CHOOSING BEST BASIS IN WAVELET PACKETS FOR FINGERPRINT MATCHING

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ABSTRACT

Fingerprint matching has been deployed in a variety of security related applications. Traditional minutiae detection based identification algorithms do not utilize the rich discriminatory texture structure of fingerprint images. Furthermore, minutiae detection requires substantial improvement of image quality and is thus error-prone. In this paper, we propose a new algorithm for fingerprint identification using wavelet packet analysis and best basis selection. Each fingerprint is decomposed using two dimensional wavelet packet family corresponding to different scales. The energy distribution of the fingerprint in each subband is extracted as a feature for identification. Wavelet packet decomposition yields a redundant representation of the image. For this reason, several algorithms for selecting the best basis from this redundant representation have been investigated. In this paper, we propose a new method for choosing best basis in wavelet packets for fingerprint matching. Experiments show that our new algorithm improves the accuracy of fingerprint matching.

1. INTRODUCTION

Fingerprint matching has become an important way for accurate personal identification. A fingerprint is composed of ridges and valleys on the surface of the finger. Fingerprint identification systems rely on one of the two classical methods: minutiae based methods and texture based methods. The minutiae-based techniques first locate the minutiae points, and then match their relative placement in a given finger and the template [1]. Detecting and matching the location of minutiae is a computationally complex and error-prone method. The texture based methods use the structure of the ridges and the valleys in a given fingerprint and use correlation based matching [2].

In this paper, we introduce a new texture-based method using wavelet packets. The wavelet packet decomposition of fingerprint reflects the characteristics of texture at different orientations and scales. The energy distribution over the subbands in wavelet packet decomposition reflects the structure of the fingerprint texture and thus can be used as an effective feature in fingerprint identification. The overcomplete structure of wavelet packet decomposition provides the flexibility for feature selection to achieve better accuracy. Different cost functions for choosing the best basis from the wavelet packet decomposition have been developed [3, 4, 5]. In this paper, we will introduce a new method for choosing the best basis based on the wavelet packet decomposition tree structure. Experimental results show that this new method has better performance compared to existing methods for best tree selection.

2. WAVELET PACKETS

As an extension of general wavelets, wavelet packets represent a generalization of multiresolution analysis and use the entire family of subband decompositions to generate an overcomplete representation of signals. This approach gives access to a collection of orthonormal bases from which the "best basis" can be chosen based on a given criterion.

In 2D discrete wavelet packet transform (2D-DWPT) analysis, an image is split into one approximation and three detail images. The approximation and the detail images are then themselves split into a second-level approximation and detail images, and the process is repeated. The standard 2D-DWPT can be described by a low-pass filter h and a high-pass filter g [6]. The 2D-DWPT of an $N \times M$ discrete image X up to level $P+1$ ($P \leq \min(\log_2 N, \log_2 M)$) is recursively defined in terms of the coefficients of level p as follows:

$$C^{p+1}_{4k,(i,j)} = \sum_m \sum_n h(m)h(n)C^p_{k,(m+2i,n+2j)} \tag{1}$$

$$C^{p+1}_{4k+1,(i,j)} = \sum_m \sum_n h(m)g(n)C^p_{k,(m+2i,n+2j)} \tag{2}$$

$$C^{p+1}_{4k+2,(i,j)} = \sum_m \sum_n g(m)h(n)C^p_{k,(m+2i,n+2j)} \tag{3}$$

$$C^{p+1}_{4k+3,(i,j)} = \sum_m \sum_n g(m)g(n)C^p_{k,(m+2i,n+2j)} \tag{4}$$

where $C^0_{0,(i,j)}$ is the image X. At each step, the image C^p_k is decomposed into four quarter-size images C^{p+1}_{4k}, C^{p+1}_{4k+1}, C^{p+1}_{4k+2}, C^{p+1}_{4k+3}. 2D-DWPT has been shown to be useful for

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image analysis in literature due to wavelets having finite duration which provides both spatial and spectral localization and efficient implementation.

The 2D wavelet packet decomposition can be visualized as a tree where each parent node has 4 children nodes. The 4 children nodes correspond to the approximation, horizontal, vertical and diagonal details of the parent node. A 2-level wavelet packet decomposition is illustrated in Figure 1.

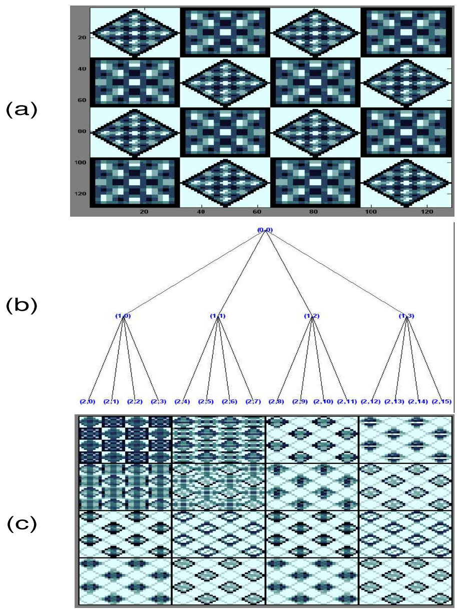

Fig. 1. A wavelet packet decomposition tree: (a) The original image, (b) The 2-level decomposition tree, (c) Projection of the original image onto each subband corresponding to the leaf nodes of the tree.

3. FEATURE EXTRACTION

2D-DWPT decomposition allows us to analyze an image simultaneously at different resolution levels. The decomposition of the fingerprint using wavelet packet basis at different scales reflects its specific recurrent ridge-valley structure. The recurring ridge-furrow structure makes the wavelet packet coefficient of fingerprint image different from most natural images. At the level that the scale of wavelet packet basis best matches the spatial frequency of the ridge-valley structure, the energy in the corresponding subband will reach a local maximum. Therefore, the energy distribution over different scales and orientations is a quite informative feature for fingerprint identification. The energy of different subbands gives information regarding both the edge spatial frequency as well as the ridge orientation. This characteristics has been applied to different applications, including fingerprint identification, face recognition and handwritten characters recognition. [3, 4, 5, 7].

In this paper, the energy in each band will be used as the feature. The energy in different subbands is computed from the subband coefficient matrix:

$$\sigma_p^2(k) = \sum_i \sum_j (C_k^p(i,j) - \frac{1}{N_p^2} \sum_i \sum_j C_k^p(i,j))^2 \quad (5)$$

where N_p is the size of the subband matrix and $\sigma_p^2(k)$ is the energy of the fingerprint corresponding to the subspace at node (p, k). The energy of each subband provides a measure of the image characteristics in that subband. The energy distribution has important discriminatory properties for fingerprint images and as such can be used as a feature for fingerprint matching. A simple demonstration of energy distribution over different scales and orientations is given in Figure 2.

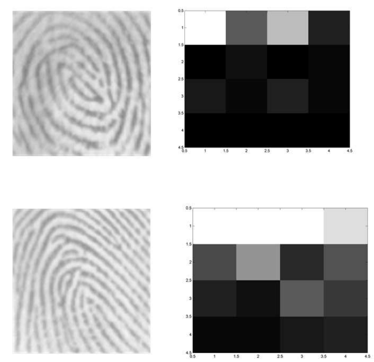

Fig. 2. The energy distribution map over the leaf nodes of the wavelet packet tree for two fingerprints: the left side is the fingerprint image, and the right side is the corresponding energy distribution over the leaf nodes of wavelet packet decomposition tree shown in Figure 1b.

4. BEST TREE SELECTION

Due to the overcomplete representation provided by the wavelet packet decomposition, many approaches have been proposed for choosing the best tree from the wavelet packet tree using different cost functions [8, 9]. Most of these methods focus on obtaining the best representation for efficient signal compression. Some researchers also developed techniques for pruning the wavelet packet tree for applications in pattern recognition [3, 5]. In these methods, the feature extracted from the parent node is compared to its children nodes based on some evaluation criterion. This selection process is iterated starting with the leaf nodes of the tree until an optimally pruned tree is obtained. The deficiency of the pruning process is that it implicitly assumes independence of the features extracted at the neighboring parent nodes. This assumption is a potential cause for degrading the performance of the identification algorithm. To weaken the assumption of independence and at the same time to keep the computational complexity at a low level, we propose a best tree selection algorithm that considers the combination of the smallest neighboring subtrees. Rather than comparing the parent node with its children nodes, we assume dependence between two smallest neighboring subtrees. Four combinations are considered in the comparisons : $< p1, c2 >, < p1, p2 >, < c1, p2 >, < c1, c2 >$. This idea is illustrated in Figure 3b. The combination that gives the best score for the cost function will be kept to represent the image.

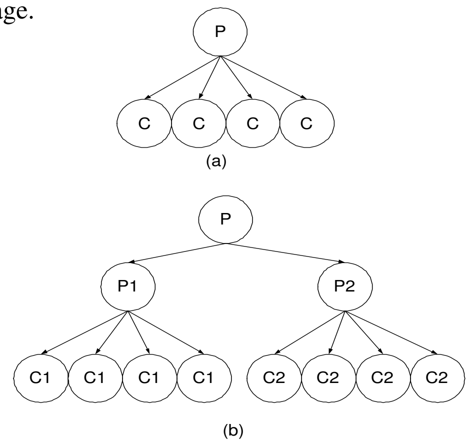

Fig. 3. The two methods for comparing the parent node and the children nodes: (a) The classic method (b) The proposed method.

The selection of the optimal tree and the cost function can be described as follows:

1. Compute the wavelet packet decomposition matrix C_k^p at all nodes for each fingerprint image.

2. Compute the energy corresponding to each node, $\sigma_{p,k}^2$ in the wavelet packet tree using equation *5*.

3. For each fingerprint, form the feature vector $F = [\sigma_0^2, \sigma_{1,0}^2, \sigma_{1,1}^2, ..., \sigma_{P,0}^2, \sigma_{P,1}^2 ..., \sigma_{P,4^P-1}^2]^T$ where P is the highest scale in the decomposition.

4. Beginning at scale P, compare the cost function values for the four combinations illustrated in Figure 3 (b). The corresponding feature vector $\tilde{\mathbf{F}}$ is formed with the energy values of the corresponding nodes in the combination. $\tilde{\mathbf{F}}$ is a subset of the whole feature vector $\mathbf{F}$. We propose a measure γ that evaluates the ratio of inner-class distance to inter-class distance for a given set of nodes. The ratio is defined as follows and is used for selecting the nodes to construct the best basis for fingerprint identification.

$$\gamma = \frac{\sum_{i=1}^{C} \sum_{j=1}^{S} (\sum_{n=1}^{R} \tilde{F}_{ij}(n) - M_i(n))}{\sum_{i,i'=1}^{C} (\sum_{n-1}^{R} (M_i(n) - M_{i'}(n))^2)} \tag{6}$$

$$M_i(n) = \frac{1}{N_i} \sum_{j=1}^{N_i} \tilde{F}_{ij}(n), \tag{7}$$

where C is the number of different fingerprint classes, S is the number of different images for a finger, R is the number of nodes in a particular node combination, and N_i is the number of samples in a given class. γ is an indicator of how well the chosen node combination can discriminate between different classes of fingerprint images. It is computed for different collections of nodes and the nodes that give the highest value for γ forms the best tree used in the identification algorithm.

5. RESULTS

The experiments are conducted on 520 128×128 fingerprint images. The training set includes 240 images(30 fingers, 8 images/finger) and the test set includes 280 images (35 fingers, 8 images/finger). All images are preprocessed and centered around the core point.

It has been shown that local features and global features are both useful for matching fingerprints. To combine these two kinds of features, the image is first divided to *W* by *W* image blocks. Matching results are based on the combination of results from all blocks. The image blocks are decomposed by using Daubechies wavelet packets with 5 vanishing moments. Energy at each subband for each image is extracted from the wavelet packet decomposition tree. The best tree selection is performed with the 240 training images. The selected tree structure is used for identification on the test images. The distance between two feature vectors is computed using Kullback-Leibler distance:

$$d(F_j, F_k) = \sum_n F_j(n) \log_2 \frac{F_j(n)}{F_k(n)}, \tag{8}$$

where F_j and F_k are the feature vectors corresponding to images j and k respectively. The false acceptance rate (FAR) and the false rejection rate (FRR) are calculated. Equal error rate (EER), the value where FAR is equal to FRR, is computed and used as the evaluation criterion.

For purposes of comparison,we implement three other algorithms for best basis selection (or feature selection). The first one is the well known entropy based best basis algorithm [8]. This algorithm is referred to as ”ent” in the following discussions. The second algorithm developed by

Block Size	Ent	Tree8	Tree4	SFS	OPT
32	0.1653	0.1622	0.1634	0.1635	0.1642
64	0.1357	0.1196	0.1245	0.1653	0.1534
128	0.1694	0.1543	0.1581	0.1612	0.1561

Table 1. EER for different feature selection algorithms and image block sizes

Koller et al. has a sound theoretic framework for optimal feature selection in general setting, which is not limited to tree structure (abbreviated as "opt" in the following discussions) [10]. Sequential forward feature selection is another widely used sub-optimal algorithm for general feature selection (abbreviated as "sfs" in the following discussions). The algorithm proposed in this paper (considering the combination of sibling subtrees) and the algorithm that compares only the parent node to its children nodes are referred to as "tree8" and "tree4", respectively (See Figure 3 for illustration). The 5 algorithms are evaluated for different image block sizes (128×128, 64×64 and 32×32). The EERs for different parameter settings and algorithms are presented in Table 1.

The experiments show that the "tree8" algorithm is consistently the best among the 5 algorithms. The extension from "tree4" to "tree8" is a relatively small step in weakening the independence assumption. So the performance improvement of "tree8" over "tree4" is not as that significant as the improvement over "ent". However, the consistent superior performance of "tree8" over "tree4" shows that the research in this direction is promising. Also, the algorithms based on the tree structure ("tree8" and "tree4") consistently outperform the other three algorithms, including the theoretically "optimal feature selection" algorithm "opt".

It should be noted that block sizes that are too big or too small are not the best choice for fingerprint identification. The selection of block size should take into account the tradeoff between capturing the local features and containing enough pixels for reliable estimation of energy in each subband. In this experiment, the resolution for fingerprint images is 500 dpi, and the suitable W value is found to be 64.

6. CONCLUSION

In this paper, we proposed a new algorithm that choose the best basis of wavelet packet decomposition for fingerprint matching. Current best basis selection algorithms assume independence of the extracted features at neighboring subtrees. In this paper, we weaken this assumption by considering the dependence between the closest neighboring subtrees. This modification consistently achieves lower error rate in fingerprint matching experiments.

The proposed algorithm can be improved by exploiting the dependence among more neighboring nodes in the wavelet packet tree. We can also extend the current algorithm by extracting multiple features at each node of the wavelet packet tree, rather than using only the energy distribution.

7. REFERENCES

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