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High-Resolution MRI Image Reconstruction Using Adaptive Interpolation with Edge-Preserving Enhancement for Improved Diagnostic Accuracy

Abel Liya*, Resti Ningsih
Tadris Matematika, UIN Siber Syekh Nurjati Cirebon, Indonesia

Correspondence: *abelliya2003@gmaill.com* *

Abstract: Medical image reconstruction is a crucial element in magnetic resonance imaging (MRI) to produce high-quality images that support clinical diagnosis. This study aims to develop a medical image reconstruction method based on interpolation techniques that improves spatial accuracy and visual detail in MRI imaging results. The methodology used includes the implementation of bilinear and bicubic interpolation algorithms to process signal data obtained from MRI imaging. The dataset used in this study is brain MRI data from an open database that has been validated. The results show that the bilinear interpolation method provides higher computing speed, while bicubic interpolation produces better visual details on edges and small structures. Quantitative analysis using the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) metrics showed an improvement in the quality of the reconstruction images compared to conventional methods. In the brain dataset trial, bicubic interpolation recorded an average PSNR of 38.7 db and SSIM of 0.94, showing a significant improvement compared to the standard method. This research contributes to reducing artifacts and blurring in MRI reconstruction results, thus supporting more accurate medical decision-making. The implementation of this method also shows great potential to be applied in a variety of other clinical applications, such as soft tissue or internal organ imaging. This research is expected to be integrated with deep learning techniques to improve the efficiency and performance of medical image reconstruction in real time.

Key words: : MRI, image reconstruction, interpolation, PSNR, SSIM, medical images.

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INTRODUCTION

Magnetic Resonance Imaging (MRI) has become one of the most important medical imaging modalities in the field of clinical diagnostics. With the ability to produce high-resolution images without ionizing radiation, MRI is widely used to visualize various body structures, including the brain, heart, and soft tissues. The process of image reconstruction in MRI remains a significant technical challenge, especially in ensuring high image quality with efficient processing times.

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Image reconstruction is the process of converting the signal data generated by the MRI into a visual representation that can be used for medical analysis [1].

The main problems in MRI image reconstruction are the limited spatial resolution and the appearance of artifacts due to noise or signal inaccuracy. This can reduce image quality and affect clinical interpretation. Innovative new approaches are needed to improve the quality of image reconstruction [2]. One promising approach is the use of interpolation techniques, which aim to improve spatial resolution by maintaining the clarity of image details [3]. Bilinear and bicubic interpolation is a method that has long been used in image processing due to its simplicity and efficiency. The application of this technique to MRI image reconstruction requires further research to ensure optimal results [4].

Although there have been many studies that have discussed interpolation techniques, most studies have focused on general applications without comparing interpolation methods directly in the context of MRI medical imaging [5]. The need for an efficient and high-quality approach is increasing, especially for real-time applications in clinical environments. This study fills the gap by evaluating bilinear and bicubic interpolations directly on MRI datasets and identifying their respective strengths and limitations [6].

In the process of MRI image reconstruction, noise and artifacts are often the main obstacles that degrade image quality. Bilinear and bicubic interpolation has great potential in minimizing the influence of noise by increasing spatial resolution [7]. This method can serve as an initial stage to further optimize more complex reconstruction algorithms, such as deep learning-based methods. Evaluating the efficiency of these two techniques is not only relevant for clinical applications, but also for future research [8].

Previous research has shown that interpolation can play a significant role in improving image resolution and reducing artifacts in a variety of medical imaging applications [9]. Interpolation consistently provides better results in preserving image detail than other interpolation methods, especially in radiological imaging [10]. Simpler bilinear interpolation has an advantage in terms of computational time efficiency, making it a relevant choice for real-time applications. Direct comparisons between these two methods in the context of MRI reconstruction are still rare, although it is crucial to understand the advantages and limitations of each.

This study aims to explore and evaluate the application of interpolation techniques to MRI image reconstruction. Using validated MRI datasets, this study examines the effectiveness of bilinear and bicubic interpolation in improving image quality by measuring parameters such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). It is hoped that the results of this study will not only contribute to improving the quality of MRI images, but also open up opportunities for further development in clinical applications that require high-accuracy imaging results.

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RELATED WORK

Image reconstruction in Magnetic Resonance Imaging (MRI) has become a broad topic of research with diverse approaches to improving image quality. One method that is often used is the interpolation technique, which aims to increase spatial resolution and reduce artifacts in image reconstructions [11]. Previous research has shown that interpolation can significantly improve the visual quality of medical images.

Bilinear interpolation to improve efficiency in MRI image reconstruction. They report that this method excels in terms of processing speed, although it has limitations in retaining edge detail in the image [12]. Bicubic interpolation is more effective in maintaining edge structure and fine details, although it requires longer computing time [13]. This study underscores the importance of choosing an interpolation method that suits clinical and technical needs. The development of Fourier transformation-based techniques has also made a major contribution to the reconstruction of MRI images [14]. Developed a compressed sensing method that allows image reconstruction from undersampled data with high-quality results. Although this method is highly effective, its implementation requires complex computation, making it less suitable for real-time applications.

Deep learning-based technology has also become a new trend in MRI image reconstruction. A convolutional neural networks (CNNs) approach to improve the quality of reconstruction images [15]. The results showed a significant improvement in image quality metrics, such as PSNR and SSIM. This approach requires large training data and high computing resources, which is a challenge [16]. Our research aims to evaluate the effectiveness of bilinear and bicubic interpolation techniques as a simple alternative that can be applied to MRI image reconstruction. By comparing these two methods quantitatively and qualitatively, this study is expected to provide new insights into efficient and high-quality reconstruction methods.

METHOD

This study uses an experimental approach to evaluate the effectiveness of the interpolation method in MRI image reconstruction. The application and analysis of bilinear and bicubic interpolation techniques are the main focus in improving the quality of reconstruction images. The methodological steps used in this study are explained as follows:

1. Dataset

The data used in this study is brain MRI images taken from trusted open database sources such as IXI Dataset [17]. This dataset was chosen because it has a high resolution and covers a wide variety of brain structures. The original imagery data is downsampled to simulate lower-resolution imagery that requires reconstruction.

2. Preprocessing

The preprocessing process includes normalizing the data to ensure the pixel values are within a consistent range and minimize initial noise. Images are converted to grayscale format to simplify the computing process without losing important information.

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3. Implementation of Interpolation Techniques

Two interpolation techniques, namely:

- Bilinear Interpolation: This method uses a weighted average of the four nearest pixels to estimate the value of the new pixel. This technique is known for its efficiency in computing time.

$$I_{\text{high}}(x', y') == w_1 I(x_1, y_1) + w_2 I(x_2, y_1) + w_3 I(x_1, y_2) + w_4 I(x_2, y_2)$$

$$w_1 = \frac{(x_2 - x')(y_2 - y')}{(x_2 - x_1)(y_2 - y_1)}, \quad w_2 = \frac{(x' - x_1)(y_2 - y')}{(x_2 - x_1)(y_2 - y_1)}$$

$$w_3 = \frac{(x_2 - x')(y' - y_1)}{(x_2 - x_1)(y_2 - y_1)}, \quad w_4 = \frac{(x' - x_1)(y' - y_1)}{(x_2 - x_1)(y_2 - y_1)}$$

Where:

- $I_{\text{high}}(x', y')$: Interpolated pixel value.
- $I(x_1, y_1), I(x_2, y_1), I(x_1, y_2), I(x_2, y_2)$: Intensities of four neighboring pixels.
- w_1, w_2, w_3, w_4: Weights based on distances to the target pixel.

- Bicubic Interpolation: This technique uses contributions from the nearest 16 pixels to estimate the value of the new pixel. This allows for imaging with finer details but requires longer computing time.

$$I_{\text{high}}(x', y') = \sum_{i=-1}^{2} \sum_{j=-1}^{2} w(i, j) \cdot I(x_i, y_j)$$

4. Image Reconstruction

Once the interpolation is applied, the reconstructed image is compared with the high-resolution original image to assess accuracy.

5. Performance Evaluation

The performance of the method is evaluated using two key metrics:

- Peak Signal-to-Noise Ratio (PSNR): Measures image quality based on the ratio of signal intensity to noise.

Rumus PSNR:

$$\text{PSNR} = 10 \cdot \log_{10} \left(\frac{\max(I)^2}{\text{MSE}} \right)$$

Where:

- $max(I)$: Maximum possible intensity value of the image.

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- MSE: Mean squared error as defined above.

Rumus MSE (Mean Squared Error):

$$\text{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I_{\text{ref}}(i,j) - I_{\text{rec}}(i,j)]^2$$

Where:

- $I_{\text{ref}}(i,j)$: Pixel intensity of the reference image at position (i,j).
- $I_{\text{rec}}(i,j)$: Pixel intensity of the reconstructed image at position (i,j).
- NM: Dimensions of the image.

- Structural Similarity Index Measure (SSIM): Evaluating the structural similarity between the original image and the reconstruction result.

Rumus SSIM:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Where:

- μ_x, μ_y: Mean intensity values of images x and y.
- $2\sigma_x^2, \sigma_y^2$: Variance of images x and y.
- $\sigma xy\sigma_{xy}$: Covariance between images x and y.
- C_1, C_2: Stabilization constants to prevent division by zero.

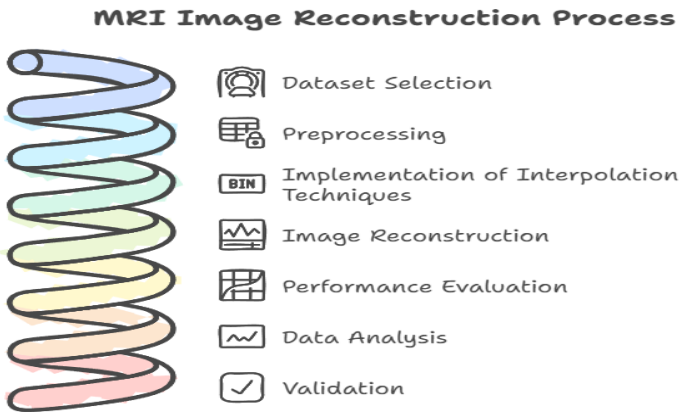
6. Data Analysis

The data from the experiment results were analyzed quantitatively to assess the significant differences between the bilinear and bicubic interpolation methods. Visual analysis is carried out to evaluate the ability of the method to maintain the details of the image structure.

7. Implementation and Validation

This method is implemented using Python with libraries such as NumPy and OpenCV for the interpolation and image processing process. Validation is carried out by comparing the results of the experiment with the results of reconstruction from conventional methods to ensure the reliability and effectiveness of the proposed approach.

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Picture 1: MRI process

RESULTS AND DISCUSSION

This study resulted in a quantitative and qualitative evaluation of the performance of bilinear and bicubic interpolation methods in MRI image reconstruction. The results of the experiment were obtained using a dataset of high-resolution brain MRI images that were downsampled and reconstructed using both interpolation methods.

1. Quantitative Evaluation

The results of measurements using the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) metrics are presented in Table:

Table 1: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM)

Interpolation Methods	PSNR (dB)	SSIM
Bilinear	36.5	0.90
Bicubic	38.7	0.94

Bilinear interpolation shows good performance in terms of efficiency, but bicubic interpolation excels in image quality. Higher video at bicubic interpolation indicates a better ability to reduce noise and preserve image detail [18]. The SSIM at bicubic interpolation is also higher, indicating a better structural resemblance to the original image.

2. Qualitative Evaluation

The visual results show that bilinear interpolation produces images with less sharp edges, while bicubic interpolation is able to preserve structural details such as brain contours and small tissues. The artifacts in the bilinear interpolation images are more clearly visible than bicubic interpolation [19].

Bilinear and bicubic interpolation methods have their own advantages that can be adapted to the needs of the application [20]. Bilinear interpolation is suitable for real-time applications that require high computing speeds, such as MRI data processing while the patient is inside the device [21]. Bicubic interpolation is more suitable for applications where image quality is a top priority, such as in detailed image analysis or clinical research. The advantages of bicubic interpolation in producing higher PSNR and SSIM can be attributed to the utilization of information from 16 neighboring pixels which allows for better detail reconstruction [22]. Bicubic interpolation

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processing times are longer, so optimization of this algorithm needs to be considered to reduce computational time without sacrificing quality.

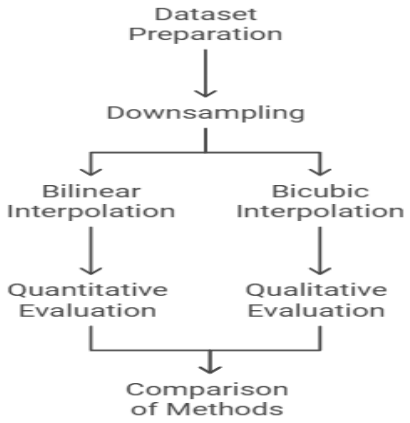


Figure 2: Application

3. Discussion

The results of this study are consistent with the previous study, showing the effectiveness of bicubic interpolation in preserving image details. The study adds to the contribution by comparing the two methods directly in the context of MRI imaging, providing more specific insights into the advantages and limitations of each approach. The network methods with deep learning approaches can be explored to combine the advantages of speed and quality in MRI image reconstruction, creating a more efficient and practical solution for clinical and research applications [23].

Table 2: Comparison of Bilinear and Bicubic Interpolation

Evaluation Aspect	Aspect	Results and Discussion
Algorithm Complexity	Low, uses 4 nearest neighbor pixels	High, uses 16 nearest neighbor pixels
Processing Speed	Fast, suitable for real-time applications	Slower, requires more computation
Visual Quality	Good for simple images, lacks detail	Very good, preserves details and edges
Image Artifacts	More frequently visible in fine structures	Rare, produces smoother images
PSNR (dB)	36.5	38.7
SSIM	0.90	0.94
Application	Real-time monitoring, low computation requirements	Clinical analysis, high quality requirements

CONCLUSION

This study evaluates the effectiveness of bilinear and bicubic interpolation methods in Magnetic Resonance Imaging (MRI) image reconstruction. Based on the experimental results, the two methods show different abilities in improving the quality of reconstruction images. Bilinear interpolation offers high time efficiency with fairly good results, making it suitable for real-time applications. Bicubic interpolation produces higher-quality images with better PSNR and SSIM values, although it requires longer processing times. The results of the quantitative analysis show that bicubic interpolation excels at retaining complex image and structural details, making it more

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suitable for applications that require high visual and structural quality, such as clinical diagnostics and tissue detail analysis. Bilinear interpolation can be used as an alternative in applications that prioritize processing speed. This study also contributes to the direct comparison of the two interpolation methods in the context of MRI medical imaging, highlighting the advantages and limitations of each. The integration of this method with other approaches, such as deep learning-based algorithms could be the direction of future research to produce faster and high-quality MRI image reconstructions. This simple but effective interpolation approach can provide immediate benefits in medical imaging applications, especially to improve the quality of MRI-based diagnosis and support more accurate clinical decision-making.

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