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FULL AND PARTIAL CONNECTED LOCAL BINARY PATTERN ANALYSIS FOR FINGER KNUCKLE CLASSIFICATION USING SUPPORT VECTOR MACHINES

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Abstract— Hand-based biometric through finger knuckle print has emerged as a more reliable and promising alternative to conventional personal identification solutions. One of the most collaborative keys using the finger knuckle print is its ease to use, widespread public acceptance, and mostly non-intrusive procedure. This paper presents a method to retrieve texture analysis performance by making several orientations for calculating the interconnection between pixels using the fundamental local binary pattern (LBP). The study comprises two fundamental processes: feature extraction and SVM classification. The local Binary Pattern (LBP) algorithm comprises fully, and two orientations of partial LBP analysis are used to extract the feature from the images. We generated three version codes of LBP descriptors to compare the classification accuracy with the SVM classifier. The assessment found that different performance with an average of more than 90% has been achieved for all the suggested orientations.

I. Introduction

A hand-based biometric system becomes an excellent instrument to identify a person by analyzing their biometric traits characteristics. The human skin contains a ubiquitous texture where this natural appearance can be used as a critical component of a biometric identification system. A crucial element of texture classification is texture features, which expect to fulfill two primary processing goals. It comprises low computational complexity and extracting the most respective texture representation that can distinguish various imaging distortions such as illumination, rotation, point of view, scaling, and so on [1].

Recently, researchers have reported that finger knuckle print (FKP) provides a reliable and potential biometric identifier. FKP is the skin pattern of the outer surface around the phalangeal joint of the fingers that contains precise information [2]. The features include lines, contours, and creases, as shown in Figure 1, providing a unique pattern of individuals, which is possible to gain with less intrusive to the end-user [3]. The local features of the finger knuckle surface have higher discrimination and are robust against deformation because the extraction is commonly performed to a sub-block of a knuckle image.

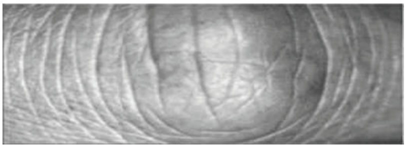


Figure 1: Example of finger knuckle print [2]

The finger knuckle texture appears on the outer side of the hand, and it lasts very long. It is challenging to scrap and focus on the inner surface of the hand, which is acquired using less constraint and contact style [4]. It predominantly enhanced this way for ensuring security in trying to access with the genuine trait. To perform the identification or classification process, an optimal feature extraction method needs to be defined. It is a crucial stage that could reduce the dimension of the images for accurate features representation. The feature extraction method needs to be carefully formalized to extract the essential features for highly accepting genuine users and rejecting imposters. Different extraction techniques can be used, and it usually depends on the modality studied.

Therefore, in this paper, the solution to extract the features from finger knuckle textures is proposed by manipulating the fully and partial analysis based on the feature-based local binary pattern (FbLBP) concept. We choose the LBP to observe the effect of local measurement on the performance when each pattern of the knuckle print is differently extracted according to the specific direction of the pixels. The approach will entirely confine all the discriminative information with both magnitude and sign information on the difference vector.

The remainder of this paper is subdivided into the following sections: Section 2 summarizes the related works of the finger knuckle print classification. Section 3 and Section 4 describe the method used and the results, respectively. Then, Section 5 presents the conclusion.

II. Related Works

Finger knuckle biometrics have received wide attention for person identification by using multiple texture features. Earlier work in this research field has successfully classified several categories from finger knuckle images [5]. Researchers have proposed various promising feature extraction methods for hand-based biometrics in the literature, including finger knuckle print. Multiple approaches have been proposed, such as Gabor feature extraction [6], Difference of Gaussian (DoG) filtering with two Gaussian kernels [7], Gradient Ordinal Relation Pattern [8], and many.

One of the well-known methods is Local Binary Pattern (LBP) which is widely used in the image processing field. To extract the texture features, LBP cannot wholly encapsulate the discriminative information. Only the sign information on the difference vector of the local region is used for computation [9]. An effective strategy based on central pixel selection into the LBP framework has been introduced where the method assigned an adaptive sampling radius to each central pixel [10]. The strategy is used to extract more local texture features and can be integrated with other LBP variants. Spatially weighted order binary pattern is another approach to extract the features specifically for color texture classification. In this method, the color components are encoded into multi-channel spatially weighted binary templates for features that are assigned as histograms textures descriptors [11]. Orthogonal difference local binary pattern (OD-LBP) is another approach that initiated the different levels of computing the pixel window [12]. In this method, three gray level differences are used on orthogonal position to produce a 24-bit vector of 8-bit binary patterns, which are transformed into three sub-divided regions of histogram extraction.

The texture descriptors based on the characteristics of uniform LBP called Attractive-and-Repulsive Center-Symmetric Local Binary Patterns (ACS-LBP and RCS-LBP), has also been proposed to extract local texture that inherits the concept of Center-Symmetric LBP [13]. The proposed method considers two diagonal directions over 3 × 3 neighborhoods to capture both microstructure and macrostructure of the texture.

Besides LBP, the FKP texture is also extracted using Gabor with Exception-Maximization (EM) algorithm in which the features vector is acquired by implementing the Scale Invariant Feature Transform (SIFT) algorithm [14]. Extracting minor and major regions on the images for verification using Gabor filter and Gray Level Co-occurrence matrix (GLCM) is also proposed where the results from both approaches are used to be classified by k-nearest neighbor and fuzzy k-nearest neighbor classifier [15]. A method based on an encoding scheme to decompose the FKP image into several blocks is also proposed [16]. They used a Gabor filter bank to convolve each block before applying the LBP histogram to the convolved images. Besides that, they also combined a Binarized Statistical Image Features (BSIF) filter and LBP coefficients to obtain the features from Finger Knuckle-Print. To select the features vector, they applied the Principal Component Analysis (PCA) method to find the higher coefficients.

Employing multiple orientation and texture information integration according to LBP and Gabor filtering is the scheme that has been studied for FKP classification [17]. For this case, Gabor filtering responses are needed to extract the LBP map before furthering to a CompCode coding scheme in the texture features extraction stage. Computational based on the matrix projection that considered the horizontal and vertical knuckle lines is another approach for extracting the line features from the FKP [18]. A shift and difference matrix are computed from a knuckle print image, and the sigmoid activation is used to enhance the resultant difference image. Two directional line features are fused at the score level to observe the performance.

III. Methodology

In this paper, several stages of processes are involved, which are performed under MATLAB

R2019b environment. There are two main stages consists of feature extraction and classification. Figure 2 shows the flowchart of the processes where the feature extraction stage is divided into three elements: full analysis and two partial analyses called X and + type. In Figure 2, pre-processing is performed purposely to enhance the greyscale image. In this paper, we used the finger knuckle print database from IITD[19], and only the segmented samples are used for the assessment. The database contains five images per finger, and 66 classes are used to assess the method.

The greyscale images of the finger knuckle print are used in the second stage through the LBP approach. Three representation schemes are chosen to extract the features from the greyscale images to minimize the computation into smaller numbers of features vectors. The full analysis type uses the conventional LBP calculation, which generally can be defined by Equation (1) and Equation (2) where g_i and g_c are the intensity of index i_{th} and the central pixel, respectively.

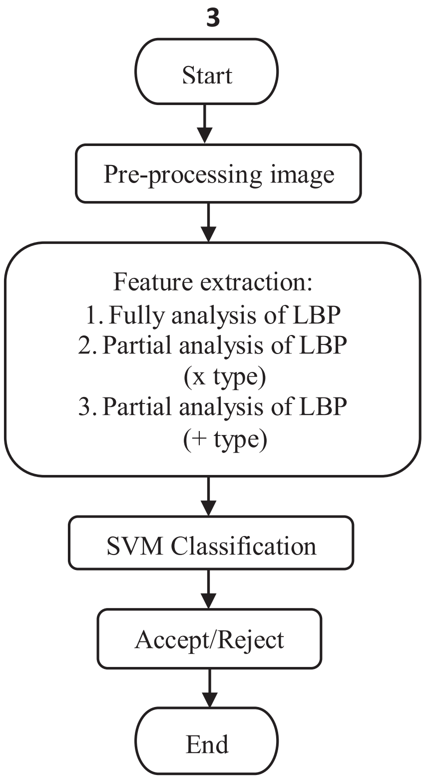


Figure 2: Overall flowchart of the project

$$s_i = \begin{cases} i = 7 \\ i = 0 \end{cases} \quad (g_i - g_c) \qquad (1)$$

$$\text{where, } \begin{cases} 1 \; if \; s_i \geq 0 \\ 0 \; Otherwise \end{cases} \qquad (2)$$

Then, the bit values are weighted by a factor of 2^i and is summed to produce the LBP operator. The computation process can be characterized by Equation (3).

$$LBP = \sum_{i=0}^{7} s_i \times 2^i \tag{3}$$

The full analysis scheme requires 256 bins to produce all the possible patterns that capture the textures' fundamental information. Using the similar concepts as depicted in Equation (1) to Equation (3), another two-partial analysis of LBP is also performed, but only the X and + cross-section of pixels as shown in Figure 3 are considered for descriptor calculation. Equation (4) and Equation (5) illustrate the calculation for X type, whereas Equation (6) and Equation (7) is the calculation for + type. To assess the generated features' performance in classifying each subject's class in the database, Support Vector Machine (SVM) is used, and the assessment is made according to one versus one classification.

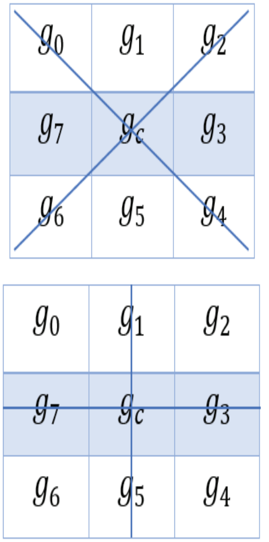


Figure 3: X and + cross section of the LBP calculation

$$LBP = s(g_0 - g_C)2^0 + s(g_2 - g_C)2^2 + s(g_4 - g_C)2^4 + s(g_6 - g_C)2^6 \tag{4}$$

$$s(x) = \begin{cases} 1 \; if \; x \geq 0 \\ 0 \; if \; x < 0 \end{cases} \tag{5}$$

$$LBP = s(g_1 - g_C)2^1 + s(g_3 - g_C)2^3 + s(g_5 - g_C)2^5 + s(g_7 - g_C)2^7 \tag{6}$$

$$s(x) = \begin{cases} 1 \; if \; x \geq 0 \\ 0 \; if \; x < 0 \end{cases} \tag{7}$$

In this paper, there are two kernels: Linear and Polynomial kernels with appropriate kernel parameters settings are chosen. To evaluate the performance, the confusion matrix is utilized by calculating True Positives (*TP*), False Negatives (*FN*), False

Positives (*FP*), and True Negatives (*TN*). From these four values, the accuracy rate is calculated for all the classes which are depicted by Equation (8). Sensitivity and specificity are also considered calculated by Equation (9) and Equation (10).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (8)$$

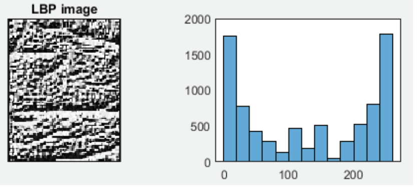
$$Sensitivity = TP/(TP + FN) \quad (9)$$

$$Specificity = TN/(TN + FP) \quad 10)$$

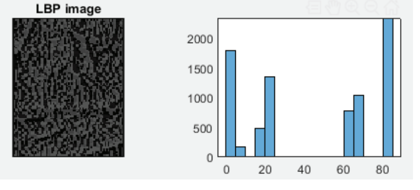
IV. Results and Discussion

This subsection discusses the results of the involved stages consisting of feature extraction and classification. For feature extraction, the pre-processed images undergo features extraction stages where three different LBP processes are performed. We choose a local 3 × 3 neighborhood of gray texture image to derive the LBP texture operator. Figure 4 shows the examples of the generated images and the image's histogram after performing the suggested LBP approaches.

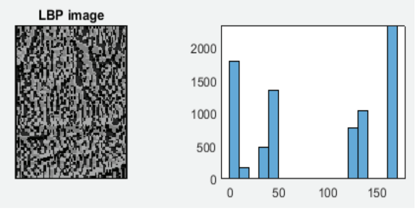
From Figure 4, there are apparent differences in terms of images and bin histograms on each type of LBP process. The significant features of each image are articulated via bin histogram, which is used as feature vectors. The bin histogram provides the distribution of image textures in the range of 0 to 255. For classification, the bin histogram values are considered for representing each class. Assessment is made by choosing various bin numbers of the LBP histogram. For example, Table 1 shows the arrangement of the features vector for twelve bin numbers for each sample for both class +1 and +2. From the features vector shown in Table 1, three samples for each class are used for training, and the remaining two samples are used for testing.



(a)



(b)



(c)

Figure 4. Image of the LBP and its bin histogram, a) Fully LBP, b). X-type LBP, c). + type LBP

The samples for each subject in the training dataset are randomly exchanged multiple times, where the computation for the accuracy is obtained for each time the exchange is made. The average for the accuracy is then calculated for each subject.

This paper used the SVM classifier on one versus one classification mode to classify the class using the mentioned two types of kernels. The performance of the methods is assessed using the FKP images from IIT Delhi Finger Knuckle Database [19]. We selected 66 classes and randomly divided them into three and two images for training and testing, respectively, for each class. In this classification mode, z(z-1)/2 binary classifiers are needed, with two subjects are used in each classifier. In order to obtain an optimal training model, appropriate penalty and kernel parameters have been tuned.

Table 1: An example of LBP features vector arrangement

*1.txt - Notepad

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```
+1 0:1428 1:1033 2:295 3:196 4:75 5:367 6:133 7:408 8:23 9:171 10:476 11:939 12:2456
+1 0:1552 1:838 2:421 3:213 4:105 5:424 6:157 7:451 8:43 9:195 10:456 11:846 12:2299
+1 0:1485 1:861 2:450 3:199 4:88 5:458 6:134 7:520 8:32 9:127 10:483 11:895 12:2268
+1 0:1444 1:829 2:396 3:209 4:81 5:493 6:130 7:453 8:16 9:174 10:502 11:924 12:2349
+1 0:1496 1:826 2:414 3:239 4:78 5:518 6:132 7:520 8:21 9:170 10:490 11:870 12:2226
+2 0:1756 1:753 2:359 3:257 4:158 5:481 6:214 7:509 8:55 9:267 10:451 11:962 12:1778
+2 0:1804 1:778 2:419 3:231 4:150 5:499 6:228 7:508 8:40 9:239 10:434 11:993 12:1677
+2 0:1781 1:858 2:370 3:226 4:144 5:457 6:224 7:488 8:55 9:259 10:399 11:972 12:1767
+2 0:1815 1:679 2:367 3:306 4:183 5:491 6:273 7:505 8:81 9:301 10:405 11:889 12:1705
+2 0:1783 1:766 2:391 3:259 4:145 5:502 6:218 7:505 8:51 9:280 10:422 11:960 12:1718
```

For the assessment, we have chosen different bin numbers for feature vectors 32, 64, 128, and 256 to evaluate the effect on the accuracy score. For the bin numbers of 256, the feature vectors are counted from 0 to 255 of bin values. The result for the assessment is tabulated in Table 2. The results show that the accuracy score is likely depending on the number of feature vectors required. In terms of the SVM kernels, it is shown that both kernels provide an average accuracy score which is the difference between both are not more than 2% and has achieved similar accuracy for particular bin numbers. In terms of LBP type, it is shown that the X type has achieved a better accuracy score compared to others.

Table 2: Performance analysis for different bin number

Parameters	Kernels	Full	X Type	+ Type
32	Linear	86.36	87.87	85.60
	Polynomial	86.36	88.63	86.36
64	Linear	91.67	91.67	90.15
	Polynomial	92.42	91.67	90.15
128	Linear	92.42	93.18	90.90
	Polynomial	92.42	93.18	90.90
256	Linear	93.93	94.69	93.93
	Polynomial	93.93	94.69	93.18

From the results, it is argued that the suggested approach can be used to extract the information on finger knuckle images where X type provides a better promising scheme. It is found that the SVM classifier can produce a reliable model though it is trained using a minimal amount of training data. We also found that randomly changing the training dataset for each testing cycle produces different accuracy scores. Based on this outcome of the assessment, it is found that choosing a suitable training dataset is needed to produce a better accuracy score.

The results show that the number of feature vectors used for training datasets in model production also affects the accuracy score. The features vectors with a minimum of 128 and a maximum of 256 may require to produce appropriate accuracy. The accuracy proportionally decreases when fewer feature vectors are used in the training dataset. The assessment also found that the sensitivity and specificity are between 0.94-0.96 for both kernels are achieved, specifically for bin histogram parameters of 128 and 256. Generally, the results obtained show that all three schemes have the same ability to provide relevant results.

V. Conclusion

This paper proposed a finger knuckle print-based classification system on three connected Local Binary Pattern analyses using Support Vector Machines classifier. We have analyzed different bin numbers for features vector to evaluate the accuracy score and discuss how those bin numbers affect the average accuracy score. It is found that the approach has achieved more than a 90% accuracy score, and the experiments show that our proposed approach can manage to extract the abundant features for producing unique representation for each individual via various types of LBP analysis.

In future work, we will improve and optimize the approach for rotation invariant and fusion with other approaches of LBP analysis for better accuracy score. Further assessment using more images is required to observe the capability of the approach.

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