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Research/Review

Noise Reduction in Lumbar Sagittal Short Tau Inversion Recovery (STIR) MRI Images Using a Combination of Wiener Filtering With Contrast Stretching and Unsharp Masking

Wahyu Sartika Dewi[1]*, Daniel Kartawiguna[2], Panji Wibowo Nurcahyo[3]

[1] Poltekkes Kemenkes Semarang, Indonesia: sartika.dewi.wsd6@gmail.com
[2] Poltekkes Kemenkes Semarang, Indonesia: daniel.kartawiguna@gmail.com
[3] Poltekkes Kemenkes Semarang, Indonesia : panjitrrpwt@gmail.com
* Corresponding Author : Wahyu Sartika Dewi

Abstract: Background: Magnetic Resonance Imaging (MRI) is one of the most important imaging modalities in medicine, especially for diagnosing spinal disorders. The Short Tau Inversion Recovery (STIR) sequence has the advantage of suppressing fat signals, but often produces images with a low Signal-to-Noise Ratio (SNR), so that noise can interfere with diagnostic quality. Therefore, image optimization methods through noise reduction and image quality enhancement techniques are needed. Objective: This study aims to analyze the effectiveness of combining the Wiener Filter with Contrast Stretching and Unsharp Mask in reducing noise and improving the quality of Lumbar Sagittal STIR MRI images. Method: This study used an experimental quantitative approach with lumbar sagittal STIR MRI images as the research object. The research process included applying the Wiener Filter as a noise removal method, then improving the quality with Contrast Stretching and Unsharp Mask. Image quality was evaluated quantitatively using the SNR, CNR, PSNR, and MSE parameters. Results: The application of a combination of Wiener Filter with Contrast Stretching and Unsharp Mask showed an increase in SNR and CNR values compared to before processing, as well as higher PSNR values with lower MSE. This indicates that this combination method is effective in reducing noise while sharpening the anatomical structure details in Lumbar Sagittal STIR MRI images. Conclusion: The combination of Wiener Filter with Contrast Stretching and Unsharp Mask has been proven to improve the quality of Lumbar Sagittal STIR MRI images with significant noise reduction, contrast enhancement, and image sharpness. This method has the potential to be implemented in radiology practice to improve diagnostic accuracy.

Keywords: Contrast Stretching; Lumbar MRI; Noise Reduction; STIR; Wiener Filter.

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1. Introduction

Medical imaging technology has advanced rapidly in recent decades, with Magnetic Resonance Imaging (MRI) becoming one of the most important diagnostic modalities in modern medicine. MRI is a medical imaging method that has become the standard in diagnosing various health conditions. By utilizing the phenomenon of nuclear magnetic resonance or NMR, with the help of a strong magnetic field and radio waves, MRI is able to produce detailed images of the internal structures of the body's soft tissues. Without the use of ionizing radiation, MRI is a safe option for patients. With advances in technology, MRI has evolved into a more efficient and effective tool, especially in detecting serious diseases such as cancer, neurological disorders, heart disease, various musculoskeletal and spinal disorder.

One of the spinal abnormalities that is often examined using MRI is the lumbar vertebra. The lumbar sagittal section is very effective in displaying abnormal anatomy such as aponylolisthesis, subluxation, and the relationship between the intervertebral disc and the adjacent vertebral body and spinal canal. Lumbar MRI examinations generally use the STIR sequence, which has the advantage of suppressing fat signals, allowing lesions or soft tissue abnormalities to be visualized more clearly. The STIR sequence is particularly useful in cases of infection, tumors, or edema, where the contrast between normal and pathological tissue is crucial for accurate diagnosis.

STIR is one of the MRI sequences that excels at suppressing fat signals and improving the visualization of pathological lesions. According to research in the American Journal of Roentgenology, STIR has good fat saturation capabilities, even outside the central magnetic field area, and remains effective even in the presence of metal implants. Although STIR has advantages in uniformly suppressing fat signals, this sequence has a relatively low Signal-to-Noise Ratio (SNR) compared to other sequences. This is due to the use of a 180° inversion pulse, which causes an overall reduction in signal. Low SNR can result in noise in the image, which can interfere with diagnostic interpretation. This can affect the ability to detect active inflammation and reduce overall image quality.

SNR is the ratio of signal intensity to noise level in an image. Optimal MRI image quality is determined by three characteristics, namely image contrast, spatial resolution, and signal to noise ratio (SNR). There are many factors that affect SNR. Some factors can be adjusted, but there are also factors that cannot be adjusted by the operator, such as magnetic field strength, magnetic field homogeneity, and proton density. Meanwhile, parameters that can affect SNR and can be adjusted or selected by the operator include voxel volume, pulse sequence type, number of phase encoding steps (PE), number of data samples (frequency encoding), bandwidth, slice thickness, FOV, and NSA. High SNR produces clearer and more detailed images, while low SNR causes images to appear noisy and makes anatomical information difficult to interpret.

The main challenge in utilizing MRI is image quality, which is often affected by noise. Noise in MRI images can originate from various sources, such as magnetic field fluctuations, patient movement, or acquisition device limitations. The impact of noise on MRI images is quite significant, as it can cause a decrease in image quality that interferes with clinical interpretation, reduces contrast, and complicates the segmentation and diagnosis processes. Noise causes the loss of important details and worsens the accuracy of image analysis, especially in contexts that require high precision, such as in the diagnosis of spondylitis or tumors. With these considerations in mind, selecting the right MRI parameter trade-offs is very important to optimize image quality by minimizing noise in the image. However, while parameter optimization can reduce noise, the use of additional noise removal techniques is necessary to suppress noise without extending scanning time. Therefore, optimizing image quality through effective noise removal techniques is essential.

Advances in digital image processing techniques have opened up opportunities for optimizing MRI image quality. According to several sources, efforts to reduce noise in STIR images can be carried out using noise removal techniques that can improve SNR and enable more accurate evaluation of MRI images. The significance of this research is further reinforced by the need for efficient and effective optimization methods, given the need for STIR MRI in lumbar examinations in clinical practice. The American Journal of Neuroradiology states that STIR sequences are needed in clinical MRI applications, particularly for metastasis screening.

The Wiener filter in the MRI image noise removal process is based on its ability to reduce noise by minimizing the mean squared error between the original image and the filtered image. The Wiener filter is adaptive, capable of adjusting to noise levels and image details, making it effective in preserving important features while reducing spatially distributed noise. In addition, the Wiener filter is also known to have advantages in overcoming Gaussian, Rician, and Spackle noise, so it can be used as a basic method in the process of improving medical image quality.

Several previous studies have attempted to apply various noise removal methods to MRI images. Xiaobo Zhang's (2016) study concluded that noise reduction using the Wiener Filter significantly improved image quality. However, this study did not directly address aspects of contrast and sharpness enhancement, nor did it examine the STIR sequence. A study entitled "Performance Comparison of Median and Wiener Filters in Image De-noising" compared Median and Wiener Filters and concluded that Wiener produced better image quality. However, the focus of this study was still limited to filtering alone without combining image enhancement techniques. Other studies, such as Fabio et al (2018), focused on the application of the Wiener filter in ultrasound imaging, not MRI. This shows a difference from this study, which discusses STIR MRI and combines filtering and enhancement directly.

This study aims to develop a comprehensive optimization method by integrating noise removal methods using the Wiener filtering approach and a combination of image enhancement with contrast stretching and unsharp masking techniques. This method is expected to overcome the limitations of previous studies. The main contribution of this study is to examine the impact of applying a combined approach to optimize the quality of lumbar STIR MRI images, namely using a Wiener filter for noise removal followed by contrast stretching and unsharp masking to improve contrast and structural sharpness. This research is also expected to develop an optimization framework that can significantly improve the diagnostic quality of STIR MRI images, while maintaining computational efficiency and ease of implementation in clinical practice.

Based on this background, this study aims to implement and analyze the effectiveness of combining noise removal techniques using the Wiener Filter method with image enhancement in optimizing the quality of STIR lumbar MRI images. This study is expected to produce an optimization method that can be implemented practically to improve the diagnostic quality of lumbar STIR MRI images, which in turn will contribute to improving diagnostic accuracy and healthcare efficiency.

2. Preliminaries or Related Work or Literature Review

Magnetic Resonance Imaging (MRI)

Magnetic Resonance Imaging (MRI) is a medical diagnostic imaging technique that produces high-quality images of the inside of the human body without using ionizing radiation . MRI is based on the principle of magnetic resonance of hydrogen atoms in the body. This technique utilizes a strong magnetic field, rapid and repeated gradient fluctuations, and radio waves to produce cross-sectional images of objects. MRI is particularly suitable for diagnosing soft tissues, especially the brain, spinal cord, and central nervous system, providing detailed images with significant contrast differences compared to CT scans and X-rays.

The basic principle of MRI involves utilizing the magnetic properties of hydrogen atoms, which are abundant in the human body. The human body consists mostly of water (H2O), which contains two hydrogen atoms with odd atomic numbers. Hydrogen atoms have free nuclei that produce magnetization networks and have strong magnetic moments. Under normal circumstances, hydrogen protons in the body are arranged randomly. When a patient is placed in the strong magnetic field of an MRI machine, these protons tend to align in the same direction (parallel) or in opposite directions (anti-parallel) to the magnetic field, while performing a precession movement. A small difference between the number of protons aligned in the same direction and those aligned in opposite directions creates net magnetization.

The formation of an MRI image involves several key stages, beginning with excitation, in which radio wave (RF) pulses are delivered at the Larmor frequency to excite hydrogen protons in body tissue. This excitation causes transverse magnetization, in which the magnetic moments of the protons move to the transverse plane, producing a detectable signal. During the signal detection stage, this transverse magnetization induces a signal in the receiver coil. The strength of the received signal affects the intensity of the MRI image, with strong signals producing bright areas (hyperintense) and weak signals producing darker areas (hypointense). After the RF pulse is stopped, the protons return to their original state through a process of relaxation, which consists of longitudinal relaxation (T1), which describes the time required for protons to return to their initial magnetization equilibrium, and transverse relaxation (T2), which describes the loss of phase coherence of the transverse magnetization due to interactions between protons.

To determine the location of the signal in space, magnetic field gradients are used, namely spatial variations in the magnetic field applied through gradient coils, enabling the formation of two-dimensional (2D) or three-dimensional (3D) images. Finally, the received signal is processed in the image reconstruction stage, where the acquired data is converted into an image using Fourier transformation, producing an MRI image with resolution and contrast that can be adjusted according to diagnostic needs.

Sequence Short Tau Inversion Recovery (STIR)

Sequence Short Tau Inversion Recovery (STIR) is an MRI sequence used to suppress fat signals in images. STIR is a variant of the Inversion Recovery sequence that uses a short inversion time (TI) to achieve effective fat suppression. This sequence is very useful in various clinical applications, especially in musculoskeletal imaging and edema detection.

The STIR sequence works based on the difference in T1 relaxation time between fat and other tissues in the body. This sequence begins with a 180° inversion pulse that reverses the longitudinal magnetization. After a short inversion time (TI), a 90° excitation pulse is applied. The TI is chosen so that when the 90° pulse is applied, the fat magnetization is at zero (crossing the transverse axis), thus producing no signal. By suppressing the signal from fat, the STIR sequence increases sensitivity in detecting pathological changes in other tissues, such as edema, inflammation, and lesions adjacent to fat.

Lumbar MRI examination

The largest part of the vertebral column is the lumbar vertebrae, which consists of five vertebrae, namely L1 to L5. The lumbar vertebrae have large, kidney-shaped vertebral bodies that are specifically designed to support the weight of the upper body. The lumbar vertebrae have short, thick spinous processes, long transverse processes, and strong laminae and pedicles to provide maximum stability. This complex anatomical structure includes the posterior vertebral arch that protects the spinal cord, as well as the intervertebral foramen that serves as the exit route for the spinal nerve roots. Each lumbar vertebra is connected by an intervertebral disc that acts as a cushion and allows mobility without compromising the supportive strength of the vertebral column. The lumbar vertebrae have three main functions in the human musculoskeletal system: providing structural support for the upper body, facilitating mobility and flexibility of the spine, and protecting the spinal cord and spinal nerve branches.

The lumbar vertebrae are clinically significant because this area is most susceptible to injury, arthritis, herniated nucleus pulposus (HNP), and various other degenerative conditions. The L5-S1 segment and its connection to the sacrum and soft tissue elements in between are the most clinically relevant anatomical structures in the spine. Common pathologies include spinal stenosis, spondylolisthesis, compression fractures, bone tumors, and various age-related degenerative conditions.

Lumbar MRI allows for comprehensive evaluation of various anatomical components, including bones, cartilage, ligaments, nerves, and muscles that make up the lumbar complex. The examination protocol can be adjusted based on specific clinical indications, with the addition of special sequences such as STIR (Short Tau Inversion Recovery) used for fat suppression.

Noise in MRI Images

In Magnetic Resonance Imaging (MRI) imaging, noise is a significant factor that can reduce image quality. Noise is a signal or pixel that interferes with image quality. Noise can obscure important details in an image, making medical interpretation and diagnosis difficult. Therefore, understanding the types of noise, their characteristics, and their impact on image quality is crucial for optimizing MRI image acquisition and processing techniques. The types of noise in images are as follows:

1. *Gaussian noise*
2. Salt and Pepper Noise
3. Speckle noise
4. *Rayleigh noise*
5. Periodic Noise

Noise in MRI images can have a significant impact on image quality and clinical interpretation. Noise can obscure fine details in images, reducing spatial resolution and the ability to visualize small structures. Noise can reduce the intensity differences between different tissues, making it difficult to distinguish between normal and pathological tissues. Noise can obscure lesions or other abnormalities, leading to errors in diagnosis. Noise in MRI images is problematic because it obscures areas of image detail, reducing image quality and making it difficult to detect disease in the image. Optimal MRI image quality is determined by two characteristics: signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR). Noise directly affects SNR and CNR, which are measures of image quality.

3. Proposed Method

The type of research used in this thesis is quasi-experimental research with a Pre Post Test Only Group Design (30). This study aims to optimize the reduction of noise in the Lumbar Sagittal Sequence Short Tau Inversion Recovery (STIR) MRI through the application of the Wiener Filter method in noise removal and a combination of Contrast Stretching and Unsharp Mask in image enhancement. A quantitative approach was used to measure the effectiveness of the applied methods based on objective image quality parameters.

This study, entitled "Noise Reduction in Lumbar Sagittal Short Tau Inversion Recovery (STIR) MRI Images Using a Combination of Wiener Filter with Contrast Stretching and Unsharp Mask," uses the following design:

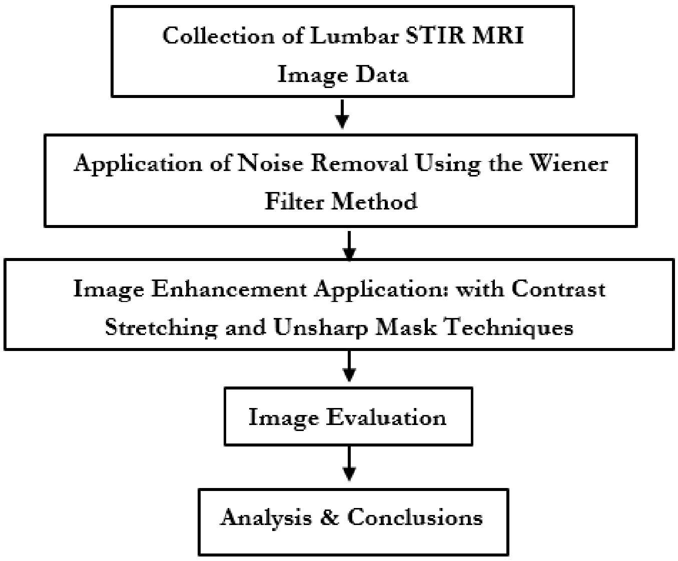

Figure 1. Research design.

In the first stage, the research began with the collection of data in the form of lumbar sagittal STIR MRI images obtained from hospital datasets. After that, the original images were assessed for SNR and CNR. Then, a noise removal technique using a Wiener Filter in Matlab was applied. Next, image enhancement was performed to improve image quality after noise removal. The techniques used in this stage included Contrast Stretching and Unsharp Mask. Image quality was evaluated using objective parameters such as Signal to Noise Ratio (SNR) and Contrast to Noise Ratio (CNR), as well as Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) to see the effect of the noise removal and image enhancement methods used. This research was conducted at the radiology department of Prof. Dr. Margono Soekarjo Regional General Hospital, taking a population of lumbar MRI images in May 2025, namely 105 patients.

4. Results

This study was conducted using a quasi-experimental method of noise removal using the Wiener Filter method, then combined with image enhancement using contrast stretching and unsharp mask techniques on lumbar sagittal sequence STIR MRI images. This study was conducted at Prof. Dr. Margono Soekarjo Regional General Hospital using 1.5T MRI modality. The sample used consisted of 51 MRI images of the lumbar sagittal sequence STIR. The images before and after the application of the Wiener Filter in combination with contrast stretching and unsharp mask were assessed for image quality using the quantitative parameters Signal to Noise Ratio (SNR), Contrast to Noise Ratio (CNR), Peak Signal-to-Noise Ratio (PSNR), and Mean Squared Error (MSE) using Matlab 2022a software.

Application of a combination of Wiener filter with contrast stretching and unsharp mask

The input images used in this study were medical images in 16-bit DICOM format. The initial images showed noise that could affect diagnostic quality, requiring an enhancement process to improve the Signal-to-Noise Ratio (SNR) and Contrast-to-Noise Ratio (CNR). The image processing steps in Matlab were as follows:

1. Enter the STIR lumbar sequence MRI image data.

The first step in this study was to import the noise image in DICOM format, which in this study used a lumbar sagittal STIR sequence MRI image.

Figure 2. MRI image of the lumbar STIR sequence before processing.

2. Calculation of SNR and CNR before the filtering process

To measure the quality of the initial image, the Signal-to-Noise Ratio (SNR) and Contrast-to-Noise Ratio (CNR) values are calculated. This process involves separating the region of interest (ROI) into two areas, namely the background region and the foreground region. The background region is the area selected as the noise reference (marked with a red box), while the foreground region is the area containing important information about the object (marked with a blue box) located at Lumbal 5. This cropping process is important for obtaining accurate SNR and CNR measurements, as these two parameters require a clear separation between signal and noise.

Figure 3. Cropping background region and foreground region.

3. Noise removal with wiener filter

The noise removal process was carried out using a Wiener filter with a 10x10 kernel. This filter was designed to reduce noise in images by taking into account the local statistical characteristics of the image. After this process, the filtered image was displayed to show the improvement in visual quality.

Figure 4. Implementation *Wiener Filter*.

4. contrast stretching to normalise image contrast

After the noise removal process, the image contrast is normalised using the contrast stretching method. This process involves adjusting the minimum and maximum values of the pixel intensity in the original image to a new range. With this method, the windowing is adjusted so that the details in the image become clearer. The image results after contrast stretching are displayed to show the contrast improvement.

Figure 5. implementation *Contrast Stretching.*

5. Image sharpening with unsharp mask

The next step is to sharpen the image using the unsharp mask method. This method aims to enhance the details in the image by highlighting the edges of objects in the image. The sharpened image is displayed to show the improvement in visual detail.

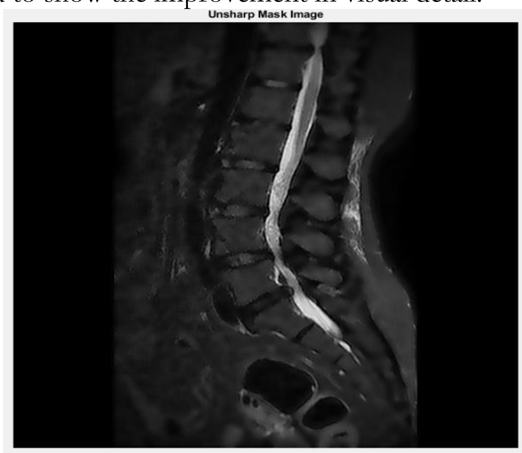

Figure 6. implementation *Unsharp Mask*.

6. Calculation of PSNR and MSE values

After all processing steps are complete, the quality of the processed image is compared to the original image using two metrics: Peak Signal-to-Noise Ratio (PSNR) and Mean Squared

Error (MSE). PSNR is used to measure the ratio between the maximum pixel intensity value and the existing noise. A higher PSNR value indicates better image quality. MSE is used to measure the average squared error between the original image and the processed image. A smaller MSE value indicates that the processed image is more similar to the original image.

Figure 7. PSNR and MSE calculations.

7. Calculation of SNR and CNR after the filtering process

After all processing steps are complete, the SNR and CNR values are recalculated to evaluate the improvement in image quality. This process is carried out using the same method as in the initial step, namely by cropping the background and foreground areas, then calculating the mean and standard deviation values.

8. Save data

The final step is to save the image processing data for further analysis. The data saved includes the processed images and quality metric values such as SNR, CNR, PSNR and MSE.

Quantitative Evaluation of SNR and CNR Image Quality

SNR and CNR measurements were performed with ROI on the background and foreground areas of the lumbar 5 corpus. Signal-to-Noise Ratio (SNR) was used to measure signal quality relative to noise in the image. A higher SNR value indicates better image quality. The calculation used the formula SNR = μ_foreground / σ_background.

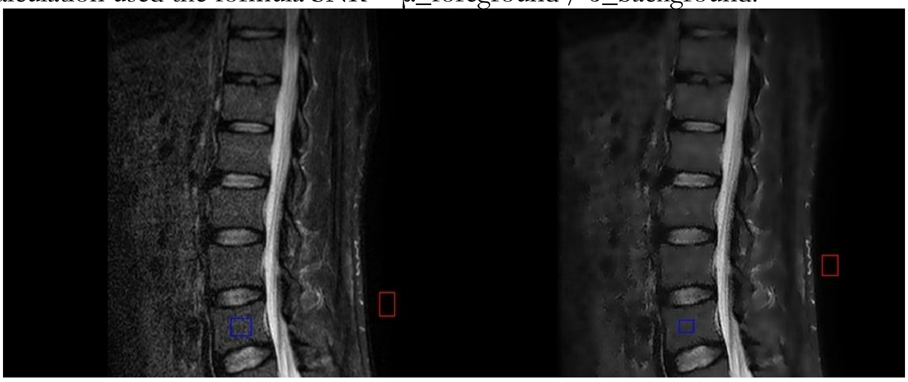

Figure 8. Calculation of SNR & CNR of image 29.

Table 1. Calculation of SNR values.

SNR value		
	Before	**After**
Min	**0,271**	**0,9523**
Max	**2,237**	**12,18**
Mean	**1,122486**	**3,459908**

Based on the SNR calculation data before applying the Wiener filter, contrast stretching, and unsharp mask methods, the SNR values varied between 0.271 and 2.237. The average SNR value before applying the Wiener filter, contrast stretching, and unsharp mask methods was 1.12, indicating that the image quality was not yet optimal.

After applying the Wiener filter, contrast stretching, and unsharp mask, the SNR value increased significantly. Based on the calculated SNR values after applying the Wiener filter, contrast stretching, and unsharp mask methods, the SNR values varied between 0.9523 and 12.18, with an average of 3.45. This indicates that the application of the Wiener filter, contrast stretching, and unsharp mask methods used successfully improved image quality significantly.

Overall, there was an average SNR increase of 208.19% after applying the Wiener filter, contrast stretching, and unsharp mask methods. This increase shows that the methods used are very effective in improving image quality by reducing noise.

Table 2. Calculation of CNR values.

	CNR value	
	Before	**After**
Min	**14,82**	**18,57**
Max	**305,7**	**150,7**
Mean	**71,36843**	**74,41667**

CNR is a metric used to measure the ability of an image to distinguish objects (foreground) from the background. A higher CNR value indicates better contrast between objects and the background. It is calculated using the formula CNR = |μ_foreground-μ_background| / σ_background.

Based on CNR calculation data, the CNR value before applying the Wiener filter, contrast stretching, and unsharp mask methods varied between 14.82 and 305.7, with an average of 72.92. This value indicates that the image contrast before applying the Wiener filter, contrast stretching, and unsharp mask methods was still quite low, especially in images with high noise.

After applying the Wiener filter, contrast stretching, and unsharp mask methods, the CNR values varied between 18.57 and 150.7, with an average of 81.96. Overall, there was an average increase in CNR of 4.27% after applying the Wiener filter, contrast stretching, and unsharp mask methods. Although there was a slight increase on average, the CNR conditions remained relatively the same and did not show any significant improvement.

PSNR and MSE evaluation

Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) are used to measure the objective quality of the enhancement results. PSNR is used to measure the quality of the resulting image relative to the reference image. Meanwhile, MSE is used to measure the average square difference between the original image and the enhanced image.

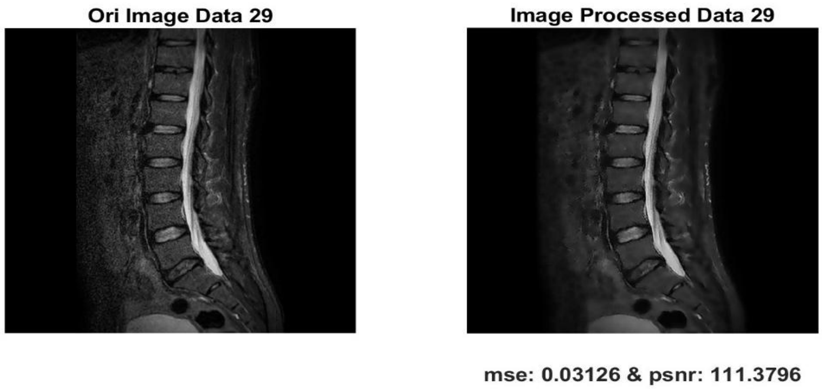

Figure 9. PSNR & MSE calculations for image 29.

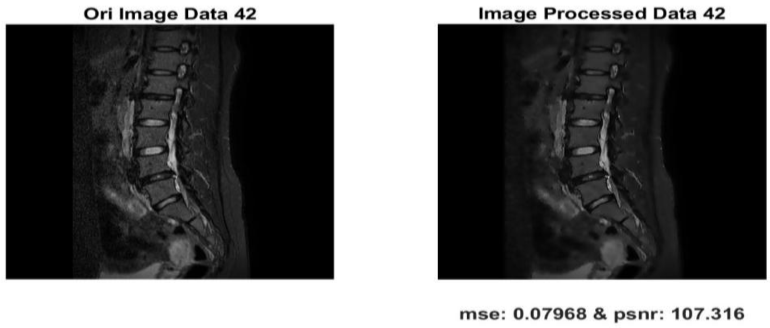

Figure 10. PSNR & MSE calculations for image 42.

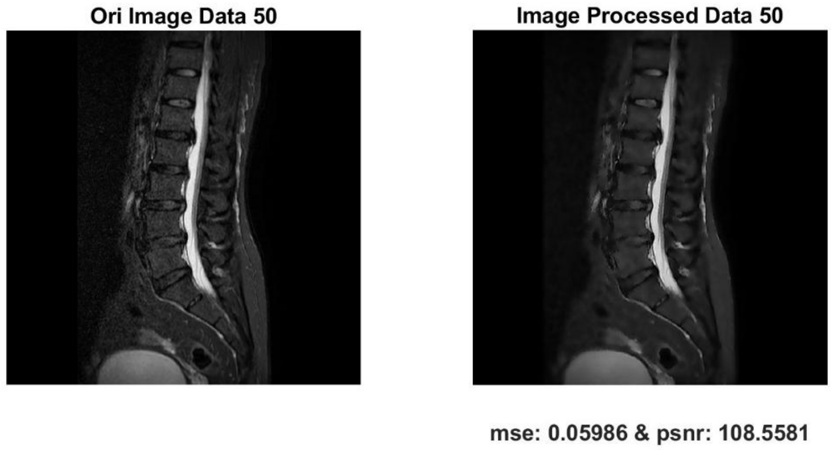

Figure 11. PSNR & MSE calculations for image 50.

Table 3. PSNR value calculation

	PSNR value
Min	**99,18**
Max	**117,6**
Mean	**108,4192**

Table 4. MSE value calculation

	Nilai MSE
Min	**0,007449**
Max	**0,5189**
Mean	**0,081454**

High PSNR (average 108.41 dB) indicates excellent image quality, with very low noise after applying the Wiener filter, contrast stretching, and unsharp mask methods. PSNR for almost all images is above 99 dB, with some images reaching over 110 dB, indicating a significant improvement in quality.

The very low MSE (average 0.0814) indicates that the results of applying the Wiener filter, contrast stretching, and unsharp mask methods are very close to the original image, with minimal error. Most images have an MSE value below 0.1, indicating good consistency in the processing results.

5. Discussion

The quality of digital images is often affected by the presence of noise, which can reduce the clarity of visual information. To improve image quality, various image processing methods are used, such as the Wiener Filter, Contrast Stretching, and Unsharp Mask. This study used 51 samples of lumbar sagittal sequence STIR MRI images. Noise removal was applied to the lumbar sagittal sequence STIR MRI images using the Wiener Filter method, then combined with image enhancement using the contrast stretching and unsharp mask techniques. In this study, image quality was measured using the Signal to Noise Ratio (SNR), Contrast to Noise Ratio (CNR), Peak Signal-to-Noise Ratio (PSNR), and Mean Squared Error (MSE) parameters using Matlab 2022a software.

Application of a combination of Wiener filter with contrast stretching and unsharp mask in the process of noise removal and image enhancement in lumbar sagittal sequence STIR MRI images

Implementasi Wiener Filter untuk noise removal

The lumbar sagittal STIR (Short-TI Inversion Recovery) MRI sequence has specific characteristics in terms of fat signal suppression, which produces good contrast between pathological and normal tissue. However, this sequence is also susceptible to noise, which can reduce diagnostic quality. Noise in MRI is generally Gaussian in nature and can affect pixel intensity additively. The Wiener filter was selected as the primary method for noise removal due to its optimal properties in minimising the mean square error between the original image and the filtered image. This filter works on the principle of optimal statistical estimation, which simultaneously considers the spectral characteristics of the signal and noise.

The results of the study indicate that the implementation of the Wiener filter significantly improved the SNR. This demonstrates that the Wiener filter effectively suppresses noise while preserving important signal information. This significant improvement in SNR is consistent with the research of Snan'A Khudayer (2018), which shows the superiority of the Wiener filter in medical image noise removal applications (31).

The effectiveness of noise removal can also be seen from the low MSE value, which indicates that the filtering process does not cause significant distortion to the anatomical structure. This is important in the context of medical imaging because maintaining anatomical details is a top priority.

Implementasi Contrast Stretching untuk image enhancement

Image enhancement through contrast stretching is implemented to maximise the use of the existing intensity histogram, thereby optimally enhancing the contrast between different anatomical structures. One of the advantages of contrast stretching is its ability to maintain relative intensity relationships between pixels by normalising the contrast comprehensively. This is important in medical imaging because relative intensities play a significant role in diagnostics. Research by Huang et al. (2013) shows that adaptive contrast enhancement can improve the visibility of details without causing an unnatural appearance (32).

The implementation of contrast stretching in this study shows consistent results by maintaining a high PSNR. Contrast stretching in medical images serves to increase contrast by expanding the range of image intensity values so that image details become more visually clear. However, even though the contrast is visually enhanced, contrast stretching can cause a decrease in CNR in some situations. The use of contrast stretching on images with low contrast can enhance contrast. However, when applied to images with good or high contrast, the application of contrast stretching has no effect or even reduces the initial contrast. This shows that contrast stretching functions to normalise or standardise contrast optimally. Therefore

Implementasi Unsharp Mask untuk meningkatkan detail citra

Implementation of unsharp mask to improve sharpness and edge definition. In this study, unsharp mask was implemented with parameters optimized for enhancement of lumbar anatomical structures without over-enhancement that could cause artifacts. This is important for STIR sequences used to evaluate edema and inflammation, where optimal morphological detail is important for accurate diagnosis.

The results of the Unsharp Mask implementation showed a significant improvement in the edge definition of anatomical structures. The sharpened images showed clearer details compared to the images after Wiener filtering, without causing disturbing artifacts. This shows that the combination of noise removal followed by sharpening provides optimal results.

Research by Polesel et al. (2000) shows that adaptive unsharp masking can produce optimal enhancement. In this study, the implementation of unsharp mask successfully improved edge definition while maintaining overall image quality, as shown by the PSNR value.

Implementing unsharp masking with the right parameters can prevent artifacts such as overshoot, undershoot, and haloing, which can reduce diagnostic value. Quality control is carried out by monitoring PSNR and MSE values to ensure that the enhancement process does not cause detrimental degradation.

Comparison of image quality in terms of Signal to Noise Ratio (SNR) and Contrast to Noise Ratio (CNR) before and after applying a combination of Wiener filter with contrast stretching and unsharp mask

Digital images are often affected by noise, which can reduce visual quality and hinder further analysis, especially in medical or technical applications. The Signal-to-Noise Ratio (SNR) and Contrast-to-Noise Ratio (CNR) parameters are two important metrics used to evaluate image quality. SNR measures the ratio between the desired signal and noise, while

CNR measures the contrast difference between the object and the background relative to noise. In this study, the Wiener Filter, Contrast Stretching, and Unsharp Mask methods were applied in combination to improve image quality. The analysis was performed by comparing the SNR and CNR values before and after applying these image processing methods to 51 image samples.

Signal to Noise Ratio (SNR)

SNR is a parameter that indicates how dominant the signal is compared to noise in an image. A higher SNR value indicates better image quality because the noise is relatively smaller than the main signal. This hypothesis test was conducted to determine whether there was a significant difference between the Signal-to-Noise Ratio (SNR) values before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods. The null hypothesis ($H_0 1$) states that $\mu_1 = \mu_2$, which means that there is no difference in the average SNR value before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods. Conversely, the alternative hypothesis (Ha_1) states that $\mu_1 \neq \mu_2$, meaning that there is a difference in the average SNR after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods.

This test was performed using a paired t-test because it compares two conditions from the same subject. With a significance level of $\alpha = 0.05$ and degrees of freedom $v = n - 1 = 50$, the critical value of the two-tailed t-test distribution is $t(0.025;50) = 2.008$. Therefore, the test decision is to reject $H_0 1$ if $|t\ \text{count}| > 2.008$ or if the significance value (Sig. 2-tailed) < 0.05. If $H_0 1$ is rejected, it can be concluded that the application of the Wiener Filter, Contrast Stretching, and Unsharp Mask methods to the Lumbar sagittal sequence STIR MRI image has a significant effect on the change in SNR value, which means that there is an increase or decrease in signal quality in the image after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods.

Based on the test results to determine whether there was a difference in the average SNR results before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods, a value of t=7.082 and Sig. (2-tailed) = 0.000 was obtained. Where 7.082 > 2.008 and 0.000 < 0.05, so H01 was rejected. Thus, the test results show that there is a significant difference in the average SNR results before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods.

Based on the results of the paired sample t-test analysis, it can be concluded that there is a significant difference between the SNR values before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods. The average SNR value before applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods is 1.12249 with a standard deviation of 0.433870, while after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods, the average increased to 3.45991 with a larger standard deviation of 2.417357. This increase indicates a significant change after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods. By looking at the much higher average SNR after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods and the significant statistical test results, it can be concluded that the image results after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods are better than before.

Contrast to Noise Ratio (CNR)

CNR is a parameter that measures the contrast difference between objects and backgrounds relative to noise. CNR is important for assessing the ability of methods to improve object visibility in images. Hypothesis testing of the Contrast to Noise Ratio (CNR) value was conducted to determine whether there was a significant difference between the CNR values before and after application using the Wiener Filter method combined with contrast stretching and unsharp mask. The hypothesis formulation used is: $H_0 2$: $\mu_1 = \mu_2$, meaning that there is no difference in the average CNR before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods, and Ha2: $\mu_1 \neq \mu_2$, meaning that there is a difference in the average between the two.

This test was performed using a paired sample t-test because it compares two conditions from the same sample. With a significance level of $\alpha = 0.05$ and a degree of freedom of $v = n - 1 = 50$, the critical value based on the two-tailed t-test distribution is $t(0.025;50) = 2.008$. The test decision is to reject $H_0 2$ if the value of $|t\ \text{calculated}| > 2.008$ or if the significance value (Sig. 2-tailed) < 0.05. If both conditions are not met, then $H_0 2$ cannot be rejected, which means that statistically there is no significant difference between the CNR values before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods. The two-tailed t-test approach is used because the test does not assume the direction of change—both increases and decreases are considered relevant for assessment.

Based on the results of the paired sample t-test on the CNR values before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods, it is known that the average CNR before applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods is 71.36843 with a standard deviation of 53.533288. Meanwhile, after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods, the average CNR increased slightly to 74.41667 with a standard deviation of 32.245810. Although there was an increase on average, the large standard deviation indicates that there is quite a high variation in the data, especially in the values before applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods.

However, statistical test results show that the difference is not statistically significant. This can be seen from the mean difference value of 3.04824 and the t-value of only 0.371. The p-value (Sig. 2-tailed) is 0.712, which is much greater than the significance threshold of 0.05. Thus, the null hypothesis ($H_0 2$) cannot be rejected, which means that there is no significant difference between the CNR values before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods.

In conclusion, the treatment given did not have a significant impact on increasing the CNR value. Although there was a slight increase on average, this was not statistically significant enough to state that the treatment had a real effect. Thus, both before and after applying the Wiener Filter, Contrast Stretching, and Unsharp Mask methods, the CNR conditions were relatively the same and did not show any meaningful improvement.

Effectiveness of combining Wiener filter with contrast stretching and unsharp mask based on Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) values in improving the quality of STIR lumbar sagittal sequence MRI images

Lumbar MRI STIR sequences have the advantage of suppressing fat signals so that pathological lesions can be visualized more clearly. However, one of the main challenges in this sequence is the low Signal-to-Noise Ratio (SNR), which causes significant noise in the image. This noise can reduce the diagnostic quality of the image, so image processing methods are needed to improve its quality. A combination of the Wiener Filter, Contrast Stretching, and Unsharp Mask methods is used to address this issue. The effectiveness of the methods is evaluated using the Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) parameters, which are standard quantitative metrics in digital image processing.

Peak Signal-to-Noise Ratio (PSNR)

PSNR is a parameter that measures the ratio between the maximum possible signal and the noise affecting the image. A higher PSNR value indicates better image quality. Based on the results of the study, the application of a combination of the Wiener Filter, Contrast Stretching, and Unsharp Mask methods resulted in a significant increase in the PSNR value.

A hypothesis test for the Peak Signal-to-Noise Ratio (PSNR) value was conducted to determine whether the average PSNR of the processed image was significantly higher than 30 dB, which is considered the minimum quality threshold for a good image. The hypothesis formulation is: $H_0 3$: $\mu \leq 30$ (average PSNR is not more than 30 dB) and Ha3: $\mu > 30$ (average PSNR is more than 30 dB).

This test uses a significance level (α) of 0.05 and a degree of freedom (df) of $v = n - 1 = 51 - 1 = 50$. Based on the t distribution table, the critical value for t (0.05;50) is 1.676. Thus, the test result is to reject $H_0 3$ if the calculated t value is greater than 1.676 or if the significance value (Sig. 2-tailed) is less than 0.05. This test is used to prove that the overall image quality, such as the PSNR parameter value, is significantly better than the minimum standard set. If the test results meet the criteria for rejecting $H_0 3$, it can be concluded that the image processing method used actually improves the visual quality of the image above the expected minimum threshold.

Based on the results of the one-sample t-test, it is known that the average PSNR in the sample is 108.419 with a standard deviation of 3.2135. The calculated t-value obtained is 174.273, where 174.273 > 1676. Meanwhile, the significance value (sig.) is 0.000, which is much smaller than the significance level of 0.05, so H03 is rejected. Thus, the null hypothesis is rejected, and it can be concluded that the average PSNR value is statistically significantly greater than 30.

Even practically, the difference between the average PSNR value and the hypothesis test value (30dB) reaches 78.419dB, with a 95% confidence interval in the range of 77.515dB to 79.323dB. This means that all values in this range are also well above 30dB. Therefore, these results reinforce the conclusion that the PSNR value in the tested conditions is at a very good level and far exceeds the minimum limit assumed in the null hypothesis.

This increase in PSNR is due to the Wiener Filter's ability to reduce noise adaptively, while Contrast Stretching expands the pixel intensity range to enhance contrast, and Unsharp Mask sharpens object edges so that anatomical details are more visible.

Mean Squared Error (MSE)

MSE is a parameter that measures the average square error between the original image and the processed image. A smaller MSE value indicates that the processed image is more similar to the ideal original image. A hypothesis test for the Mean Square Error (MSE) value is performed to test whether the average MSE of the processed image is significantly less than 100, which indicates a low error rate in image reconstruction. The null hypothesis is formulated as $H_0 4$: $\mu \geq 100$ (the average MSE is greater than or equal to 100), while the alternative hypothesis is Ha4: $\mu < 100$ (the average MSE is less than 100).

The test was conducted with a significance level of $\alpha = 0.05$ and a degree of freedom of $v = n - 1 = 51 - 1 = 50$. Based on the t-distribution, the critical value is t(0.05;50) = 1.676, so the test result rejects $H_0 4$ if the calculated t-value is < -1.676 or if the significance value (Sig. 2-tailed) is < 0.05.

This test is important because the lower the MSE value, the higher the image quality, meaning that the difference between the processed image and the original image is smaller. If the analysis results meet the requirements for rejecting $H_0 4$, it can be concluded that the image processing method significantly reduces errors and improves the visual accuracy of the resulting image.

Based on the results of the one-sample t-test, the calculated t-value is -9151.450 with a p-value of 0.000, which is much smaller than the significance level $\alpha = 0.05$. When viewed from the critical t-value (t(0.05; 50) = 1.676), $H_0 4$ will be rejected if t < -1.676. Because the t-value is much smaller than -1.676, the decision is to reject H04. Thus, it can be concluded that the average MSE value is significantly less than 100.

The average MSE value obtained is very close to zero (0), with an average of 0.081454. In image quality evaluation, the lower the MSE value, the smaller the error between the resulting image and the original image.

6. Conclusions

(a) The application of a combination of the Wiener filter method with contrast stretching and unsharp mask in the process of noise removal and image enhancement in lumbar sagittal sequence STIR MRI images shows a good combination in improving medical image quality. The Wiener Filter is successful in reducing noise. The Unsharp Mask increases sharpness after noise is reduced, and Contrast Stretching maximizes visibility by utilizing the full dynamic range.

(b) Based on the statistical analysis that has been conducted, it can be concluded that the combination of the Wiener filter, contrast stretching, and unsharp mask methods significantly improves medical image quality in terms of noise reduction (208% increase in SNR), but does not provide a significant improvement in terms of specific contrast between the foreground and background (CNR). The results of this study indicate that the methods applied are effective for applications that require noise reduction, but still require optimization to improve the ability to differentiate contrast between different anatomical structures. This provides a basis for further development in the selection and combination of medical image processing methods that are more comprehensive and balanced in improving both image quality parameters.

(c) Based on the results of the study, the combination of the Wiener Filter method with Contrast Stretching and Unsharp Mask proved to be effective in improving the image quality of the Lumbar STIR sequence MRI. This was demonstrated by a significant increase in the PSNR value (average 108.419 dB) and a significant decrease in the MSE value (average 0.081454). This combination of methods can be practically implemented to improve the diagnostic quality of MRI images, especially in STIR sequences that have high noise challenges.

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