remya et al [4] proposed a system with a novel finger-vein recognition algorithm. Here, a Haar classifier is used to extract the features and matching is done by calculating the Euclidean distance. The results showed that it takes minimal time to verify, consumes less power and has less computational complexity. Richardo James [5] proposed an identification system based on the dorsal hand vein pattern authentication with curvelet transforms for feature detection of images and random forest classification method. Naiema et al [6] proposed the finger vein based user recognition system that provided more efficient features using LBP and PCA (Principal Component Analysis) algorithm. They used SVM classifier which gave an accuracy of 96% when run real time and an accuracy of 70% of the database images. Ashwini Dange et al [7] proposed a study describing the texture classification of images based on their accuracy and time complexity along with the comparison of Wavelet transforms like the Haar, Symlets and Daubechies wavelets and Co occurrence Matrix methods. The results showed that the accuracy of the co-occurrence matrix method is greatly reduced. It is as less as 2.5%, whereas for Haar wavelet, it is around 66.66 % (average). Kang Ryoung Park [8] proposed a new algorithm for finger vein based on LBP by extracting the global information based on wavelet transform and then by combining the two score values of LBP and wavelet transform using the SVM. Experimental results showed the EER (Equal Error Rate) as 0.011% and the total processing time as 98.2ms.

III. SYSTEM METHODOLOGY

There are four major steps to be performed in a vein pattern recognition system. They are:

- Data Input: The data stored in the database are taken as the input and given for further processing.
- Pre-processing: The raw data is then preprocessed by either filtering noise or enhancing the data so as to make the input readable.
- Feature extraction: Then the relevant features of the processed data are extracted.
- Matching: Matching is done to authenticate the person.

The overall system description, is shown in figure 1.

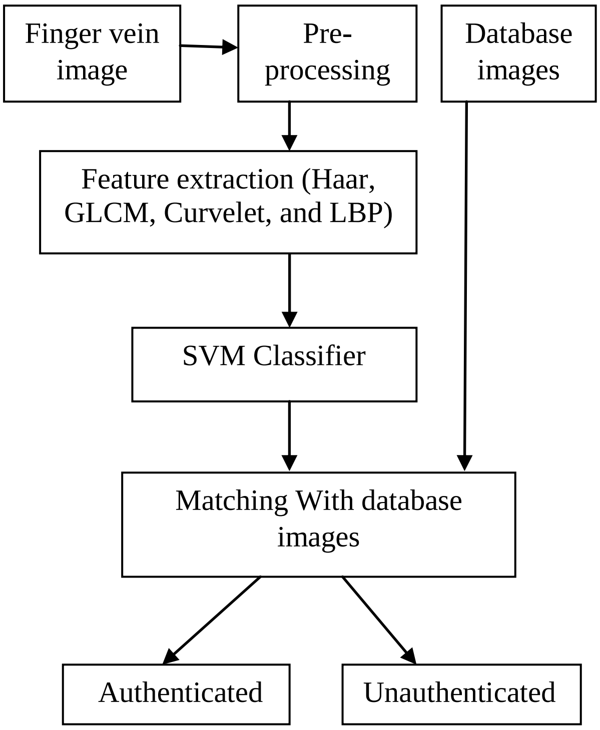
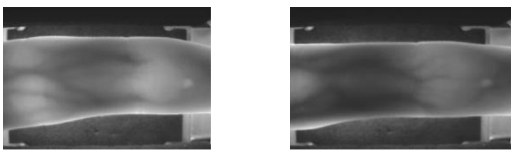


Figure 1: Functional block diagram

1) Input data:

The images used for this study is obtained from SDUMLA-HMT a finger vein database which, is the first open source finger vein database. The device used to capture this finger vein image is designed by Joint Lab for Intelligent Computing and Intelligent Systems of Wuhan University. This finger vein database composes of 3,815 images with index finger, middle finger and ring finger of both hands stored in "bmp" format with 320×240 pixels in size. The sample images are shown in figure 2.



(a) (b)

Figure 2: (a) Index finger (b) Middle finger

2) Pre-processing:

Image pre-processing can be done for later analysis. Its role is to prepare the images for feature extraction by enhancement, segmentation, filtering, ROI extraction etc. to make the input readable. It is done by using different image processing techniques and the software used here is MATLAB.

a) Image Denoising

The image captured may consist of salt and pepper noise and the gray level distribution, here the Median filter is used to reduce the noise. We choose a median filter because the other filters like low pass has assumed that the neighboring pixels represent an additional sample of the same feature and blurring of feature results. It is proved that median filters have no reduction in contrast, does not shift boundaries and can do a better job of preserving edges. [10] The noise filtered image is shown in figure 3.

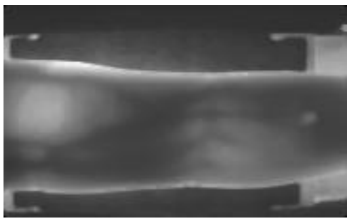


Figure 3: Noise filtered image

b) Image Enhancement

Initially the image is enhanced by equalizing the histogram of the image for higher image quality to extract the features and for better matching performance.

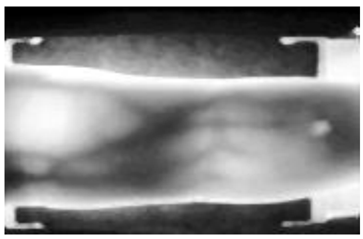


Figure 4: Histogram Equalized image

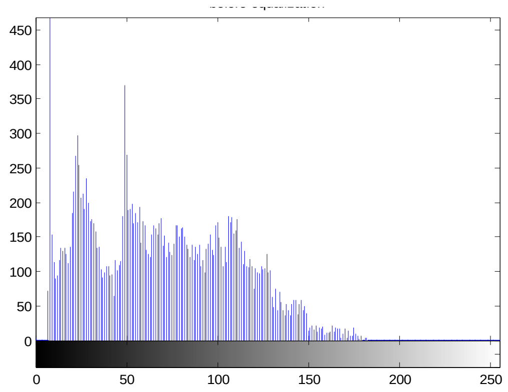


Figure 5: Histogram of Original image

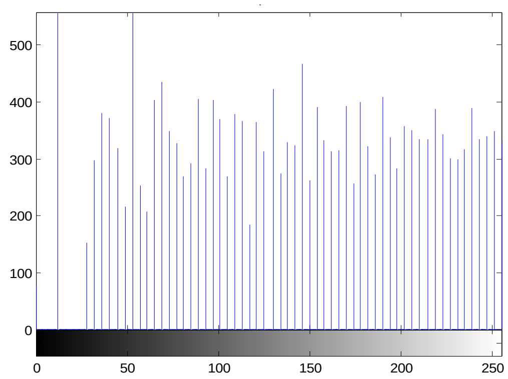


Figure 6: Histogram of Equalized image

The equalized image and the histogram of original and equalized images are shown in the above figures.

c) Region of interest (ROI) extraction

In the finger vein images, there are many unwanted regions which have to be removed by choosing the interested area in that image. The useful area called the "Region of Interest" alone is grabbed from where the finger vein patterns are extracted.

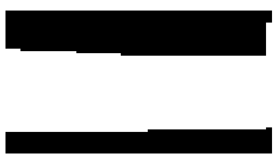


Figure 7: ROI Extracted image

3) Feature Extraction Methods

After pre-processing, the different methods like Curvelet, LBP, Haar wavelet and GLCM are used for feature extraction of finger vein. The different extracted features are given to the SVM classifier for evaluating their performance based on accuracy, Computational time, FAR and FRR.

Curvelet

Curvelets are the basis for representing images which are smooth apart from singularities along smooth curves, and the curves have bounded curvature, i.e. where objects in the image have a minimum length scale. The curvelet transform is the most appropriate feature extraction method for anisotropic biometric images with angles, lines and points. The 2D-FFT (two- dimensional Fast Fourier Transform) must be applied to the image before the implementation of the curvelet transform, because the 2D frequency plane is divided into wedges that are nothing more than the results of partitioning the Fourier plane in radial division and angular division. Concentric circles are responsible for decomposing the image into multiple scales defined by j and angular divisions defined by l. In the spatial domain each wedge corresponds to a given curvelet at scale and angle. The values of the curvelet coefficients are determined in relation to alignment with the actual image, the more accurate the alignment of a curvelet with a curved image, the higher its value coefficient. The curvelet transform of a function f is expressed as:

$$c(j,l,k) = \langle f, \varphi_{j.l.k} \rangle \qquad (1)$$

Where φ (j, l, k) is the curvelet, j, l, k are the scale parameters, directions and position, respectively. The curvelet transform is organized in such a way that most of the energy of the object can be localized in just a few coefficients and quantified

Local Binary Pattern

Local Binary Pattern (LBP) is a type of feature extraction method. An LBP can be defined as an ordered set of binary values determined by comparing the gray values of a center pixel and its neighboring pixels.

The local binary pattern (LBP) operator is an image operator which transforms an image into an array or image of integer labels describing small-scale appearance of the image. The feature vector is obtained by the following steps

- In LBP, a window is placed on each pixel in the image and divided into cells.
- The intensity of the center pixel is taken as threshold and compared against that of the neighboring pixels.
- After comparison, bigger intensity values are taken as 1 and smaller values as 0.
- Compute the histogram, over the cell, of the frequency of each "number" occurring and concatenate it.

The value of the $LBP_{P,R}$ operator is defined as:

$$LBP_{P,R} = \sum_{p=0}^{p=1} s(g_p - g_c)\, 2^p \qquad (2)$$

where g_c denote the gray level of an arbitrary pixel (x, y).
g_p denotes the gray value of a sampling point in an evenly spaced circular neighborhood of P sampling points and radius R around point (x, y).

Haar wavelet

The recognition accuracy is enhanced by extracting global features with the use of Wavelet transform. The Haar wavelet is a sequence of rescaled "square-shaped" functions which combine to form a wavelet family. Wavelet analysis is same as the Fourier analysis in that it allows a target function over an interval to be represented as an orthonormal function basis. A window of the target size is moved over the input image, and for each subsection of the image the Haar feature is calculated. This difference is then compared to a learned threshold that separates the regions. The key advantage of a Haar feature is its calculation speed.

GLCM:

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM). The GLCM functions extract the statistical measures by creating a matrix from the texture of an image by calculating how often pairs of pixel with specific values and occur in a specified spatial relationship in an image. The statistical features such as contrast, auto-correlation, correlation, uniformity, dissimilarity, energy can be extracted from the finger vein.
Some feature equations related to GLCM are shown below:[14]

$$\text{Mean}= \Sigma_i\, \Sigma_j\, P(i,j) * i \qquad (3)$$

$$\text{Contrast}= \Sigma i \Sigma_j\, P(i,j) * (i-j)^2 \qquad (4)$$

$$\text{Entropy}= \Sigma_i \Sigma_j -P(i,j)*\log_e P(i,j) \qquad (5)$$

$$\text{Correlation}=\Sigma_i \Sigma_j (i-\mu_x)*(j-\mu_y)*P(i,j)$$

$$\text{when } \mu_x = \Sigma j\, P(i,j) / n$$

$$\text{and } \mu_y = \Sigma_i\, P(i,j) / n \qquad (6)$$

where P(i,j) is the gray level matrix and n is the no of elements.

Table 1: Some features extracted using GLCM

Static	Description
Contrast	Refers to the local variations in the gray-level co-occurrence matrix.
Correlation	Refers to the joint probability occurrence of the specified pixel pairs.
Entropy	Gives the sum of squared elements in the GLCM.
Energy	Measures the closeness of the distribution of elements to the diagonal.

Figure 8: Vein extracted image

4) SVM Classifier

SVM classifier is a supervised learning which is used for training the images. In general, the SVM model is a representation of the examples as points in space, which are mapped so that they can be categorized separately or classes are divided by a dividing plane that maximizes the margin between various classes. This is due to the fact if the separating plane has the largest distance to the nearest training data points of any class, it lowers the generalization error of the overall classifier.[9] The goal of SVM Classification is to produce a model, based on the training data, which will be able to predict class labels of the test data accurately.

A main advantage of SVM classification is that SVM performs well on datasets that have many attributes, even when there are only a few cases that are available for the training process. The images are trained using SVM Classifier and features are extracted using the four methods. The feature vectors of LBP method are very high and ranges from 200-255. Figure 9 shows a graph describing the feature vector ranges.

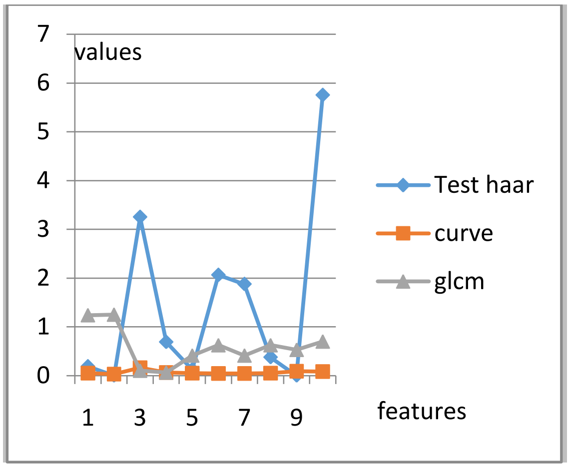


Figure 9: Range of feature values

5) Matching

Matching refers to the degree of match between feature values of test and trained images. The basis of many measures of similarity and dissimilarity is the Euclidean distance. The distance between vectors X and Y is defined as:

$$d(x,y) = \sqrt{\sum_{i}^{n} (x_i - y_i)^2} \quad (7)$$

Euclidean distance is the square root of the sum of squared differences between corresponding elements of the two vectors.

The input image is compared with the stored database images using Euclidean distance and a message box will appear as authenticated or unauthenticated based on the matching output.

IV. RESULTS & DISCUSSION

From the performance evaluation metrics, SVM shows an accuracy of 100% for Haar and LBP methods, 46% and 54% for GLCM and Curvelet respectively for a dataset containing 150 images. When computational time is considered, LBP and Haar show less time consumption.

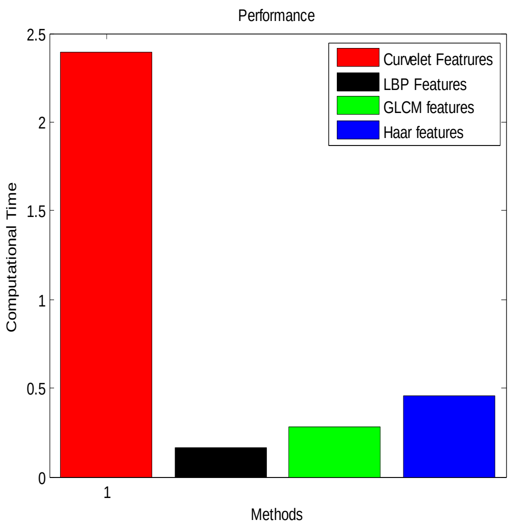


Figure 10: Computational time for all methods

After matching, Recognition rate, FAR and FRR are other factors considered for performance of biometric systems:[11]

- **False acceptance rate (FAR)**: The probability that the system incorrectly matches the input pattern to a non-matching template in the database. It measures the percent of invalid inputs which are incorrectly accepted.
- **False rejection rate (FRR)**: The probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent of valid inputs which are incorrectly rejected.

Table 2: FAR and FRR

Methods	FAR	FRR
Haar	0.1	0.9
GLCM	0.5	0.5
Curvelet	0.33	0.66
LBP	0.26	0.71

The FAR and FRR shown in Table 2 is obtained by taking 6 different images of the same individual. From the Classifier performance, we obtain the following accuracy and time for the different methods. The recognition rate for different techniques after matching is also tabulated below.

Table 3: Performance Analysis

Methods	Accuracy	Recognition rate	Time
Haar	100%	98.3%	0.45ms
GLCM	46%	96%	0.35ms
Curvelet	54%	96.4%	2.4ms
LBP	100%	92%	0.2ms

V. CONCLUSION

In this study, we compared the feature extraction methods like GLCM, Haar, Curvelet and LBP with the help of SVM classifier. We come to a conclusion that, even though Haar and LBP show good accuracy (100%), when they are compared with regard to their computational time, LBP consumes less time. But LBP cannot be termed as a better method because time is a primary factor of performance. Finally Haar can be referred as the best method when compared to other methods as the recognition rate is very high and it also gives a better FAR, FRR.

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VI. REFERENCE

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