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ADAPTIVE-3D-WIENER FOR HYPERSPECTRAL IMAGE RESTORATION: INFLUENCE ON DETECTION STRATEGY

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ABSTRACT

In this paper we consider the problem of multichannel restoration. Current multichannel least squares restoration filters utilize the assumption that the signal autocorrelation, describing the between-channel and within-channel relationship, is separable. We propose a Wiener solution for a multichannel restoration scheme, the *Adaptive-3D-Wiener* filter, based on a local signal model, without using the assumption of spectral and spatial separability. Moreover, when the number of channels is superior to 3, the restoration is in many cases the preprocessing to a given application such as classification, segmentation or detection, so it seems to be important to perform a restoration which suits to the application in fine. In this aim, the proposed filter is developed to be used as a preprocessing step for detection in hyperspectral imagery. Tests on real data show that the proposed filter enables to enhance detection performance in target detection and anomaly detection applications with two well-known detection algorithms in hyperspectral imagery.

1. INTRODUCTION

The aim of this work is to propose a multidimensional algorithm for the restoration of noisy multicomponent images in the final objective to improve the performances of target detection in hyperspectral imagery.

In imagery as in signal processing, there are various noise sources and it is fundamental to take it into account. With the emergence of multichannel data, new methods of multimodal processing are necessary, because the use of 2D method for multimodal data involves individual image plane restoration without using the related information between image planes. An example is the restoration of color images by individual monochrome processing in which each color is treated separately.

Most of the multimodal restoration methods are based on the least squares estimation using a statistical modelling of the noise, which is a generalization of Wiener filtering to multimodal data. But this generalization is not immediate. In [1], Hunt and Kubler present a multichannel restoration scheme based on the assumption that the signal autocorrelation, describing the between-channel (or spectral) and the within-channel (or spatial) relationship, is separable. It is enables the formulation of a linear transformation to decorrelate the signal between image channels, generally performed by a principal component analysis (PCA) [2]. In other words, this transformation makes the channels orthogonal. It follows that the multichannel restoration of the transformed signal is equivalent to the application of the restoration of individual channel independently, without losing any between-channel information. This separability hypothesis allows to generate a family of filters named here "hybrid filters". Each hybrid filter is characterized by a channel decorrelating transformation, which can be for example the Fourier transformation or the principal component analysis, and by a classic method of 2D restoration such as stationary wavelet denoising [3], Lee's adaptive Wiener filter [4] or filtering in the Fourier domain (Figure 1). Atkinson and All use the separability hypothesis with the aim of restoring hyperspectral data in [5] with a hybrid filter composed of the fast Fourier transform and 2D-wavelet analysis, and in [6] with a hybrid filter composed of PCA and 2D-wavelet analysis.

However, the separability assumption is questionable because of the variability and merging of the areas and of the components of the scene. That is the reason why current researches try to form a filter without using the assumption of spectral and spatial separability. Solutions were proposed for color images but the significant number of bands in hyperspectral imagery poses a problem for their direct application. Thus there are few restoration algorithms which seem to be adapted to the special features of hyperspectral data, except hybrid filters.

Paradoxically, we can notice that the hyperspectral imagery field is at the present time really increasing. Many applications open up to it from military to agriculture, including the detection of atmospheric pollution. New acquisition systems are set up and of course, new research works are developed in which the most widespread used are classification, segmentation and detection. There are two types of detections. Detection, when the target signature is known, amounts to identify the presence of mineral or organic compound in a scene from the knowledge of its spectral answer. When the target spectral signature is unknown, detection amounts to identify the areas whose spectral answer is significantly distant from the environment one and is known as anomaly detection.

There are many detection algorithms in hyperspectral imagery [7]. The detection performance depends of course on the noise level. We propose to reduce the noise in the images before performing the detection. This point of view is not usually adopted in multicomponent detection methods, and this is the reason why we develop in this paper a new restoration filter suited to detection application in hyperspectral imagery and we compare the detection performance after a restoration by classic methods and by the proposed filter.

This paper is organized as follows. In section 2, we present the multichannel *Adaptive-3D-Wiener* filter, we have developed. In section 3, we compare the restoration results obtained with this filter to those of four other filters on an hyperspectral image. Then in section 4, we compare the results obtained for target detection and for anomaly detection on the hyperspectral images restored with different algorithms. Finally, we give a conclusion on these works with some perspectives.

2. ADAPTIVE-3D-WIENER FILTERING

We develop a multidimensional algorithm for the restoration of multichannel images in order to improve the performances of detection in hyperspectral imagery.

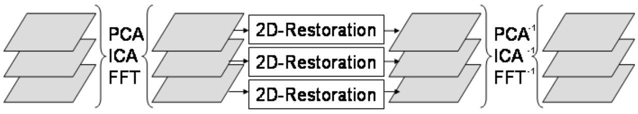


Figure 1: Hybrid filter scheme

Table 1: MSE of HSI data restored with the five filters realized for 100 noise observations.

Noise level	20	50	80
DWT	17.02	22.14	28.09
PCA-DWT	15.44	16.03	**22.32**
Lee'sWiener	21.72	23.40	29.88
PCA-Lee'sWiener	**8.88**	**14.93**	22.82
Adaptive-3D-Wiener	11.75	17.88	26.63

Let us consider tri-dimensional data with two homogeneous dimensions. The third will be named here channel. These data can be for example color images, multispectral images, hyperspectral images, multidate images or any set of images describing an image scene as a function of a given parameter.

As developed in introduction, the classic bi-dimensional restoration filters can be applied on each channel, but in these conditions, the intra-channel information can not be taken into account. To be able to use the intra-channel information, we need a tri-dimensional filter.

However, it is important to understand that it is really difficult to apply the Least Squares (Wiener) solution on the whole because the data covariance matrix is not block Toeplitz circulant matrix due to the multiband structure of the data [8]. That is the essential problem encountered by the current researches [1, 5, 6, 9, 8]. The development of a local filter enables us to by-pass this problem.

In hyperspectral imagery, targets have usually very small spatial feature: only a few tens of pixels at the most. So, a global noise reduction method might merge the statistical, spectral and spatial properties of the targets with those of their environment and as a consequence it might reduce the probability of a good detection. This remark has already been formulated by Chandran and All [10] in detection of mines in acoustic images. They were using a local restoration 2D-filter: the Lee's adaptive Wiener filter [4]. However, spectra contain the most crucial information and have to be preserved as a whole. That is the reason why we have chosen to develop a local-spatial and global-spectral algorithm based on the same hypotheses as the well-known Lee's adaptive Wiener filter.

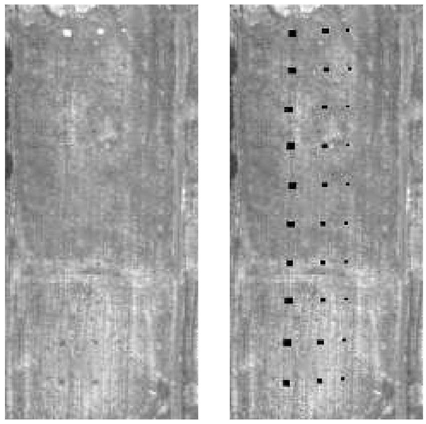
2.1 Hypothesis and image formation model

2.1.1 Noise

As it is usually done, we assume that the channel vector $\mathbf{v}(n_1, n_2)$ represents a zero-mean white Gaussian noise, uncorrelated with the original image. Its covariance matrix is $\Gamma_{vv} = \sigma_v^2 \mathbf{Id}_L$, where $\mathbf{Id}_L$ is the L-identity matrix. The degraded image $\mathbf{g}$ can be expressed as follows

$$\mathbf{g}(n_1, n_2) = \mathbf{f}(n_1, n_2) + \mathbf{v}(n_1, n_2), \tag{1}$$

where $\mathbf{f}(n_1, n_2)$ is one channel vector of the original image and $\mathbf{g}(n_1, n_2)$ the noisy channel vector observation at pixel (n_1, n_2).



(a) (b)

Figure 2: (a) A 30-panels HYDICE image scene. (b) Ground truth map of target in Figure 2(a).

2.1.2 Local region

Let us consider a small local region in which the signal pixel-vector $\mathbf{f}(n_1, n_2)$ is assumed homogeneous (locally stationary). Within the local region, the signal is modelled by

$$\mathbf{f}(n_1, n_2) = \mathbf{m}_f + \mathbf{w}(n_1, n_2), \tag{2}$$

where $\mathbf{m}_f$ is the local mean of $\mathbf{f}(n_1, n_2)$ and $\mathbf{w}(n_1, n_2)$ a zero mean white noise.

This hypothesis is a multichannel adaptation of the Lee's adaptive Wiener filter hypothesis [4].

2.2 Adaptive-3D-Wiener : theory

The linear minimum mean square error (LMMSE) solution of Equation (1) (Wiener restoration) is produced by

$$\hat{\mathbf{f}} = \mathbf{m}_f + \Gamma_{fg}\Gamma_{gg}^{-1}(\mathbf{g} - \mathbf{m}_g), \tag{3}$$

where Γ_{fg} and Γ_{gg} are the covariance of $\mathbf{f}$ and $\mathbf{g}$, and the variance-covariance matrix of $\mathbf{g}$, respectively. See [11] for details.

From the degraded image, we can only estimate $\Gamma_{gg}(n_1, n_2)$, but as the signal and the noise are uncorrelated

$$\begin{gathered} \Gamma_{gg} = \Gamma_{ff} + \Gamma_{vv}, \\ \Gamma_{fg} = \Gamma_{ff}, \end{gathered} \tag{4}$$

where Γ_{ff} and Γ_{vv} are the channel variance-covariance matrices of the multichannel image and noise, respectively. As the noise is a zero mean

$$\mathbf{m}_f = \mathbf{m}_g, \tag{5}$$

so the equation (3) changes to

$$\hat{\mathbf{f}} = \mathbf{m}_g + \mathbf{H}(\mathbf{g} - \mathbf{m}_g), \tag{6}$$

with the filter

$$\mathbf{H} = (\Gamma_{gg} - \Gamma_{vv})\Gamma_{gg}^{-1}. \tag{7}$$

Due to the local region model hypothesis (Eq. 2), the Γ_{gg} estimate is easy. Γ_{gg} and $\mathbf{m}_g$ are updated at each pixel.

2.3 Adaptive-3D-Wiener : Computation issues

The local hypothesis we have done enables us to apply the least squares (Wiener) method. We will see in the following what is to be done to obtain a reliable estimation in these conditions.

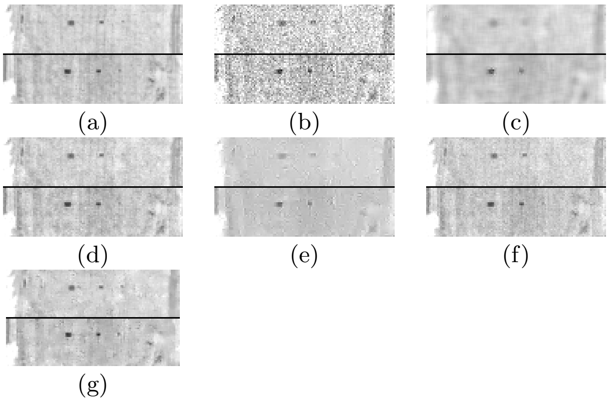


Figure 3: Channel number 121 for targets 6 and 10: (a) Original, (b) Noisy(MSE = 50). Restoration with: (c) $Lee'sWiener$, (d) PCA-$Lee'sWiener$, (e) DWT, (f) PCA-SWT, and (g) $Adaptive$-$3D$-$Wiener$.

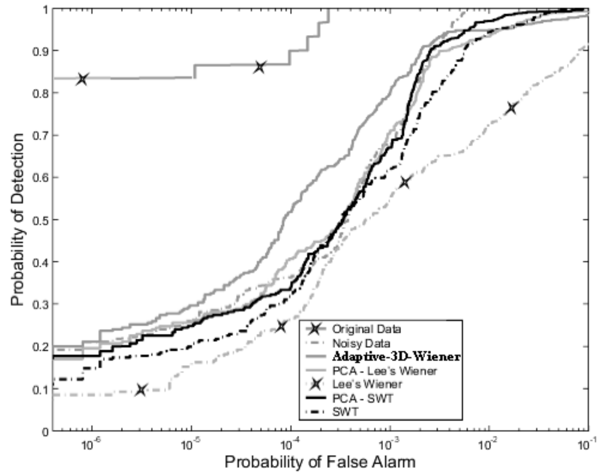


Figure 4: ROC curves for target detection (AMF) on restored data.

2.3.1 Window Size

Given our objective in fine, in the following tests we have considered windows with a size of 5×5 so that the size of the targets in the hyperspectral images is in accord with the size of the window. Moreover, it corresponds to the standard size used in the Lee's adaptive Wiener filter for greyscale images restoration.

We have also compared the following results with those obtained with windows with a size of 7×7, and no notable difference has been noticed.

2.3.2 Covariance matrix estimate

As we have said in the section 2.2, the variance-covariance matrix estimate Γ_{gg} is locally done, on small windows and thus on a small data sample.

When we process hyperspectral images, the number of channels (spectra) is important and the number of realizations does not change. So we come up against Hughes phenomenon, characteristic of parameters estimate in high dimensional spaces [12]. Γ_{gg} estimate will not be much reliable.

In addition, the covariance matrix inversion requires its diagonalisation and so the estimate of its eigenvectors. Each eigenvalue λ_i is characteristic of the energy of signals contained in the vector subspace formed by the associated eigenvector. So the eigenvectors with the largest eigenvalues are associated to the signal subspace and the other ones to the noise subspace. As the noise is white, its power is the same in each subspace. So the signal to noise ratio is in inverse proportion to the eigenvalue. Consequently, the reliability of the eigenvectors estimate is in inverse proportion to the associated eigenvalue.

In these conditions, if we consider these two aspects, we understand easily that it is necessary to limit the signal subspace dimension to obtain a correct estimate.

Thus we put forward the hypothesis that the signal subspace dimension is small, hypothesis which is justified insofar as we consider that the signal is made of some targets that we try to detect, and corresponds to the envisaged application in fine.

2.3.3 Algorithm complexity

As the covariance matrices are high dimension, and as we make a lot of diagonalisations, the treatment of an image becomes long. To limit this calculation time, we have used the inverse power method [13] in order to calculate the couples eigenvectors / eigenvalues. As we have seen in the section 2.3.2, we only calculate a few couples eigenvectors / eigenvalues. So this method will enable to accelerate the process and to reach a calculation time close to the images capture time.

3. RESTORATION EXPERIMENTS AND RESULTS

In order to assess our results objectively, we have chosen two restoration filters widely used in unimodal imagery. The first one is the well-known Lee's adaptive Wiener filter [4]. It filters an intensity image that has been degraded by white and additive noise. It uses a pixel-wise adaptive Wiener method based on statistics estimated from a local neighborhood of each pixel. This comparison filter was chosen because the $Adaptive$-$3D$-$Wiener$ filter is in a way the multidimensional version of the $Lee'sWiener$ filter (see section 2.1.2).

The second comparison filter is a soft threshold of Stationary Wavelet transform [3] (named SWT here). This filtering has been chosen for the well-known quality of its results.

If we combine these two unimodal restoration filters with a principal component analysis, as seen in Figure 1, we obtain two other hybrid filters of multimodal restoration (named PCA-$Lee'sWiener$ and PCA-SWT respectively). Thus we obtain 4 comparison restoration filters.

The performances of methods are visually assessed and with the Mean Square Error (MSE) defined for a given denoised image estimate $\hat{X}(i,j,k)$ of $X(i,j,k)$ by

$$MSE = \frac{1}{M*N*L}\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{k=1}^{L}[X(i,j,k)-\hat{X}(i,j,k)]^2, \quad (8)$$

where M and N are the size of the image, and L the number of components.

In hyperspectral images, the 3-dimension is the spectral dimension, and one 3-dimension value represents a spectral band. A high spatial resolution hyperspectral digital imagery collection experiment (HYDICE) scene considered in most of research test was used for experiments. The HYDICE image shown in Figure 2(a) has a size of 243×113 with 10 nm spectral resolution and 1.5 m spatial resolution. The low signal / high noise bands (bands 1-3 and bands 202-210) and water vapor absorption bands (bands 101-112 and bands 137-153) have been removed. It results in a total of 169 bands. There are 30 target panels located on the field,

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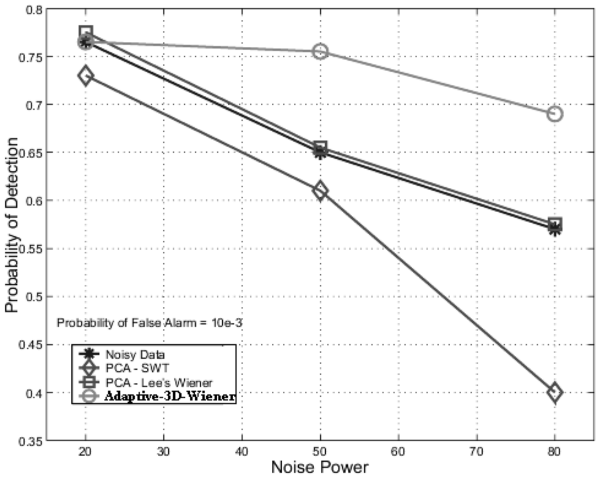

Figure 5: Anomaly detection (RX filter): Probability of detection with respect to the noise power, with a probability of false alarm = 10^{-3}.

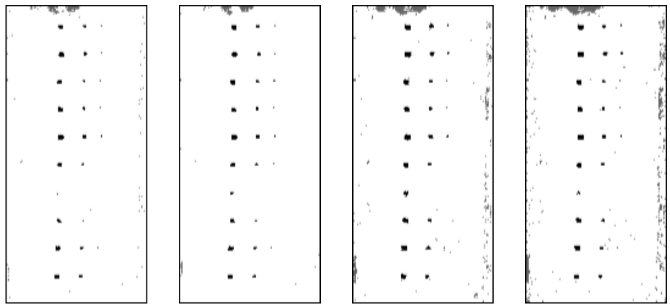

Figure 6: Anomaly detection map with a detection probability of 0.83 : (a) on the noisy HYDICE image with MSE = 50, (b) after restoration with the $Adaptive$-$3D$-$Wiener$, (c) with PCA-$Lee'sWiener$, (d) with PCA-SWT.

and they are arranged in a 10×3 matrix. Figure 2(b) shows the ground truth map of 2(a) and provides the precise spatial locations of these 30 panels. The sizes of the panels in the first, second and third columns are $3m \times 3m$, $2m \times 2m$, and $1m \times 1m$, respectively.

We add noise to the HSI image, according to the Equation (1) and we restore it with the five filters. Some visual results are presented in Figure 3. We show the restoration results of one channel for the targets number 6 and 10. We notice on 3-(a), that the two targets can be seen in the three resolutions. It means that this channel contains some informations for these two targets. The targets with the lowest resolution (column 3) are not visible anymore in the noisy image 3-(b), as well as in the restored images 3-(c)(d)(e)(f), but they appear after a restoration by the $Adaptive$-$3D$-$Wiener3D$ filter. So that latter has enabled to keep better the statistical, spectral and spatial properties of the small targets.

Now if we look at the mean of MSE values for 100 noise realizations presented in Table 1, we notice that hybrid filters are again more efficient than the unimodal ones. On the contrary, the MSE does not seem to be revealing concerning the conservation of small targets because the MSE of the filtering by $Adaptive$-$3D$-$Wiener$ does not give the best results. It can be explained by the fact that the MSE is a global criterion and so a good restoration of small target only has a small influence on it.

In hyperspectral imagery, the restoration is often the first step of an application. The visual interpretation of an hyperspectral image is not relevant because of the high number of channels. That is the reason why we have chosen to assess the filters within the framework of a target detection application rather than on a MSE criterion or on a visual result.

4. IMPROVEMENT OF DETECTION RESULTS IN HYPERSPECTRAL IMAGERY

With the aim of assessing the restoration performances of the five precedent filters, we assess the detection results associated to the different restored images. We perform these tests for two types of detection: target detection and anomaly detection. The Adaptive Matched Filter (AMF) [7] is the most popular Constant False Alarm Rate (CFAR) of the hyperspectral imaging target detection algorithms, and, the RX algorithm [7] is the reference in anomaly detection.

We assess the results from the probabilities of good detection and false alarms. With the aim of giving the same importance to the small, medium and large targets in the results, one target is detected if one of the pixels which composed it is greater than the threshold.

4.1 Target Detection : Adaptive Matched Filter (AMF)

In target detection, there are some difficulties: firstly to extract each target from the composite background noise, but secondly and above all to discriminate the targets between them. Actually the ten spectral signatures of the represented targets are quite close. That is the reason why these first results essentially highlight the impact of the restoration on the discrimination of the different targets.

The Receiver Operating Characteristic (ROC) Curves are presented Figure 4. We work out an average on the ten targets and on ten noise realizations with a standard deviation of 50. The zone of interest corresponds to probabilities of false alarm going from 10^{-5} to 5.10^{-2}.

It can be noticed that the four restoration filters of comparison do not improve, and even sometimes degrade the detection performances. The visual restoration results Figure 3 (b)(c)(d)(e) has enabled us to expect these results. On the contrary, the data restored with the $Adaptive$-$3D$-$Wiener$ filter give better detection results than the others. It is in keeping with the quality of the restoration noticed Figure 3 (f). In particular, with a probability of false alarm fixed at 10^{-3}, we have a probability of detection of 0.7 on the non restored data or those restored with one of the hybrid filters, whereas, the probability of detection is higher than 0.8 on the data restored with the $Adaptive$-$3D$-$Wiener$ filter. That is a gain of about 15%.

The improvement of the performances can be explained particularly by a better discrimination of the targets, given that they have very close spectral signatures. The proposed filter is at the same time local spatially, multichannel and non separable (spectral/spatial), and it enables to restore spectrally and spatially each area in an adapted way. It explains the results.

4.2 Anomaly Detection : RX-algorithm

In the section 4.1 to obtain good detection results, it was necessary to have a good restoration of the different targets and the restoration of the background was minor. In this part, it is totally different. In anomaly detection, there are no problem of discrimination, all targets have to be detected on the same detection map.

In the Figure 5, we show the probability of detection with respect to the noise power, with a probability of false alarm equal to 10^{-3}. These results show that the restoration with the *Adaptive*-3*D*-*Wiener* filter enables to improve the detection performances whatever the noise power may be, and that the average gain is about 10%. The other restorations do not improve and even sometimes degrade these performances.

Anomaly detection maps are presented Figure 6 with a probability of detection equal to 0.83 (25 targets out of 30). We notice, that the *Adaptive*-3*D*-*Wiener* filter enables to denoise without degrading the characteristics of the targets. The separable restoration filters give worse detection results than non restored data for high detection probabilities. Given that the RX algorithm estimates the Mahalanobis distance of the test pixel from the mean of the background, so it highlight the fact that the separable filters merge the characteristics of the background with those of the targets, when the *Adaptive*-3*D*-*Wiener* filter does in a certain extent independent restorations. It can specially be noticed with high detection probabilities because they are reached when we detect the small targets, which are those who might be merged in the background.

5. CONCLUSION

In this paper, we have done a state of the art of the existing multichannel restoration methods which can be applied to hyperspectral data.We have noticed that the most efficient methods are the hybrid ones; they are composed of a channel decorrelating transformation and of a 2D-image restoration classic filter. These methods are based on the hypothesis that the spectral and spatial restorations can be done separately.

Then we have developed a new image restoration multichannel filter: the *Adaptive*-3*D*-*Wiener* filter. This local-spatial and global-spectral filter makes a non separable spectral / spatial restoration.

Afterwards, we have compared these different restoration filters and we have noticed that hybrid filters give better visual results than those of the proposed filter, in particular the *PCA*-*SWT* filter. However, the results on the HSI image have shown that the proposed filter enables to keep some details finer than with the other comparison filters. The hybrid filters seems to be sufficient when the number of bands is small or when the details do not have a major interest (visualization, classification, segmentation, ...).

On the contrary, it is totally different in detection. We have noticed that the restoration with the *Adaptive*-3*D*-*Wiener* filter enables to improve the detection performances of the AMF filter in target detection, and those of the RX filter in anomaly detection, although the targets are small. The separable filters merge the characteristics of the background with those of the targets, when the proposed filter does, in a certain extent, independent restorations between targets and the background.

The proposed method should be tested on many other data in order to assess its performances on a variety of situations. Furthermore, we noted that the Lee's adaptive Wiener filter was subject of many extensions [14, 15, 16, 17]. This is why, with an aim of looking further into this study, we view to introduce a Markovian model to locally characterize the signal.

REFERENCES

[1] B. R. Hunt and O. Kbler, "Karhunen-love multispectral image restoration. part 1: Theory," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 32, pp. 592–599, June 1984.

[2] X. Jian and J. A. Richards, "Segmented principal components transformation for efficient hyperspectral remote-sensing image display and classification," *IEEE Trans. Geosci. Remote Sensing*, vol. 37, pp. 538–542, Jan. 1999.

[3] G.P. Nason and B.W. Silverman," *The stationary wavelet transform and some statistical applications*, Lecture Notes in Statistics, Ed. 1995.

[4] J. S. Lee, "Digital image enhancement and noise filtering by use of local statistics," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 2, pp. 165–168, March 1980.

[5] I. Atkinson, F. Kamalabadi, and D.L. Jones, "Wavelet-based hyperspectral image estimation," in *IGARSS '03*, 21-25 July 2003, vol. 2, pp. 743–745.

[6] I. Atkinson, F. Kamalabadi, Satish Mohan, and D.L. Jones, "Wavelet-based 2-d multichannel signal estimation," in *ICIP 2003*, 14-17 Sept. 2003, vol. 3, pp. II 141–144.

[7] D. Manolakis, "Hyperspectral signal modelisation and implications to material detection algorithms," in *IEEE Int. Conf. Acoust., Speech, Signal Processing*, 17-21 May. 2004, vol. 3, pp. III 117–20.

[8] N.P. Galatsanos, K. Katsaggelos, R. T. Chin, and A. D. Hillery, "Least squares restoration of multichannel images," *IEEE Trans. Signal Processing*, vol. 39, no. 10, pp. 2222–2236, oct. 1991.

[9] N. P. Galatsanos and R. T. Chin, "Digital restoration of multichannel images," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 37, no. 3, pp. 415–421, March 1989.

[10] V. Chandran, S. Elgar, and A. Nguyen, "Detection of mines in acoustic images using higher order spectral features," *IEEE J. Oceanic Eng.*, vol. 27, no. 3, pp. 610–18, July 2002.

[11] W. K. Pratt," *Digital Image Processing*, New York: Willey, Ed. 1978.

[12] G. Hughes, "On the mean accuracy of statistical pattern recognizers," *IEEE Trans. Inform. Theory*, vol. 14, no. 1, pp. 55–63, 1968.

[13] W. Helton, "A numerical method for computing the structured singular value," *Systeme and Control Letters*, pp. 21–26, 1988.

[14] R. Adriaanse and M.E. Jernigan, "Recursive adaptive wiener filtering," in *Canadian Conference on Electrical and Computer Engineering*, 25-28 May 1997, vol. 2, pp. 496 – 499.

[15] G. Angelopoulos and I. Pitas, "Multichannel wiener filters in color image restoration based on ar color image modelling," in *IEEE Int. Conf. Acoust., Speech, Signal Processing*, 14-17 April 1991, vol. 4, pp. 2517 – 2520.

[16] F. Jin, P. Fieguth, L. Winger, and E. Jernigan, "Adaptive wiener filtering of noisy images and image sequences," in *IEEE Int. Conf. Image Processing*, 14-17 Sept. 2003, vol. 3, pp. III – 349–52.

[17] F.C. jeng and J.W. Woods, "Inhomogeneous gaussian image models for estimation and restoration," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 36, no. 8, pp. 1305–12, 1988.