Palmprint Recognition Using Fusion of Local Binary Pattern and Histogram of Oriented Gradients

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Abstract

In this paper, unique features of the segmented image samples are extracted using two major feature extraction techniques: Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG). After this, these features are fused to get more precise and productive outcomes. The average accuracy of the three distinct datasets that were generated using the LBP and HOG features is determined. To calculate the accuracy of the three distinct models, classification techniques like KNN and SVM are adopted.

Keywords: Palm Print Recognition; Region of Interest; Local Binary Pattern; Histogram of Oriented Gradients.

1. Introduction

These days, biometrics is an implausible and powerful strategy for robust security functions in many applications [1]. In recent times, it has picked up a gigantic measure of consideration from researchers over the world. Various biometric characteristics, including fingerprint, face, iris, gait, key-stroke, and palmprint, are being widely used based on the suitability of the applications in the market [2– 4]. Compared with the other biometric traits, palmprint has solid and strong stability, high uniqueness, and nominal distortion [5]. Regrettably, specific components may alter palmprint patterns, for example, changes in orientations, fluctuations in illuminations, and sensor noise that may lead to misclassification. The fluctuations significantly influence the capability and efficiency of such systems in illuminations and alterations in the orientation of multispectral palmprint pictures. The general block diagram is shown in Fig. 1.

Experimental solutions have been proposed for these issues by using distinct feature extraction, matching, and reduction algorithms. These works can be majorly classified into 4 significant groups: line-based, statistical-based, subspace-based, and coding-based ways. The line-based methodologies have been introduced to detect the palmprint lines using edge detection techniques. For instance, Han and others [6] presented a technique based on the Sobel edge detector with morphological operations to find the line features from palmprint images. Wu and others [7] used the Sobel mask to compute the magnitude of palmprint lines and project these magnitudes on both the x and y coordinates for generating the histograms as discriminative features.

Various studies propose statistical-based methodologies and produce sensible outcomes [8– 10]. Various statistics have been used in this group of approaches, for example, different types of central moments, mean, mean square

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error, variance, energy, and second-order moments. Various transforms have been applied to extract the essential features from palmprint image samples. For instance, Gan and Zhou [1] used wavelet coefficients,

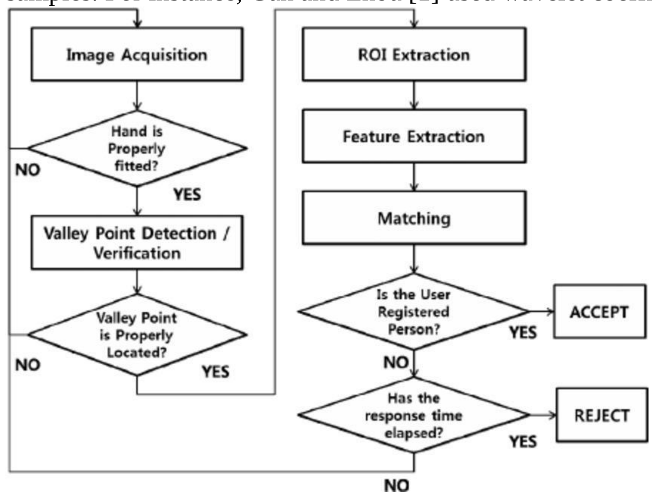

Figure 1: Block diagram of the System

then compute the variance and the mean of these coefficients, and finally generate a feature vector of the palmprint image. Li and others [12] proposed a two-phase test sample representation (TPTSR) method as a feature extractor for effective palmprint recognition. To improve the accuracy of the palmprint recognition system, a Coarse to Fine - Nearest Neighbor Classifier (CFKNNC) was developed by Xu and others [13]. However, the CFKNNC is more complicated than FKNNC as it comprises more steps. Zhang and Gu [14] also proposed a novel palmprint recognition technique based on the mapping of the radial basis function kernel. In this procedure, the training set is linearly combined in the feature space and then used to show the testing dataset. Numerous techniques based on texture features of palmprints are also introduced by some of the researchers in the area of palmprint recognition. These techniques are introduced to compute the statistical features after extracting the palmprint textures using some filters and transforms, for example, Gabor wavelet, wavelet transform, Gaussian derivative filters, and Fourier transform. In this context, Xu and others [15] proposed a technique based on a quaternion matrix for palmprint recognition. This method employed the principal components analysis (PCA) and wavelet transform for extracting the palmprint texture features from the quaternion matrix. For palmprint matching, the Euclidean distance classifier is used to compute the similarity between the extracted features. Subspace-based techniques are used to extract subspace features for enhancing the palmprint recognition system. Principal component analysis (PCA), Linear discriminant analysis (LDA), and Independent component analysis (ICA) are included in the different subspace learning approaches. An approach was proposed by Lu and others [16] that could transform a small feature space set, called Eigen palms, from the original palmprint images. In fact, the Eigen's palms are also referred to as eigenvectors of the PCA, which shows the training dataset of the palmprint images. Euclidean distance classifier is used for matching in this method. In [17], a vertical and horizontal two-dimensional Linear discriminant analysis (2DLDA) is executed to extract the Gabor features. Then a distance-based versatile technique is employed to merge the vertical and horizontal features. Recently, Xu and others [18] proposed a multispectral palmprint recognition technique that uses the Digital Shearlet transform and multiclass projection extreme learning machine. Singular Value Decomposition (SVD) was employed to calculate the projection matrix from the training dataset. Following that, relying on the greatest values in the singular matrix, the singular vector is extracted. The preliminary outcomes of [18, 19] have demonstrated the capability of the Extreme Learning Machine (ELM) classifier to distinguish the palmprint patterns. However, ELM isn't robust to many changes of the palmprint template like translation and rotation. It needs some regularization parameters for generality during the training phase. El-Tarhouni and others [20] proposed a strategy for multispectral palmprint feature extraction. In this method, a kernel discriminant analysis (KDA) is used to decrease the dimensionality of features. For classification, a KNN classifier is used; however, it isn't robust to inter and intraclass variations of palmprint. Coding-based approaches are the fourth group that is

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broadly used in numerous works of palmprint recognition. Some coding methods are used to generate palmprint codes, for example, palm code [5], fusion code [21], ordinal code [22], competitive code [23], and Log-Gabor code [24]. For example, Kong and others [21] proposed a technique for encoding the phases and responses of the six Gabor filters as a fusion code which was used later for competition. Jia and others [25] proposed a Robust Line Orientation Code (RLOC) technique to extract the orientation features of palmprints. A modified finite Radon transform is used in this technique, and the extracted feature vector is employed as a competitive code. Classification is accomplished using a KNN classifier. Nevertheless, the large size of features may lead to the overfitting of palmprint classification. Hong and others [26] proposed an approach to extract the palmprint orientation features. In this technique, rough features and fine features are extracted using Block Dominant Orientation Code (BDOC) and Block-based Histogram of Oriented Gradient (BHOG), respectively. Tragically, this methodology might be changed by variations in the illumination and shadowing of palmprint images. Fei and others [27] introduced a half orientation code (HOC) for palmprint feature extraction. The authors used half of the Gabor filter to show the HOC. Another technique in [28] is introduced to extract the palmprint features based on a double orientation code (DOC) of Gabor filters with a nonlinear classifier for matching.

To enhance the efficiency and working of palmprint recognition systems, we recommended a novel methodology based on Local Binary Pattern and Histograms of Oriented Gradients. This paper shows an inventive methodology for deciding the ROI of the palm print. The edges, for instance, principal lines, wrinkles, and ridges catch the most noteworthy traits of the palm print pictures; subsequently, such highlights need to be heightened. Furthermore, to obtain the texture description of the palm pattern in different directions, LBP and HOG are applied.

2. Image Segmentation

Segmentation classifies an image into various regions containing every pixel with related traits. These distinct regions ought to unambiguously determine the depicted objects or features of interest in order to be significant and useful for analyzing and interpreting the image. In low-level image processing, segmentation is the initial step that changes a color or greyscale image into at least one other picture to high-level image description with respect to features, objects, and scenes. The success of image analysis depends upon the reliability of segmentation, yet an exact apportioning of an image is a major issue. In this paper, we use online palmprint segmentation. The sole purpose of this procedure is to obtain the key points by determining the gaps between fingers on a palm print. Therefore, by utilizing these key points, a curvilinear system with all the systems perpendicular to each other is configured. Then ROI is cropped from these coordinates.

a. **Acquiring the points of interest**

P1 and P3 are the key points which are the intermediate spots of the valley between two fingers. They are situated on the boundary of the skin. This algorithm navigates the outline of the palm print image and analyzes every single point on the outline, as depicted in Fig. 2.

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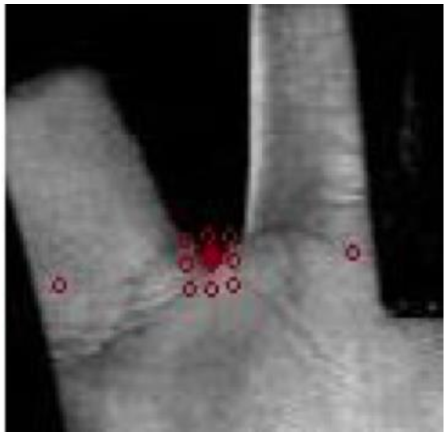

Figure 2: Detecting the Points of Interest

b. **Obtaining the Region of Interest**

The steps to obtain the region of interest are as per the following:

- First, apply a Gaussian low pass filter to the image; the output of the filter is a convolution of the obtained output and the original input. The palm print image is converted to a binary image from a grayscale image by using a specific threshold (T) using Eq. (1)

$$B_i(i,j) = 1 \quad \text{if } G_f(i,j) * Im(i,j) > T$$

$$B_i(i,j) = 0 \quad \text{otherwise} \qquad (1)$$

Where $B_i(i,j)$ and $I'm(i,j)$ are the Binary image and the original image, respectively. $G_f(i,j)$ is the output of the Gaussian filter.

- The key points between the forefinger and the middle finger are detected by using the point-finding algorithm, as depicted in Fig. 3(a). The key points (P1 and P3) are joined by the line segment(M1). As the key points are not altered by the rotation of the image caused during image procurement, therefore, these key points are used to correct the rotation of the image. Thus, making it rotationally invariant.

- After detection, a perpendicular line (M2) is drawn through the midpoint of P1 and P3. Finally, a square region which is the Region of Interest (Square ABCD), is obtained from the lines as shown in Fig. 3(b).

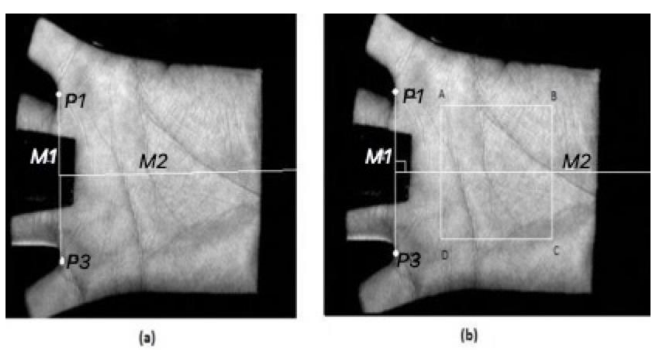

Figure 3: (a) Palm Image just before the rotation (b) ROI just before cropping

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c. **Image Preprocessing**

The region of interest is compressed with the wavelet decomposition technique to increase the computational efficiency [6]. Further, a Laplacian filter to the region of interest is applied in order to sharpen the image, trailed by adaptive histogram equalization [3] to enhance the ROI, and eventually, the edges of the ROI are smoothened out by applying a Gaussian filter.

3. Feature Extraction

Feature extraction includes minimizing the number of resources needed to depict a large data set. One of the significant issues while analyzing the complex data originates from the number of associated variables. A considerable amount of memory and computation power is required while analyzing a large number of variables; additionally, due to this, a classification algorithm may overfit training samples and generalize to new samples poorly. Therefore, to overcome these problems, combinations of variables are created with the help of the feature extraction technique while yet depicting the data with sufficient accuracy.

a. Local Binary Pattern

With the help of this Linear Binary Pattern operator [4], every pixel in the palm image is assigned a label by thresholding the 8 neighborhood pixels by the gray value of its center. After obtaining the 8 thresholded binary bits, these bits are connected in the counterclockwise direction, and a feature vector is created, represented in Fig. 4.
The local binary pattern code is resistant to a monotonous pixel value change. That is why it is exceptionally feasible to show palms that are enlightened from a particular distance, however with changing light intensity every time.

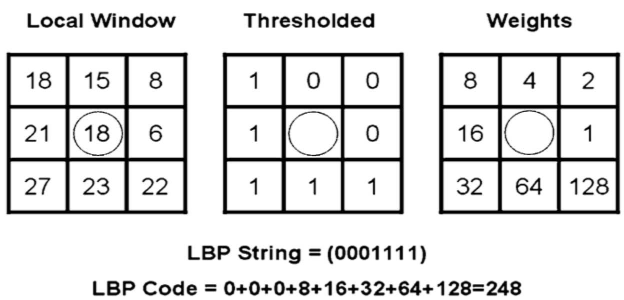

Figure 4: Thresholding Neighbourhood Pixels

A Local Binary Pattern string is classified as uniform if it comprises a maximum of 2 bit-wise changes from 1 to 0 or the other way around. For instance, uniform LBP strings are represented as 01111111 and 11111101, whereas non-uniform is represented as 10111011 and 10110100. There are only 58 possible labels of uniform patterns, whereas the remaining 198 patterns are non-uniform, whose values are stored in the 59th label. Hence there are total of 59 labels. This operation produces a set of 59 local binary patterns indicated by {1,2,… .,59}. Having the labels handy, a histogram of labels is made :

$$H = \sum \{I(x,y) = i\} \text{ , } i = 1,.......n-1. \quad (2)$$

n is the number of different labels.

The histogram of the label created above is used as the texture descriptor that contains the local image description. Following the approach in [12], the texture descriptor of the palm print image is autonomously extracted from each region after the partitioning into nine equal local regions. Further, to form a global image descriptor, these local descriptors are then concatenated. This operation is performed repeatedly in seven other directions on palm print

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components. Along these lines, the texture descriptor for a given palm print will have a size of {59(number of marks) x 9 (number of sub-windows)}.

b. **Histograms of oriented gradients**

Histograms of Oriented Gradient (HOG) are an object detection technique. HOG features extract an object's textural properties. The local object's appearance can be described by the magnitude of the gradient and the directions of the edges. The HOG features can be obtained by the following procedures :

- The gradient operator is implemented in 2 horizontal and vertical directions to extract the gradient of the image. In addition, the edges in these two directions and the magnitude of the gradient and orientation in each pixel are also extracted in the vertical and horizontal range of [0^0-180^0] of the image. The gradient operator on the image I, gradient magnitude, and orientation are developed as below:

$$G_x = \partial I/\partial x \qquad G_x = \partial I/\partial y \tag{3}$$

$$\text{Magnitude} = \sqrt{(G_x^2 + G_y^2)} \tag{4}$$

$$\text{Orientation} = 180/\Pi(\tan^{-1}(G_y/G_x) + \Pi/2) \tag{5}$$

c. **Concatenation of LBP and HOG features**

By combining the features extracted using LBP and HOG, the accuracy of biometric identification can be increased. Combining two vectors to form a single vector is called the concatenation of vectors. The vector of the features extracted by LBP and the vector of the features extracted by HOG are concatenated together. A total of 531 features through LBP feature extraction and 144 features through HOG feature extraction were obtained. On combining these features together, 675 features in total were obtained. As a result, the number of features increased after concatenation. Each sample can be distinguished from others more accurately as compared to only with LBP or HOG. If there are two matrices, A and B, they can be concatenated to form a new matrix, C, using

$$C = [A\ B] \tag{6}$$

4. **Classification**

Palmprint classification is basically a correlation between two given palm prints. This procedure either returns a dichotomy result (yes/no), which tells whether the two palmprints are the same or not, or returns a dimension of likeness or divergence, which tells how far one palm is from another palm. The sole purpose behind the palmprint matching is that the huge intra-class and small inter-class variations lead to degradation of recognition or verification performance. So after extracting features from palmprint with the help of feature descriptors like LBP or HOG, we match the input sample with the already recorded samples of the authorized users and discover the closeness between the two prints, which causes us to distinguish the individual.

a. K- Nearest Neighbor

KNN ("K-Nearest Neighbor") is one of the most widely used classification techniques. It usually helps to classify feature vectors or objects into the class depending on their closeness with examples in the training set. In this algorithm, an obscure vector would find the nearest "k" precedents and is assigned to the class of its k closest neighbors that appear most frequently. Grouping of the cluster of images between the test image and train image is

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known as classification. The mean distance between the centroid of the train image and the test image is measured. The closest point is picked and plots the value, which forms a cluster. On the off chance that the value is too far, it isn't taken into consideration.

b. Support Vector Machine

To match palm prints, a matching score is calculated. This matching score is calculated according to the points of their palm lines. To show the whole palm print, the sample palm image, which is 256x256, is then portioned into four pictures, each 128x128. Preprocessing can incredibly reduce the translation and rotation of the palm prints obtained from a similar palm. SVM (Support Vector Machine) is applied to match of palm. SVM is a widely used classifier. But then, to get the best results with SVMs, an understanding of their workings and the different ways by which a user can impact their accuracy is required. Because of its high accuracy, ability to manage high-dimensional information like gene expression, and flexibility in modeling diverse sources of data, the SVM classifier is broadly utilized in biometrics. For the better use of SVMs, an understanding of how they work is specifically required. When working with an SVM, one needs to make various judgments: how the information must be preprocessed, what kernel must be used, and lastly, setting the parameters of the SVM and the kernel. Uninformed choices can result in extremely reduced performance.

5. **Results**

Table 1 shows the recognition rate comparison among LBP, HOG, and the concatenation of both when classified with KNN and SVM. It can be clearly seen that the concatenation fusion feature (LBP+HOG) has outperformed its single counterparts. Figures 5 and 6 display the graphical accuracy comparison among all the feature extraction algorithms used when classified with KNN and SVM, respectively. Figure 7 displays the combined accuracy comparison for KNN and SVM. Comparative ROC curves for KNN and SVM are shown in Figures 8 and 9. It can be seen that the concatenate fusion (LBP+HOG) has the highest area under the curve.

Table 1: Comparison of Recognition Rate of different classifiers

ALGORITHM	**KNN (in %)**	**SVM (in %)**
LBP	88.19	79.07
HOG	86.11	74.28
CONCATENATION	89.32	80.94

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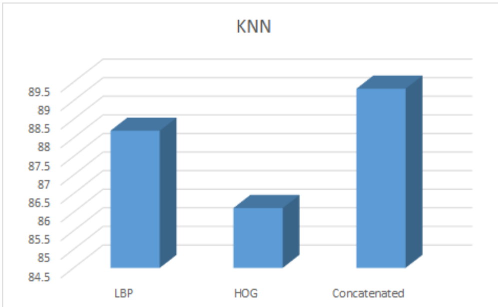

Figure 5: Comparison of accuracies through KNN Classifier

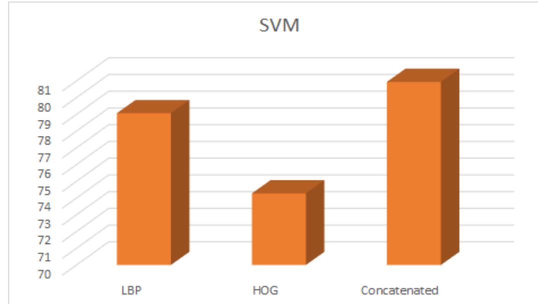

Figure 6: Comparison of accuracies through SVM Classifier

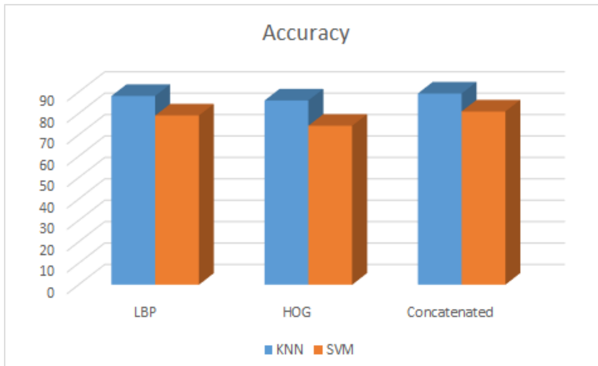

Figure 7: Comparison of accuracies through KNN and SVM classifiers

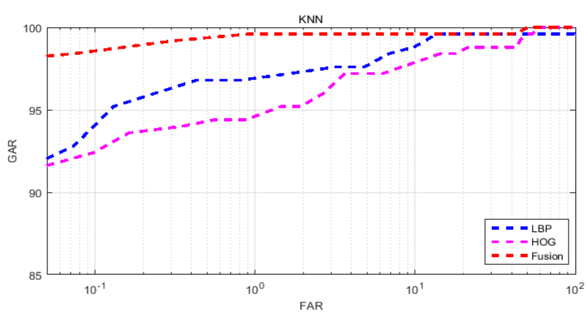

Figure 8: Comparative ROC for KNN

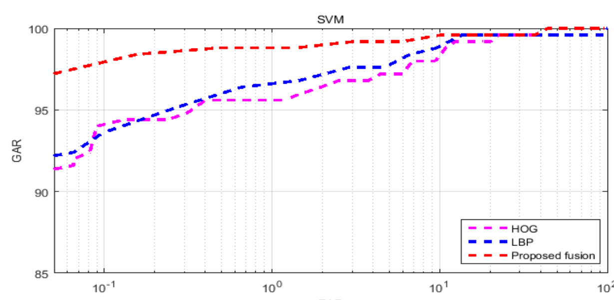

Figure 9: Comparative ROC for SVM

6. **Conclusion**

In this paper, the Key Point Detection Algorithm is employed to retrieve the ROI of the non-segmented palm images. After obtaining the ROI, unique features of the segmented image samples were extracted by using two major feature extraction techniques: Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG). A total of 531 unique LBP and 144 unique HOG features were extracted for every image sample. After this, these features were concatenated, getting a total of 675 features for every sample image, with the end goal of getting more precise and productive outcomes. In conclusion, the average accuracy of the three distinct datasets that were generated using the LBP and HOG features were determined. To calculate the accuracy of the three distinct models, classification techniques like KNN and SVM were adopted. Accordingly, it was seen that the accuracy was most elevated when the dataset of the concatenated features was employed in the classification algorithms.

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