Journal of Theoretical and Applied Information Technology
15th December 2012. Vol. 46 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

FINGER-KNUCKLE-PRINT RECOGNITION BASED ON LOCAL AND GLOBAL FEATURE SETS

[1]MOUNIR AMRAOUI, [2]MOHAMED El AROUSSI, [2]RACHID SAADANE, [3]MOHAMMED WAHBI

[1]Phd Student, RT-LARIT, FSK, Morocco

[2]Asstt Prof., Department of Electrical Engineering, EHTP, Morocco

[3]Prof., Department of Electrical Engineering, EHTP, Morocco

E-mail: [2]moha387@yahoo.fr , [1]amrayor@hotmail.com

ABSTRACT

A new biometrics recognition, finger-knuckle-print (FKP), has attractive interests of researchers. Based on the results of psychophysics and neurophysiology studies, both local and global information is crucial for the image perception, Therefore we present a novel approach for finger-knuckle-print recognition combining classifiers based on both micro texture in spatial domain provided by local binary pattern (LBP) and macro information in frequency domain acquired from the discrete cosine transform (DCT) to represent FKP image. The classification of these two feature sets is performed by using support vector machines (SVMs), which had been shown to be superior to traditional pattern classifiers. The experiments clearly show the superiority of the proposed classifier combination approaches over individual classifiers on the recently published PolyU knuckle database.

Keywords: *Finger-Knuckle-Print (FKP), Local Binary Pattern (LBP), Discrete Cosine Transform (DCT), Support Vector Machines (SVM), Gabor.*

1. INTRODUCTION

In the past three decades, many biometric characteristics have been investigated, including fingerprint, face, iris, retina, voice, gait and signature, etc [1].

Researchers noticed that the texture in the outer finger surface, especially in the area around the finger joint, has the potential to do personal authentication.

In addition skin pattern on the finger-knuckle is highly rich in texture due to skin folds and creases, and hence, can be considered as a biometric identifier [3]. Further, advantages of using FKP include rich in texture features [4], easily accessible, contact-less image acquisition, invariant to emotions and other behavioral aspects such as tiredness, stable features [5] and acceptability in the society [6].

It is often the case that no single feature descriptor is rich enough to capture all of the classification information available in the pattern image. Thus, one of the key challenges for improving FKP recognition performance is finding and combining efficient and discriminative information about FKP patterns. Worth noting, by observing the errors misclassified by the different approaches, one can observe that a certain classifier is better suited for the recognition of a certain patterns than another one and therefore, some recognition errors committed by the best approach can be well resolved by the inferior methods.

Systems reported in literature have used global features, local features and few work in their combinations [16] to represent FKP images. Efforts have been made to build a FKP system based on global features. In[8], FKP features are extracted using principle component analysis (PCA), independent component analysis(ICA) and linear discriminant analysis (LDA). These subspace analysis methods may be effective for face recognition but they are not found to be effective to represent the FKP [10]. In [9], FKP is transformed using the Fourier transform and the band-limited phase only correlation (BLPOC) is employed to match the FKP images.

According to the literature, existing FKP recognition schemes can be classified into local-based methods and global-based ones. However,few papers have yet discussed the local-

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

global information combination for FKP recognition.

Such an idea has already been explored in our previews Work [12] in witch we proposed a face recognition approach using two complementary feature extraction algorithms, Discrete Cosine Transform (DCT) [35] and Local Binary Patterns (LBP) [33].

In designing robust FKP recognition system, the classifier combination scheme is likely to improve the overall classification performance if the individual classifiers are largely independent and this can be achieved, for instance, by using different type of feature sets (see figure 2). Information fusion can be considered at the feature level or at the classifier level. The feature level fusion is believed to provide better recognition results than classifier level fusion since the features contain richer information about the input data than the matching score or the output decision of a classifier/matcher. However, selecting appropriate and complementary component features is crucial for good performance. Motivated in part by the work presented in [10], we propose in this paper a fkp recognition approach using two complementary feature extraction algorithms, Discrete Cosine Transform (DCT) [35] and Local Binary Patterns (LBP) [33]. The Support Vector Machine (SVM) with one-against-one strategy [18] is used for classification. The reasons underlying the choice of using these feature sets and Support Vector Machines are the following: from one hand, DCT and LBP coefficients have been chosen for their complimentary in the sense that LBP captures small appearance details of FKP appearance and texture in the spatial domain while DCT encodes FKP texture and edge information in the frequency domain. Moreover local appearance information are captured using the block based DCT while the global appearance information are encoded using the global LBP histogram. On the other hand, even if a considerable dimensionality reduction is obtained by these feature extraction techniques with respect to considering the whole image, the resulting space is still large. Standard classifiers could be affected by the so called curse of dimensionality problem; SVMs, instead, are well suited to work in very high dimensional spaces. Each feature set is classified separately using SVM to obtain the individual scores. The fusion of these two classifiers can be implemented at the score/decision level using a modified version of the majority voting rule. Experiment results conducted on PolyU knuckle database show that combining DCT-based SVM and LBP-based SVM classifiers at the decision level gives better performance than individual classifiers.

The remainder of this paper is organized as follows: section 2 gives an overview of the use of the DCT and LBP as means of feature extraction algorithms for FKP representation. In section 3 a brief description of the FKP recognition based SVM is given. The proposed classifier combination scheme is presented in section 4; experimental results of the proposed technique are discussed in section 5. Finally, in section 6 we draw conclusions and give avenues for future work.

2. FEATURE EXTRACTION METHODES

In this work, we propose to use two common feature extraction algorithms based on both local and global appearance descriptors, block-based Discrete Cosine Transform (DCT) and uniform Local Binary Patterns (LBP). In this section, an overview of these two algorithms is given.

A. Discrete Cosine Transform

Discrete Cosine Transform (DCT) is a predominant tool first introduced by Ahmed et al. [13]. Since then, it was widely used as a feature extraction and compression in various applications on signal and image processing and analysis due to its fine properties, i.e., de-correlation, energy compaction, separability, symmetry and orthogonality [35]. In face recognition, DCTs are used to reduce image information redundancy because only a subset of the transform coefficients are necessary to preserve the most important facial features.

The local information of a candidate FKP can be obtained by using block-based DCT as follows: A FKP image is divided into blocks of 8 by 8 pixels size. Each block is then represented by its DCT coefficients. From the obtained DCT coefficients only a small, generic feature set is retained in each block. Ekenel et al. [22] have proved that the highest information necessary to achieve high classification accuracy is contained in the first low frequency DCT coefficients via zigzag scanning.

B. Local Binary Pattern

The Local Binary Pattern operator was first introduced by Ojala et al [33] who showed the high discriminative power of this operator for texture classification. The original LBP operator labels the pixels of an image by thresholding the 3 _ 3 neighbourhood of each pixel with the center value and considering the result as a binary string or a

Journal of Theoretical and Applied Information Technology
15th December 2012. Vol. 46 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

decimal number and uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3 _ 3 neighborhoods, giving 8 bit codes based on the 8 pixels around the central one. Formally, the LBP operator takes the form

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n s(i_n - i_c) \qquad (1)$$

Where in this case n runs over the 8 neighbors of the central pixel c, i_c and i_n are the gray-level values at c and n, and $s(u)$ is 1 if $u \geq 0$ and 0 otherwise. The LBP encoding process is illustrated in Fig. 1.

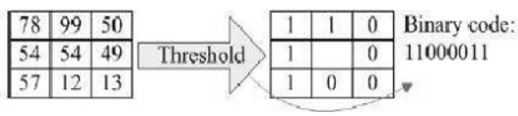


Fig. 1. Illustration of the basic LBP operator

An extension to the original operator was made in [34] and called uniform patterns: an LBP is 'uniform' if it contains at most two bitwise transitions from 0 to 1 or vice versa.In a matter of fact this means that a uniform pattern has no transitions or two transitions. Only one transition is not possible, since the binary string needs to be considered circular.The idea behind the LBP uniform is to detect characteristic (local) textures in image, like spots, line ends, edges and corners.

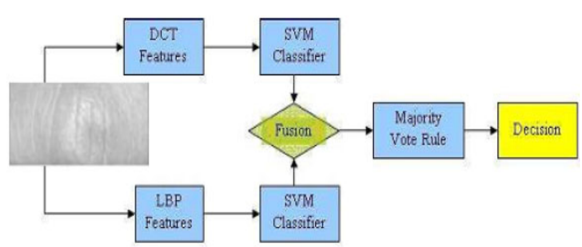
Through its recent extensions, the LBP operator has been made into a really powerful measure of image texture, showing excellent results in terms of accuracy and computational complexity in many empirical studies. computational time is significantly reduced. Moreover, LBP's are resistant to lighting effects in the sense that they are invariant to monotonic gray-level transformations, and they have been shown to have high discriminative power for texture classification [33].

3. SVM CLASSIFIER FOR FKP RECOGNITION

Recently, the Support Vector Machine learning (SVM) has been gaining popularity in the field of pattern classification due to its promising empirical performance, moderate computation complexity and its strong mathematical foundation. More details about SVM can be found in [18]. SVM are binary classifiers and different approaches like "one-againstall" and "one-against-one" are built to extend SVM to the multi-class classification case for face recognition [18]. For a K -class classification task, the common method is to use " one-gainst-all" [37] principle to construct K binary SVMs. Each SVM distinguishes one class from all other classes. The final output is the class that corresponds to the SVM with the highest output value. Another major method is the "one-against-one" method. It was introduced in [26], and the first use of this strategy on SVM was in [27]. This method consists in building up all possible $K(K-1)/2$ binary SVMs representing all possible pairs out of K classes, each of which is used to discriminate two of the K classes only. When a testing pattern is to be classified, it is presented to all the SVMs, each providing a partial answer that concerns the two involved classes. Different schemes are used to combine the results of binary SVMs. In the classification stage, a majority voting strategy is used: each binary classification is considered to be a voting where votes can be cast for all data points, in the end point is designated to be in a class with maximum number of votes.

4. CLASSIFIER COMBINATION SCHEME

A combined system can be based on one or a combination of the following fusion scenarios: in the first scenario, all the classifiers use the same representation of the input pattern whereas in the second scenario, each classifier uses its own representation of the input pattern. In other words, the features extracted from the pattern are unique to each classifier. In our work we focus on classifier combination in the second scenario. The input data is processed with different feature extraction algorithms in order to create templates with different information content. Each feature set resulting from DCT and LBP are then used as input data for a 2nd degree polynomial SVM. To make a stronger final classifier, the individual classifiers based on both DCT and LBP feature sets are combined at the score/decision level [31]. Kittler et al. [25] have also demonstrated that combining the scores of several classifiers can lead to better recognition results. The diagram illustrating the proposed algorithm is presented in the figure below 2.



Journal of Theoretical and Applied Information Technology
15th December 2012. Vol. 46 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Fig. 2. Classifier Combination Scheme

Schemes for integration of information after the classification/matcher stage can be divided into the following categories:

A. Score level fusion

Score level fusion refers to the combination of matching scores provided by the different classifiers to generate a single scalar score which is then used to make the final decision. Since the matching scores generated by the different modalities are heterogeneous, normalization is required to transform these scores into a common domain before combining them. Normalization can be performed using the Min-Max and Gaussian normalization as described below. Some of the rules used to combine the classifiers at the score level are [25]: Sum rule, Product rule, Max rule and Min rule.

Next to the feature vectors, the matching scores output by the classifiers contain the richest information about the input pattern.

B. Decision level fusion

Decision level fusion refers to the combination of decisions already taken by the individual classifiers. Several ways to implement the fusion of the classifiers are then obtained using a variety of strategies like majority voting [29], behavior knowledge space [28], weighted voting based on the Dempster-Shafer theory of evidence [41], AND rule and OR rule [21]. The majority vote is by far the simplest, and yet it has been found to be just as effective as more complicated schemes in improving the recognition results.

In the proposed algorithm, the combined decision of the k^{th} classifier is 1 when the decision of DCT-based classifier and LBP-based classifier are both positives, -1 when they are negatives and 0 when they are of different signs resulting to a neutral position. Then for each class, we simply count the votes received from the individual combined classifiers. The class which receives the largest number of votes is then selected as the majority decision.

5. EXPERIMENT RESULTS

In this section, we will demonstrate the robustness of the combination of classifiers based DCT and LBP in decision fusion level. To assess the robustness of our method against other approaches, we have choose PolyU knuckle database [10].

A. PolyU knuckle database

We use the PolyU FKP database [10] to evaluate the performances of PCA, LDA, LBP, DCT and the proposed method. The PolyU FKP database was collected from 165 volunteers, including 125 males and 40 females. Among them, 143 subjects are 2030 years old and the others are 3050 years old. The images were collected in two separate sessions. In each session, the subject was asked to provide 6 images for each of the left index finger, the left middle finger, the right index finger and the right middle finger. In total, the database contains 7920 images from 660 different fingers. The original image size is 110200. Figure.3 shows the 12 images of one finger. In the first experiment, we only compare some subspace learning methods on the left index finger-knuckle-print image database. According to the protocol of this database, the images captured in the first session are used for training and the images captured in the second session for testing. Thus, for each class, there are six training samples and six testing samples.

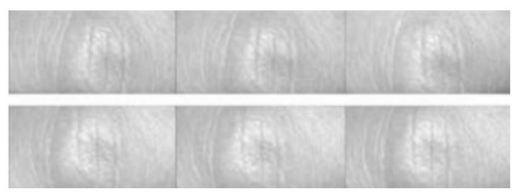


Fig. 3. Samples Of The Polyu FKP Database

B. DCT and LBP feature extraction

To implement this algorithm, we have only considered the FKP from the training and test images of the database. The DCT and LBP features are extracted from these images to construct different feature sets of FKP information. The DCT of a candidate FKP is computed on block by block basis of 8 by 8 pixels. Each block is then represented by its DCT coefficients. From the obtaining DCT coefficients only a small, generic feature set is retained in each block. Ekenel et al. [22] has proved that the highest information necessary to achieve high classification accuracy is contained in the first low frequency DCT coefficients via zigzag scanning. Hence, we have choose to retain the lowest 3 DCT coefficients; the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

remaining coefficients form a one dimensional feature vector of (3 × 14 × 28 = 1176) size.

To extract the LBP feature set a FKP images, we have choose to use the uniform LBP's within the whole image. This choice can be justified by the fact that the global LBP histogram retrieves the global appearance information since the block-based DCT gives us local appearance information but ignores the global ones. To compute the uniform LBP, the operator takes a 3 by 3 local neighbourhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. Subsequently we retain just the pixels that contain at most two bitwise transitions from 0 to 1 or vice versa. In a matter of fact this means that a uniform pattern has no transitions or two transitions. Only one transition is not possible, since the binary string needs to be considered circular. Finally, the local descriptors are histogrammed to produce a global descriptor vector of ($P(P - 1) + 3 = 57$) with $P = 8$ (pixel's neighbor).

C. Decision level fusion results

Once the DCT and LBP feature sets are extracted, each feature set is presented to all the SVM classifiers. The SVM with a 3nd degree polynomial kernel has been found in our simulations to outperform linear and RBF kernel functions. In the present work, the library LIBSVM [20] was used. This library implements the SVM with one-againstone voting terminology to handle more than two classes. In this pair-wise classification, we need to train $k(k - 1)/2$ SVMs representing all possible pairs out of k classes. The i^{th} individual binary SVM classifier provides a partial score that determines whether the input vector is "class *m*" or "class *n*". The individual matching scores are then combined using the Majority vote rule to generate the final decision. Since there are more than two classes, the combined decision is correct when a majority of the decisions are correct, but wrong when a majority of the decisions are wrong and they agree. A rejection is considered neither correct nor wrong, so it is equivalent to a neutral position or an abstention. The results of the classifier combination are summarized in table I.

The results demonstrate that high recognition accuracy can be achieved using DCT+LBP approach for FKP recognition. The proposed system has been compared with all well known knuckleprint based systems reported in [11]. It is found that the Recognition Accuracy of the proposed system which is more than 97% for all 4 fingers is better. Recognition Accuracy of various systems obtained from various fingers of the PolyU database are shown in TableI. When compared to the best performing method in the table (LGBP[11]), DCT-LBP fusion features work the best and show 4:06%,

Table I: Comparative Study.

Approach	LIndex	LMiddle	RIndex	RMiddle
PCA[11]	56.38%	53,64%	60,51%	60,10%
LDA[11]	72,83%	70,30%	76,06%	75,25%
ICA	70,04%	68,5%	58.4%	63.6%
Gabor + LDA[11]	94,85%	92,63%	96,26%	93,23%
Gabor + PCA[11]	92,53%	91,01%	95,86%	92,93%
LBP[11]	90,10%	89,09%	95,56%	91,21%
DCT	91.5%	90.2%	92.6%	92.3%
LGBP[11]	94,14%	94,24%	97,27%	94,75%
LBP+DCT	**98,2%**	**98%**	**98,7%**	**97,1%**

3.76%, 1.43% and 2.35% gain in accuracy for Left Index, Left Middle, Right Index and Right Middle respectively.

6. CONCLUSIONS AND FUTURE WORKS

In this paper we have presented a combined appearance-based FKP recognition approach, which uses two different representations of the FKP image. The underlying algorithm utilizes the block-based DCT and the uniform LBP for local representations of the FKP image. Indeed, these two feature sets capture different and complementary information. We investigated the impact of fusing two classifiers based on two different feature sets DCT and LBP. We have shown that the classifier combination at decision level using a majority vote rule outperforms the accuracy of each classifier itself. As a future work, we want to try different classifier combination such as support vector machine, radial basis function networks and fuzzy logic.

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