PALM VEIN RECOGNITION SCHEME BASED ON HOG

N. Subathra[1], Dr.K.Merriliance[2]

[1]Research Scholar, Register Number : 18121172282014, Sarah Tucker College (Autonomous)

[1]Manonmaniam Sundaranar University,Abishekapatti, Tirunelveli 627 012 ,Tamilnadu, India

[2]Assistant Professor, Department of MCA

[2]Sarah Tucker College (Autonomous),Tirunelveli 627 007, Tamilnadu, India

[1]subathra30@gmail.com ,[2]merrilliance@gmail.com

Abstract

Finger palm vein recognition is one of the methods used for identification because of its individuality, firmness, live body identification, elasticity and difficulty to cheat. This paper focuses on the technique for palm vein recognition. It comprises of three modules, Preprocessing, Histogram of Image Gradient, Palm Vein matching. Preprocessing is done with the help of OTSU and CLAHE techniques. Palm vein features are extracted using HOG. In palm vein matching, Chi-square distance value is used. The CASIA Palm Print Database is used for palm vein recognition. The performance of the proposed method is measured by the evaluation metrics such as accuracy, specificity, sensitivity, error rate, recall and precision.

Keywords: Biometrics, Palm Vein, HOG, ROI,CASIA Database.

1. INTRODUCTION

Biometrics is the automated recognition technique which confirm a person's identity by extracting and comparing patterns in their behavioral and natural characteristics such as face, iris, palm or finger vein patterns,fingerprints, ear structure, voice patterns. Biometric performance evaluation task is important one , particularly for Palmprint identification, given its widespread applications [1]. Palmprint refers to an image required of the palm region of the hand. Palmprint is also distinctive and can easily be captured with low resolution devices. Palmprint is suitable for everyone and besides it has one big plus: it does not require personal information. The palm of each person consists of principle lines, wrinkles secondary lines and ridges. Palm also contains such information as texture, indents and marks which are used during the comparison of one palm with another. This palm vein patterns are considered stable and reliable, which means that once a person has reached adulthood, the hand structure, veins and configuration remain relatively stable throughout the person's life [4].

2. Literature Review

Pawan Dubey et.al.[2] presented a novel Palmprint recognition scheme by applying Anisotropic Filters (AFs) which outweighs the Gabor Filters. Gabor Filters although used extensively are inefficient for image recognition under varying illuminations, possess high complexity and have large storage requirement. The Anisotropic Filters were applied optimally followed by Local Binary Pattern (LBP) known as Optimal Local Direction Binary patterns (OLdirBP) for feature size reduction [2]. Thus a Palmprint recognition system was proposed with low computational complexity, small features length and robust to noise.

Gaurav Jaswal et.al.[3] presented a texture based Palmprint recognition method which employ 2D Gabor filter to extract texture information from the palm and use subspace methods for dimension reduction. The test and training images were compared in terms of calculating Euclidean distance between them. The proposed algorithm was tested on standard benchmark databases (CASIA and IIT Delhi) and the results emphasize on the accuracy of proposed method in terms of the Correct Recognition Rate and Computation Time.

P. Cancian et.al.[5] presented an Embedded Gabor-based Palm Vein Recognition System which described the development of an embedded standalone palm vein authentication system. Image is captured for contact-less acquisition on the keypoints are isolated by Hand tracking algorithm. Then the image is enhanced by CLAHE preprocessing and the feature is extracted through multiple Gabor filters and the modules are matched. Thus the user can be identified or authenticated by the resultant vector.

J.C. Lee [6] discovered a texture descriptors Local Binary Patterns (LBP) and Uniform Local Binary Patterns (LBPU). Extract methods for biometric verification, which employ hand segmentation, Meaningful point detection and ROI detection and enhancement to preprocess the image. Then the biometric features are represented by Texture description and it is tested by Uniform Binary Patterns [21] and LBP are compared

Leila Mirmohamadsadeghi et.al.[7] presented texture based palm vein recognition which employs two operators. There are local binary pattern (LBP) operator as well as the local derivative pattern (LDP) operators, that were brought into a comparison and LBP is observed to be the efficient descriptors for palm vein recognition. Then palm vein recognition is investigated by LDP histograms. Finally the framework of identification and verification are compared along with the evaluation of both the feature extraction methods.

Yingbo Zhou et.al.[8] presented human identification using palm-vein images to decide the identity which employs preprocessing, feature extraction and module matching which is finally compared to database.

Wenxiong Kang [9] presented Contactless Palm Vein Recognition Using a Mutual Foreground-Based Local Binary Pattern which employs MPC and K means method for texture extraction. Then LBP matching strategy between gray scale images. The best matching region is obtained by MPR and the matching score is obtained. And Finally the computational efficiency is increased.

3. METHODOLOGY

The proposed work has three modules as shown in Figure 1.

i. Preprocessing
ii. HOG
iii. Palm Vein Matching

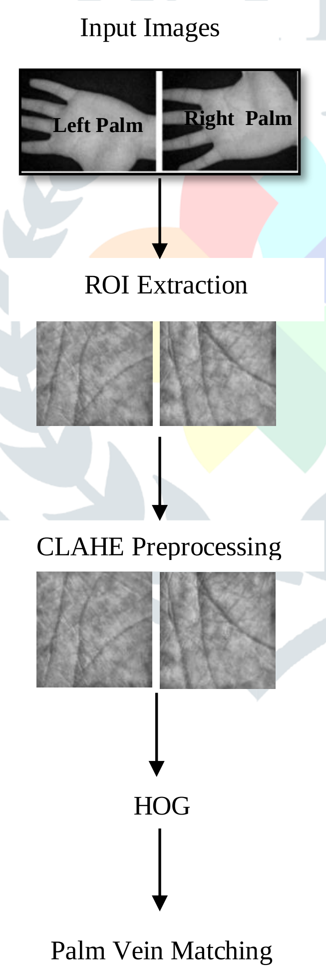

Figure 1. Modules of Palm Vein Recognition

Preprocessing

In this preprocessing module, to select an input image from CASIA Ms Palm Print database. The data base has the images of both left and right hands. First the region values are determined by ROI extraction Technique. Region of Interest used to extracting the region values from both left and right hand.

The steps of ROI extraction for palm vein are as follows:

1) The original image of palm vein is the grayscale image as shown in Figure 2.

Figure 2. Left palm

2) Apply OTSU technique

3) CLAHE Preprocessing

OTSU

Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either fall in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum.

Normalization Size (Dimension)

Normalization of ROI image size is done by resizing the image ROI to the smallest size of all images ROI palms used to the system. ROI image normalization size used was 256 x 256 pixels.

CLAHE Preprocessing

Apply the CLAHE preprocessing method to enhance the contrast of gray scale images. This preprocessing uses the parameter values such as Distribution and Rayleigh. Distribution parameter means that desired histogram shape and Rayleigh parameter is used to create a bell shaped histogram.

A Histogram of Image Gradient (HOG)

Histogram of Orientation gradient technique used to calculate the Chisquare distance.HOG [11] is used in this study because local shape information such gaits is often well described by the distribution of local intensity gradients or edge directions. The first step of calculation is to compute a gradient value on each pixel in Bi . To do this, Bi is filtered to obtain x and y derivatives of pixels by using following spatial filter masks. Actually, the more complex spatial filter masks such as 3 × 3 Sobel masks [12] can be adopted. However, they generally do not exhibit better performances in practice.

$$G_x = [-1\ \ 0\ \ 1],\ G_y = [-1\ \ 0\ \ 1]^T \quad (1)$$

Therefore, the x derivative (I_x) and the y derivative (I_y) of Bi are calculated as:

$$I_x(x, y, t) = \sum_{j=-1}^{1} j \times Bi(x+j, y, t)$$

$$I_y(x, y, t) = \sum_{j=-1}^{1} j \times Bi(x, y, +j, t) \quad (2)$$

Then, the magnitude ($|Bi(x, y,t)|_{hog}$) and the orientation ($\angle_{hog}Bi(x, y,t)$) of the gradient are computed as:

$$|Bi(x, y,t)|_{hog} = I_X^2(x, y,t) + I_y^2(x, y,t)\ \ _{hog}Bi(x,y,t)=\arctan \frac{Iy\ (x,y,t)}{Ix\ (x,y,t)} \quad (3)$$

The second step of calculation is to create cell histograms.

The a orientation bins ({Oj} a j=1) are used for [0°, 360°] interval. Thus, the a bins are defined as O_j : $[\frac{(j-1)360}{a}, \frac{(j)360}{a}]$ .For each pixel's orientation $_{hog}Bi(x, y,t)$, the corresponding orientation bin is found and the orientation's magnitude $|Bi(x, y,t)|_{hog}$ is voted to this bin, as:

$$O_j = O_j + |Bi(x, y,t)|_{hog} \quad (4)$$

where

$$_{hog}B_i(x, y,t) \in O_j : [\frac{(j-1)360}{a}, \frac{(j)360}{a}] \quad (5)$$

The last step is a process of histogram normalization. L2-norm normalization is applied on the histogram to generate the a−bin HOG descriptor as:

$$\frac{\{Oj\}_{j=1}^{a}}{\sqrt{\sum_{j=1}^{a} o_j^2}} \quad (6)$$

Palm Vein Matching

In this module , new algorithm for palm vein matching is introduced.

Algorithm

Input : Let n image from CASIA MSPALM PRINT

Output : The feature vector of all samples as database

Steps

- Browse an Image from CASIA MSPALM PRINT Database.
- Apply ROI Extraction using OTSU technique
- Apply CLAHE Preprocessing
- Find the Histogram of Orientation Gradient
- Calculate the Chi-square distance for Palm vein matching using the following Equation 7.

$$x^2(x_i, x_j) = \frac{1}{2}\sum_{l=1}^{d}\frac{(x_{il} - x_{jl})^2}{x_{il} + x_{jl}} \qquad (7)$$

- To analyze the performance evaluation

Database description

The CASIA Multi-Spectral Palmprint Image Database V1.0 [10], collected by the Chinese Academy of Sciences Institute of Automation (CASIA), has been used for evaluation purposes. It contains 5,502 palmprint images captured from 312 subjects. For each subject, collect palmprint images from both left and right palms.

4. PERFORMANCE EVALUATION

The performance evaluation can be defined based on the confusion matrix shown on Table 1. In this table, the row indicates the predicted class and the column indicates the actual class. From this confusion matrix, *tp* and *tn* denote the number of positive and negative instances that are correctly classified. Meanwhile, *fp* and *fn* denote the number of misclassified negative and positive instances, respectively.

Table 1. Confusion Matrix for Binary classification

Actual Positive Class	Actual Negative Class
True positive (tp)	False negative(fn)
False positive (fp)	True negative (tn)

The performance of the classifier is evaluated with the different values derived from Accuarcy, Error rate , Sensitivity, Specificity , Recall ,Precision and so on.

Accuracy(acc)

Accuracy is calculated to measure the ratio of correct predictions over the total number of instances evaluated using Equation 8.

$$acc = \frac{tp + tn}{tp + fp + tn + fn} \qquad (8)$$

Error Rate (err)

Error Rate is used to measures the ratio of incorrect predictions over the total number of instances evaluated. It is calculated using Equation 9.

$$err = \frac{fp + fn}{tp + fp + tn + fn} \qquad (9)$$

Sensitivity (sn)

Sensitivity is used to measure the fraction of positive patterns that are correctly classified. It is calculated using Equation 10.

$$sn = \frac{tp}{tp+fn} \quad (10)$$

Specificity (sp)

Specificity is used to measure the fraction of negative patterns that are correctly classified. It is calculated using Equation 11.

$$sp = \frac{tn}{tn+fp} \quad (11)$$

Precision (p)

Precision is used to measure the positive patterns that are correctly predicted from the total predicted patterns in a positive class. It is calculated using Equation 12.

$$p = \frac{tp}{tp+fp} \quad (12)$$

Recall (r)

Recall is used to measure the fraction of positive patterns that are correctly classified. It is calculated using Equation 13.

$$r = \frac{tp}{tp+tn} \quad (13)$$

F-Measure (FM)

F-Measure is used to represents the harmonic mean between recall and precision values. It is calculated using Equation 14.

$$FM = \frac{2*p*r}{p+r} \quad (14)$$

5. EXPERIMENTAL RESULTS

Accuracy, Sensitivity, Precision, Recall, F-Measure for both left and right palm images are compared.

Table 2: COMPARISON OF PERFORMANCE OF HOG TECHNIQUES FOR CHI-SQUARE DISTANCE

METHOD	LEFT PALM	RIGHT PALM
Accuracy	0.9866	0.9866
Sensitivity	0.8981	0.8955
Specificity	0.9869	0.9869
Precision	0.9039	0.9039
Recall	0.8981	0.8955
F-Measure	0.896	0.8935

In Table 2 shows values of the accuracy,specificity, precision of both the palm images which are equal for Chi-Square distance. The values of Sensitivity , Recall and F-Measure of both the palm images are different for Chi-Square distance.

The proposed method is compared with the already existing method LBP [13] and LDTP[13]. Multispectral CASIA database is used. Table 3 shows the comparison study of palm vein recognition using different feature extraction techniques.

Table 3. COMPARISON STUDY

METHOD	ACCURACY	ERROR RATE
LBP [13]	87.5%	0.125
LDTP [13]	92.5%	0.075
HOG	**98.66%**	**0.0134**

In Table 3, the accuracy values of HOG is better than the LBP and LDTP methods. HOG method is found to be the better and advantageous one.

6. CONCLUSION

In this research paper, the palm vein recognition is performed based on HOG. Three modules are implemented. To detect palm vein matching, Chi-square distance found using HOG methods. Finally, HOG method in Chi-Square distance shows good result in recognition and prediction of palm vein matching.

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