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Comparison of different spatial filters for identification of the gray matter in brain imaging

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Autor de correspondencia:

Jiménez-Builes, J. A.
Doctor en ingeniería
Correo electrónico:
jajimen1@unal.edu.co

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Alejandro Uribe-Sánchez[1]
Jaime A. Restrepo-Carmona[2]
Jovani A. Jiménez-Builes[2]

1. Universidad de Antioquia, Colombia
2. Universidad Nacional de Colombia

Abstract

Objective: The study aims to compare different spatial filters for the identification of gray matter in brain images, with the goal of enhancing image contrast and improving interpretation in medical diagnostics. **Materials**: Ten spatial filters were selected, implemented, and evaluated using a graphical user interface (GUI) in Matlab. The filters ranged from grayscale conversions to more complex filters like Gaussian and sharpening filters. The effectiveness of each filter was measured through the correlation coefficient between pixel intensity curves generated by the filters and an ideal model curve. **Results**: The non-linear median spatial filter showed the highest correlation coefficient (0.8974), indicating that it closely approximates the ideal model curve for differentiating between white and gray matter. In contrast, the emboss filter displayed the lowest correlation coefficient (0.6972), suggesting it is not suitable for tissue identification. **Conclusions**: The median filter proved to be the most effective for identifying gray matter in brain images. The research suggests that combinations of different filters could further improve outcomes, and the developed GUI allows for thorough exploration of these combinations to optimize the filtering and analysis of medical images.

Keywords: Spatial Filters, Brain Imaging, Digital Image Processing, Graphical User Interface.

Comparación de diferentes filtros espaciales para la identificación de la materia gris en imágenes cerebrales

Resumen

Objetivo: comparar diferentes filtros espaciales para la identificación de la materia gris en imágenes cerebrales, con el fin de mejorar el contraste en las imágenes y facilitar su interpretación en diagnósticos médicos. **Materiales**: se seleccionaron diez filtros espaciales que fueron implementados y evaluados mediante una interfaz gráfica de usuario (GUI) en Matlab. Los filtros incluyen desde conversiones a escala de grises hasta filtros más complejos como el gaussiano y el de enfoque. La eficacia de cada filtro se midió a través del coeficiente de correlación entre las curvas de intensidad de píxeles generadas por los filtros y una curva modelo ideal. **Resultados**: el filtro espacial no lineal de mediana fue el que mostró el coeficiente de correlación más alto (0.8974), indicando que se aproxima mejor a la curva modelo ideal para la diferenciación entre materia blanca y gris. En contraste, el filtro de relieve (emboss) mostró el coeficiente más bajo (0.6972), lo que sugiere que no es adecuado para la identificación de tejidos. **Conclusiones**: el filtro de mediana demostró ser el más efectivo para la identificación de la materia gris en las imágenes cerebrales. La investigación sugiere que combinaciones de diferentes filtros pueden mejorar aún más los resultados, y que la GUI desarrollada permite explorar exhaustivamente estas combinaciones para optimizar la filtración y análisis de imágenes médicas.

Palabras clave: Filtros espaciales, imágenes cerebrales, procesamiento de imágenes digitales, interfaz gráfica de usuario.

1. Introduction

For the purpose of advancing the research community, medical imaging is a new research field in the field of image processing. A significant amount of information is provided by features computed from images and used in medical diagnosis (Hamid & Khan, 2020; Mall et al., 2023). Filters have traditionally been used to enhance contrast and sharpness of the images, and on rare occasions, they have also been employed to extract specific information from the images (Isufi et al., 2024). This method is employed in a variety

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of industries, including autonomous vehicle research, traffic management, monitoring of public and historically significant structures, and medical, among others (Quqa et al., 2023; Chauhan et al., 2023). The computer was formerly only employed as a means of storing data. Iterative exposures of a photographic film were produced using the stored data until the proper photographic density was attained. The time needed to repeat the study on the patient was therefore spared (Debevec et al., 2023).

The comparison of brain image filters is crucial in medical imaging because it directly impacts the accuracy and reliability of diagnostic processes. Brain imaging plays a vital role in identifying and understanding various neurological conditions, including tumors, stroke, and neurodegenerative diseases. However, the raw images obtained through imaging modalities like MRI or CT scans often contain noise and other artifacts that can obscure critical details (Goceri, 2023; Mirza et al., 2023).

Different spatial filters can enhance various aspects of the images, such as contrast between gray and white matter, edge detection, and noise reduction. By comparing these filters, researchers can determine which ones best highlight the anatomical features of interest, improving the visibility of pathological changes. This comparison also helps in optimizing the image processing pipeline, ensuring that the most relevant information is preserved and that diagnostic accuracy is maximized (Rasheed et al., 2023; Khudhair et al., 2023).

Moreover, understanding the strengths and limitations of each filter allows for the development of more advanced techniques, potentially leading to new methods that combine the benefits of multiple filters (Chen et al, 2023). This not only enhances the quality of the images but also supports more accurate interpretations by clinicians, ultimately leading to better patient outcomes. The use of a GUI, as explored in the study, further facilitates the application and evaluation of these filters, enabling tailored approaches to different diagnostic challenges in brain imaging (Jawad et al., 2024).

Since its humble beginnings, image processing software has developed to incorporate complex algorithms that perform the following four tasks: a) Highlight specific features of the original image; b) Manipulate the presentation of the image c) Identify and correct acquisition equipment distortions; and d) Perform other mathematical analyses in order to extract diagnostically useful information.

To create this work, a collection of spatial filters was first chosen, followed by the definition of a comparison criterion, the acquisition of data using this criterion, and analysis of the outcomes. The visual data is kept in numerical form, which enables its mathematical manipulation, making a number of procedures possible (Núñez, 2008).

The materials and methods are presented in the next section, which is how the chapter is organized. Third session describes the process. The results and discussion are then presented in section four, which closes with the conclusions and bibliographical references.

2. Materials and methods

The process of highlighting or downplaying spatial elements in an image in order to enhance visual interpretation or facilitate further processing is known as spatial filtering (Andersen & Dalal, 2022; Lavanya & Nagasundaram, 2023). It is one of the techniques included in image enhancement. Typical instances include using filters to improve image edge detail or to lessen or get rid of noise patterns. In image processing, spatial filtering is a “local” operation in that it alters each pixel’s value in accordance with the values of the pixels around it. It entails altering the intensity levels so that they resemble or deviate more from the equivalent, surrounding pixels (Lukin et al., 2019).

Different types of spatial filters are employed depending on the desired outcome and the aspects of the image that should be highlighted (Pannekoucke et al., 2014; Stanković & Mandic, 2023). Based on this, a filter that produces the best results when modifying the image and giving it the attributes required for further processing should be searched out and applied.

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In digital image processing, the choice of a spatial filter for data enhancement depends mostly on the state of the image, on what we want to look for in it (pattern recognition, distinction of features, among others) and on the details that we want to attenuate or highlight (Bao et al., 2022; Lepcha et al., 2023). When dealing with brain images, the goal is to reduce acquisition noise and boost the contrast between the tissues present to create a better image and make it easier for the viewer to understand.

3. Methodology

3.1. Selected filters

The selected filters correspond to the Matlab main filter tool summarized in Table 1. These were chosen mostly due to the fact that some of them match to spatial filters in Matlab, as well as the ease of implementation, the clarity of the findings, and the ease of analysis (Kaur & Devendran, 2023).

Table 1. Selected filter. Source: the authors

Number	Name of filter
1	Gray scale
2	Average filter
3	Median filter
4	Gaussian filter
5	Focus filter
6	Emboss filter
7	Global uniform equalization
8	Uniform Enhancement
9	Exponential Enhancement
10	Enhanced Rayleigh

Each of the selected filters corresponds to a single Matlab command or a group of related instructions. Table 2 lists the filter number and its associated command.

Table 2. *Commands for selected filters. Source: the authors.*

Number	Command
1	rgb2gray
2	imfilter(mascara de 3x3)
3	medfilt2
4	fspecial(‘gaussian’, 3, sigma);
5	imfilter(filter = [0 -1 0; -1 5 -1; 0 -1 0])
6	imfilter(filter = [-2 -1 0; -1 1 1; 0 1 2])
7	Equalize
8	adapthisteq(original,’distribution’,’uniform’)
9	adapthisteq(original, ‘distribution’, ‘exponential’)
10	adapthisteq(original,’distribution’,’rayleigh’)

Through the use of a graphical interface created to make using the filters easier, each of the aforementioned filters was applied to the images. For grayscale image processing, a total of 10 filters were chosen, and their application produced very clear results. They were selected based on their high application in the different branches of digital image processing, not all of them correspond to simple or spatial filters, some use functions previously defined by Matlab (Solomon & Breckon, 2011) or defined in this research.

3.2. Comparison criteria

The procedure used to determine the comparison criteria involved choosing a figure to serve as the model image for the process’ initial comparison stage (see Figure 1).

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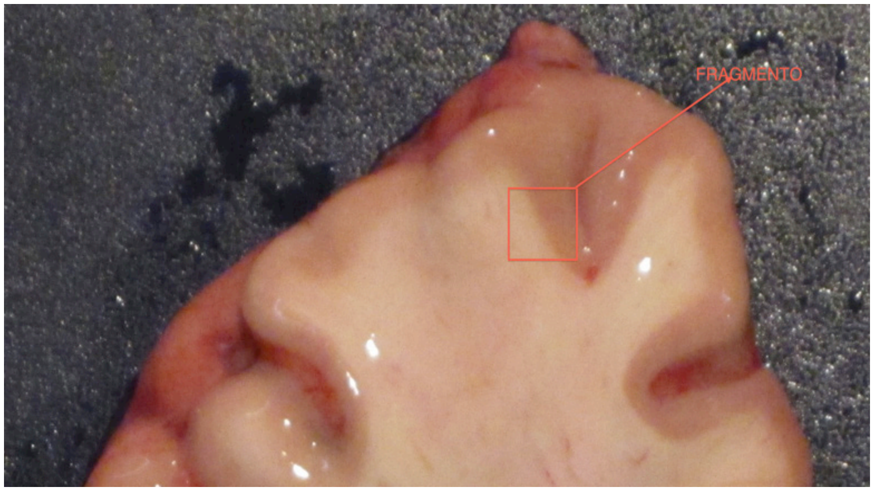
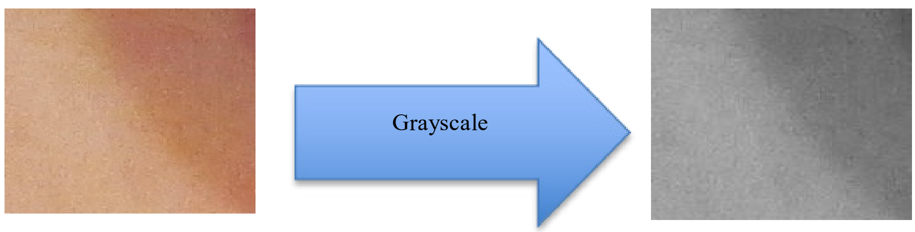
Figure 1. *Brain image (model). Source: Authors' own creation.*



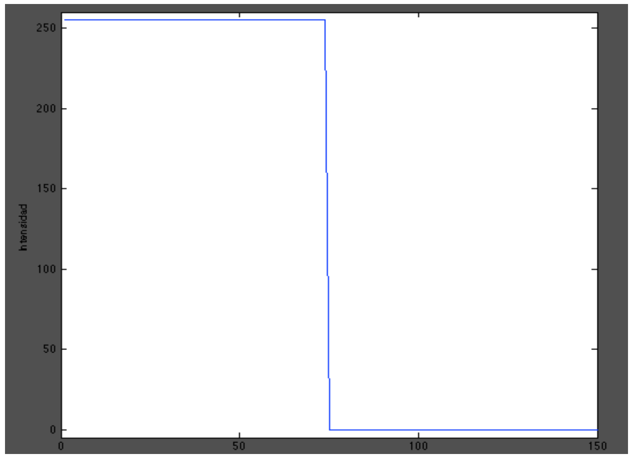
Then a fragment corresponding to a 150x150 pixel square image is extracted. To use all the many filters that are only compatible with this type of format, the image is first converted to grayscale.

Figure 2. *Fragment of grayscale image. Source: Authors' own creation.*



After converting the image to grayscale, we used a variety of filters to find the one that best distinguished between the white and gray substance. The curve produced by the test filter is compared to the model curve for an ideal filter given in Figure 1.

Figure 3. *Model curve. Source: Authors' own creation.*



The goal is to use the correlation coefficient to identify the filter that creates a curve that resembles this model curve (see Figure 3) the most. Each pixel's intensity level in one of the image's rows is represented by the curve the filter produces. The transition from white matter to gray matter is depicted by the model curve.

4. Results and discussions

The results obtained are presented for each of the filters used:

4.1. Filter number one

This filter simulates a grayscale version of the original image. To establish the connection between the original image's pixel count and intensity, the curve for this filter must be obtained. Based on the average of the intensity in each of the RGB planes, this filter converts an image with three components in the RGB planes into one that is in a single grayscale plane.

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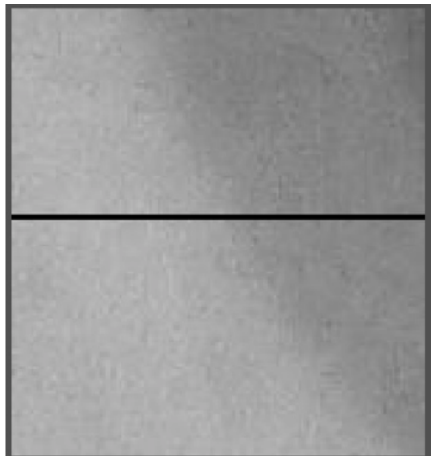
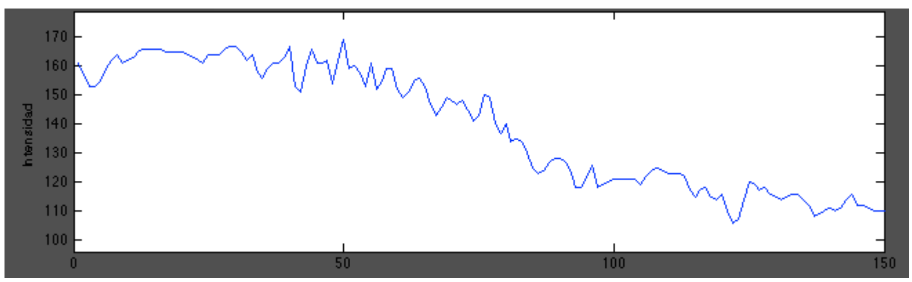
Figure 4. *Gray scale model image. Source: Authors' own creation.*



T In this case of the image, 150x150 corresponds to level 70, and the black line represents the level at which the pixel intensity was measured. The image's high noise level is shown by the intensity vs. pixel graph, which is displayed below.

Figure 5. *Intensity vs pixel for the first filter. Source: Authors' own creation.*

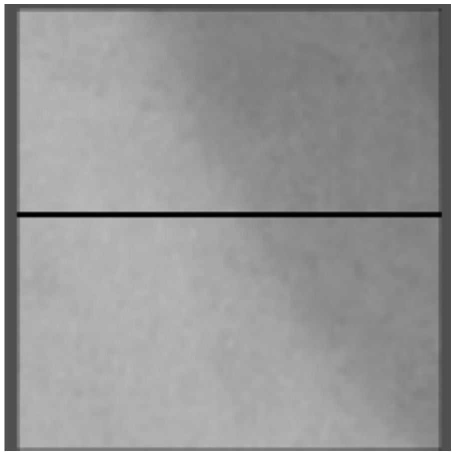


The above graph, which clearly deviates from the predicted curve, has a correlation coefficient of 0.8937.

4.2 Filter number two

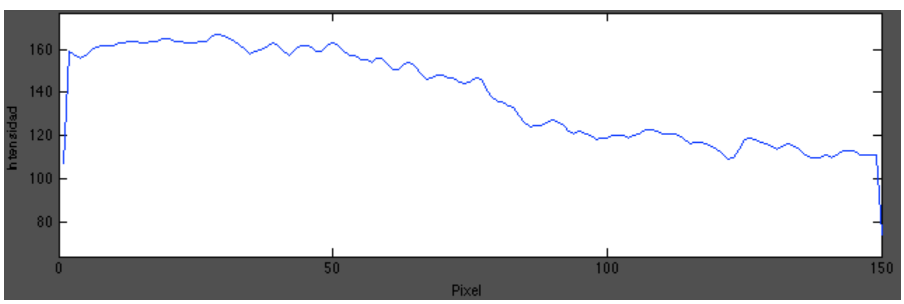
This filter is an implementation of Matlab's imfilter, an extremely flexible filter that allows users specify a Kernel or a mask to adjust the intensity value of each new pixel. A 3x3 unit mask was applied in this instance. This is equivalent to a mask that creates an average pixel, often lowering the noise in the image.

Figure 6. *Image filtered with imfilter. Source: Authors' own creation.*



This filter's intensity vs. pixel plot is remarkably similar to filter 1's, with the exception that this filter's peaks are smoother and the curve appears to be more smoothed.

Figure 7. *Intensity vs. pixel for the second filter. Source: Authors' own creation.*



Due to the fact that the average filter frequently causes information loss by attempting to bring everything to the same level of intensity, a correlation coefficient of 0.8660 for this curve was reported, which is further away from 1 than the prior coefficient.

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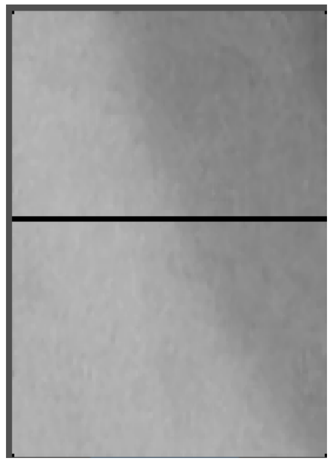
4.3 Filter number three

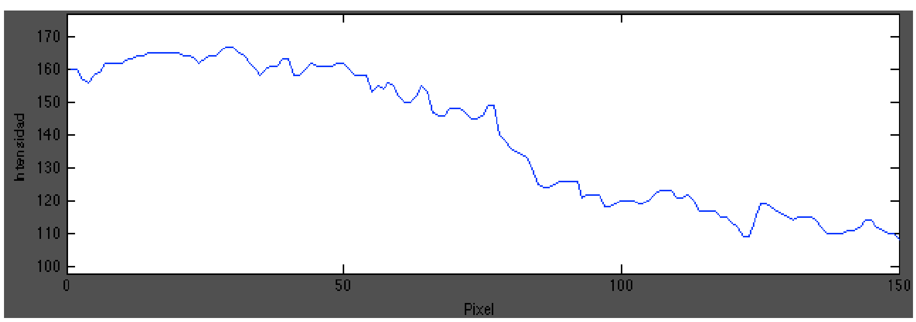
This median filter lessens "salt or pepper" noise via a nonlinear operation. When both edge preservation and noise reduction are desired, a median filter is superior to convolution. There are no obvious differences between the resulting image and the original one (Escalante, 2006).

Figura 8. *Image filtered with medfilt2. Source: Authors' own creation.*



Compared to the two previous curves, the curve produced by this filter is significantly more similar to the model curve. Its shape and the correlation coefficient, which is significantly more similar to 1 than the two preceding ones, both show this. The obtained correlation coefficient is equal to 0.8974.

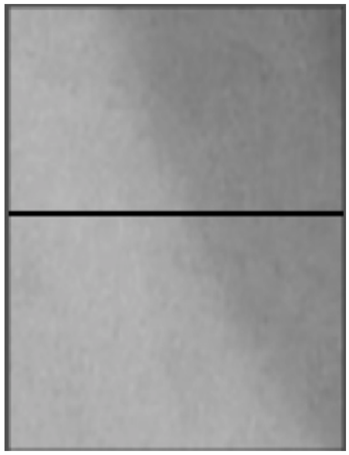
Figure 9. *Intensity vs. Pixel for the third filter. Source: Authors' own creation.*



4.4 Filter number four

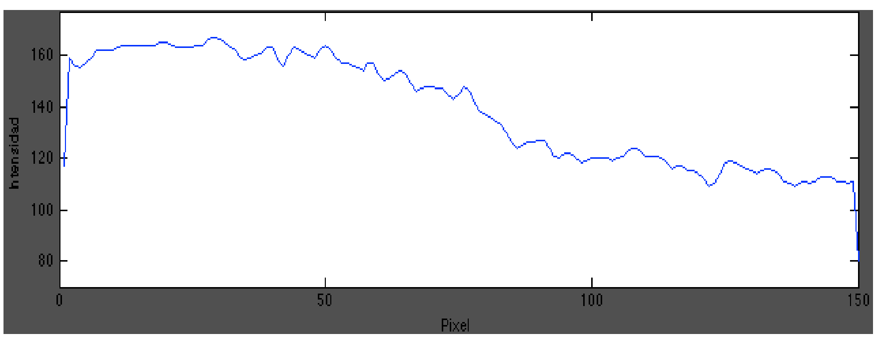
Two commands in Matlab are used to create this filter. The first command, fspecial, creates a mask or kernel with the specified parameters. In this instance, a 0.5 deviation Gaussian Kernel is used, and imfilter is then used to filter the image by using Kernel.

Figura 10. *Filtered with fspecial. Source: Authors' own creation.*



A Guassian filter is similar to an average filter, only this time the pixels are fitted to a Gaussian distribution, and the value of each pixel is subject to normalization to the selected statistical distribution. For the desired resemblance to the model curve, the filter is less effective. The pixel vs. intensity plot obtained is as follows:

Figure 11*. Intensity vs. pixel for the fourth filter. Source: Authors' own creation.*



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Correspondingly, the correlation coefficient is 0.8751. The filter begins to behave like an average filter when the standard deviation is greater than 10, and the correlation coefficient stabilizes at 0.8660.

4.5 Filter number five

Most digitized images need sharpness correction. This is because elements fainter than the sampling rate will be calculated in an average uniform color since the continuous color increase must be chopped into points with slightly varied colors during the digitization process. As a result, sharp edges appear slightly softened. When printing colorful dots on paper, the same phenomenon occurs. The focus filter emphasizes the borders, but any noise or smearing could produce noise in areas of gradual hue, like the sky or the surface of a body of water (Antl, 2020). This filter is responsible for focusing on highlight details. It consists of a spatial filter that uses a Kernel or a 3x3 mask with values that give high importance to the central pixel. The curve produced by this filter is a curve that does not present abrupt changes and tries to remain at a constant intensity level, the correlation coefficient obtained corresponds to 0.8751.

4.6 Filter number six

A predetermined mask or kernel is utilized in this filter to help emphasize any potential reliefs in the image. The correlation coefficient for the filter is 0.6972.

4.7 Filter number seven

In order to smooth the histogram of the value channel as much as possible, “equalize” automatically changes the brightness of the colors in the active layer so that each conceivable brightness value appears in the same number of pixels as for the other values. The results of this command could differ somewhat (Gonzalez & Woods, 2018). By boosting contrast in an image and accentuating elements that were previously difficult to see, “Equalize” can occasionally work quite effectively. Sometimes, the results are disastrous. It is a very powerful operation and can be tried to attempt to enhance the image. It works on both RGB and grayscale image layers. The obtained correlation coefficient is 0.8865.

4.8 Filter number eight

The default algorithm used by this filter, which transforms the values using the default Matlab algorithm, improves the contrast of the image (CLAHE). The distribution function's parameters, which in this instance are specified to use a uniform distribution, determine how it will operate. The calculated correlation coefficient is 0.7254.

4.9 Filter number nine

With an exponential distribution parameter, it is equivalent to the prior filter. The obtained correlation coefficient is equal to 0.7265.

4.10 Filter number ten

It corresponds to filter number eight but with a Rayleigh distribution function. The obtained coefficient is equal to 0.7214.

4.11 Considerations of the solutions reached

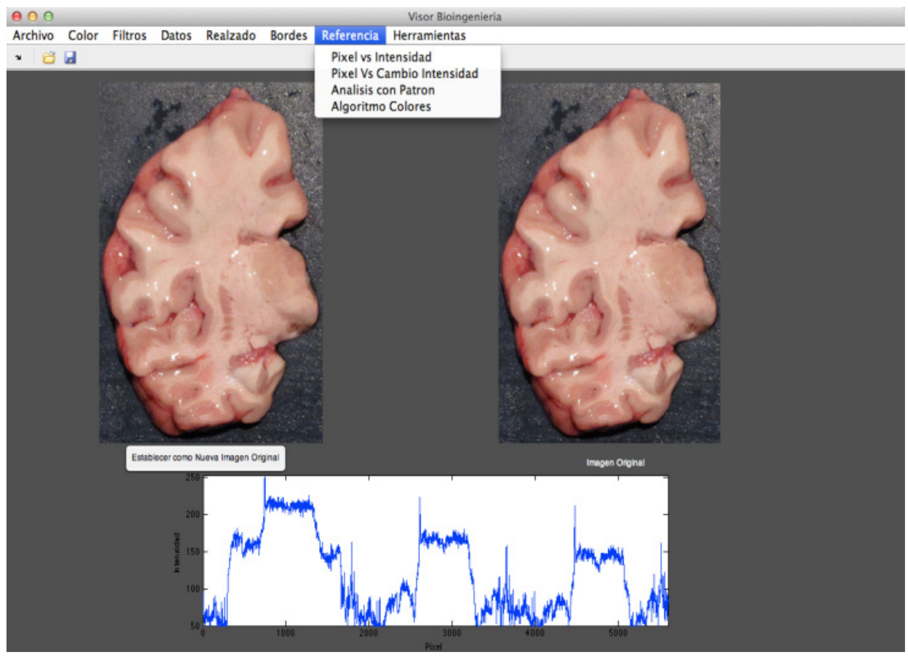
Table 3 provides a summary of the results, listing the name of the filter that was used, the details of how it was implemented, and the ratio coefficient for each result obtained.

Table 3. *Correlation coefficient for each of the filters. Source: the authors.*

Filter	Specifications	Correlation coefficient
Grayscale	Converts an image in the RGB plane to grayscale	0.8937
Median filter	A 3x3 unitary mask was used.	0.866
Median filter	The grayscale median filter was used.	0.8974
Gaussian filter	A 3x3 mask with sigma 1 was used.	0.8751
Focus filter	Kernel = [0 -1 0; -1 5 -1; 0 -1 0] was used.	0.7405
Emboss filter	Kernel = [-2 -1 0; -1 1 1; 0 1 2] was used.	0.6972
Global uniform equalization	An equalization algorithm was used.	0.8865
Uniform Enhancement	The uniformly distributed enhancement algorithm was used.	0.7254
Exponential Enhancement	The exponential distribution enhancement algorithm was used.	0.7265
Rayleigh Enhancement	The Rayleigh distribution enhancement algorithm was used.	0.7214

Figure 12 illustrates the capabilities that the created Graphical User Interface (GUI) provides for, ranging from the application of basic filters to an algorithm developed to determine the optimal colors to use when filtering these brain images.

Figure 12. *Graphical User Interface (GUI) developed. Source: Authors' own creation.*



Following is a list of some of the functions of the application (see Table 4):

Table 4. *Functions of the application. Source: the authors.*

Items	Functions
File	You can load or save an image using this option. You can also designate a filtered image as the image of interest.
Color	With this option, you can work with color images and examine each of their planes before switching to grayscale, getting an image's negative, thresholding it, or moving it to the HSI plane.
Filters	You can use any of the several spatial filters that employ a mask or kernel in this option.
Data	This option allows you to access the image's characteristic data, including the histogram, accumulated histogram, mean value, and standard deviation.
Enhancement	You can add enhancing filters to the chosen image using this option.
Borders	You can apply the image's primary border filters with this option.
Reference	This option allows you to get pixel vs. intensity curves, pixel vs. intensity change, and analyze data using the model of your choice.
Tools	This option allows you to select a particular region of the image to which various filters will be applied or where the analysis of interest will be carried out.

The chosen initial parameters determine which combinations of each of the RGB elements of the image are ideal for gray matter differentiation. The planned color algorithm primarily consists of three for nested cycles (see Figure 13).

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Figure 13. *Matlab source code of the designed color algorithm. Source: Authors' own creation.*

```
function AlgoritmoColor_Callback(hObject, eventdata, handles)
global original;
global modificada;

preguntas = {'Valor maximo', 'Valor minimo','Factor de Ruido',...
    'Pixel de Cambio','nivel de la curva'};
titulo = 'Curva Patron en para imagen cuadrada 150x150';
defecto = {'255', '0','0','66','70'};

respuesta = inputdlg(preguntas,titulo,1,defecto, 'on');
[a b] = size(respuesta);
if a==0
    return;
end
maxi = str2double(respuesta(1));
mini = str2double(respuesta(2));
factor = str2double(respuesta(3));
cambio = str2double(respuesta(4));
nivel = str2double(respuesta(5));

l_patron =[1:1:150];
                l_patron(1:cambio) = maxi;
                l_patron((cambio + 1):150) = mini;
if(factor>0)
   x=[1:1:150];
    l_patron = l_patron + factor*sin(x);

end
axes(handles.original);
plot(l_patron); xlabel('Pixel'); ylabel('Intensidad');
xlim([0 150]); ylim([-5 260]);
axis on; cont=0; max=0;
```

5. Conclusions

This study has demonstrated that the median nonlinear spatial filter, with a correlation coefficient of 0.8974, most closely approximates the ideal model curve for distinguishing between gray and white matter in brain imaging. The high correlation coefficients observed across the filters indicate that they are all effective to varying degrees, though the emboss filter, with the lowest correlation coefficient, is unsuitable for tissue differentiation due to its emphasis on image relief.

The grayscale conversion method, while providing a reasonable correlation coefficient, may not be optimal for scenarios involving multiple tissue types. Combining various filters in specific sequences can enhance results significantly, given that the study reveals 3,628,800 potential combinations from the ten filters evaluated. The custom-designed Graphical User Interface

(GUI) developed in this work facilitates the application of these combinations and the real-time assessment of their correlation coefficients (Govindhan et al., 2023).

As its mask seeks to give importance to the reliefs of the image, the embossing filter is not suited for distinguishing tissues and had the lowest correlation coefficient.

Although it is not advised, leaving the image in grayscale ensures a decent correlation coefficient because it would be challenging to establish results if you had many tissues. Better results can be obtained by combining various filters that are applied in different sequence. With these ten filters, there are a total of 3628800 potential filtering combinations that can be made.

Overall, this research underscores the effectiveness of image filtering techniques in medical diagnostics, particularly when applied through robust platforms like Matlab, as supported by recent studies. The insights gained here are valuable for further developments in medical image processing, particularly in the context of improving diagnostic tools for brain imaging.

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