PALMPRINT RECOGNITION USING COARSE-TO-FINE STATISTICAL IMAGE REPRESENTATION

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ABSTRACT

Recent literatures have revealed that statistics of local texture measures can provide accurate descriptions of palmprint appearances. In this framework, one palmprint image is divided into local blocks with multiple spatial resolutions. The statistical texture descriptions of each block are then concatenated to form a multi-scale image representation. However, resultant high-dimensional statistical features lead to increasing of computational cost. In this paper, we tackle this problem by performing a coarse-to-fine cascade scheme, which makes use of information redundancy of statistical texture descriptions between different spatial scales. In contrast with non-cascade strategies, the proposed method reduces most of computational burden and achieves accurate classification simultaneously.

Index Terms: *Biometrics, palmprint, hierarchical texture representation, coarse-to-fine classification*

1. INTRODUCTION

Palmprint recognition is a hot topic in recent progress of biometrics. Inside regions of human palms contain rich discriminative directional line-like textures, which can be captured by low resolution imaging devices and used for accurate identity verification task. These characteristics make palmprint recognition an efficient way for personal identification in civil use.

The central idea of palmprint recognition focuses on developing a proper texture representation to describe both directional properties and spatial layout of palm lines. In recent progress, statistics of local texture measurement is used as an accurate representation of palmprint appearances [1][2][3]. This approach is motivated by achievements in object recognition [4][5][6]. Statistics of image descriptors obtained within a local region, like histogram or covariance, are used to represent local texture properties. Benefited from statistical procedure, this kind of feature representation is robust against local variations of appearances which are caused by illumination changes, image noise and non-rigid deformation of object surfaces. To compensate loss of spatial information in the statistical procedure, one palmprint image is firstly divided into separate blocks. Statistical descriptions of each block are concatenated into a spatial enhanced representation according to spatial layout of the blocks. In a further step, Han et al proposed a hierarchical statistical palmprint representation [1], which is similar with the spatial pyramid [4]. It divides images at increasing finer spatial scales. The statistical descriptors derived at each scale then compose a hierarchical representation. This approach provides distribution properties of palmprint textures from coarse scales to fine scales. However, it increases memory and computation demands in two aspects. For one thing, it needs excess space to store multiple layers of statistical descriptors as feature templates. For another thing, during image matching, all layers of the hierarchical structure have to be used in parallel [1]. In our work, we tackle these issues by analyzing information redundancy between different layers in the hierarchical representation. We propose a coarse-to-fine cascade classification scheme. In this method, for each layer in the hierarchical structure, a discriminative classifier is constructed based on information provided by the current layer and all coarser ones. We evaluate confidence of decision of the classifier according to its ROC performance. Only input samples with confidence values lower than a pre-defined threshold are sent into the next finer layer for more accurate classification.

In the rest of this paper, we extend the hierarchical statistical representation [1] and analyze information redundancy between different layers in Section 2. Section 3 introduces the proposed coarse-to-fine cascade classification scheme. Section 4 presents experimental results on a large palmprint database. Section 5 concludes the whole paper.

2. HIERARCHICAL STATISTICAL PALMPRINT IMAGE REPRESENTATION

In the Hierarchical Appearance Statistics (HAS) [1], one palmprint image is firstly convolved with a set of derivates of Gaussian (DoG) filters with six orientations $\{0, \pi/6, \pi/3, \pi/2, 2\pi/3, 5\pi/6\}$. The resultant 6-d filtering response vector derived at each pixel is encoded into a 6-d binary vector according whether each component of the vector is positive or not. Each binary vector corresponds to a unique integer index between 1 and 64. Secondly, the whole image is divided into non-overlapped blocks. Histograms of the binary vectors in each block R_j are concatenated into a histogram sequence *HS* according to spatial layout of blocks, as shown in Eqn.1:

$$HS_{i,j} = \sum_{x,y} I\{f(x,y)=i\} I\{(x,y)\in R_j\} \quad i\in[1,64] \tag{1}$$

f(x,y) represents the index of the binary vector obtained at (x, y) inside the region R_j. Finally, the image is divided into non-overlapped square blocks with size of 32*32, 16*16 and 8*8 respectively, ranging from coarse-level to fine-level scale of division. The spatial enhanced histograms derived at all four scales form a multi-layer representation. Fig.1 illustrates the whole procedure.

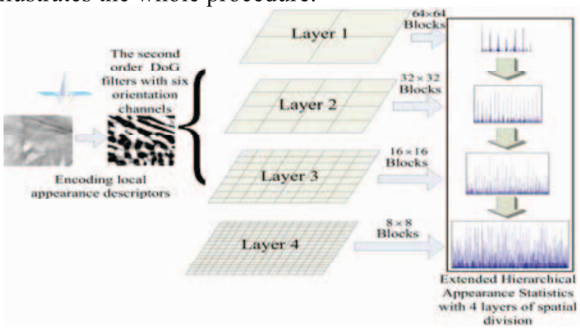

Fig.1 The extended Hierarchical Appearance Statistics

As we can see in Fig.2, each block R_j in the *mth* scale of division is divided into four sub-blocks $SR_{j,k}$ (k =1,2,3,4) in the *(m+1)th* finer scale in this method. Thus, one histogram $HS_{i,j}$ (i = 1,2…64) derived at the former coarser scale is split into four histogram $HS_{i,SR_{j,k}}$ (i = 1,2…64, k=1,2,3,4) with the same length at the latter finer scale. Each histogram bin value in the $HS_{i,j}$ is an average of the bin values at the corresponding position in the four histograms $HS_{i,SR_{j,k}}$, as illustrated in Eqn.2:

$$HS_{i,j} = \sum_{k=1}^{4} \frac{HS_{i,SR_{j,k}}}{4} \tag{2}$$

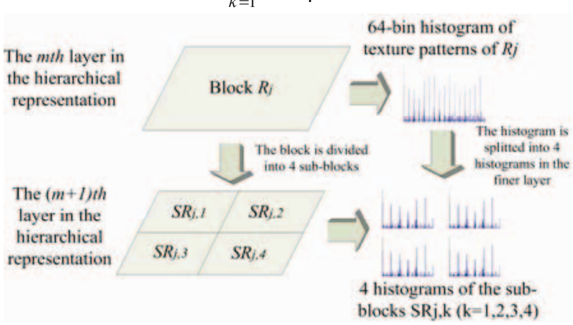

Fig.2 Sub-division of one block with a finer scale

According to Eqn.2, assuming that the histogram sequences obtained at the *mth* and successive *(m+1)th* spatial scales are HS^m and $HS^{(m+1)}$ respectively, HS^m is actually a projection of $HS^{(m+1)}$ onto a lower dimensional subspace, which is obtained by performing local averaging on the $HS^{(m+1)}$. Through subspace projection, HS^m loses fine spatial relations between local texture patterns and focuses on global characteristics. Thus, it is less discriminative than $HS^{(m+1)}$. This results in information redundancy between HS^m and $HS^{(m+1)}$, which denotes that it is more efficient to use hierarchical layers in a coarse-to-fine way than in parallel. Classifiers constructed in coarser layers handle input samples with significant distinctness in global texture characteristics and leave difficult samples to the next finer layers. Following this idea, we extend the hierarchical structure by following settings of the filters in [1], which includes 4 layers of image division as shown in Fig.1. The kth layer {k=1,2,3,4} divides the whole image into non-overlapped $2^{(k+1)}$ square blocks. Further coarser division losses all spatial information of palmprint textures, which is not suitable for classifying palmprints. To save cost of storage, we only store HS^4 with 16384 bins as feature templates. The spatial enhanced histogram sequences in left three layers are generated dynamically during recognition using Eqn.2.

3. COARSE-TO-FINE CASCADE CLASSIFICATION

We assume that the extended hierarchical appearance statistics of two input palmprint images are $\{HA^k\}$ and $\{HB^k\}$ (k = 1,2,3,4). The proposed cascade classification contains four successive stages. The first stage (k =1) provides dissimilarity measure between the histogram of texture patterns HA^1 and HB^1, which are obtained at the coarsest level in the hierarchical structure. In our work, we make use of chi-Square distance $d(HA^k, HB^k)$ to evaluate dissimilarity between histograms. In the first stage, we estimate distributions of intra-class and inter-class similarity measures $d(HA^1, HB^1)$ based on a training data set. They are then used to generate the false acceptance rates (FAR) and false rejection rates (FRR) by changing thresholds performed on the similarity measure distributions, as illustrated in Eqn.3 and Eqn.4.

$$FAR = \frac{\textit{false accepted inter} - \textit{class samples}}{\textit{the total number of inter} - \textit{class samples}} \tag{3}$$

$$FRR = \frac{\textit{false rejected intra - class samples}}{\textit{the total number of intra} - \textit{class samples}} \tag{4}$$

We utilize them as smooth estimation of two posterior probability $P(\textit{Inter-class}|x)$ and $P(\textit{Intra-class}|x)$ respectively, which represent posterior class probabilities given similarity measure x between a pair of histograms. As a result, classification error then arises from the regions of similarity measures where the largest of the posterior probability is less than unity. We are uncertain about class membership of samples in this region. To avoid making decision on these difficult cases, we introduce a threshold θ ($1>\theta>0$) and reject any input similarity measure for which the largest posterior probability is less than θ. This forms a rejection region, as illustrated in Fig.3. Input similarity measures dropped in this region may introduce high error rate in the current layer. They are passed to the next layer for fine descriptions of palmprint textures.

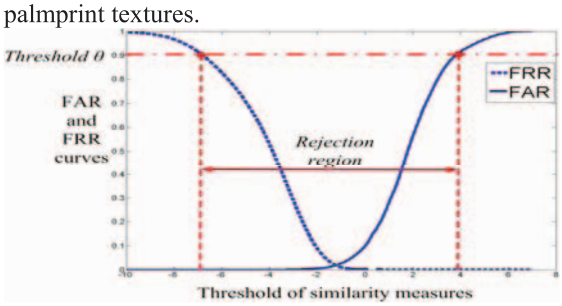

Fig.3 Construction of the rejection region

One input of *kth* stage (k>1) in the cascade is a k-dimensional vector $\{d_m\}$. It is composed by chi-Square distance d_k (HA^k,HB^k) and all the chi-Square distances d_m between HA^m and HB^m ($k>m\geq1$). We train a SVM on the vectors $\{d_m\}$ obtained in the training set. Rather than using the sign of the output scalar value S_k of SVM, we estimate the intra-class and inter-class distribution of direct outputs of SVM at the kth stage. A scalar output of SVM is proportional to signed distance measures between input similarity vectors to the decision hyper-plane of SVM. Thus, they represent degree of similarity between two palmprint images which are passed to the current stage. After that, we can choose proper threshold θ to set the reject region in the current stage following the same operations in the first stage. Difficult samples are further passed to (k+1)th stage until they reach the bottom layer of the hierarchical structure where the final decision is made. By setting the rejection region, only a small part of input samples are passed to the next finer stages where we need much more computation resource to store higher dimensional histogram sequences obtained in the finer stages and calculate chi-Square distance measure between them. Furthermore, each stage makes a decision-level fusion between the current layer and all precedent coarser layers in the hierarchical representation, which achieves a more comprehensive description of palmprint textures. Thus, the cascade scheme reduces much computational cost and improves performances of recognition compared with the parallel use of different layers which is adopted in [1]. Choice of the thresholds θ in each stage results in a trade-off between computational efficiency and accuracy of recognition. Higher θ reduces classification error in the current stage while it increases of amount of samples passed to the next stage. We can adjust them to meet different requirements on overall performances of palmprint recognition systems.

4. EXPERIMENTAL RESULTS

We test the proposed method on PolyU Palmprint Database [12]. It contains 7,752 palmprint images captured from 386 different palms. For each palm, there are two sessions of images. Average time interval between the two sessions is about two months. Furthermore, illumination conditions and focus of the image device are changed manually during image capturing. All of the factors introduce both non-rigid deformation of skin textures and variations of local contrast between the two sessions, which proposes a challenge to robustness of palmprint image representations. In our method, we adopt the extended hierarchical appearance statistics which is described in Section.2. After that, we choose 100 classes of palmprints randomly from the database to construct a training set. The training data set contains totally 2000 images. Left 5,752 images forms a testing set.

In the verification test, we use all samples to estimate intra-class distribution. Five images are selected randomly from each session for inter-class matching. Thus, the whole training set generates 19,000 intra-class comparisons and 495,000 inter-class comparisons. For testing, there are 54,340 intra-class matching and 4075,500 inter-class matching. We set rejection regions and train SVM using 4-fold cross-validation in each stage based on distributions of intra-class and inter-class scores derived at the current stage [10]. In the experiment, we set the confidence thresholds θ to 0.9 for the first three layers on both training and testing data sets, which generate wider rejection regions. With this strict setting, our method can still show its advantage over parallel use of all four layers. We compare final recognition performance of the proposed cascade classifier on the testing set with the HAS model proposed in [1] and the other three state-of-the art approaches [7] [8] [9].

Table 1 Comparisons of performances on the testing set

Algorithm	EER[11]	*d'*[11]
Fusion Code [7]	0.195%	5.38
Ordinal Code [8]	0.042%	6.85
Competitive Code [9]	0.035%	5.84
Hierarchical Appearance Statistics (HAS) [1]	0.024%	5.50
The proposed cascade scheme	0.009%	7.74

Fig.4 and Table.1 show EER [11] and discriminating index *d'* [11] of verification on the testing set of methods involved in comparison. Table.2 illustrates amount of false rejected samples (FR), false accepted samples (FA). It also shows fractions of intra-class and inter-class samples which are passed to the next layers in the total intra-class and inter-class testing samples, named as respectively P_{intra} and P_{inter}. Assuming C is the time cost to calculate one histogram sequence in the first layer, time cost to compute individual histogram features in the following three layers are 4C,16C and 64C respectively. The average time cost $AVG_{parallel}$ for feature extraction in the non-cascade strategy [1] is represented by Eqn.5:

$$AVG_{parallel} = C + 4C + 16C + 64C \tag{5}$$

Table 2 Performances of different stages on the testing set

Stage	FR	FA	P_{intra} (%)	P_{inter} (%)
The first stage	3	10	51%	62.8%
The second stage	2	5	37%	31.5%
The third stage	0	2	16.9%	10.4%

According to Table 2, the first three layers remove more than 80 percent of testing samples with very low FAR and FRR. Many input samples are classified immediately with coarse layers. For those samples, it does not need to generate finer layers of representation. Thus, for the proposed coarse-to-fine scheme, the average time cost for feature extraction $AVG_{cascade}$ is defined in Eqn.6. Benefited from the cascade scheme, the average time cost can be reduced to less than twenty percent of that in the non-cascade strategy in theory.

$$AVG_{cascade} \le C + 0.63 * 4C + 0.32 * 16C + 0.11 * 64C \tag{6}$$

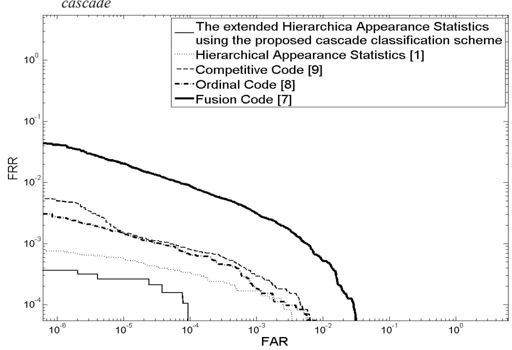

Fig.4 ROC curves of all the methods on the testing data set

The proposed method also achieve higher accuracy than the hierarchical appearance statistics [1] and the other three state-of-the-art approaches [7][8][9]. Finer statistical representation for those difficult samples can be generated on-line using Eqn.2. Thus, the coarse-to-fine classification scheme improves computational efficiency greatly.

5. CONCLUSION

In this paper, we have proposed a coarse-to-fine scheme for both palmprint image representation and classification. In this method, we firstly extend the hierarchical appearance statistics model for palmprint description. This model is composed by multi-scale spatial enhanced statistics of texture patterns. During recognition, we perform a cascade classification scheme. Each stage in the cascade constructs a classifier based on distributional properties of textures obtained from the corresponding scale and all its precedents in the hierarchical representation. We set a rejection region for each classifier. Through this way, only difficult input dropped into this region is handed over to the next stages. Left input samples are classified with high accuracy and much less computational source at the beginning stages. Furthermore, to act in coordinate with the cascade scheme, during recognition, we generate different layers of the hierarchical representation dynamically only when it is necessary. This cascade classification scheme is not restricted to be performed with the histogram based features. Actually, any multiple scale image representation which contains information redundancy between neighboring scales can utilize the proposed method to improve computational efficiency.

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