TEXTURE CLASSIFICATION WITH A BIORTHOGONAL DIRECTIONAL FILTER BANK

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ABSTRACT

Classifying textures is a problem that has been considered by many researchers. Many of the high performance methods are based on extracting features from the textures and performing classification in the feature space. In this paper, we consider the application of a new directional filter bank (DFB) to the problem of texture classification. The DFB is used to provide a compact and efficient representation in which fast classification can be performed using classical statistical methods. The resulting method is shown to yield higher performance than feature-based techniques reported previously. Furthermore, the approach has the added attraction that both the computational complexity and storage requirements are relatively low. Experimental comparisons using the Brodatz texture database are presented at the end of the paper.

1. INTRODUCTION

Texture classification can play an important role in image processing and computer vision problem areas. In the area of database retrieval, for instance, texture features are often used to search an image database to find images that are "similar" to the sample submitted by the user [1, 2]. In remote sensing and radar applications, texture features have been used to identify forest regions and their boundaries, and to identify and analyze various crops [3, 4]. The use of texture features has even found use in analyzing seismic signals [5].

Many classes of representations and features have been proposed, attempting to maximize classification performance with a minimal set of compact discriminates. Algorithms using statistical features, fractal features, Markov models and multichannel representation are some of the most popular and effective in this regard. Of particular recent interest are the multichannel approaches for texture analysis, because of their association with human visual system models of perception that involve scale and orientation.

*Prepared through collaborative participation in the Advanced Sensors Consortium sponsored by the U.S. Army Research Laboratory under the Federated Laboratory program, Cooperative Agreement DAAL01-96-2-0001. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation thereon.

The work reported herein focuses on a novel multichannel approach, based on the directional filter bank (DFB), originally introduced in [6]. Improvements to the DFB were introduced in [7] that enabled a higher quality subband representation, which turned out to be attractive for analysis applications. In follow-on work, this DFB was applied successfully to automatic target recognition using both neural network and hidden Markov model classifiers [8] and most recently to image denoising and texture segmentation [9, 10]. Following this evolutionary trajectory, we have considered the extension of the DFB to the challenging problem of texture classification. The discussion begins in the next section with an overview of the particular DFB we develop for this application and is followed by a discussion of the classification algorithm.

2. THE BIORTHOGONAL DIRECTIONAL FILTER BANK

The DFB partitions the frequency plane into a set of complementary wedge-shaped passband regions as described in [6]. For reasons of efficiency, we constrain the DFB to be a tree structured filter bank with the number of subbands given by 2^n, where n is the number of stages in the tree; this is conceptually described in Figure 1 where we show an analysis section for $n = 3$. The shaded portions of frequency planes illustrate the filter bank passband regions associated with each stage output.

Each stage in the tree consists of a two-band filter bank structure that splits the input image into two subband images using two complementary fan filters. The downsampling matrix $\mathbf{M}$ is given by $\left[\begin{smallmatrix} 1 & 1 \\ -1 & 1 \end{smallmatrix}\right]$, which results in output images that lie on a quincunx lattice.

After the second stage, it is necessary to use unimodular resampling matrices U_i so that the data are rearranged (but not downsampled) to conform to a sampling lattice that gives fan-shaped support in the frequency domain [6, 11, 7]. To realize a more natural and visualizable subband representation, a reformulation of the DFB structure is employed, as described in [7], where specific rules on the selection of the resampling matrices are presented. The objective of the reformulation is to undo rotations and skewings within each of the subbands that have arisen in the tree structure. The improved representation is achieved through backsampling matrices such that the data are rearranged on a rectangular lattice. Backsampling will generate rectangular nonuniform subbands which are easier to manipulate.

The DFB representation described above is only half of the challenge in our application. The second half deals with the actual implementation of fan-shaped filters with the perfect reconstruction (PR) property. In our DFB we keep the tree structure and use the two-band fan filter bank described in [12], which allows efficient implementation of *diamond and fan filters* in the polyphase domain. However, we employ the digital ladder structure shown in Figure 2, which was originally proposed by Mitra et al. in 1973 [13].

This allows for perfect reconstruction using N-order FIR filters and with about half the computational complexity required for the comparable filters used in [6]. The 1-D filter bank is generalized to two dimensions by a simple 1-D to 2-D transformation. The expressions for the corresponding 2-D diamond filters are

$$\begin{aligned} H_0(z_0,z_1) &= \frac{1}{2}(z_0^{-2N} + z_0^{-1}\beta(z_0z_1^{-1})\beta(z_0z_1)) \\ H_1(z_0,z_1) &= -\beta(z_0z_1^{-1})\beta(z_0z_1)H_0(z_0,z_1) + z_0^{-4N+1} \\ F_0(z_0,z_1) &= -H_1(-z_0,-z_1) \\ F_1(z_0,z_1) &= H_0(-z_0,-z_1), \end{aligned} \tag{1}$$

where $\beta(z)$ is a linear phase filter with even length N. Fan filters are obtained by letting $z_0 \to -z_0$ in equation (1).

Most natural images have spectral characteristics similar to those of an AR(1) process, that is, predominately low frequency with a moderate spectral rolloff. Edge and texture information is generally spread across the full spectrum. As it turns out, practical DFBs present a problem for this application regarding the way they handle DC. Ideally, the passband wedges associated with M-band DFB filters contain infinitely sharp passbands that split the DC signal energy evenly across all M-bands. However, for real world DFBs, the partitioning at the point of DC does not have infinite precision, resulting in an uneven distribution of DC energy among the bands. Given this non-uniform distribution of DC energy, we separate the input images before hand into low frequency and upper frequency component images using the structure shown in Figure 3 and restrict the decomposition to the upper frequency component. The filter $L_{\omega_c}(\omega_0,\omega_1)$ is a lowpass 2-D separable filter whose 1-D prototype has a cutoff frequency at ω_c. For the case of texture classification, this “preprocessing” helps remove the problem of DC energy division among the subbands and allows the representation to focus texture information, unbiased by misplaced DC energy.

3. TEXTURE CLASSIFICATION WITH THE DIRECTIONAL FILTER BANK

Multichannel approaches have been of special interest since there is strong experimental evidence that preattentive texture discrimination in humans is done by groups of visual cortex cells tuned to respond to specific orientations and spectral location (i.e. they work as bandpass filters). The use of 2-D Gabor bases [14, 15], wavelet transforms [16, 17], wavelet frames [18] and the 2-D dual-tree complex wavelet transform (DT-CWT) [19] conform to this framework, and have been successfully used to segment and classify textures.

A drawback of multichannel approaches like Gabor functions and wavelet frames (shift invariant wavelet transforms), is that they are expensive to compute and highly redundant. More recently, good results have been obtained using the discrete wavelet transform (DWT) and wavelet packets (WP) [17] which reduced the storage and computational complexity. However, these maximally decimated systems are limited in their orientation selectivity, and require higher complexity at the classification stage in order to perform competitively. For instance, in [17] the features have to be extracted by doing a quadtree search of the subband tree. A more recent effort using the 2-D DT-CWT has again shown the relevance of exploiting directional information for the texture classification [19]. This newer representation is still overcomplete and is limited to analysis in six directions. The proposed DFB fits perfectly in the multichannel framework by providing excellent directional selectivity while remaining maximally decimated. In fact we have used it succesfully for texture segmentation [10].

The texture classifier we use is an adaptation of a commonly used statistical scheme based on Bayes distance given by equation (3). Good classification results for a variety of multichannel decompositions have been reported [18, 17], often achieving perfect classification rates with the proper number of features.

The classification experiments were performed on the 30 Brodatz textures [20] used in the experiments of [17]. From each 512×512 texture class, one hundred 256×256 samples where extracted. Each sample was processed with the structure of Figure 3, setting $\omega_c = \pi/2$. The variance of each subband was estimated and grouped in a vector

$$\mathbf{v}_{k\ell} = (v_1, \ldots.., v_8). \tag{2}$$

The index k denotes the texture sample $k = 1, 2..., 30$, and $\ell = 1, 2...100$ corresponds to each sample.

A common assumption in pattern recognition is that the conditional probability functions of the class features have a mutivariate Gaussian distribution with mean vectors and covariance matrices $(\mathbf{m}_k, \mathbf{C}_k)$, for $k = 1, 2, \ldots, 30$. The classification of a vector of subband variances $\mathbf{v}$ is done by assigning it to the class with minimum distance value

$$d_k(\mathbf{v}) = (\mathbf{v} - \mathbf{m}_k)^T \mathbf{C}_k^{-1}(\mathbf{v} - \mathbf{m}_k) - \log(\det(\mathbf{C}_k)). \tag{3}$$

Under this assumption, this distance is equivalent to the minimum error Bayes classifier. Each feature vector was tested using the leave-one-out method to estimate the distance parameters.

We obtained 100% classification with the 8 features. The same experiment was performed using the ℓ_1 norm and a robust variance estimate commonly used in the wavelet denoising literature [21]. In both cases, again, we achieved 100% correct classification. All the experiments were repeated with $\omega_c = \pi/4$, and similar results were obtained.

Hence, we see that for this type of classifier, the DFB provides and extremely effective feature set for texture discrimination.

4. FEATURE REDUCTION

It is always desirable to achieve the best possible performance with the smallest possible number of features in order to keep low computational and storage requirements. In this section, we study the performance of the DFB classifier when it is modified so that a partial set of the features is used.

We repeat the classification experiment described in the previous section. However, we start with a reduced feature vector given by $\mathbf{v}_{k\ell} = (v_1)$, i.e., the variance of the first channel. Note that the ordering of the features in equation (2) is completely arbitrary. Next, we repeat the classification experiment with two features (v_1 and v_2) and continue adding features until we reach eight features. The results of this experiment are plotted in Figure 4 together with results from similar experiments reported in [17]. We see that starting from one feature the DFB performs way above than the other schemes with 70.7% correct classification. With just two features, the correct classification goes up to 98.73%. From here on the classification rate increases until 100% is achieved with just seven features.

It is important to note that we have not rank ordered the channels according to their energy content, as in [17], to form the reduced feature sets. An important difference that we believe contributes to the improved performance is that we are retaining orientation information in the process of extracting the energy features.

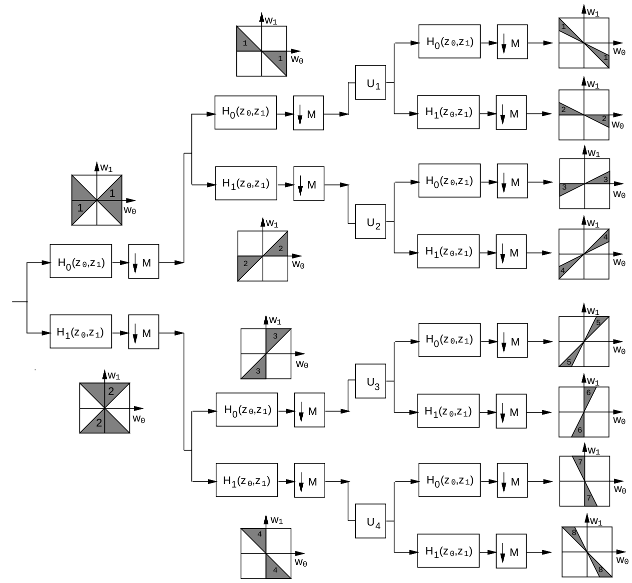

Fig. 1. The tree-structured directional filter bank concept

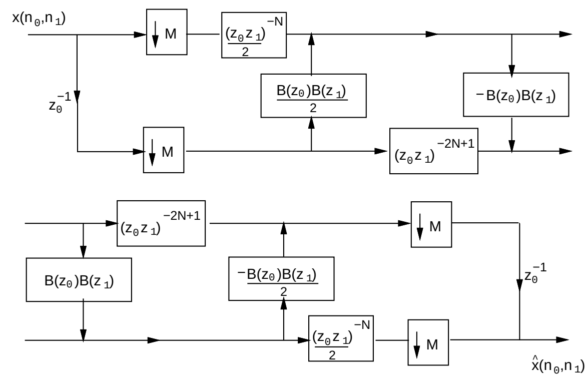

Fig. 2. Ladder structure for the implementation of a 2-D 2-channel biorthogonal filter bank.

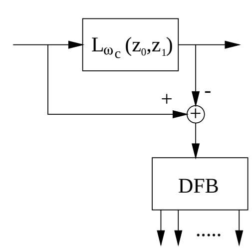

Fig. 3. Adaptation of multiresolution component to the DFB.

5. SUMMARY

We have introduced a new multichannel texture classification scheme using a flexible and efficient directional decomposition. We have shown the performance of the feature set is attractive relative to other schemes reported in literature in the sense that less computational effort is required to achieve high classification rates. Our current efforts are focussed on taking advantage of the directional selectivity of the system to add rotation invariance to the classification algorithm.

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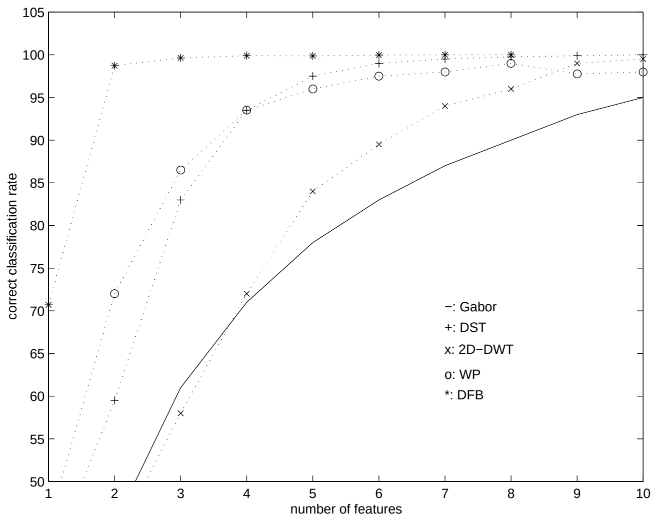

Fig. 4. Comparisson of DFB-based classification with other multichannel texture classification methods.

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