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Performance Analysis of Laplacian of Gaussian and Chebyshev Filters in Medical Image Edge Detection

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ABSTRACT

Keywords
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In the medical field, image analysis is essential for diagnosis and patient care planning. This study compares two edge detection methods: the Laplacian of Gaussian (LoG) filter and the Chebyshev filter. The LoG filter combines Gaussian smoothing with the Laplacian operator for noise reduction and smooth edge detection, while the Chebyshev filter, known for sharp edges, allows for adjustable frequency response but is more sensitive to noise. Medical images were pre-processed to reduce artifacts and noise before applying each filter. The performance metrics, including PSNR, SSIM, and EPI, were used to evaluate the results. The Chebyshev filter achieved the highest PSNR of 20.2202 and SSIM of 0.48089 for Meningioma with a low-pass filter of order 2. The LoG filter's highest PSNR was 12.5731 and SSIM was 0.99876 for Meningioma at sigma 0.5. The highest EPI for the Chebyshev filter was 0.13067 for Pituitary with a low-pass filter of order 2, compared to the LoG filter's highest EPI of 0.39688 for Glioma at sigma 1.5. These results guide the selection of edge detection methods, enhancing diagnostic accuracy and patient care planning, and contribute to advanced medical image processing technologies.

1. Introduction

In the medical field, image analysis is essential for diagnosis and patient care planning, utilizing MRI, CT scans, and ultrasonography to provide detailed internal body visuals. To maximize the benefits of these images, image processing techniques that highlight important features like edges and boundaries of organs or tissues are necessary. Edge detection, which identifies sudden changes in color intensity, is fundamental for distinguishing different objects in an image and is particularly useful for identifying bones, blood vessels, and tumors in medical imaging. Therefore, choosing the appropriate edge detection method is crucial for accurate and effective medical diagnoses.

The Laplacian of Gaussian (LoG) filter and the Chebyshev filter are two commonly used methods for edge detection. The LoG filter works by combining image smoothing using a Gaussian filter with edge detection through the Laplacian operator. This smoothing process helps reduce noise before detecting edges, resulting in smoother edge detection that is less affected by noise. This filter is highly effective in the context of medical images, which often have a high level of noise. On the other hand, the Chebyshev filter, an IIR filter, is designed to have a specific frequency response that can be adjusted according to specific needs. This filter is known for its ability to produce very sharp edges, although it is more sensitive to noise. In medical imaging, the use of the Chebyshev filter can help identify small details that might not be visible with other filters, albeit with the risk of increased noise.

The Laplacian of Gaussian (LoG) filter is a widely used edge detection method in image processing and computer vision, known for its ability to combine smoothing and edge detection in a single operation. This technique involves applying a Gaussian filter to smooth the image and reduce noise, followed by the application of the Laplacian operator to detect edges [1][2][5]. The Gaussian filter works by averaging the pixel values over a defined area, which helps in reducing high-frequency

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noise [2][5]. Once the image is smoothed, the Laplacian operator, which is a second-order derivative filter, is applied to highlight regions of rapid intensity change, effectively detecting edges in the image [1-3]. This combination of smoothing and edge detection helps in revealing important spatial patterns while minimizing the impact of noise, making LoG particularly useful in medical image analysis where clarity and accuracy are crucial [1][3][5]. The effectiveness of the LoG filter has been demonstrated in various applications, including boundary detection in graphs for visual analysis of spatio-temporal data [1], keypoint detection in computer vision tasks [3], enhancing edge-preserving decompositions in multi-scale processing [4], and improving robustness in adaptive filtering scenarios [6][7]. These diverse applications underscore the versatility and robustness of the LoG filter in handling various image processing challenges.

The Chebyshev filter is utilized across various domains due to its ability to offer a specific frequency response with adjustable ripple characteristics, making it effective for applications requiring precise control over signal processing. In cardiac disease detection, the Chebyshev Type II filter is used to remove high-frequency noise from ECG signals, enhancing the accuracy of disease classification when combined with machine learning algorithms [8]. In the context of permanent-magnet synchronous motors (PMSM), the Chebyshev filter is employed to suppress harmonic distortions in the winding current, thus improving motor performance by reducing the fifth- and seventh-order current ripples [9]. The filter's design for reflectionless one-port configurations and harmonic suppression demonstrates its capability to produce zero reflection and manage frequency response efficiently [10]. Additionally, in graph filter design, the Chebyshev polynomial approximation helps achieve optimal filter coefficients, facilitating applications like graph signal denoising [11]. The Chebyshev filter's integration with fuzzy neural networks for power filter control further showcases its utility in managing harmonic distortions and system uncertainties [12]. Innovations in fractional-order Chebyshev filters, such as using the Sallen-Key topology and optimization algorithms, highlight the filter's adaptability to various circuit designs [13]. For dual-band waveguide filters, the second kind Chebyshev polynomials ensure high out-of-band rejection and symmetrical dual-band properties, demonstrating the filter's effectiveness in high-order applications [14]. Lastly, wideband bandpass filters incorporating Chebyshev equal-ripple responses exhibit broad bandwidth and extended stopband characteristics, validating the filter's versatility and robustness in complex signal environments [15].

This study aims to analyze the performance of the Laplacian of Gaussian and Chebyshev filters in edge detection on medical images. The results of this study are expected to provide better insights for researchers and practitioners in the field of medical image processing in choosing the edge detection method that best suits their needs. In the initial stage of the research, the medical images used will undergo pre-processing to reduce artifacts and noise. Then, each filter will be applied to detect edges in the images. The edge detection results will be analyzed using the previously mentioned evaluation metrics. This analysis will help identify the strengths and weaknesses of each filter under various medical image conditions. The results of this study are expected to provide practical guidance for medical professionals in selecting the most suitable edge detection method for their specific applications. With the right method selection, it is expected to improve diagnostic accuracy and the effectiveness of patient care planning. Additionally, this research is also expected to contribute to the development of more advanced and efficient medical image processing technology in the future.

2. The Proposed Method

The proposed method is a GUI-based application developed for edge detection in medical images using two primary methods: Laplacian of Gaussian (LoG) and Chebyshev filter. This program allows users to upload medical images, which are then displayed on the GUI. Users can choose to apply the LoG filter, which combines Gaussian smoothing and edge detection using the Laplacian operator, or the Chebyshev filter, which offers sharp edge detection through an IIR filter design with adjustable parameters. The system validates user input and displays the processed image results on the GUI, providing an effective tool for medical image analysis. The block diagram below illustrates the proposed system, encompassing the main steps from GUI initialization, image loading, applying the LoG and Chebyshev filters, to displaying the results.

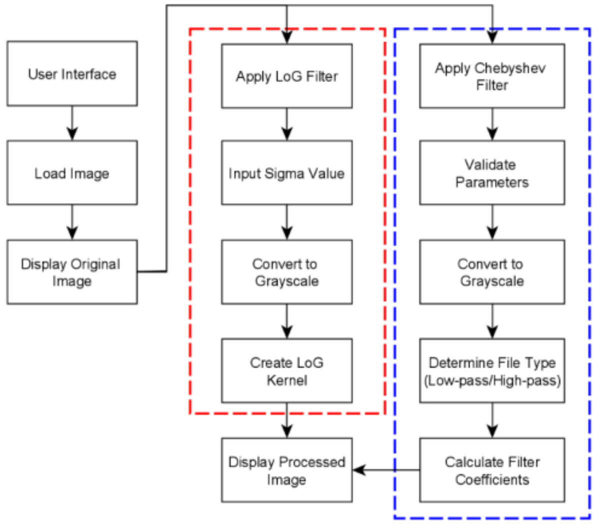

Fig. 1. Block Diagram

Fig. 2 illustrates the flowchart of applying the LoG filter. The process begins with the initialization of the GUI, followed by the user pressing the button to load an image. After opening the file dialog, the user selects the desired image. If an image is selected, the program reads and displays it on the GUI. The user can then choose to apply the Laplacian of Gaussian (LoG) filter by pressing the "Apply LoG" button. When the button is pressed, the sigma value is taken from the user's input and validated. If the sigma value is valid, the image is converted to grayscale if necessary, the LoG kernel is created, and the filter is applied to the image. The edge detection result is then displayed. This process is repeated or ended based on the user's next actions.

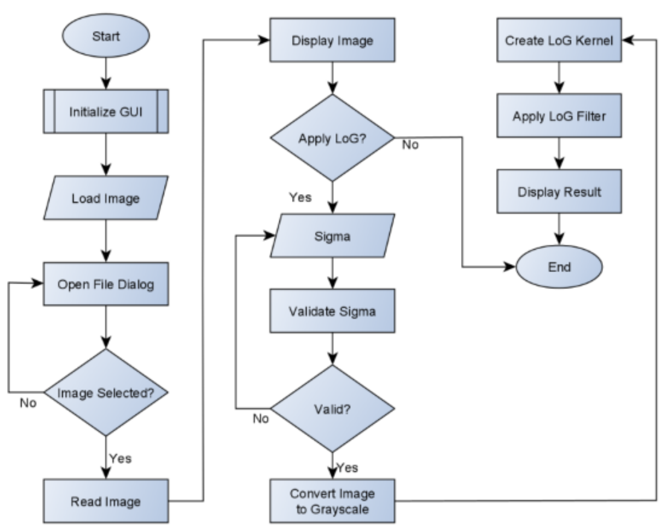

Fig. 2. Flowchart of LoG Filter

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Fig. 3 illustrates the flowchart of applying the Chebyshev filter. The process begins with the initialization of the GUI, followed by the user pressing the button to load an image. After opening the file dialog, the user selects the desired image. If an image is selected, the program reads and displays it on the GUI. The user can then choose to apply the Chebyshev filter by pressing the "Apply Chebyshev" button. When the button is pressed, filter parameters such as order and cutoff frequency are taken from the user's input and validated. If the parameters are valid, the image is converted to grayscale if necessary, the filter type (low-pass or high-pass) is determined, the Chebyshev filter coefficients are calculated, and the filter is applied to the image. The edge detection result is then displayed.

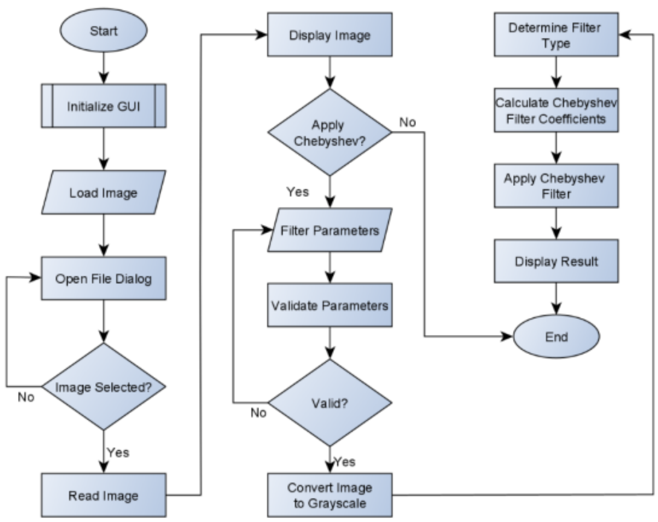

Fig. 3. Flowchart of Chebyshev Filter

3. Method

In this section, we detail the methods used for edge detection in medical images, specifically focusing on the Laplacian of Gaussian (LoG) filter and the Chebyshev filter. These filters are chosen for their distinct characteristics and efficacy in handling medical images, which often present unique challenges such as noise and the need for high precision in edge detection.

3.1. Laplacian of Gaussian (LoG) Filter

The Laplacian of Gaussian (LoG) filter is a technique that combines two fundamental operations in image processing: smoothing with a Gaussian filter and edge detection with the Laplacian operator. LoG is used to detect edges in images by reducing noise before performing the edge detection operation, resulting in smoother and more accurate edge detection. This method is particularly beneficial in medical imaging where precision and clarity are critical for diagnosis and treatment planning.

Sigma (σ) in the Gaussian Filter

Sigma (σ) in the Gaussian filter is a parameter that determines the width or spread of the Gaussian distribution. The value of sigma controls the amount of smoothing applied to the image. In the context of the Laplacian of Gaussian (LoG) filter, sigma influences the filter's sensitivity to noise and detail in the image. Choosing the right sigma value is essential as it affects the balance between noise reduction and edge preservation. Some common ranges of sigma values are:

1. Low Sigma (0.5 - 1.5):
   Usage: Suitable for images with fine details and low noise levels.
   Effect: Allows for sharp edge detection with minimal smoothing, preserving fine details while reducing slight noise.
2. Medium Sigma (1.5 - 3):
   Usage: Provides a balance between smoothing and edge detection.
   Effect: Ideal for a variety of medical images with moderate noise levels, offering a compromise that reduces noise without significantly blurring important details.
3. High Sigma (3 - 5):
   Usage: Suitable for images with high noise levels.
   Effect: Produces greater smoothing, significantly reducing noise but potentially blurring small details. Useful for noisy images where larger structures are of primary interest.
4. Very High Sigma (>5):
   Usage: Rarely used, but applicable for images with extremely high noise levels or for detecting large structures.
   Effect: Provides extensive smoothing, which can be beneficial for heavily noisy images or when the focus is on detecting large-scale structures.

Implementation in Image Processing

When implementing the LoG filter, the choice of sigma is crucial. The process involves the following steps:

1. Image Smoothing: Apply the Gaussian filter with the chosen sigma value to smooth the image and reduce noise.
2. Edge Detection: Use the Laplacian operator on the smoothed image to detect edges. The Laplacian highlights regions of rapid intensity change, indicating edges.

3.2. Chebyshev Filter

Chebyshev filters, named after Russian mathematician Pafnuty Chebyshev, are a type of analog or digital filter with a steeper roll-off and more passband ripple or stopband ripple than Butterworth filters. There are two main types of Chebyshev filters: Type I and Type II. Chebyshev Type I filters have equiripple behavior in the passband and a monotonic stopband, whereas Chebyshev Type II filters have equiripple behavior in the stopband and a monotonic passband.

Filter Order

The filter order (n) of a Chebyshev filter refers to the number of reactive components (such as inductors and capacitors) in an analog filter or the number of delay elements in a digital filter. The order of the filter determines the steepness of the filter's roll-off and the complexity of the filter design. Higher order filters have a steeper roll-off, which means they can more effectively separate closely spaced frequencies. However, higher order filters also introduce more phase distortion and are more challenging to implement.

1. Low Order (1-3): These filters are simpler and introduce less phase distortion but have a gentler roll-off.
2. Moderate Order (4-6): These provide a balance between complexity and performance, offering steeper roll-offs without excessive phase distortion.
3. High Order (>6): These filters have very steep roll-offs and can separate closely spaced frequencies but at the cost of increased complexity and phase distortion.

Cutoff Frequency

The cutoff frequency (fc) of a Chebyshev filter is the frequency at which the filter begins to significantly attenuate the input signal. For Chebyshev Type I filters, this is the frequency at which the passband ripple starts, and for Type II filters, this is where the stopband ripple begins. The cutoff frequency of a Chebyshev filter must be within the interval (0, 1), where 0 represents DC (zero frequency) and 1 represents half the sampling frequency (Nyquist frequency).

4. Results and Discussion

In this section, we present and analyze the results of the edge detection performance using the Laplacian of Gaussian (LoG) on medical images of Glioma, Meningioma, and Pituitary tumors. The evaluation metrics used include Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Edge Preservation Index (EPI). The results highlight the strengths and weaknesses of each filter, offering insights into their suitability for various medical image processing tasks.

Table 1. The Performance Metrics of The Laplacian of Gaussian (LoG) Filter

Name	Sigma	Parameters		
		PSNR	SSIM	EPI
Glioma 1	0.5	11.8093	0.998	0.31523
Glioma 2	1	11.6673	0.99791	0.36989
Glioma 3	1.5	11.2441	0.99801	0.39688
Glioma 4	2	10.4737	0.99812	0.33962
Glioma 5	2.5	9.561	0.99801	0.23965
Glioma 6	3	9.6164	0.99798	0.15443
Glioma 7	3.5	8.7254	0.99767	0.10705
Glioma 8	4	9.7976	0.99787	0.074415
Glioma 9	4.5	6.7351	0.99635	0.052949
Glioma 10	5	7.2256	0.99675	0.035264
Meningioma 1	0.5	12.5731	0.99876	0.21641
Meningioma 2	1	11.9258	0.9987	0.3151
Meningioma 3	1.5	11.2776	0.99861	0.37411
Meningioma 4	2	10.7546	0.9985	0.25268
Meningioma 5	2.5	10.2606	0.99836	0.13367
Meningioma 6	3	10.1082	0.99831	0.076189
Meningioma 7	3.5	9.1824	0.99794	0.059901
Meningioma 8	4	10.1908	0.99831	0.049376
Meningioma 9	4.5	7.4669	0.99684	0.056647
Meningioma 10	5	8.0718	0.99734	0.046268
Pituitary 1	0.5	10.167	0.99611	0.27371
Pituitary 2	1	9.6464	0.99619	0.34241
Pituitary 3	1.5	9.2347	0.99627	0.35679
Pituitary 4	2	8.8601	0.99635	0.27899
Pituitary 5	2.5	8.9892	0.99617	0.18576
Pituitary 6	3	8.7907	0.9962	0.13633
Pituitary 7	3.5	8.768	0.99613	0.11547
Pituitary 8	4	8.51	0.99616	0.093951
Pituitary 9	4.5	7.712	0.99626	0.073778
Pituitary 10	5	8.3993	0.99608	0.055686

The Table 1. presents the performance metrics of the Laplacian of Gaussian (LoG) filter applied to three types of brain tumors (Glioma, Meningioma, and Pituitary) using various sigma values ranging from 0.5 to 5. For Glioma, PSNR values show a declining trend as sigma increases, indicating a decrease in image quality due to more smoothing, with the highest PSNR at sigma 0.5 (11.8093) and the lowest at sigma 4.5 (6.7351). SSIM values remain high across all sigma values, indicating good structural similarity preservation. EPI peaks at sigma 1.5 (0.39688), suggesting moderate sigma values are optimal for edge preservation. Meningioma images exhibit a similar trend, with PSNR values decreasing from 12.5731 at sigma 0.5 to 7.4669 at sigma 4.5. SSIM values are slightly higher than those for Glioma, and EPI peaks at sigma 1.5 (0.37411). For Pituitary images, PSNR values also decline with increasing sigma, from 10.167 at sigma 0.5 to 7.712 at sigma 4.5, with consistently high SSIM values and EPI peaking at sigma 1.5 (0.35679). Overall, moderate sigma values around 1.5 provide the best balance between noise reduction and edge preservation across all tumor types, while higher sigma values result in significant loss of edge information and lower image quality.

Table 2. The Performance Metrics of The Chebyshev Filter

Name	Order	Filter	Parameters		
			PSNR	SSIM	EPI
Glioma 1	2	Low-pass	19.8118	0.00077005	0.099876
Glioma 2	2	High-pass	12.9192	0.27021	0.11626
Glioma 3	5	Low-pass	15.9948	0.00062886	0.04184
Glioma 4	5	High-pass	12.8723	0.35616	0.095575
Glioma 5	7	Low-pass	15.4129	0.00065612	0.032184
Glioma 6	7	High-pass	12.8566	0.36931	0.10665
Meningioma 1	2	Low-pass	20.2202	0.0010893	0.089356
Meningioma 2	2	High-pass	14.3716	0.29813	0.12029
Meningioma 3	5	Low-pass	17.0166	0.00087408	0.048146
Meningioma 4	5	High-pass	14.3169	0.40809	0.09989
Meningioma 5	7	Low-pass	16.6464	0.00089983	0.042398
Meningioma 6	7	High-pass	14.321	0.42449	0.092479
Pituitary 1	2	Low-pass	16.662	0.0004086	0.093944
Pituitary 2	2	High-pass	10.4536	0.17455	0.13067
Pituitary 3	5	Low-pass	13.2266	0.00033134	0.050758
Pituitary 4	5	High-pass	10.431	0.26208	0.11831
Pituitary 5	7	Low-pass	12.7591	0.00033556	0.03895
Pituitary 6	7	High-pass	10.4323	0.27486	0.10868

Table 2 presents the performance metrics for applying Chebyshev filters (low-pass and high-pass) of various orders to medical images. For Glioma, the highest PSNR (19.8118) is observed with a low-pass filter of order 2, while high-pass filters show lower PSNR values, such as 12.8566 for order 7, indicating more aggressive filtering and potential image quality loss. SSIM values are generally low, with high-pass filters showing slightly better structural similarity at higher orders (e.g., 0.36931 for order 7). EPI values are relatively consistent across filter types, with low-pass filters showing better edge preservation. For Meningioma, a low-pass filter of order 2 yields the highest PSNR (20.2202), with varying SSIM and EPI values. Pituitary images follow a similar trend, with high PSNR values for low-pass filters at lower orders (e.g., 16.662 for order 2) and lower SSIM and EPI values for high-pass filters.

Comparing LoG and Chebyshev filters, the Chebyshev filter generally achieves higher PSNR values, indicating better image quality preservation. For Glioma, the Chebyshev low-pass filter with order 2 has a PSNR of 19.8118, higher than the LoG filter's highest PSNR of 11.8093 at sigma 0.5. However, SSIM values for both filters are low, with the Chebyshev filter showing slightly better structural similarity at higher orders. EPI values are more consistent, with the LoG filter showing a slight advantage in some cases. Overall, the Chebyshev filter excels in preserving image quality, while the LoG filter provides better edge preservation in certain conditions, highlighting a trade-off between these aspects of medical image analysis.

5. Conclusions

In conclusion, the comparative analysis of the Laplacian of Gaussian (LoG) and Chebyshev filters applied to medical images of Glioma, Meningioma, and Pituitary tumors reveals distinct strengths and trade-offs between the two methods. The Chebyshev filter generally provides higher PSNR values, indicating superior overall image quality preservation, particularly at lower orders for low-pass filters. However, the LoG filter exhibits better edge preservation capabilities, as evidenced by higher EPI values in certain conditions, making it more suitable for applications where edge detail is critical. Although SSIM values are relatively low for both filters, the Chebyshev filter shows marginally better structural similarity at higher orders. This analysis highlights that the choice between LoG and Chebyshev filters should be guided by the specific requirements of the medical imaging task, balancing the need for high image quality against the importance of edge detection.

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