LAND USE CLASSIFICATION OF SAR IMAGES USING A TYPE II LOCAL DISCRIMINANT BASIS FOR PREPROCESSING

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ABSTRACT

In this paper, we present the application of the Type II Local Discriminant Basis (LDB) technique to feature extraction for land use classification in Synthetic Aperture Radar (SAR) images. Our classification algorithm incorporates spatial information into the decision process by classifying small image blocks, instead of single pixels. A feature vector composed of all the values in the image blocks is large for even small image blocks and, therefore, degrades the performance of many classifiers. The LDB technique greatly compresses the dimensionality of the feature vector, by indicating the most discriminant coordinates within the wavelet packet decomposition of an image block.

1. INTRODUCTION

Typically, land use regions cover connected areas rather than single pixels, therefore spatial indicators can improve classification. One approach is to classify images based on a block-by-block rather than a pixel-by-pixel basis. However, there are too many samples in an image block to be used directly as the feature vector for a typical classifier. For example, when classifying 8x8 blocks in an image with three layers, the feature vector would be 192 points. A preprocessing method by which the "best" portions of the feature vector are extracted is needed.

In this paper we present an algorithm, the Type II Local Discriminant Basis (LDB), for land use classification preprocessing. The power of computing a LDB is its ability to greatly compress a feature space, thus allowing the efficient use of spatial information through selection of effective sample vectors. The LDB approach has been applied to a variety of problems, including acoustic waveform classification and radar signal classification [1,2]. We show the application of this technique to land use classification of Synthetic Aperture Radar (SAR) images.

2. LOCAL DISCRIMINANT BASES

Coifman and Saito introduced the concept of a Local Discriminant Basis (LDB) for signal and image classification problems [3,4]. This preprocessing method follows the "best basis" paradigm of Coifman and Wickerhauser [5].

2.1 Type II LDB Technical Description

As part of a classification solution, samples from the classes to be distinguished are decomposed into a dictionary of orthonormal bases. This dictionary is an overcomplete set of vectors from which subsets may be systematically drawn to form orthonormal bases [4,5].

After decomposition, energies for each coefficient are collected separately for each class to form a distribution of energies in that coefficient for each class. Next, a basis is selected from the dictionary which maximizes the differences between energy distributions for each class, i.e., which does the best possible job of distinguishing members of different classes. After the basis is determined, expansion coefficients for the most important coordinates (i.e., the most-discriminant coordinates) are used as the training samples in a traditional classifier. The class of a test sample is then determined by computing its most discriminant coefficients and putting them into the classifier. Thus, the LDB method acts as a preprocessor for selecting out those few coefficients which will be most useful for classification purposes, enormously reducing the dimensionality of the ordinary classification problem.

2.1.1 Decomposition and Best Basis Selection

The decomposition step is implemented using the wavelet packet transform [5]. First, a typical 2D wavelet transform is performed on the original image. Next, each of the four image blocks is similarly decomposed. The process is repeated until the desired level of transformation is reached.

When the decomposition is complete, we have a highly redundant representation of the image. Any four "child" blocks at a decomposition level may be replaced by their single "parent" block from the previous level. The idea is to selectively replace child blocks by their parents. The final set of selected blocks must completely cover the image exactly once to form a complete basis from which the original image can be reconstructed. Figure 1 shows a sample basis.

There are two general techniques, the Type I and Type II LDB algorithms, for determining block replacement. In both techniques, the selection criteria is based on a comparative metric such as relative entropy.

2.1.2 Type I LDB

The original (Type I) LDB algorithm calculates the distribution of sample energies from each class over a block of coefficients, whereas the Type II LDB algorithm calculates the distribution of energies within a coefficient itself. A short example will illustrate the difference. Suppose we are working with two classes of vectors, *A* and *B*, with three training samples drawn from each class, and we are evaluating the discriminant potential of a block of four coefficients associated with the vectors v_1, v_2, v_3, v_4 in a waveform dictionary. The Type I LDB algorithm calculates the normalized total energy $e(v_1,A)$ associated with the class *A* and the coefficient v_1 in each of the four coefficients, and for each class, as follows:

$$\varepsilon\left(v_1, A\right) = \frac{\sum_{x \in A} x \cdot v_1^t}{\sum_{x \in A} \|x\|^2} \qquad \textbf{(1)}$$

An energy distribution vector of length four,

$$E(A)\left(\varepsilon\left(v_1, A\right), \varepsilon\left(v_2, A\right), \varepsilon\left(v_3, A\right), \varepsilon\left(v_4, A\right)\right) \qquad \textbf{(2)}$$

is then calculated for each class, and the “distance” between energy distribution vectors, defined by a distance function, D, and denoted

$$D(A, B) = D(E(A), E(B)) \qquad \textbf{(3)}$$

is calculated for the block of coefficients. A large distance value indicates that the distribution of energy in coefficients within the block of coefficients is different for each class, and suggests that the block of coefficients, used as a whole, will be good for distinguishing the classes. However, the block of coefficients as a whole is typically not used to solve the classification problem; a few “most discriminant coordinates” are chosen on which the energy of projections from each training set most differ, and the classifications are made based on those projections. Thus, the basis selection criterion differs slightly in underlying philosophy from the projection coordinate selection criterion.

Furthermore, it is possible to construct a simple classification problem which is intractable by this method. Suppose one class of functions, class A, consists of a single basis function in a waveform dictionary, with its amplitude 10, buried in white Gaussian noise with zero mean and unit variance. Suppose the other class of functions, class B, consists of the same basis function, with amplitude -10, buried in the same white Gaussian noise. Their energy distributions will then be identical, and the Type I LDB algorithm will be unable to find the right discriminating coordinate. This example, taken from [4], suggests that it is sometimes necessary to consider the distribution of expansion coefficients for individual coordinates. In this example, the class A expansion coefficients for the selected basis function would have a Gaussian distribution with unit variance and mean 10, whereas the class B expansion coefficients would have a Gaussian distribution with unit variance and mean -10. It would, therefore, be easy to do the classification based only on that single coordinate. To address this sort of problem, a new LDB technique, called the Type II LDB algorithm, was devised by Coifman and Saito [4].

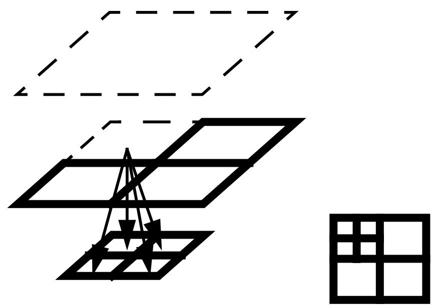
2.1.3 Type II LDB

The Type II LDB algorithm uses coordinatewise, as opposed to blockwise, probability density functions as the basis selection criteria. In this technique, the values of the projections of training samples onto basis vectors are collected, and a discrete model of the distribution of the coordinate values is made for each class. The distributions are then compared, and a measure of the distance between distributions is made. Those blocks of basis functions having the best separability in coordinatewise distributions are then selected.

Usually, the summed distribution difference is used as the separability indicator [4]. While the basis selection criterion and the projection coordinate selection method still differ slightly - it is, in theory, possible to have a high summed distribution difference measure in a block of coordinates, causing it to be chosen as part of the discriminant basis, when projecting onto a single coordinate in another block might serve as a better classification strategy. This basis selection method is in line with the goal of reducing the dimensionality of a classification problem. We have designed a measure d_s (distribution separability) defined as

$$d_s = \frac{\left|\mu_A - \mu_B\right|}{\sigma_A + \sigma_B} \qquad \textbf{(4)}$$

where μ_A, σ_A and μ_B, σ_B are the means and standard deviations of the distributions for classes A and B, respectively. This measure models the desired goal in that coordinates are selected with the separability of classes in mind.



A sample basis:

This represents a basis extracted from the tree at left. Note that if you look down from above, the entire image space is covered exactly once by the blocks of the basis.

The decomposition defined by this basis is, in fact, an ordinary **discrete wavelet transform.**

Figure 1: A sample basis

3. RESULTS

The entire classification process consists of several steps. First, sample image blocks with known land use type are interactively selected for each class. Then, Type II LDB preprocessing and classification is performed on each class pair for each image layer. Specifically, for each pair of classes, the Type II LDB is computed and the top few most discriminant coordinates for each image plane are saved. The entire image is then broken into blocks of the same dimensions as the sample blocks and subjected to the Type II LDB preprocessing. A feature vector is then formed from the top few most discriminant coordinates for each image plane. The Type II LDB preprocessed training and testing samples are then submitted to a maximum likelihood classifier. Finally, the pair-wise classifications are combined to form an overall classification result.

We designed object-oriented software in C++ to compute the Type II Local Discriminant Basis for 2D samples. In addition, scripts to allow interactive selection of training samples from SAR images and for training and classification of the Type II LDB preprocessed image blocks were designed in PV-WAVE (Visual Numerics, Boulder, CO).

We investigated the effect of parameters such as the size of training blocks, the amount of overlap between extracted image blocks and the number of coordinates selected from the Type II LDB expansion. The following sections present a portion of our results.

3.1 SAR Images

Two 512x512 pixel SAR images from sections of a 4096x14231 pixel Ft. Benning, GA data set were used for testing purposes. Magnitude, correlation, and elevation gradient layers were used in the tests.

3.2 Land Use Classes

Four different land use classes were extracted from the Ft. Benning images. The classes corresponded to buildings, grassy regions, trees and fields. Training blocks from these classes of dimensions 8x8 were extracted from each layer for testing purposes. Examples of the land use regions are indicated on the Ft. Benning magnitude layer image in Figure 2.

All possible combinations of the four extracted classes were submitted to the Type II LDB algorithm separately, for a total of six different basis computations for each image layer.

3.3 Classification Results

After the Type II LDB decomposition was calculated for training class combinations for each Ft. Benning image, the Ft. Benning images were broken into 8x8 blocks which overlapped by six pixels in both dimensions. The extracted image blocks were then preprocessed in each of the six different computed bases. The top one to three most discriminant coordinates from each layer of the expanded image blocks were then submitted to a maximum likelihood classifier for classification. The classification results from each combination were then combined to give an overall classification result for the image. Pixel by pixel class assignment was then determined using the majority vote of the class assignments from all overlapping blocks containing the pixel. Additional tests were run for the two SAR images using block sizes of 4x4 and 16x16 with two and fourteen pixel overlaps, respectively.

In preliminary tests, we determined that the best results were obtained when only one coefficient was used from each of the three planes. The classification results for 16x16 blocks, using the top coefficient from each plane, are shown in Figures 3 and 4 for the first Ft. Benning image. Figure 3 displays simply a four level grayscale image of the four classes. Figure 4 depicts the classes overlaid onto the original magnitude layer of the SAR image. Figure 5 shows the land use classification using a maximum likelihood classifier on a pixel by pixel basis without Type II LDB preprocessing. For the pixel-by-pixel classification results, the classifier feature vector for each pixel was simply composed of the magnitude, correlation, and elevation gradient values. By comparing these results, we can see that the spatial information from using blocks and the Type II LDB preprocessing of the blocks does significantly improve the classification results. In Figure 4, we see good grouping of the tree and grass regions as well as good identification of buildings and fields. Similar success was achieved for the second Ft. Benning image, but the results are not shown in this paper.

Figure 2: Land Use Regions - Ft. Benning Image 1

It is difficult to directly correlate classification success to block size. We can, however, consider the limitations imposed by the block dimensions. Specifically, there is a trade-off between the size of the blocks and the depth of the Type II LDB decomposition. The typical limit for decomposition, d, is defined by

$$d = \log_2(x) - 1 \qquad \textbf{(5)}$$

where x is the block size. Because the number of decomposition levels increases with the block size, there are a larger number of points from which to choose with a larger block size. The trade-off is that larger blocks will in general contain a mix of many classes, whereas smaller blocks may encompass only a single class.

4. SUMMARY

Because land use classes regions typically cover connected areas rather than single pixels, spatial indicators can improve classification. Spatial information can be incorporated by considering small image blocks; however, many classifiers are not designed to work well with large feature vectors. We showed application of the Type II LDB technique as a preprocessing method to reduce the size of the feature space for extracted land use blocks in SAR images. With Type II LDB preprocessing, we were able to efficiently classify image blocks, and thus utilize compressed spatial information for classification. With this technique, we showed significant improvement over a pixel-by-pixel classification method.

ACKNOWLEDGMENTS

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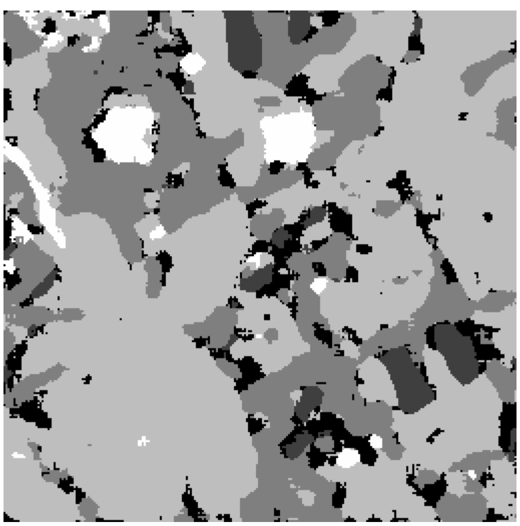

Figure 3: Ft. Benning Image 1 - Results using Type II LDB preprocessed overlapping 16x16 blocks

Figure 4: Ft. Benning Image 1 - Results using Type II LDB preprocessed overlapping 16x16 blocks overlaid on the magnitude layer

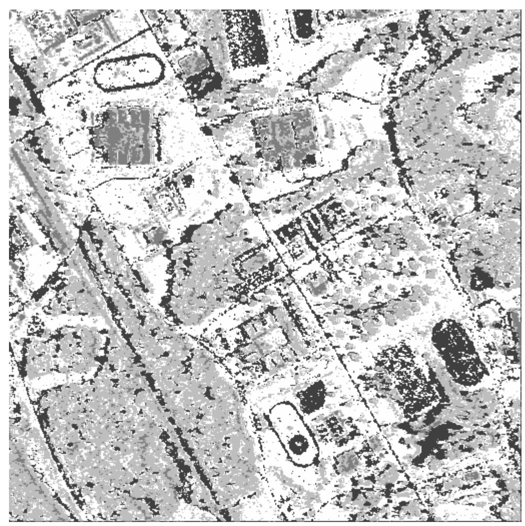

Figure 5: Ft. Benning Image 1 - Results of non-LDB preprocessed maximum likelihood classification