Textural Features for Hyperspectral Pixel Classification

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Abstract. Hyperspectral remote sensing provides data in large amounts from a wide range of wavelengths in the spectrum and the possibility of distinguish subtle differences in the image. For this reason, the process of band selection to reduce redundant information is highly recommended to deal with them. Band selection methods pursue the reduction of the dimension of the data resulting in a subset of bands that preserves the most of information. The accuracy is given by the classification performance of the selected set of bands. Usually, pixel classification tasks using grey level values are used to validate the selection of bands. We prove that by using textural features, instead of grey level information, the number of hyperspectral bands can be significantly reduced and the accuracy for pixel classification tasks is improved. Several characterizations based on the frequency domain are presented which outperform grey level classification rates using a very small number of hyperspectral bands.

1 Introduction

Hyperspectral imagery consists of large amounts of channels covering the different wavelengths in the spectrum. These images represent a very rich source of information that allows an accurate recognition of the different areas to be obtained through the use of pattern classification techniques. For this reason, traditionally, this kind of images has been used in remote sensing applications. However, nowadays they are also widely used in medical imaging, product quality inspection or even fine arts. The main problems to deal with hyperspectral images are the high dimension of this data and its high correlation. In the context of supervised classification, an additional problem is the so-called Hughes phenomenon that occurs when the training set size is not large enough to ensure a reliable estimation of the classifier parameters. As a result, a significant reduction in the classification accuracy can be observed [3], [4], [5]. To overcome the Hughes phenomenon the original hyperspectral bands are considered as features and feature-reduction algorithms are applied [11]. They process the original set of features to generate a smaller size set of features with the aim of maximizing the classification accuracy. A particular class of feature reduction methods are band selection methods [9], [10], [7], which select a subset of the original set of bands and discard the remaining to reduce redundant information in the image representation without losing classification accuracy in a significant way. Methods of band selection obtain subsets of relevant bands so as to get the best classification performance. The performance of the

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band selection is usually measured through pixel classification accuracy based on grey level pixel data.

In this paper we propose the use of several frequential texture features to describe each individual pixel. The aim of this characterization is to reduce as much as possible the number of hyperspectral bands required in the global process while keeping the final pixel classification accuracy as high as possible. We start from the band selection scheme described in [7] and compare the classification accuracies obtained using grey level features against textural features. Gabor filters as well as wavelets features are considered in our study. Also, modified versions of Gabor filters are considered with two main objectives: obtaining a more detailed analysis of medium and high frequencies, and, simplifying their computational cost without decreasing their discriminant power.

2 Textural Features

In hyperspectral imaging it is very common to characterize each pixel using a feature vector formed by the grey level values of that pixel in a given set of bands. To measure the performance of a band selection method, a series of pixels are characterized using their grey level values in the selected bands. The rate of correct classification obtained is compared to the classification rate obtained using the whole set of bands, to check the goodness of the selected group of bands as a representation of the entire hyperspectral image.

Now, our purpose is to describe the textural characteristics of a group of selected bands as they are supposed to portray the common features of pixels, that is, the texture they represent. For this reason, we have considered a series of frequential filters in order to extract features from the frequency domain to characterize pixels rewarding their textural features. In all cases, we consider a basic tessellation of the frequency domain taking into account several frequency bands and orientations [8]. A filter mask is applied over each area defined in the tessellation in order to select the frequencies within the chosen area. Then, for each area, we obtain its inverse Fourier transformation into the space domain. The result is an "image" which contains only frequencies in the chosen area, telling us which parts of the original image contain frequencies in this area. Repeating this process for all frequency areas we will have a stack of "images". Therefore, for each pixel we have as many values as frequency areas we used, that is, one value per output "image". This vector of values is used as the frequency signature of each pixel.

The first sort of filters considered are the well known Gabor filters. We construct a basic tessellation of the frequency domain considering several frequency bands and orientations. Each frequency band is double the previous one and a Gaussian mask is applied over each frequency area. Figure 1(a) shows an example of a Gabor filter considered. Figure 1(b) shows the maximum value of all Gabor filters considered for a given tessellation using four frequency bands and six different orientations. As it can be seen in this figure, each individual filter expands far away from the limit of the area defined in the tessellation. For this reason, two variations of these filters

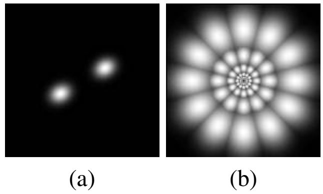


Fig. 1. (a) An example of Gabor filter in the frequency domain (b) Maximum value of all Gabor filters considered for a given tessellation using four frequency bands and six different orientation

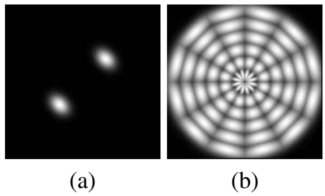


Fig. 2. (a) An example of filter keeping constant the width of the frequency band (b) Maximum value of all filters considered for a given tessellation using six frequency bands and six different orientation

(as described in [8]) could also be considered. First, similar Gaussians are applied over each frequency area, but truncating them beyond the limits of the areas in order to eliminate contributions of the same frequencies in different filters. On the other hand, the use of Gaussian masks over the frequency areas leads to the loss of importance of frequencies not lying nearby the center of these areas. That is why, also flat masks covering exactly each frequency area in the tessellation will be considered.

Another disadvantage in the application of Gabor filters using the basic tessellation scheme is that the frequency bands considered are not uniform. In this way, low frequencies are given more importance than middle or high frequencies. However, it is well known that texture information mainly falls in middle and high frequencies [1]. Therefore, we propose a detailed analysis of all frequencies by keeping constant the width of the frequency bands to be analyzed by each filter. Figure 2(a) shows an example of an individual filter using a complete Gaussian mask, while figure 2(b) shows the maximum value of all these filters considered for a given tessellation using six constant frequency bands and six different orientations. Note that, also in this case, truncated Gaussians and flat masks may be used.

Also features derived for each pixel using a wavelet decomposition will be considered. A wavelet decomposition is obtained using two appropriate filters: a low-pass filter L and a high-pass filter H. In this case, we have chosen to use a maximum overlap algorithm, that is, no subsampling is done. Therefore, after applying each filter, an image of the same size of the original image is obtained. Also, a wavelet packet analysis has been used, which means that not only low frequency components will be considered in further levels of analysis. In this case, all components will be taken into account. Figure 3 expresses the wavelet decomposition in the frequency domain for two levels of analysis using the Daubechies-4 filters.

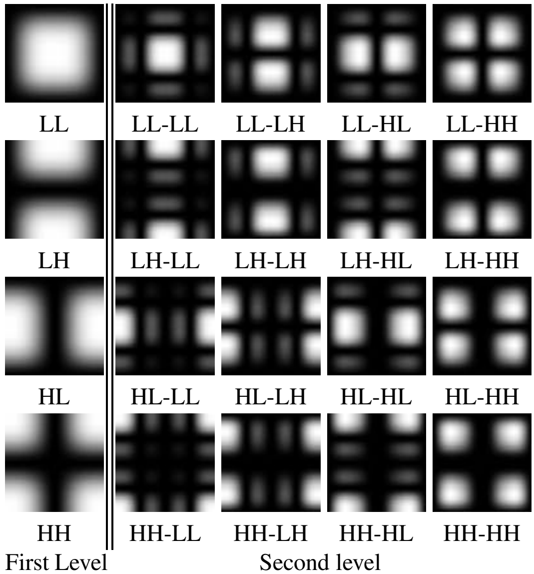


Fig. 3. Wavelet decomposition expressed in the frequency domain for the two levels of analysis using the Daubechies-4 filters

3 Hyperspectral Database

The experimental results will consist of comparing the different characterization methods named above over a widely used hyperspectral database. The 92AV3C source of data corresponds to a spectral image, 145x145 pixel-sized, 220 bands, and 17 classes composed of different crop types, vegetation, man-made structures, and an unknown class. This image is acquired with the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data set and collected in June 1992 over the Indian Pine Test site in Northwestern Indiana [2].

4 Experimental Results

Experiments to characterize the texture of each pixel were run using all the textural features described before. For the basic tessellation (where each frequency band is double the other) four different bands and six different orientations (wedges of 30^{o}) were considered, that is, a total of 24 features were used to characterize each pixel. For the constant tessellation, nine frequency bands of the same size and six directions were considered, which provide a total of 54 features for each pixel. These numbers of features are due to the symmetry of the Fourier transform when dealing with real numbers. For the wavelet decomposition, the Daubechies-4 filters were used until three levels of decomposition, providing a total of 84 features per pixel.

4.1 Results Using the Best Band for Grey Level Classification

Let our band selection method be the one in [7], which has already proved its good performance for pixel classification using grey level features. It provides with a series of clusters, that is, sets of bands grouped depending on their mutual information. The bands that composed each set depend on the cluster number as every set by itself represents the best combination for all the possibilities. To test the discriminant power of each set of textural features we will run classification experiments using the only band in cluster number one.

The selection method reported band number 4 for the cluster of size one among the bands which compose the 92AV3C database. The results of all methods of characterization named above can be seen in Table 1. Classification has been performed using the K nearest neighbor rule with 3 neighbors. With classification purposes and due to the massive data that pixel characterization generates, samples have been divided into twenty independent sets keeping the a priori probability of each class and the k-nn rule has been used to classify all sets taken in pairs, one used as training set and the other as test set (1-1 knn3 method). Therefore, ten classification attempts have been performed without data dependencies among the attempts. In this way, a mean rate of all the attempts have been reported.

Table 1. Classification rates (in percentage) for the all characterization methods considered over band number 4 from 92AV3C database

Characterization method		Classification rate
Grey level values		18.85 %
Wavelet packets		27.77 %
Basic tessellation	Gauss	41.58 %
	Truncate	40.07 %
	Flat	41.31 %
Constant tessellation	Gauss	63.77 %
	Truncate	65.05 %
	Flat	65.78 %

Results in table 1 show that all methods outperform grey level classification rates as it was obviously expected due to the higher number of features used. However, the wavelet features were worse than expected. It was the method that used the highest number of features and the percentage of correct classification was just a bit better than the grey level values. The basic tessellation performed significantly better than the wavelet features, using all sort of masks (Gaussian, truncate Gaussian, or flat). Finally, we can note that the constant tessellation outperformed the rest of features. When keeping the frequency band constant, the analysis is equally done for all frequencies bands what seems more appropriate for texture characterization. Moreover, we found that the sort of tessellation used influenced the final results much more that the sort of mask applied. Almost no difference was obtained when different masks were used. This is quite surprising as the used of truncate Gaussian masks should introduce important artifacts in the space domain, even more when the flat masks are considered. However, the classification results are almost the same or even better when the flat masks were used. Perhaps, when Gaussian masks are used, frequencies do not equally contribute to the characterization and some of them lose their characterization significance. Thus, applying flat masks allows all frequencies to contribute equally and uniquely the characterization providing very good results and requiring less computational effort.

4.2 Results Using Individual Bands

Previously, we have seen that using flat filters with a constant tessellation provided the best results of all the characterization methods studied. In consequence, we are now going to test these features for all the bands that make up the 92AV3C database.

Figure 4 shows the maximum, minimum, and mean percentage of correct classification for the same ten independent classification experiments described before run for each band in the database.

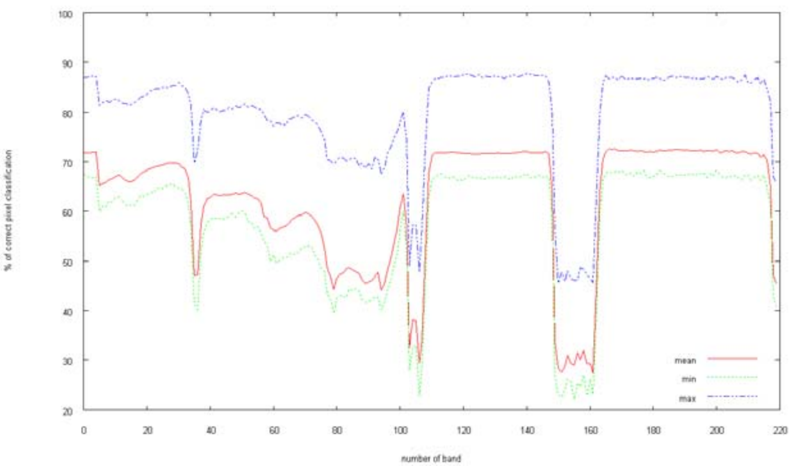


Fig. 4. Classification rates for each band of the 92AV3C database

From figure 4 we can observe that the maximum classification accuracy is not obtained at band number 4 as the chosen band selection method suggested. However, there are several bands, such as 171, that got better performance and consequently are more convenient. These results show that the textural features may be taken into account from the beginning in the band selection process, at least, as a testing criterion.

We can also notice in figure 4 that there are significant differences in the percentage of correct classification between bands. It is well known that several bands in the 92AV3C database are generally dismissed due to their low signal-to-noise ratio. These ranges are known to be bands $0-3$, $102-109$, $148-164$, $216-219$, as described in [6]. All these ranges provided the worst classification results, except for the range $0-3$ which provided similar results to other bands. If these bands were not considered, even the worst band would provide quite good classification results taking into account that only one band is being used in each case.

4.3 Results for Clusters of Bands

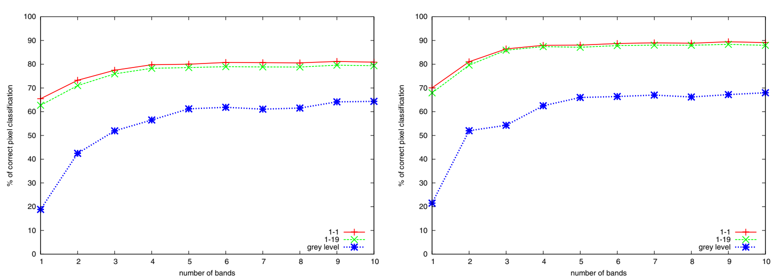
In this section we will show that textural characterization improves itself by using a higher number of bands even when the clusters of bands selected could not be optimal for these features, as it has been previously seen.

When more than one band is considered, all possible pairs of bands will be taken into account and textural features will be derived from them. Taking each pair of bands, a complex band will be formed using one of them as the real part and the other one as the complex part. When the Fourier transform is computed for these complex bands, the symmetric property if no longer fulfilled. Consequently, the number of filters to apply over each complex band doubles since each of the previous filter must be split into two parts due to the non-symmetrical transform.

The feature set obtained for each cluster will be divided into twenty random sets keeping the a priori probability of each class. In first place, as described in the previous sections, classification has been performed with the k-nn rule using 3 neighbors using pairs of sets, one used as training set and the other as test set (1-1 knn3 method). Other classification experiment consists of using each set once as training set whereas all the rest 19 sets are joined together to be used as a test set (1-19 knn3 method). In both experiments, a mean, maximum and minimum rate may be calculated, with ten and twenty independent attempts, respectively. For our current purpose, only the mean will be representative of our results and compared with classification rates reported in [7].

92AV3C database contains 17 different classes of textures, among them, the background class is composed by a heterogenous mixture of non-classified classes. Including this class into the classification process may confuse and decrease the performance rate due to its heterogenous nature, as different characterizations are assigned to the same class. For this reason, the more representative the characterization is of a class the less the classifier will fail, as pixels with a specific class will be properly characterized and so properly fit into its class by the classifier.

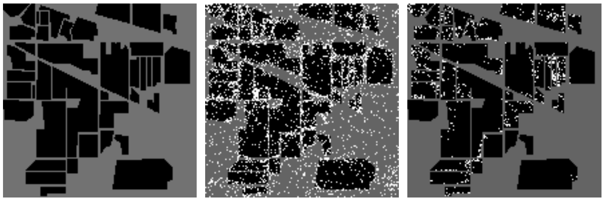
Fig. 5(a) shows classification results including the background class while Fig. 5(b) shows similar results without using the background class, in both cases for different numbers of bands in the cluster. It could be noted that textural features reaches



(a) (b)

Fig. 5. Classification rates for clusters of 92AV3C database, with two methods of classification and compared with grey level characterization (a) taking into account the heterogenous class of background (b) without background class

stability sooner than the old method does, which means that a smaller number of bands is required in the whole process to reach a higher performance. As expected, when background is not taken into account performance enhances since background mistakes are removed (see Fig. 5(b)).



(a) (b) (c)

Fig. 6. (a)Ground truth of the 92AV3C database. Localization of classes in the space. (b) Maps of misclassified pixels (in white) using a clusters of 5 bands classified with a 1-1 knn3 method including the background class (c) Same map without the background class.

Fig. 6 presents the classification errors for the cluster composed by 5 bands. It shows misclassified pixels (white) by representing them in the space of the image superposed by the image's ground truth in order to distinguish the original classes recognized in the real image. Notice that the majority of the mistakes will be due to the heterogenous class or the proximity to it (see Fig. 6(b)). To avoid mistakes due to the background class and being able to analyze mistakes of the known classes, the background class may be ignored (observe Fig. 6(c)). In this case, misclassified pixels may be easily recognized and classification rates increase. Note that misclassified pixels fall mainly in the borders of the regions.

5 Conclusions

Results of hyperspectral texture characterization using several frequential filters has been presented in order to test band selection methods and reduce significantly the number of bands required in pixel classification tasks while improve the classification rates. Constant frequency band tessellation performed significantly better than traditional tessellation and the different masks tested performed similarly. We have chosen the flat masks due to its low computational cost. Different classification experiments have shown the stability of the textural features over different spectral bands, as well as when they were obtained from individual bands or from complex bands. Band selection methods usually take grey level pixel characterization as the validation criteria for their selection. We have shown that other validations should be taken into account as better classification rates may be obtained with textural information.

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