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# Efficient Texture Classifier for Hand-dorsa Vein Recognition System using Completed LBTP (C-LBTP) Feature Descriptor

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**Abstract:**
Hand-dorsa Vein Recognition System is a biometric authentication system using inherent physiological characteristics to enable identification of individuals. Texture Description and classification are important feature analysis methods in hand-dorsa vein Recognition. In this paper a new feature description method such as Completed LBTP (C-LBTP) has been proposed to represent selected features from Hand vein image system. C-LBTP combines the features of Local Binary Pattern (LBP) and Local Ternary Pattern (LTP). C-LBTP is a texture descriptor used to extract the local information from the input image. To find the efficient patterns from feature vectors, a new efficient classifier based on minimum distance classification is proposed. The classification results are checked with accuracy and reliability. 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 C-LBTP feature descriptor achieved good performance.

Keyword : Feature Descriptor, LBP and LTP

## 1. Introduction

In the field of image processing, the analysis function such as image classification plays on vital role to find different unseen patterns. This classification analyzes the important properties of various image features and organizes them into categories or classes. The Classification algorithms typically employ different phases such as image acquisition, preprocessing, feature extraction, sampling of training data, analysis and pattern evaluation. In our proposed approach, the initial phase of image acquisition consists of retrieving images of hand vein system and it is filtered in pre-processing phase.

Feature extraction is the process of finding measured data and obtains derived values from the image. This information is non redundant and used for subsequent learning. It would be used for better human interpretation. When the input data is too large and contains large attributes then it is required to be transferred into reduced set of features called feature extraction. The extracted features are available in to feature vector for further analysis. The important characteristics of any object are taken as a features and it should be extracted to provide feature description of the object.

This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image containing many other objects. To perform reliable recognition, it is important that the features extracted from the training image be detectable even under changes in image scale, noise and illumination

In order to find the relationship between different images in various applications, it is necessary to identify a set of salient points in each image. The basic operations in image processing are to detect interest regions. The feature vector representation for each detected regions is constructed. Feature descriptors extracted from the image can be based on second-order statistics, parametric models, coefficients obtained from an image transform, or even a combination of these measures. Two types of image features can be extracted form image content representation; namely global features and local features. Global features (e.g., color and texture) aim to describe an image as a whole and can be interpreted as a particular property of the image involving all pixels. While , local features aim to detect keypoints or interest regions in an image and describe them.

Generally, using what kind of features might greatly depend on the applications on hand. Developers prefer the most discriminative ones. Then, local features or the global pattern distilled from local feature clusters seem to be more discriminative. Whereas, for very large datasets in the web-scale image indexing application, it is appropriate to consider global features. Also, global features are useful in applications where a rough segmentation of the object of interest is available. The advantages of global features are that they are much faster and compact while easy to compute and generally require small amounts of memory.

Several image detectors are available for both local and global representation. Different techniques have been proposed to address the problem of detecting and extracting invariant image features under these conditions.

In the literature, a large variety of feature extraction methods have been proposed to compute reliable descriptors. Among these descriptors, the scale in variant feature transform (SIFT) descriptor[32] utilizing local extrema in a series of difference of Gaussian (DoG) functions for extracting robust features. Gradient location-orientation histogram (GLOH) developed by Mikolajczyk and Schmid is also an extension of the SIFT descriptor. GLOH is very similar to the SIFT descriptor, where it only replaces the Cartesian location grid used by the SIFT with a log-polar one, and applies PCA to reduce the size of the descriptor. The Speeded-Up Robust Features (SURF) detector-descriptor scheme developed by Bayetal[33] is designed as an efficient alternative to SIFT. It is much faster, and more robust as opposed to SIFT. For the detection stage of interest points, instead of relying on ideal Gaussian derivatives, the computation is based on simple 2D box filters; where, it uses a scale invariant blob detector based on the determinant of Hessian matrix for both scale selection and locations.

In this project, the LBP operator had been used. It is a texture descriptor used to extract the local information from the input image. It is based on the gray level comparison of a neighbourhood of pixels. Therefore it has the potential to extract discriminative features from the hand vein images. The size of the operator must be adapted to the size of the information to be extracted. Local Binary Pattern (LBP) operator was proposed by Ojala et al. [23] for rotation invariant texture classification LBP proposed by Ojala et al. [23] has become the research direction for many computer vision researchers. This is because it is able to distinguish the microstructures such as edges, lines, and spots. The researchers aim to increase the discriminating property of the texture feature extraction to achieve impressive rotation invariant texture classification. So, many of the variants of the LBP have been suggested and proposed for rotation invariant texture classification. The center-symmetric Local Binary Pattern (CS-LBP) proposed by Heikkil et al. [25] is an example for that. Unlike the LBP, they compared center-symmetric pairs of pixels to get the encoded binary values. Liao et al. [26] proposed Dominant LBP (DLBP) by selecting the dominant patterns from all rotation invariant patterns. Tan and Triggs [27] presented a new texture operator which is more robust to noise. They encoded the neighbor pixel values into 3-valued codes instead of 2-valued codes by adding a user threshold. This operator is known as a Local Ternary Pattern (LTP). Guo et al. [28] combined the sign and magnitude differences of each pattern with all central gray level values of all patterns to propose a completed modeling of LBP, called completed LBP (CLBP). Khellah [29] proposed a new method for texture classification, which combines Dominant Neighborhood Structure (DNS) and traditional LBP. Zhao et al. [30] proposed a novel texture descriptor, called Local Binary Count (CLBC). They used the thresholding step such as in LBP. Then they discarded the structural information from the LBP operator by counting the number of value 1's in the binary neighbor sets instead of encoding them.

Inspiredby Weber's Law, adense descriptor computed for every pixel depending on both the local intensity variation and the magnitude of the center pixel's intensity called Weber Local Descriptor (WLD) is proposed in [7]. The WLD descriptor employs the advantages of SIFT in computing the histogram using the gradient and its orientation, and those of LBP in computational efficiency and smaller support.

## 2. Local Binary Patterns

The dorsal hand vein imaging requires near-infra-red (NIR) illumination for extracting the complex vascular structures residing inside the dorsum. A key issue in dorsal hand vein feature extraction from NIR images is finding efficient and suitable descriptors for its appearance. There are several techniques like localized Radon Transform, Laplacian palm based on PCA, complex matched filtering, etc. Recently, local texture descriptors have also gained attention in dorsal hand vein recognition. Finding a good feature descriptor is one of the key issues for a well designed feature extraction method.

The LBP operator was first introduced as a complementary measure for local image contrast. The first incarnation of the operator worked with the eight-neighbors of a pixel, using the value of the center pixel as a threshold. An LBP code for a neighborhood was produced by multiplying the thresholded values with weights given to the corresponding pixels, and summing up the result as shown in figure 2.1.

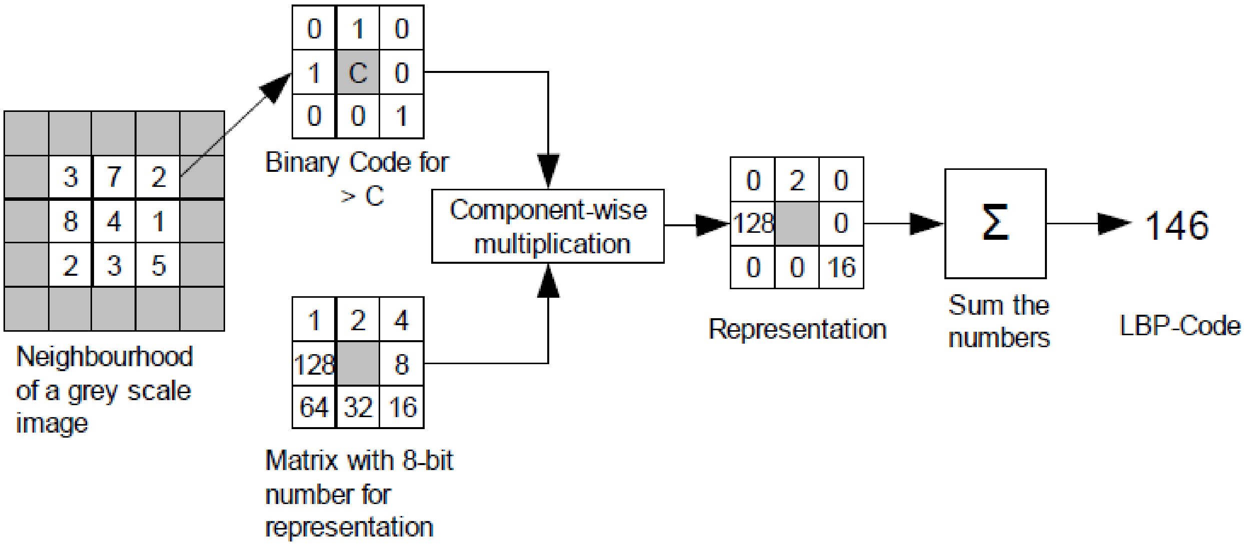


**Figure 2.1 Example of LBP binary code generators**

The local binary pattern operator is an operator that describes the surroundings of a pixel by generating a bit-code from the binary derivatives of a pixel. The operator is usually applied to gray scale images and the derivative of the intensities. In its simplest form the LBP operator takes the 3×3 surrounding of a pixel and generates a binary 1 if the neighbor of the centre pixel has larger value than the centre pixel as shown in figure 2.2. The operator generates a binary 0 if the neighbor is less than the centre.

The eight neighbors of the centre can be represented with an 8-bit number such as an unsigned 8-bit integer, making it a very compact description. Often LBP code distribution over an image is used to describe the vein image as a histogram of that image.

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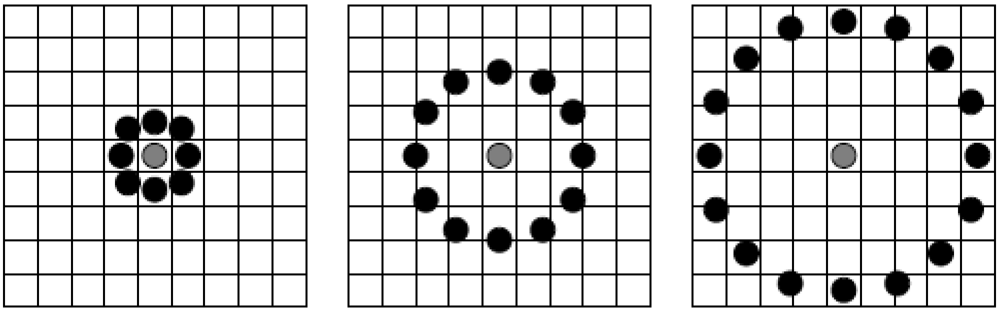


**Figure 2.2 Circular Neighborhoods with different radius**

Each resulting decimal number is considered as a value to be put in the corresponding bin of histogram. In particular, the uniform LBP places an emphasis on patterns. Figure 2.2 shows an example of LBP operator with 8-, 16-, and 24- neighbourhood pixels. In this project, the 3×3 neighbour pixels have been considered. This because only when the size of the mask is small, even the minute discriminate features from the hand vein images can be discovered without any loss or addition of information.

Dorsal hand veins are line structures with changing width, whose gray-level values differ from the background. The LBP operator is based on gray-level differences in local neighbourhoods. Therefore it has the potential to extract discriminative features from the hand vein images. The size of the operator must be adapted to the size of the information to be extracted. In the case of a neighbourhood containing a vein region, the vein will either cross the local neighbourhood or end side. Thus, the resulting patterns of interest will not present many discriminative bitwise transitions indicating gray-level changes. It is therefore logical to consider uniform patterns.

The direction of veins presents a discriminative feature; therefore it is not necessary to consider rotation-invariant patterns. In order to preserve local spatial information, the LBP operator is applied on partitions of an image and not to the whole image. A local binary pattern is said to be uniform, if it contains at most two bitwise transitions from 0 to 1, or vice versa. For example, 00010000, 10000000, 00000001, 10000001 are uniform patterns. The operator $LBP_{P,R}^{riu2}$ is defined to indicate LBP uniform patterns.

## 3. Local Ternary Pattern

The LBP is sensitive to noise, because a small gray change of the central pixel may cause different codes for a neighbourhood in an image, especially for the smooth regions. In order to overcome such a flaw, Tanand Triggs [31] extended the basic LBP to a version with three-value codes,which is called the local ternary pattern (LTP). In LTP, the indicator s(x) is further defined as:

$$LTP_{P,R,r} = \sum_{i=0}^{p-1} s(p_i - p_c) \text{ x } 3^{i.}, \quad s(x) = \begin{cases} 1, x \geq T \\ 0, |x| < T \\ -1, x \leq T \end{cases}$$

where τ is a threshold specified by the user. In order to reduce the feature dimension, a coding scheme is also represented by Tan and Triggs [31] by splitting each ternary pattern into two parts: the positive part and the negative part, as illustrated in Figure 3.1. Though the LTP codes are more resistant to noise, it is no longer strictly invariant to gray-level transformations, because τ is constant in feature extraction for all neighborhoods and all images in the database.

| | | |
|---|---|---|
| 6 | 5 | 2 |
| 7 | 6 | 1 |
| 9 | 8 | 7 |

| | | |
|---|---|---|
| 0 | 0 | -1 |
| 0 | | -1 |
| 1 | 1 | 0 |

| | | |
|---|---|---|
| 0 | 0 | 0 |
| 0 | | 0 |
| 1 | 1 | 0 |

| | | |
|---|---|---|
| 0 | 0 | 1 |
| 0 | | 1 |
| 0 | 0 | 0 |

**Figure 3.1 LTP Computation**

The LTP computation in figure 3.1, positive part is 00110000 and negative part is 10000001. Tan and Triggs [27] presented a new texture operator which is more robust to noise. The LBP is extended to 3-valued codes . Local ternary patterns (LTP) are an extension of Local binary patterns (LBP). Unlike LBP, it does not threshold the pixels into 0 and 1, rather it uses a threshold constant to threshold pixels into three values. In this way, each thresholded pixel has one of the three values. Neighboring pixels are combined after thresholding into a ternary pattern. Computing a histogram of these ternary values will result in a large range, so the ternary pattern is split into two binary patterns.

## 4. Completed LBTP (C-LBTP) Feature Descriptor

In this section we propose a simple, robust new approach for the feature extraction from the images. The new completed LBTP descriptor combines the features of LBP and LTP. Feature extraction from LBP operations are converted into histogram, similarly Operations of LTP is applied on image and separate individual histogram is generated. The following figure illustrates the complete overview on proposed framework C-LBTP.

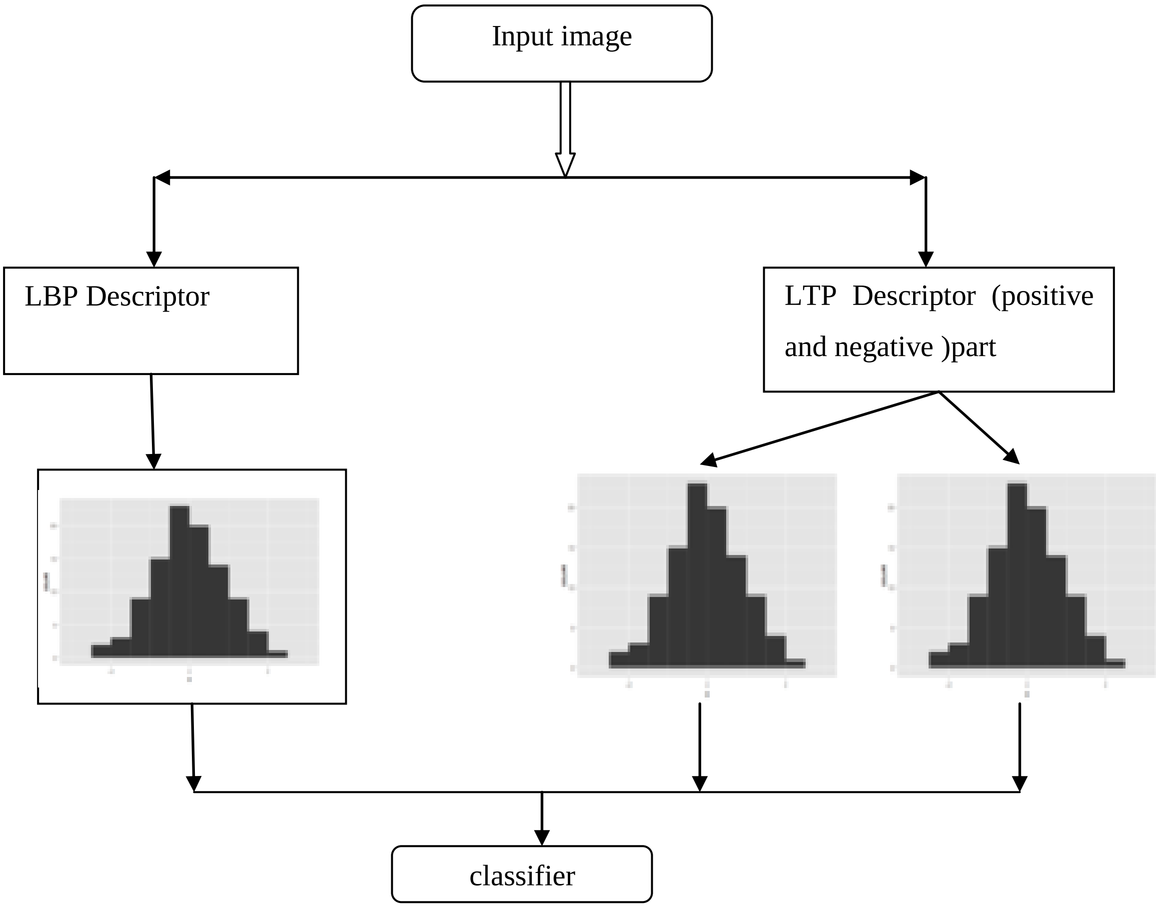


**Figure 4.1 Complete LBTP framework**

The hand vein recognition process involves capturing vein patterns with the use of infrared technologies (infrared light with wavelength between 700nm-1000nm). When the hand is placed on a scanner, infrared light passes through the tissue and the rays are absorbed by the red blood cells (Hemoglobin). The infrared-sensitive camera sees the shadow of the veins as black lines and the rest of the hand structure is seen as white. The extracted vein template is then compared with the previously stored patterns and a match is made.

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.

In this work, the centroid is considered as the centre to extract the ROI. The centroid (x0, y0) of vein image f(x, y) can be calculated as shown in (4.1, 4.2). 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

$$x_0 = \frac{\sum_{i,j} i \times f(i, j)}{\sum_{i,j} f(i, j)} \qquad (4.1) \qquad\qquad y_0 = \frac{\sum_{i,j} j \times f(i, j)}{\sum_{i,j} f(i, j)} \qquad (4.2)$$

After finding the image centroid the image cropping is subsequently performed to yield a sub-image of 360×360 pixels. LBP operator is applied on input image and the resultant histogram is the specific output. The operator assigns a label to every pixel of an image by thresholding the 3x3-neighborhood of each pixel with the center pixel value and considering the result as a binary number. Then the histogram of the labels can be used as a texture descriptor. Similarly LTP operation is applied and the output of separate histogram is generated. Both have combined together to form a combined features of histogram.

The minimum distance algorithms are simple classifiers that select the training samples with the closest distance. These classifiers will compute the distance from the query sample to every training sample and select the best neighbour or neighbours with the shortest distance.

## 5. 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

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

Four distance measures namely Chi – square, Euclidean, City block, Minkowski is used to measure the performance of the system. According to the Euclidean distance formula, the distance between two points in the plane with coordinates $(a, b)$ with k dimensions is given by,

$$\text{Dist}_{\text{Euclidean}} = \sqrt{\sum_{j=1}^{k} (a_j - b_j)^2}$$

The City block distance is always greater than or equal to zero. The measurement would be zero for identical points and high for points that show little similarity. The City block distance between two points, a and b, with k dimensions is calculated as,

$$\text{Dist}_{\text{Cityblock}} = \sum_{j=1}^{k} \left| a_j - b_j \right|$$

Notice that for the special case of p = 1, the Minkowski metric gives the city block metric and for the special case of p = 2, the Minkowski metric gives the Euclidean distance.

$$\mathrm{Dist}_{\mathrm{Minkowski}} = \sqrt[P]{\sum_{j=1}^{k} \left| a_j - b_j \right|^P}$$

The chi-squared distance is useful when comparing histograms. The chi-squared distance between two vectors is defined as,

$$\mathrm{Dist}_{\mathrm{Chi-Square}} = \sum_{j=1}^{k} \frac{(a_j - b_j)^2}{(a_j + b_j)}$$

Table 5.1 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 | 96.08 | 97.06 | 96.08 | 93.14 | 81.37 | 70.59 | 87.25 | 75.49 | 56.86 | 51.47 |
| K=2 | 204 | 93.14 | 96.08 | 91.18 | 98.04 | 89.22 | 83.33 | 94.12 | 85.29 | 66.67 | 59.80 |
| K=3 | 204 | 97.06 | 96.08 | 93.14 | 98.04 | 91.18 | 87.25 | 93.14 | 82.35 | 59.80 | 62.75 |
| K=4 | 204 | 96.08 | 98.04 | 93.14 | 91.18 | 87.25 | 85.29 | 82.35 | 59.80 | 66.67 | 51.96 |
| K=5 | 204 | 93.14 | 96.08 | 93.14 | 96.08 | 89.22 | 87.25 | 85.29 | 51.29 | 59.80 | 51.96 |
| Avg. Recognition Rate | | **95.10** | **96.67** | **93.34** | **95.30** | **87.65** | **82.74** | **88.43** | **70.84** | **61.96** | **55.59** |

Table 5.1 shows the recognition rate of various nearest neighbour classification algorithm. The Chi – Square classification have 95.10 high recognition rate. The proposed approach is also evaluated with reliability performance and it is shown in table 5.2.

Table 5.2 Equal error rate for NCUT hand vein dataset left hand images

| **Distance Measure** | **Left** | **Right** |
|---|---|---|
| | **Equal Error Rate** | |
| Chi-Square | 0.05 | 0.05 |
| Cityblock | 0.06 | 0.06 |
| Euclidean | 0.13 | 0.12 |
| Minkowski | 0.18 | 0.17 |
| Chebychev | 0.20 | 0.20 |

Table 5.2 exhibits that the chi-square have minimum error rate compared to others.

The NCUT hand vein database is experimented with different descriptors against different classification methods. The results are obtained and it is shown in table 5.3.

Table. 5.3 Comparison – NCUT hand vein database

| Distance Measure | Chi - Square | | Cityblock | | Euclidean | | Minkowski | | Chebychev | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Left | Right | Left | Right | Left | Right | Left | Right | Left | Right |
| Methods | Recognition Rate (%) | | | | | | | | | |
| LBP | 90.68 | 92.25 | 87.35 | 90.88 | 80.39 | 84.71 | 74.80 | 79.71 | 76.54 | 50.80 |
| WLBP | 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 |
| C- LBTP | **95.10** | **96.67** | **93.34** | **95.30** | **87.65** | **82.74** | **88.43** | **70.84** | **61.96** | **55.59** |

The results in table shows that the C-LBTP descriptor performs well with overall recognition rate 95.10%. The approach of Chi-square and C-LBTP performs as a best feature descriptor with highest recognition rate. Hence the experiment proves the best performance of proposed approach.

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.

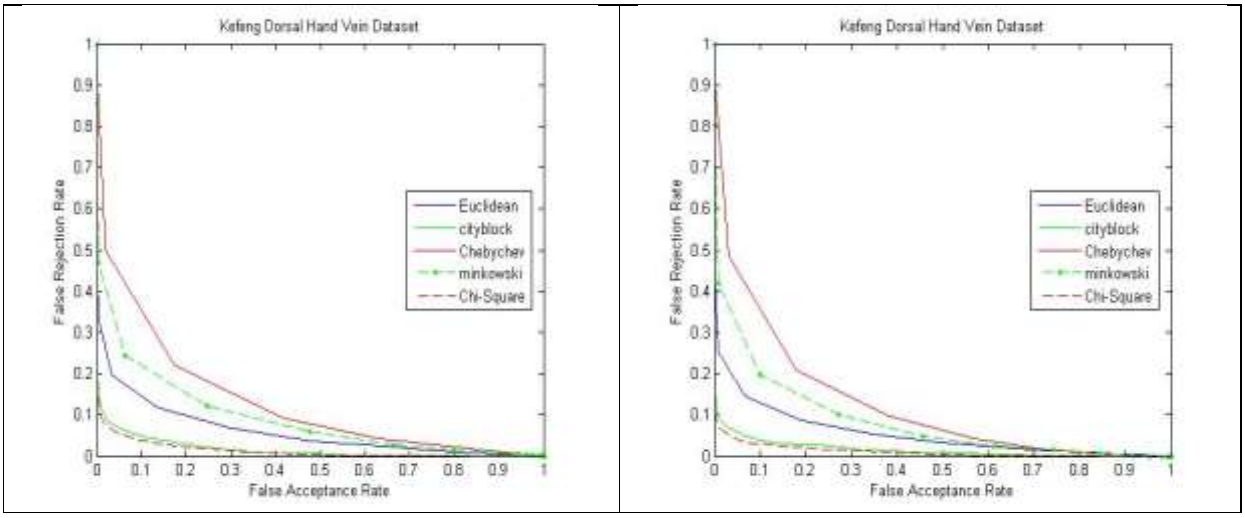


Figure 5.1 FAR and FRR for left and Right Hand Vein Dataset

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 5.2 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.

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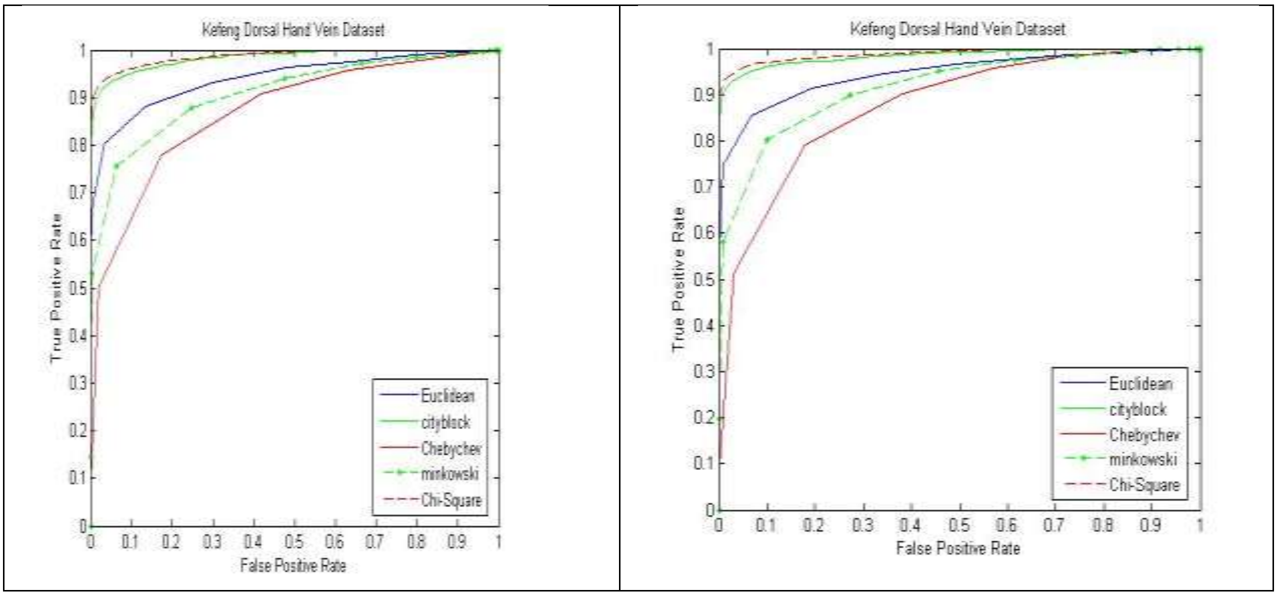


Fig 3.2 ROC for left and Right Hand Vein Dataset

## 6. Conclusion

In this paper, a framework for biometric classification system using dorsal hand vein patterns is proposed with fusion of the components LBP and LTP Feature Descriptor. 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 95.10% for NCUT Dataset. Also the results are examined with state-of- art algorithms LBP WLBP and HOG, the proposed work outperforms the existing methods.

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