Spectral denoising in hyperspectral imaging using the discrete wavelet transform

Abstract

The use of hyperspectral sensors has gained relevance in agriculture due to its potential in the phytosanitary management of crops. However, these sensors are sensitive to spectral noise, which makes their real application difficult. Therefore, this work focused on the analysis of the spectral noise present in a bank of 180 hyperspectral images of mango leaves acquired in the laboratory, and the implementation of a denoising technique based on the discrete wavelet transform. The noise analysis consisted in the identification of the highest noisy bands, while the performance of the technique was based on the PSNR and SNR metrics. As a result, it was determined that the spectral noise was present at the ends of the spectrum (417-421nm and 969-994nm) and that the Neigh-Shrink method achieved a SNR of the order of 1011 with respect to the order of 102 of the original spectrum.

Keywords: HSI, spectral denoising, wavelet transform, hyperspectral analysis.

Resumen

El uso de sensores hiperespectrales ha tomado relevancia en la agricultura, debido a su potencial en el manejo fitosanitario de cultivos. Sin embargo, estos sensores son sensibles al registro de ruido espectral, lo cual dificulta su aplicación real. Por lo anterior, este trabajo se centró en el análisis del ruido espectral presente en un banco de 180 imágenes hiperespectrales de hojas de mango adquiridas en laboratorio, y la implementación de una técnica de reducción de ruido basada en la transformada discreta de wavelet. El análisis de ruido consistió en la identificación de las bandas de mayor ruido, mientras que el desempeño de la técnica fue medido con las métricas PSNR y SNR. Como resultado, se determinó que el ruido espectral estuvo presente en los extremos del espectro (417-421nm y 969-994nm), mientras que el método Neigh-Shrink alcanzó un SNR del orden de 1011 con respecto al orden de 102 del espectro original.

Palabras clave: HSI, reducción de ruido espectral, transformada wavelet, análisis hiperespectral.
1. **Introducción**

El uso de sistemas de óptica no invasiva y no destructiva en la inspección y control de cultivos ayuda a mejorar prácticas integrales de manejo agrícola y controles fitosanitarios, al proporcionar información que permite un diagnóstico correcto de problemas potenciales que podrían afectar la producción agrícola. Dentro de estos sistemas ópticos, los sensores hiperespectrales han permitido la detección de problemas fitosanitarios en fases tempranas y la eliminación del factor humano en su detección. Las imágenes hiperespectrales (HSI) proporcionadas por estos sensores se han utilizado en años recientes para el desarrollo: métodos de inspección no invasiva y no destructiva de frutas (dos Santos Netoa et al., 2017; Munera et al., 2017; Pinto et al., 2019); la establecimiento de índices de vegetación spectral para estimar daños internos en frutas recolectadas (Vélez-Rivera et al., 2014); y la detección temprana de enfermedades de cultivos (Zarco-Tejada et al., 2018; Navrozidis et al., 2018).

No obstante, como ocurre con cualquier sensor e instrumento de medida, los datos capturados son susceptibles de anormalidades que pueden alterar la información contenida dentro de ellos y, por consiguiente, desviarse los resultados obtenidos. Técnicas como MNF o PCA, han sido aplicadas en numerosos estudios, lo que hace suponer que estas técnicas son esenciales para los análisis hiperespectrales. Por ejemplo, Bjorgan & Randeberg (2015), desarrollaron una técnica MNF aplicada a imágenes hiperespectrales de un escáner de lineas para el procesamiento de señales durante la obtención de imágenes en tiempo real. Los autores de este trabajo aseguran que los resultados obtenidos con esta técnica son comparables con los obtenidos después de capturar toda la imagen. Además, Liao et al. (2013), proponen un modelo de dos fases que combina PCA (KPCA) y un modelo para eliminar la variación total de ruido que evidencia características notables y resultados prometedores en la eliminación de ruido.

En los últimos años, técnicas basadas en redes de aprendizaje profundo (Yuan et al., 2019), y factorización bilineal (Chen et al., 2020), se han aplicado a las imágenes hiperespectrales para la detección del ruido. Yuan et al. (2019), presentaron una técnica basada en una red neuronal convolucional profunda que combina espacio y espectro a través de una mapeo end-to-end de las imágenes limpias y las ruidosas. Los resultados reportados con esta técnica son notables cuando se comparan con los métodos tradicionales, aunque su validación se realizó en parte con datos simulados. Fan et al. (2019), propusieron un método basado en factorización de matriz bilineal que utiliza el estándar químicamente parcial para restricciones bajas para detectar características de rango bajo, que se supone contienen el ruido en la imagen. Basándose en el área cubierta por Fan et al. (2019), Chen et al. (2020) propusieron una técnica basada en factorización bilineal regularizada por variación total y condujeron experimentos numéricos con 5 diferentes tipos de escenarios de ruido y 1 con datos reales.

El estado de la arte reporta una variedad amplia de técnicas y enfoques para la detección y eliminación de ruido en las imágenes hiperespectrales. Sin embargo, al mejor de nuestro conocimiento, no se ha explorado suficientemente el uso de una aproximación puramente basada en la transformada wavelet discreta. Por esta razón y considerando la importancia de este problema en las imágenes hiperespectrales, este artículo presenta la comparación y la implementación de los algoritmos Neigh-Shrink, Hard Thresholding y Soft Thresholding, basados en la transformada wavelet discreta. Estos algoritmos fueron probados con un banco de 180 imágenes hiperespectrales de muestras de mango (hojas) sometidas a estudios fitopatológicos para la detección de las enfermedades del mango. Como resultado, se encontró que las técnicas presentadas presentan un buen rendimiento en términos de denoising. La técnica Neigh-Shrink obtuvo el mejor rendimiento.

El resto de este artículo tiene los siguientes apartados. Se detalla en el apartado 2, el uso de los materiales como entrada para el desarrollo de este trabajo y los métodos de denoising en las imágenes hiperespectrales. En el apartado 3, se presentan y discuten los resultados obtenidos en cada prueba en términos de los componentes espacial y spectral, ya que las imágenes son susceptibles de ruido en ambos componentes. Finalmente, el apartado 4 presenta las conclusiones principales.
2. Methods

2.1 Samples and image capture system

For the development of the study, mango leaves (Mangifera Indica L.) of the Tommy Atkins and Keitt varieties were used from a producing farm located in Anapoima, Colombia (4°35’21.4” N 74°31’07.6” W). From this crop, 45 mature leaves were pre-selected per variety from the middle third of trees with an average life of 4 years. From these groups of leaves, 15 of them were selected per variety, for a total of 30 leaves used in the study.

The vision system used for capturing hyperspectral images corresponds to a Hyspex VNIR-1600 pushbroom sensor (Hyspex by Neo, Norsk Elektro Optikk, Norway), with spectral resolution of 3.629383 nm, 1600 spatial pixels and range of 400-1000 nm, obtaining 160 spectral bands per scan. The images were taken in a controlled environment. The hyperspectral sensor was placed on the leaf at a distance of 30 cm, which was illuminated with a halogen light source VNIR of 150 W at 45° on the plane where the sample to be photographed is located.

Each leaf was placed on a black background, with a calibration panel and a label located at the top of the scene to identify the sample photographed. Figure 1 presents an RGB image extracted from the hyperspectral image showing the disposition of the sample.

![Figure 1. Hyperspectral image in RGB of a mango sample with identification label and calibration panel on top.](image)

Each group composed of 5 samples was photographed daily from 24 to 29 November 2019. Therefore, 6 hyperspectral images were obtained per sample for each variety of mango, resulting in a bank of 180 images to be processed (90 per variety). Finally, each image had a dimension of 1600x3800x160 (width, height, spectra) encoded in 2 bytes per pixel.

2.2 Denoising methods

The problem of additive denoising in images (standard, monochromatic, hyperspectral, among others), can be addressed with the assumption that an \( X \) image can be decomposed into:

\[
X = S + \Sigma \quad (1),
\]

Where \( S \) represents the matrix with the image signal and \( \Sigma \) represents the noise in the image. Both matrices kept the same dimension. In the case of a monochromatic image matrix, \( S \) and \( \Sigma \) would have dimensions \((I_1, I_2)\), while in the case of RGB images there would be matrices with dimensions \((I_1, I_2, 3)\). This behavior can be extrapolated to larger images (as in the case of hyperspectral images), where images would have dimensions \((I_1, I_2, I_3)\), being \( I_1 \) and \( I_2 \) the spatial dimensions and \( I_3 \) the spectral dimension.

However, within dimension \( I_3 \), which in this study corresponds to the spectral dimension and has a
value of 160, there are bands that usually contain a high signal-to-noise ratio (SNR) and others that, on the contrary, have a low SNR and are highly noisy, hence, they are discarded from the dataset to be analyzed. These highly noisy bands are known as junk bands (Heylen et al., 2011), and lead directly to the total loss of the information contained in them, which means a loss of the captured data. With this intrinsic noise problem, there is a risk that the proposed spectral study be biased since it does not have all the data initially captured. Therefore, a method that allows the detection and reduction of noise in images is a necessary step in hyperspectral analysis.

In this context, this paper implements a denoising technique based on the discrete wavelet transform, an approach commonly used in the analysis of signals and computer vision, but scarcely applied to hyperspectral analysis.

Identification of noisy bands

As the spatial and spectral resolution of hyperspectral images (HSI), decreases and the number of bands that such an image can contain increases, the correlation between adjacent bands increases too (Zelinski & Goyal, 2014). This correlation applies not only to the signal itself but also to the noise of the image, which can be highly correlated between adjacent bands (Farzam & Baheshti, 2011). In HSI, this spectral correlation is usually much stronger than the spatial correlation in standard images. The reason is that the same pixel represents the same object along different bands, while an adjacent pixel at the spatial level can represent another object that is not necessarily correlated to the analyzed pixel. For example, Figure 1 shows a leaf where an adjacent pixel in the spatial component can correspond to the background of the scene, while a pixel on the leaf is composed of the different spectral bands that comprise the hyperspectral image.

To measure the spectral correlation between two bands, at the numerical level, the linear correlation coefficient or Pearson’s coefficient was defined as:

\[ p(i,j) = \frac{\text{cov}(X(i,:),X(:,j))}{\text{var}(X(i,:))\text{var}(X(:,j))} \]  

(2)

Where \( i \) and \( j \) are two different bands of the hyperspectral image. To define the appropriate correlation level in a neighborhood surrounding a band \( i \), the number \( B \) of adjacent bands was defined, in which the Pearson coefficient contains the information provided by the \( B \) bands adjacent to band \( i \). If the correlation coefficient is less than a threshold \( t \), the band is said to have no correlation with the surrounding bands and will therefore be a highly noisy band (or junk band). For calculating Pearson coefficient, Karami et al. (2014), suggest that the \( t \)-value should be 0.9, while the value of \( B \) is set in 7.

Discrete wavelet transform in 2D

The discrete wavelet transform outputs are two sets of data: one set gives information about the low frequencies (L), while the second one about the high frequencies (H) of the signal. Generally, the vast majority of the information that describes the signal is immersed in the low frequency L data.

The algorithm of the 2D discrete wavelet transform separates the image into rows and columns. In the first step, the transform is applied to all rows (horizontal transform), thus obtaining 2 initial sets, L and H. Each of these sets is half its original size. Subsequently, the procedure is repeated in the columns of the two images resulting from the previous step. From these images, a set L and H is also obtained, that is, there will be 4 sets: LL, LH, HL, HH. Each of them will be a quarter of the size of the original image. This process is repeated until the desired resolution is obtained. The resulting matrix has the form shown in Figure 2.
Each level of transformation has bands of coefficients with high frequency components in the set H. These coefficients are usually filtered with different techniques, since they usually preserve a greater part of the noise components of the signal (Chen et al., 2005). In this study, three filtering methods of high frequency coefficients (Hard Thresholding, Soft Thresholding and Neigh-Shrink) were analyzed, with the aim to obtain the best reconstruction of the hyperspectral cube without the spectral and spatial noise captured in the collecting phase of hyperspectral images on mango samples.

*Method of filtering for high frequency coefficients*

There are several methodologies to perform the filtering of high frequency coefficients. However, three main methods are usually used as the basis for denoising: Hard Thresholding, Soft thresholding and Neigh-Shrink algorithm.

**Hard Thresholding filtering method.** The Hard Thresholding method has a working principle similar to that of the binary thresholding function: any value below a certain threshold will be taken as the zero value, while the others will be kept unchanged. Mathematically, the Hard Thresholding operator is defined as:

$$\delta(w) = \begin{cases} w & |w| \geq \lambda \\ 0 & |w| < \lambda \end{cases} \quad (3),$$

Where $\lambda$ is the chosen threshold value and $w$ is the value of the matrix of high frequency coefficients. The function of Hard Thresholding is illustrated in Figure 3(a).
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**Figure 3.** Gráfico de la función de filtrado.

**Soft Thresholding**

El método Soft Thresholding funciona de manera similar al Hard Thresholding con la diferencia de que valores mayores que el umbral se recalculan restando el valor del umbral. Por el contrario, valores menores al umbral son iguales a cero, tal como se propone por el método Hard Thresholding. Matemáticamente, el operador Soft Thresholding se define como:

\[ \delta(w) = \begin{cases} 
\text{sgn}(|w| - \lambda)w & |w| \geq \lambda \\
0 & |w| < \lambda 
\end{cases} \]

Donde \(\lambda\) es el valor del umbral seleccionado, \(\text{sgn}\) es la función de signo, y \(w\) es el valor de la matriz de coeficientes de alta frecuencia. La figura 3(b) muestra el comportamiento gráfico del método Soft Thresholding.

**Neigh-Shrink filtering method.**

El método Neigh-Shrink tiene por objetivo estimar un valor de coeficientes de alta frecuencia sin ruido, definido como:

\[ \theta^\wedge = w_{ij} \beta_{ij} \]

Donde \(\theta^\wedge\) es el valor estimado del coeficiente sin ruido, \(w_{ij}\) es el valor inicial del coeficiente y \(\beta_{ij}\) es un coeficiente de estimación definido como:

\[ \beta_{ij} = \left(1 - \frac{\lambda^2}{s_{ij}^2}\right)_{+} \]

Donde el signo + indica que el valor de \(\beta\) será tomado en cuenta solo si es positivo, y será igual a cero si es negativo. El término \(\lambda\) es el valor del umbral, \(s_{ij}^2\) es la suma de cuadrados de los valores contenidos en un recuadro definido alrededor del \(w_{ij}\) valor. Este recuadro debe ser de tamaño \(I \times I\), donde \(I\) es un número impar y el valor \(w_{ij}\) a utilizar debe ser colocado en su centro. Esta operación puede ser observada en la figura 4. Matemáticamente, \(S_{ij}^2\) se define como:

\[ S_{ij}^2 = \sum_{k,l \in B_{ij}} w_{kl}^2 \]

Donde el signo + indica que el valor de \(\beta\) será tomado en cuenta solo si es positivo, y será igual a cero si es negativo. El término \(\lambda\) es el valor del umbral, \(s_{ij}^2\) es la suma de cuadrados de los valores contenidos en un recuadro definido alrededor del \(w_{ij}\) valor. Este recuadro debe ser de tamaño \(I \times I\), donde \(I\) es un número impar y el valor \(w_{ij}\) a utilizar debe ser colocado en su centro. Esta operación puede ser observada en la figura 4. Matemáticamente, \(S_{ij}^2\) se define como:

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\[ S_{ij}^2 = \sum_{k,l \in B_{ij}} w_{kl}^2 \]
Selecting the threshold value. The common element of the three methods described above is the threshold value $\lambda$. The Universal Threshold has been defined as:

$$\lambda = \sqrt{2\sigma^2\log(N)} \quad \text{(8)},$$

Where $\sigma$ is the value of the noise in the signal and $N$ is the size of the signal. Finally, when there is no a priori notion of the value of $\sigma$, since there are no conditions of controlled experimentation, an estimated value $\hat{\sigma}$ can be defined as:

$$\sigma \hat{} = \frac{\text{median} (|w_x|)}{0.6745} \quad \text{(9)},$$

Where $w_x$ refers to the values belonging to the sub-band HH, HL or LH to be treated. By defining the thresholding value, it is possible to implement and analyze the denoising methods discussed in this work.

3. Results and discussion

Laboratory hyperspectral images, acquired under controlled conditions, present low noise levels in the captured scene (Figure 1). To magnify the presence of noisy bands and facilitate denoising through the wavelet transform, a gaussian noise addition stage was executed, with levels of $\sigma=10$, 20, 30, 40 and 50 and taking into account that the maximum grey scale of the image per spectral band is 255. With the above conditions, the aim is to adequately compare the performance of the techniques presented in section 2.2, and define the best denoising scheme for hyperspectral images.

Each of the methods was tested with different iterations of decomposition (1, 2, 3 and 4 iterations) using the discrete wavelet transform. The selection of these values corresponds to previous tests indicating that more than 4 iterations produced no significant improvement in the denoising of the image. Figure 2 illustrates the decomposition performed by the transform at each iteration.

As a criterion for measuring the quality of the filtering, Peak Signal-to-Noise Ratio (PSNR) was used for denoising in the spatial component. This metric is commonly used in this field since it represents the relationship between the maximum power of the image and the noise that affects it. Regarding the spectral denoising component, SNR was used as a metric, since no signals without noise (or with a low level of noise), are required to quantify it, in contrast to the spatial component.
Finally, the three denoising methods based on the discrete wavelet transform (Hard Thresholding, Soft Thresholding and Neigh-Shrink) were tested in the bank of 180 hyperspectral images. This means that each algorithm processed 28,800 monochromatic images resulting from the decomposition of each hyperspectral image into the 160 spectral bands.

### 3.1 Denoising in the spatial component

With Hard Thresholding, it was found that when the noise is low, with $\sigma = 10$, the best result is obtained with 1 iteration of the transform (Table 1). Although the result is numerically better than in the cases of 2, 3 and 4 iterations, the improvement with respect to the worst case (4 iterations) is barely 2.5% (Table 1).

| n  | PSNR (dB) 1 iteration | PSNR (dB) 2 iterations | PSNR (dB) 3 iterations | PSNR (dB) 4 iterations |
|----|----------------------|------------------------|------------------------|------------------------|
| 10 | 30.65                | 30.34                  | 30.02                  | 29.90                  |
| 20 | 26.40                | 27.18                  | 26.90                  | 26.74                  |
| 30 | 23.71                | 25.39                  | 25.33                  | 25.14                  |
| 40 | 21.57                | 24.06                  | 24.24                  | 24.01                  |
| 50 | 19.82                | 23.00                  | 23.44                  | 23.24                  |

When the noise level increases with $\sigma \geq 20$, a single iteration with the transform is no longer enough to obtain good results. This trend becomes apparent in Figure 5, where the PSNR values decay as the noise in the image increases. PSNR values are more pronounced when the method performs 1 iteration (blue line); while for 2, 3 and 4 iterations the results are relatively better and quite similar to each other, since they manage to maintain better levels of PSNR.

![Figure 5. PSNR levels with the Hard Thresholding method.](image_url)
In the case of the Soft Thresholding method, the results showed similarity to those from Hard Thresholding: 1 iteration yields better results only when the noise level is low, however, when the noise level increases, it is also necessary to increase the number of iterations in order to obtain good results (Table 2). In this case, similar trends are also obtained for 2, 3 and 4 iterations, although the difference between the lines that describe their results (Figure 6) do not converge in the same way as in Figure 5. As an advantage over Hard Thresholding, this behavior allows differentiating the appropriate number of iterations for the transform and the method for different noise levels.

Table 2. PSNR for different levels of decomposition and noise using Soft Thresholding.

| n  | PSNR (dB) 1 iteration | PSNR (dB) 2 iterations | PSNR (dB) 3 iterations | PSNR (dB) 4 iterations |
|----|------------------------|------------------------|------------------------|------------------------|
| 10 | 29.87                  | 28.52                  | 27.64                  | 27.29                  |
| 20 | 26.37                  | 26.21                  | 25.23                  | 24.71                  |
| 30 | 23.71                  | 24.84                  | 23.96                  | 23.33                  |
| 40 | 21.57                  | 23.81                  | 23.23                  | 22.49                  |
| 50 | 19.82                  | 22.92                  | 22.65                  | 21.89                  |

Finally, the trend observed in Figures 5 and 6 with the two previous filters changed with the Neigh-Shrink method. The data obtained for this technique are shown in Table 3 and Figure 7. With 1 iteration, the PSNR decreases rapidly as the noise level increases, which indicates low robustness against external noise. But with 2 and 3 iterations this method proved to have better performance with low noises (σ = 10) and a remarkable performance in the presence of noise levels σ ≥ 20, since the PSNR level does not decrease drastically as in the case of 1 iteration. Additionally, with this technique PSNR levels decline with 4 iterations, thus demonstrating that no more than 3 iterations are needed to obtain the best results, in terms of detection and reduction of noise in a hyperspectral image.
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Table 3. PSNR for different levels of decomposition and noise using Neigh-Shrink.

| n     | PSNR (dB) 1 iteration | PSNR (dB) 2 iterations | PSNR (dB) 3 iterations | PSNR (dB) 4 iterations |
|-------|-----------------------|------------------------|------------------------|------------------------|
| 10    | 31.96                 | 32.84                  | 32.43                  | 31.24                  |
| 20    | 26.88                 | 28.73                  | 28.94                  | 28.13                  |
| 30    | 23.82                 | 26.47                  | 26.98                  | 26.73                  |
| 40    | 21.60                 | 24.88                  | 25.79                  | 25.67                  |
| 50    | 19.83                 | 23.58                  | 24.82                  | 24.83                  |

Figure 7. PSNR levels with Neigh-Shrink using different iterations.

An overview of the results indicates that a greater the number of decompositions (such as those shown in Figure 3), produces better results and higher PSNR values. However, a more detailed analysis of the data contained in Tables 1, 2 and 3 indicates that the best results for each filter were obtained with 2 and 3 iterations. The only case that differs from this behavior is with the Neigh-Shrink filter for $\sigma=50$, however, the improvement of the PSNR obtained with 4 iterations represents only 0.3% compared with 3 iterations. Consequently, it is inferred that improvement in the noise filtering quality with the discrete wavelet transform is not directly proportional to the number of iterations. A very high number of iterations could even force the algorithm to perform unnecessary filtering and there would be a significant waste of information, which is relevant in the case of hyperspectral images as it is directly related to the reflectance level of the sensed objects.

Based on the above and on the performance comparison of the filters (Tables 1, 2 and 3), it was observed that the highest PSNR levels were obtained with the Neigh-Shrink method, followed by Hard Thresholding and Soft Thresholding. Moreover, considering that the presence of noise in hyperspectral images acquired under laboratory conditions is low but significant, the configuration of the Neigh-Shrink method with $\sigma=10$ showed promising results as it resembles the noise originally contained in this type of im-
ages. Finally, the Neigh-Shrink method should be configured to work with 3 iterations for noise treatment in hyperspectral images.

3.2 Denoising in the spectral component

To identify the presence of noise in a spectral signature, it is necessary to take into account the high correlation between adjacent wavelengths (bands). Figure 8 shows the correlation of the 160 bands of an acquired hyperspectral image. It is worth noting that the main diagonal, which is colored in yellow and ideally should be a line, is represented with greater thickness than that of a line, which allows assuming the correlation level that between adjacent bands is greater than 0.95. This value was used as the initial parameter for the identification of noisy bands in the hyperspectral images acquired for this study.

However, after the identification of noisy bands, it was found that this threshold was not able to detect bands that could contain noise. An explanation for this phenomenon, lies in the foregoing fact of the high correlation between bands that hinders the sensor from capturing the reflectance changes between one band and another, even though the sensor is designed to do so. Another possible explanation is the presence of spectral noise that induces distortion of two or more adjacent spectral bands in their real reflectance level. For this reason, it is necessary to find the appropriate level of correlation between bands, to detect which of them may be subjected to a noise that must be eliminated.

Due to the consequences that the presence of noise in the spectrum can cause, the level of correlation between neighboring bands was gradually increased to 0.99. It was found that until this value (0.99) it is possible to detect bands that were classified as noisy. In particular, the wavelengths found were: 417.56, 421.19, 969.22, 980.11, 983.74, 987.37, 991.00, 994.63, which are particularly located at the ends of the spectrum (Figure 9a). This finding is explained by the noise...
induced by the sensor when capturing the spectral data. According to Hyspex, the manufacturer of this sensor, the efficiency curve in the capture of spectral data is affected at the ends, that correspond to the moments of start and ending of capture of the sensor. Additionally, electrical factors, such as voltage fluctuations affecting both the sensor and the computer equipment or lighting source, can induce alterations (noise) in the recorded data.

Although the ends of any special signature are generally eliminated in spectrum analyses, each spectrum, each band and each datum, counts when exploratory scientific studies are performed, e.g. spectral characterization of diseases in plant material. Therefore, the correction of these alterations (noise) is achieved using the discrete wavelet transform, which allows considering the entire spectrum in each hyperspectral image. Figure 9 shows a comparison of an uncorrected spectral signature (Figure 9a) with respect to the corrections made by the 3 methods studied (Figures 9b, c, d). In the original signature, the ends present alterations (or noise), which correspond to the noisy bands found, whereas the signatures filtered by each of the methods manage to reduce the amplitude of these alterations, thus achieving a better quality in the spectral signatures obtained. Although there are some remaining peaks, they are small compared with those in the original image and may correspond to specific spectral characteristics of the leaf, so aggressive denoising could eliminate these alterations that can be valuable in hyperspectral studies. These findings validate the selection of the number of iterations of the applied transform.

![Figura 9.](image)

At the quantitative level, when the SNR of each band was calculated, the results obtained (Figure 10) were conclusive and validate the above findings. The SNR of the original bands reaches 74.04 at its highest point (Figure 10a) and is located in the middle zone of the spectrum (bands with less noise), while at the ends it decreases considerably, which is plausible since these areas showed greater presence of noise in the spectral signature. Besides, when the three denoising filters are applied, the SNR increases considerably in all cases (Figures 10b, c, d), thus reaching the scale of $10^{11}$. With these filtering methods, it is also observed that the intermediate bands have a lower SNR with respect to the ends. This is consistent with the fact that these areas of the spectrum will undergo more corrections by the filters since they have a higher level of noise, which causes them to have a higher SNR after filtering.
While the SNR value may seem high at the ends, it is necessary to consider that this value is inversely proportional to the estimated σ of noise in each band. In Figure 11, it is evidenced that the noise along the bands decreased considerably: it goes from noise at a scale of $10^{-2}$ in the original image, to a scale of $10^{-11}$ in the cases of filtering with Hard and Soft Thresholding, and $10^{-5}$ in the Neigh-Shrink method.

Finally, it is worth noting the effect of filtering directly on the shape of the graphs of σ through the bands (Figure 11). On the one hand, since the Hard and Soft Thresholding methods perform thresholding, this causes the presence of several peaks in their respective graphs, which affects their results. On the other hand, the Neigh-Shrink method does not perform thresholding directly, hence it achieves a much smoother filtering effect and allows denoising to be closer to the reality of the noise found in the captured hyperspectral images. In addition, Figure 11 shows that the bands of the ends are more altered by the filters when reducing noise, since they have a much lower estimated σ than the bands of the central area of the spectrum captured.
4. Conclusions

The three methods studied for the detection and reduction of noise based on the discrete wavelet transform (Hard Thresholding, Soft Thresholding and Neigh-Shrink), achieved a reduction of the noise present in the spectral axis when applied in the spatial dimension of each band of the hyperspectral image. It was found that the ideal configuration of iterations for this transform in hyperspectral images is between 2 and 3 iterations. Performing more iterations can induce over-tuning in the algorithm, in addition to adding unnecessary extra computational load.

The Neigh-Shrink method performs better than the Hard Thresholding and Soft Thresholding algorithms, as it is more consistent and robust in noise filtering compared with its counterparts. In the spectral axis, the Neigh-Shrink algorithm also has the advantage of the smoothing performed on the data, which makes it less aggressive in the filtering process.

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