AN ADAPTIVE MULTIRESOLUTION APPROACH TO FINGERPRINT RECOGNITION

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ABSTRACT

We propose an adaptive multiresolution (MR) approach to the classification of fingerprint images. The system adds MR decomposition in front of a generic classifier consisting of feature computation and classification in each MR subspace, yielding local decisions, which are then combined into a global decision using a weighting algorithm. In our previous work on classification of protein subcellular location images, we showed that the space-frequency localized information in the MR subspaces adds significantly to the discriminative power of the system. Here, we go one step farther; We develop a new weighting method which allows for the discriminative power of each subband to be expressed and examined within each class. This, in turn, allows us to evaluate the importance of the information contained within a specific subband. Moreover, we develop a pruning procedure to eliminate the subbands that do not contain useful information. This leads to potential identification of the appropriate MR decomposition both on a per class basis and for a given dataset. With this new approach, we make the system adaptive, flexible as well as more accurate and efficient.

Index Terms— Biometrics, fingerprint images, classification, multiresolution techniques.

1. INTRODUCTION AND MOTIVATION

Personal identification has been a topic of interest for some time, with various solutions proposed. Accessing buildings or facilities, withdrawing money or using a credit card, gaining access to electronic information on a local computer or over the Internet, are all examples of situations which require accurate and reliable methods of personal identification, and solutions vary greatly. There are hundreds of modalities for personal identification, from items one might keep in one's possession (for example, identification cards or keys) to combinations of numbers and information one might memorize (for example, Social Security numbers and passwords). Using human biometric characteristics (fingerprints, irises, faces, etc) has great advantages over other techniques: the information cannot be lost or forgotten, and forgery requires greater skill.

The most familiar and studied modality of biometric recognition is the fingerprint. Because acquisition of fingerprint images is minimally invasive and requires little hardware (ink, paper and a digital camera are the minimum requirements), fingerprint recognition is a highly researched field. A crucial goal in processing such biometric data is to do so automatically, accurately and fast.

Modern fingerprint image classification systems have proven effective to accuracies of well over 90% recognition. Most of them fall into one of the two major categories: minutiae-based or image-based methods. The former are based on computation of minutia features, require expensive pre-processing and are error-prone. The latter extract features directly from the original image; they are computationally efficient, but require elaborate algorithms to make them robust to plastic distortions and low image quality. A number of image-based algorithms use multiresolution (MR) techniques. Examples include the use of wavelet coefficients [1, 2], as well as the energy distribution between MR subspaces [3, 4]. In [5], the authors used correlation filters in the wavelet packet domain for fingerprint verification and recognition. They adaptively construct wavelet packet trees using a correlation energy cost function along with a match score, with excellent results.

In our previous work [6, 7], we showed that introducing MR techniques into the classification of biological images greatly improves the classification accuracy. The power of MR tools is threefold: (a) They provide space-frequency localized information in the MR subspaces, the so-called *subbands*. (b) They are adaptive to the data at hand. (c) They are fast and efficient to compute. In [6, 7], the idea was to use the MR subspaces as images to be classified. To output a class label for an image, local decisions made at the level of each subband were combined into a global decision using a weighting algorithm. With this process, we showed that the subbands had a discriminative power and that the adaptivity provided by the weighting procedure helped increase the classification accuracy over a system that did not contain neither the MR decomposition nor the weighting algorithm.

In this paper, we use the same type of idea and explore the power of adaptive MR techniques in the classification of fingerprint images. We introduce a new weighting algorithm along with a pruning procedure to help us gain insight into the role of each subband, as well as, given a dataset, find the most suitable MR decomposition tree. We also attempt to expand our understanding of the role of various MR transforms by exploring the use of different MR transforms in the classification of fingerprint images.

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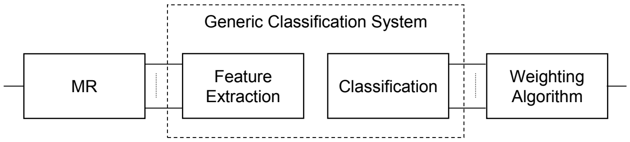

Fig. 1. Schematic of the current classification method [7].

2. BACKGROUND

2.1. MR Classification

We now briefly describe the MR classification system developed in [6, 7]. We denote as *no MR (NMR)* the standard classification system consisting of a feature extractor followed by a classifier (see Fig. 1). We add an MR block in front of NMR and compute features in MR subspaces (subbands). Classification is then performed on each of the subbands yielding local decisions which are then weighed and combined to give a final decision.

Images to be classified undergo an MR decomposition that creates a total of S subbands. Following this decomposition, any set of features can be extracted from each of the S subbands; here, we use texture features as we have found them to be most powerful. The feature vectors are then input into S separate generic classifiers (neural networks for instance). Finally, each of the S classifiers outputs a decision vector.

Given K classes, we define a *target decision vector* as $d = (d_1, d_2, \ldots, d_K)^T \in \mathbb{R}^K$. Ideally, d has all its coefficients but one equal to 0. A nonzero coefficient at position k implies that the image belongs to class k. The intended interpretation is that d_k is a measure of the resemblance of the image to class k.[1] To assign a "wining" class to an image, we assign it the index of the highest coefficient in the decision vector:

$$k_{win} \;=\; \arg\max_k d_k.$$

Let us now define the decision vector, c_s as the output after each subband classifier s. The weighting block takes as input the different local decision vectors and combines them into a single output decision vector. For each image, given the set of S decision vectors, we concatenate them into a matrix C of size $K \times S$, where each element $C_{k,s}$ is position k of the decision vector of classifier s.

2.2. Weighting Procedure

Assume that we have N training images. Then, at the output of the classifiers we have N decision matrices $C^{(l)} = \{C_{k,s}\}^{(l)}$, for $l = 1, \ldots, N$, $k = 1, \ldots, K$ and $s = 1, \ldots, S$. To these N matrices, we associate N target decision vectors $d^{(l)}$, $l = 1, \ldots, N$.

The weighting procedure combines the decision vectors together by weighing each of them with a subband-specific weight w_s. In matrix notation, the system computes:

$$d \;=\; Cw, \qquad (1)$$

where $w = (w_1, \ldots, w_S)^T$ is of size $S \times 1$, C is of size $K \times S$ and thus, d is of size $K \times 1$. (We omitted the superscript that indicates the training image since the equation is valid for all of them.)

[1]The concept of resemblance is intentionally left underdefined.

Given a set of training data, a possible solution for w is the one that minimizes the error in the least-square sense:

$$w_{win} \;=\; \arg\min_w \sum_{i=1}^{N} \|d^{(i)} - C^{(i)} w\|^2. \qquad (2)$$

Define a target output vector o of size $KN \times 1$, as a vector which concatenates all the target decision vectors $d^{(l)}$ as follows:

$$o \;=\; \left(d_1^{(1)}, d_2^{(1)}, \ldots, d_K^{(1)}, \ldots, d_1^{(N)}, \ldots, d_K^{(N)}\right)^T, \qquad (3)$$

and let T be the $KN \times S$ matrix consisting of the all the decision matrices $C^{(l)}$ of all the training data stacked on top of each other:

$$T \;=\; \begin{pmatrix} C_{1,1}^{(1)} & \ldots & C_{1,S}^{(1)} \\ \vdots & \ddots & \vdots \\ C_{K,1}^{(1)} & \ldots & C_{K,S}^{(1)} \\ \vdots & \ddots & \vdots \\ C_{1,1}^{(N)} & \ldots & C_{1,S}^{(N)} \\ \vdots & \ddots & \vdots \\ C_{K,1}^{(N)} & \ldots & C_{K,S}^{(N)} \end{pmatrix}. \qquad (4)$$

We can now rewrite (2) in a direct error minimization form:

$$w_{win} \;=\; \arg\min_w \|o - Tw\|, \qquad (5)$$

which possesses a closed-form solution and can be efficiently computed.

3. PROPOSED ALGORITHM

3.1. Problem Statement

The problem we are addressing here is that of finding a single weight vector for each of the fingerprint classes. This allows better characterization and adaptivity to each individual class. Based on the training data for a specific class, the weight vector for this class weighs the local decisions made by each classifier so as to minimize the classification error for the images of that class. In the process, we use a pruning procedure to eliminate any information or subbands that are not useful for the classification. This yields an efficient system without sacrificing the accuracy. Thus, the input to the class-adaptive weight algorithm is the decision vectors $C_k^{(l)}$ for $l = 1, \ldots, N$ of all of the S classifiers and the output is the weight vectors w_k associated to each class k for $k = 1, \ldots, K$.

3.2. Weight Matrix Model

To make the system truly adaptive, it is reasonable to assume that different classes require different weight vectors. Thus, we propose a system where, instead of a single weight vector w for the whole training data set, each class k has its own weight vector w_k. As opposed to (1), the entries in the output decision vector are now computed as:

$$d_k \;=\; Cw_k, \qquad k = 1, \ldots, K, \qquad (6)$$

where d_k is the decision vector associated with class k.

Now, the weights can be grouped together to form an $S \times K$ matrix W so that each column represents a class-specific weight vector. Equation (6) can be rewritten as:

$$d \;=\; \mathrm{diag}\,(CW)\,. \qquad (7)$$

Recall that C is of size $K \times S$ and thus d is of size $K \times K$ (compare this to (1)). To learn these weights, we again use the training set and look for a solution that minimizes the squared error:

$$W_{win} \ = \ \arg\min_{W} \sum_{i=1}^{N} \| d^{(i)} - \mathrm{diag}\left(C^{(i)} W^{(i)} \right) \|^2. \qquad (8)$$

To obtain an expression analogous to (5) and be able to apply standard methods, we have to define v as the vector of the concatenation of all class-specific weight vectors:

$$v \ = \ (W_{1,1}, W_{1,2} \ldots W_{1,K}, \ldots, W_{S,1}, \ldots, W_{S,K})^T . \qquad (9)$$

We now define $T^{(new)}$ as the following block matrix, where $c_k^{(l)}$, $l = 1, \ldots, N$, is the vector $(C_{k,1}^{(l)}, C_{k,2}^{(l)}, \ldots, C_{k,S}^{(l)})$:

$$T^{(new)} = \begin{pmatrix} c_1^{(1)} & 0 & 0 & \ldots & 0 \\ 0 & c_2^{(1)} & 0 & \ldots & 0 \\ 0 & 0 & c_3^{(1)} & \ldots & 0 \\ 0 & 0 & 0 & \ldots & 0 \\ 0 & 0 & 0 & \ldots & c_K^{(1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ c_1^{(N)} & 0 & 0 & \ldots & 0 \\ 0 & c_2^{(N)} & 0 & \ldots & 0 \\ 0 & 0 & c_3^{(N)} & \ldots & 0 \\ 0 & 0 & 0 & \ldots & 0 \\ 0 & 0 & 0 & \ldots & c_K^{(N)} \end{pmatrix} . \qquad (10)$$

We can now write a minimization problem equivalent to the one in (8), and which we can solve using standard techniques:

$$v_{win} \ = \ \arg\min_{v} \| o - T^{(new)} v \|. \qquad (11)$$

3.3. Decomposition Tree Pruning

Our long-term goal in developing an adaptive MR classification system was to find a wavelet-packet-like decomposition, where each class would induce a different MR subtree. While we have done just that in [5], we needed a cost function which is specific to the data set used. Our goal is thus have a more generic system and to achieve a "wavelet-packet"-like system but without the need for a cost function. We come close to this goal here, where we identify the set of discriminative subbands for each class (not necessarily a subtree).

Once the weight vectors are computed, we use the values of the weights to regulate the MR decomposition. In particular, subbands which are given a low weight by the weighting procedure can be pruned away as long as the remaining subbands are still sufficient to classify the image correctly. This way, the pruned subbands and their associated features need not be computed, resulting in computational savings. We propose to keep the high-weight subbands, so that at least a certain ratio η, defined as the fraction of the sum of kept weights over the sum of all the weights, of subbands are kept.

This pruning can be done over a single weight vector and is thus suitable for both the previous model with a weight vector per entire dataset as well as for the new model with a weight vector per class (6). The process is formalized as Algorithm 1.

Algorithm 1: Pruning the decomposition tree

Input: The vector of weights w, fraction of kept weights/subbands η $(0 < \eta \leq 1)$
Output: Set of subbands $\mathcal{S}$

$\mathcal{S} \leftarrow \{\}$
while $\left(\sum_{i \in \mathcal{S}} |w_i|\right) < \eta \sum_{i=1}^{S} |w_i|$ **do**
  $s \leftarrow \arg\max_{s \notin \mathcal{S}} w_s$
  $\mathcal{S} \leftarrow \mathcal{S} \cup \{s\}$
return $\mathcal{S}$

4. EXPERIMENTAL RESULTS

4.1. Data Set

To test our system we used images from a subset of the NIST 24 fingerprint database [8]. The data set contains 10 classes with 50 512×512 images each . The images were acquired while individuals were rolling their thumbs, which induces different plastic distortions that make the data set realistic and challenging. Figure 2 shows two examples from an easy and a hard class.

4.2. Experimental Setup

We use 45 images per class to train the system. Each image undergoes different 2-level MR transforms. These can be divided in two main categories: nonredundant unitary (MR bases) and redundant (MR frames). Amongst the unitary ones, we used the Discrete Wavelet Transform of size 2×2, and different transforms of size 4×4: the Discrete Fourier Transform (DFT) [9], the Discrete Cosine Transform (DCT) [9], the Discrete Hartley Transform (DHT) [9], the Walsh-Hadamard Transform (WHT) [10], the Discrete Triangle Transform (DTT) [11] and two random unitary transforms, RU1, which has a an all ones row (lowpass filter) and RU2 which is completely random. All of these are separable 2D transforms apart from the DTT, which is nonseparable. The redundant MR decompositions tested here are the Double-Density DWT (DD-DWT) [12], the Dual-Tree Complex Wavelet transform (DT-CWT) [13] and the Stationary Wavelet Transform (SWT) [14].

We use modified Haralick texture features (26 features) [7] and a two-layer neural network as our generic classification system, and perform ten-fold cross validation on the weight calculation. We set the value for η at 0.8 as initial observations showed that this value achieved a good balance between pruning away the decomposition tree while keeping the accuracy high.

4.3. Results and Discussion

All the results are shown in Table 1. By observing the results, we can draw the following conclusions:

- MR does better than NMR.
- The redundant transforms (MR frames) do better than the unitary ones (MR bases) and the SWT achieves the best classification accuracy of 99.50%.
- The choice of the transform amongst MR bases does not seem to be crucial. One might as well use a random unitary transform and still achieve similar performances.
- As expected, pruning does not improve the accuracy of the system, but it does make it more efficient.

	Pruned		Not pruned	
	Class-adaptive	Not class-adaptive	Class-adaptive	Not class-adaptive
NMR	96.22	96.22	96.22	96.22
MR bases				
DWT	**98.86**	98.82	98.58	98.68
DFT	98.26	98.18	98.42	**98.46**
DCT	95.08	94.46	**98.10**	98.02
DHT	95.48	95.06	**98.00**	97.78
WHT	95.02	94.34	**98.12**	98.08
DTT	98.02	97.92	**98.30**	98.28
RU1	97.12	97.00	**99.00**	98.98
RU2	94.90	94.84	98.12	**98.18**
MR frames				
DD-DWT	98.96	99.10	98.70	**99.12**
DT-CWT	99.06	98.52	**99.14**	98.80
SWT	99.36	99.38	99.42	**99.50**

Table 1. Accuracies in [%] obtained with different MR transforms using two weighting algorithms and a pruning procedure. We indicate in bold the highest accuracy achieved by each transform.

Fig. 2. Samples of fingerprint images from an easy class (left) and a difficult class (right).

- In general, the class-adaptive method seems to do better than the data set adaptive one.

Considering the two main MR decompositions DWT and SWT, using $\eta = 0.8$ in the pruning procedure removed almost half of the subbands, enabling significant computational savings in computation with a small impact on the classification accuracy.

For future work, we intend to use a much smaller training set of images to train our system, use a much larger data set as well as optimize η for each transform.

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