# REGION BASED KLT FOR MULTISPECTRAL IMAGE COMPRESSION

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## ABSTRACT

In this paper we present a new approach of spectral decorrelation for multispectral image compression. It is based on the merging of two main tendencies such as the use of KLT as spectral decorrelator and object based image coding schemes. The use of the principal component in multispectral imagery is described and used to perform a multispectral segmentation. This segmentation is taken as the basis for a specific spectral decorrelation for each segmented class. The resulting *eigenimages* present lower variance than classical KLT approaches, leading to better compression ratios.

## 1 INTRODUCTION

Many efforts have been done on the compression of multispectral images. Algorithms have been applied for lossless [1], near-lossless and lossy applications. Most of them use the spectral correlation existing between spectral bands in order to achieve better compression ratios. Among others, classical algorithms are based on Vector Quantization [2], 3-dimensional transformation, spectral prediction [3], wavelets or hybrid methods such as DPCM-DCT [4] or KLT-DCT [5]. The use of KLT (Karhunen-Loève Transform also known as Hotelling or Principal Component) as spectral decorrelator has been shown to be one of the most effective [6]. In this paper we present a compression scheme that can be used from near-lossless to lossy applications.

On the other hand, in the image analysis field, the use of principal components is also widely used. In multispectral image analysis it offers a dimensionality reduction very useful for a subsequent classification.

In this paper we use the KLT in both of mentioned issues: *i*) for a multispectral classification and *ii*) for compression. Once the scene is segmented, each one of the "spectrally homogeneous" regions is coded separately by means of the *region based KLT*. Important variance reduction is achieved by this method compared with *classical* KLT or block based KLT without large increase of overhead information. Results obtained are compared with the other KLT methods and compression standards.

## 2 KLT AND MULTISPECTRAL IMAGERY

One very successful application of the KL transformation is in multispectral images. The transformation is applied in the spectral dimension taking each one of the pixels of the scene as $N$ dimensional vectors being $N$ the number of spectral bands. Let $X$ be the vector containing the $N$ components for a given pixel and $U$ the mean vector $U = E[X]$. The covariance matrix $C_x$ is defined as:

$$C_x = E[(X-U)(X-U)^t] \tag{1}$$

The Karhunen-Loève Transformation ($T$) is defined as the one that diagonalizes $C_x$ in the following way:

$$C_y = TC_xT^t = \Lambda \tag{2}$$

being $C_y$ the covariance of the transformed vector ($Y$) and $\Lambda$ the diagonal matrix representing eigenvalues. $Y$ can then be obtained by the equation:

$$Y = T(X-U) \tag{3}$$

Since the transformation optimally diagonalizes the covariance matrix between spectral bands, the spectral correlation of the transformed components is removed. The images in the transformed domain are sorted in order of *importance* or with decreasing variance (value of the eigenvalues). This energy compaction in the spectral axis is quite suitable for selection of the main spectral components for analysis as well as for image compression. The use of both applications is explained in the following sections.

## 3 MULTISPECTRAL SEGMENTATION

Given a multispectral dataset the KLT is applied in the spectral dimension. From the obtained main components, one can select the most important. Experimental results show that selecting the first three main components is a good trade-off between complexity of the subsequent analysis and spectral information retrieval. Of course, this may vary with the nature of the scene. The advantage of using KLT is twofold in the following sense: it reduces the problem of band selection for the classification to a simple choice of the total number of images. On the other hand, it assures that the selected images for classification are the most representatives of the spectral content in the scene.

Different clustering techniques can be applied for segmentation. We have chosen the multidimensional histograming of the three main components because it does not require any recursive calculation that would slow down the system. Once the 3-dimensional histogram is built, some morphological operators are applied to the four dimensional surface that represents the histogram, these are: smoothing and peak detection by morphological opening operators. Maximal peaks are extracted, sorted in order of importance and selected depending on the number of required classes. All the pixels are classified following the criterion of maximum correlation and a segmentation map is generated. This segmentation has been successfully applied to cloud extraction for a 3D cloud visualization[7]. Figure 1 shows the visible band and a 3 classes segmentation map.

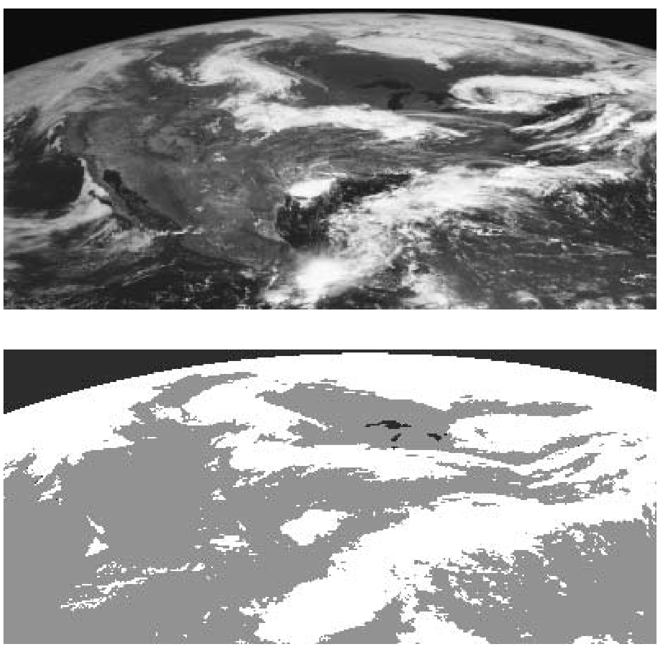


Figure 1: a. Original GOES8 image, visible band. b. Segmentation map for 3 classes.

# 4 MULTISPECTRAL COMPRESSION

## 4.1 Classical KLT approaches

The KLT applied to multispectral images for image compression has been used in several approaches. The basic approach is the one that takes all the spectral images and computes the KLT in the spectral axis. Since the resulting components are sorted in order of importance they can be easily quantized with criteria that take into account the *importance* factor, achieving high compression ratios. Better results have been obtained when the images are partitioned in regular blocks and the KLT is computed within these blocks[8]. The drawback of the latter approach is the high overhead information needed when the number of bands increases (images can contain hundreds of blocks and hundreds of bands).

## 4.2 Region Based KLT

We introduce a new approach to the application of KLT for multispectral image compression. Taken the multispectral segmentation described in section 3 a different transformation ($T_i$) is calculated for each class in the following way:

$$C_{yi} = T_i C_{xi} T_i^t = \Lambda_i \qquad (4)$$

where $i$ is the class number and $C_{xi}$ is the covariance matrix calculated from the pixels belonging to the class $i$. Since the obtained segmentation is the result of the classification of the principal components, all the pixels of the same class are likely to have similar KLT transformation, thus the transformation is going to be better adapted to statistics of the set. If we apply a different KLT to each class, the energy is going to be optimally compacted for each region, giving at last highly energy compacted *eigenimages* with less variance than the obtained by a simple KLT. Since a different transformation is computed for each class (not objects) the overhead data volume does not increase substantially as discussed in section 5. Figures 2 and 3 illustrate the region based KLT approach and the general scheme of the coder, respectively.

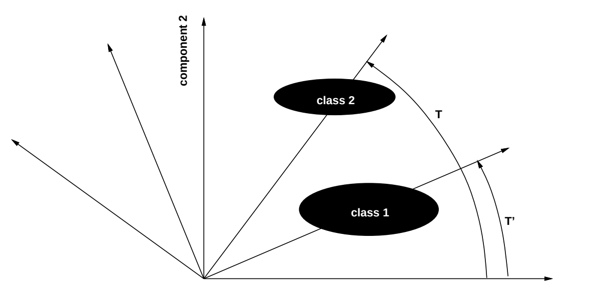



Figure 2: Graphical illustration of region based KL transform.

# 5 OVERHEAD INFORMATION

As overhead information we understand all the data needed for the decoder not directly related to the pixel values. In a KLT based algorithm this information is reduced to the covariance $C_x$ matrix and the mean vector

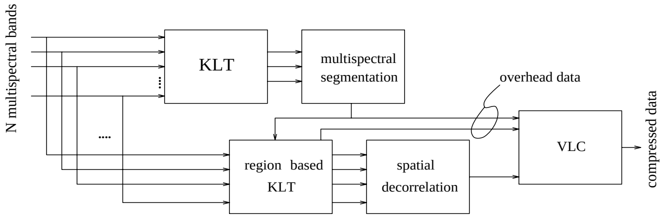



Figure 3: Block diagram of the proposed coding algorithm

$U$ of Eq. 1. The volume of this overhead will depend on the number of bands and the number of transformation needed in the algorithm (i.e. the number of blocks in a block based scheme or classes in our approach). Note that in the presented region based transform, a different KLT is applied to each class and not to each single region. That means that in a satellite image we define a KLT for the class of clouds, one for the class of land, etc... and not for every single cloud. Since all the clouds have similar spectral signatures, the KLT is always optimal but the overhead information to code does not increase substantially.

In the presented algorithm, a second overhead component is the coding of the segmentation information. We have to point out that this overhead information can be highly compressed (few classes are usually defined) and that its cost has to be divided by the number of bands to compress leading to a derisory extra cost in the case of hyperspectral images.

Figure 4 shows the evolution of the overhead information as the number of bands to code increases. Values are plotted for a block based KLT ($64 * 64$ block size) and for 3 and 6 region KLT. Note that for a given number of bands, the overhead of the block based scheme is largely above the region based ones even if the latter ones have the segmentation cost included.

## 6 SPATIAL CODING

After the spectral decorrelation, all the spatial correlation existing in the principal components remains to be exploited. Several approaches can be observed at this point and they are related to classical still image coding ( DCT, subband coding, ..). Furthermore, since we are working in a region based approach, object based spatial coding can also be considered (shape adaptive DCT, morphological coding,..).

In this paper, we would like to focus our attention to the spectral decorrelation performances and by applying block based or object based spatial coding we would introduce a distortion on this measure. For this reason, a simple spatial coding of the components has been adopted. Images are quantized differently depending on its importance factor and a DPCM followed by run-length coding is applied. Finally, the resulting bitstream is entropy coded. The final compression ratio obtained may not be optimal but it will be useful to compare the different spectral decorrelation approaches.

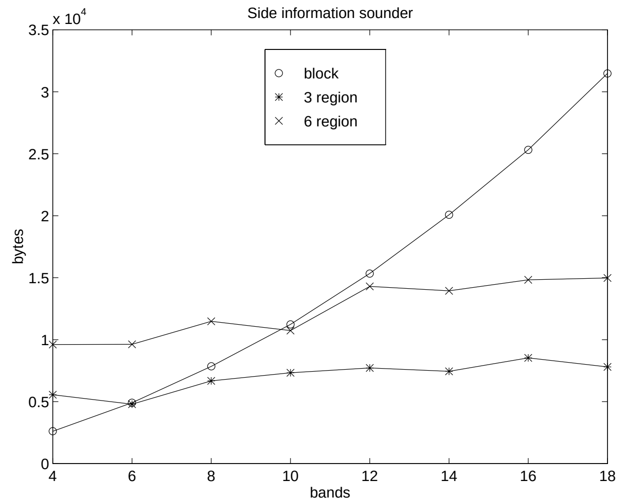
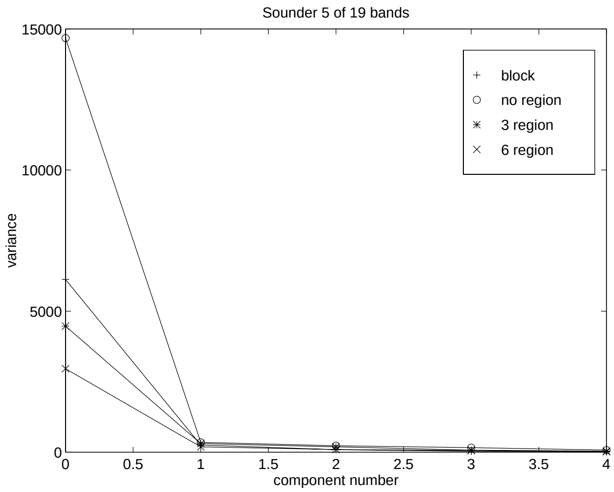



Figure 4: Overhead information when increasing the number of spectral bands.

## 7 RESULTS

The presented method was applied to multispectral images of the *sounder* instrument of GOES-8 NOAA satellite. This dataset contains 19 spectral low resolution bands. Figure 5.a shows the variance of the first eigenimages obtained for the several forms of KLT explained in section 4. The variance reduction in the main component when the region based KLT is applied is of more than 75% respect to the normal KLT and about 35% when compared with the block based KLT ($64 * 64$ block size). Final compression results are shown in figure 5.b and compared to the standard JPEG when coding the bands separately. The proposed algorithm has a gain of 3-4dB over JPEG and 1-2dB over non-region based KLT algorithms. The results obtained with such a simple spatial coding scheme allows to hope that more refined object based coding methods should be able to improve them. The use of the scheme in hyperspectral imagery should also give good performance.

Finally, we would like to point out that on the performance evaluation one should also take into account that the compressed images embed the segmentation map that can be useful in some scientific applications. Furthermore, multispectral classes can be coded differently according to some user priorities giving a flexibility to the coder that none of the other *classical* methods have.



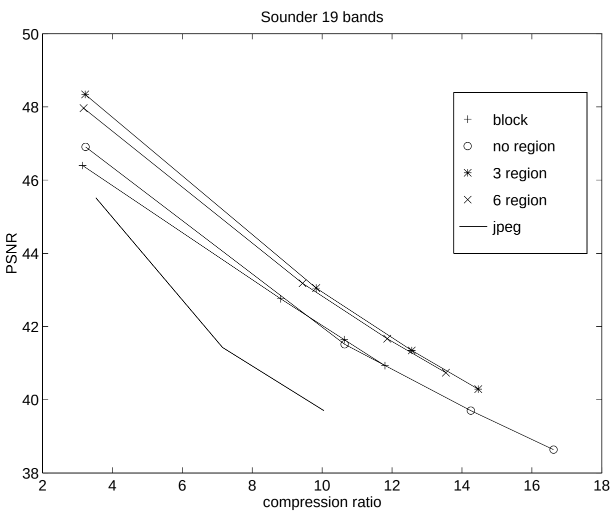




Figure 5: a. Variance for the first eigenimages. b. Mean Peak SNR versus compression ratio.

## 8 CONCLUSIONS

In this paper we have presented a new approach on the coding of multispectral images. It is based on the merging of two tendencies in image coding and remote sensing coding. The classical spectral decorrelator such as KLT is combined with region based coding techniques, obtaining the so-called region based KLT. In order to produce an accurate multispectral segmentation, this method can take advantage of another very well known image processing domain such as the one of the multispectral image analysis. Experimental results have shown that the region based KLT reduces the variance of the transformed components very substantially and that this reduction is translated to better performance in rate distortion terms. Furthermore, the advantages of object based coding systems must also be taken into account in the performance evaluation.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