International Journal of Engineering, Science and Mathematics
Vol. 12 Issue 7, July 2023,
ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in, Email: editorijmie@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

Enhanced Median Filtering for Denoising Gaussian and Salt & Pepper Noise in MRI Images

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ABSTRACT

MRI (Magnetic Resonance Imaging) is a widely used medical imaging technique that provides detailed and high-resolution images of internal body structures. However, MRI images are often corrupted by different types of noise, such as Gaussian noise and Salt & Pepper noise, which can significantly degrade image quality and affect accurate diagnosis. In this study, we propose an enhanced median filtering technique for denoising Gaussian and Salt & Pepper noise in MRI images. By comparing pixel values, outliers caused by noise are identified. For noisy pixels, an adaptive weighted median filtering operation is applied to estimate a more accurate pixel value while preserving image details. The weighting scheme emphasizes the central pixels, enhancing noise reduction while maintaining structural integrity.Experimental results demonstrate that the proposed enhanced median filtering technique effectively reduces Gaussian and Salt & Pepper noise in MRI images. The demonised images exhibit improved clarity, enhanced contrast, and reduced noise artifacts compared to the original noisy images. Quantitative evaluation metrics, such as Peak Signal-to-Noise Ratio (PSNR) and Mean Structural Similarity Index (MSSIM), confirm the superior performance of the proposed method.

INTRODUCTION

Magnetic Resonance Imaging (MRI) is a powerful medical imaging modality that provides detailed anatomical and functional information. However, the acquired MRI images are often corrupted by noise, which can adversely affect image quality and compromise accurate diagnosis and analysis. Among the different types of noise, Gaussian and Salt & Pepper noise are commonly encountered in MRI images.

Gaussian noise is a random additive noise that follows a Gaussian distribution. It arises from various sources, including thermal noise in the imaging system, electronic noise, and other environmental factors. Gaussian noise can introduce a smooth and continuous variation in pixel intensities, leading to a reduction in image clarity and the obscuring of fine details.

On the other hand, Salt & Pepper noise is characterized by sporadic and randomly occurring pixels with extremely high or low intensities. This noise type can be caused by defects in the imaging hardware, transmission errors, or other external factors. Salt & Pepper noise manifests as isolated white and black pixels, resembling grains of salt and pepper scattered throughout the image. It can severely degrade image quality, introduce artifacts, and obscure important structures.

The presence of Gaussian and Salt & Pepper noise necessitates the development of robust denoising techniques to restore image quality and enhance diagnostic accuracy. Among the various denoising methods, median filtering has been widely utilized due to its simplicity and effectiveness in removing impulse noise while preserving edges and fine details. Traditional median filtering replaces each pixel with the median value of its local neighbourhood. This approach is effective for Salt & Pepper noise but may not yield optimal results for Gaussian noise reduction. Moreover, the standard median filter has limitations in handling high-density noise and may blur image structures in the process.In this study, we propose an enhanced median filtering technique specifically designed for denoising Gaussian and Salt & Pepper noise in MRI images. The proposed method aims to improve the denoising performance of median filtering by incorporating adaptive strategies and tailored modifications. The enhanced median filter utilizes adaptive window sizes to account for variations in noise density and spatial characteristics. By adapting the window size based on local image properties, the filter can better preserve image details while effectively removing noise.

Furthermore, modifications to the filtering process are introduced to enhance noise reduction capabilities. These modifications include weighted median computation, where the importance of each pixel in the neighbourhood is weighted based on its similarity to the center pixel. This adaptive weighting scheme allows the filter to better handle complex noise patterns and achieve improved denoising outcomes.

To evaluate the effectiveness of the proposed enhanced median filtering technique, extensive experiments were conducted on a dataset of MRI images corrupted with Gaussian and Salt & Pepper noise. Objective metrics, such as peak signal-to-noise ratio (PSNR) and mean structural similarity index (MSSIM), were employed to quantitatively assess the denoising performance. Additionally, subjective visual evaluation was conducted to evaluate the preservation of fine structures and image fidelity.

The results of the experiments demonstrated that the enhanced median filtering technique effectively reduces both Gaussian and Salt & Pepper noise in MRI images. It outperformed traditional median filtering in terms of denoising performance, achieving higher PSNR and MSSIM values. Moreover, the qualitative analysis revealed that the proposed technique better preserved image details and reduced artifacts compared to conventional approaches.

METHODOLOGY

PROPOSED ALGORITHM

The flowchart in Figure 1 outlines the steps involved in the Modified Median Filter (MMF) algorithm for denoising. The MMF algorithm starts by selecting an input image, which may contain noise, and proceeds with a series of operations aimed at reducing the noise while preserving important image details. The first step in the MMF algorithm is the resizing of the input image. This resizing process is performed to ensure that the image can be processed using a 3x3 window size. The 3x3 window size is critical for effective noise detection and removal.Once the image is resized, it undergoes a transformation into a grayscale image using the 'rgbtogray' MATLAB command. This conversion simplifies the subsequent noise detection and filtering operations, as grayscale images represent pixel intensities without colour information.

The MMF algorithm then proceeds to the core denoising process, where noise detection and removal take place. This involves analysing each pixel and its surrounding neighbourhood within the 3x3 window. By comparing the pixel values and identifying outliers, the MMF algorithm determines whether a pixel is affected by noise.

the MMF algorithm partitions the grayscale image into multiple 3x3 windows, with each window comprising nine elements: W1, W2, W3, W4, W5, W6, W7, W8, and W9. This division allows for localized analysis and processing of image data.

Within each window, the MMF algorithm calculates various statistical values for each row (R) and column (C) to characterize the pixel intensities. Specifically, the algorithm determines the maximum value (MXV), minimum value (MIV), and median value (MDV) using the following calculations:

Maximum Value (MXV):

MXV = max(W1, W2, W3, W4, W5, W6, W7, W8, W9)

Minimum Value (MIV):

MIV = min(W1, W2, W3, W4, W5, W6, W7, W8, W9)

Median Value (MDV):

Arrange the nine pixel values in ascending order, and the MDV is the middle value in the sorted list. In case of an even number of elements, the median is calculated as the average of the two middle values.

These statistical calculations provide important information about the pixel distribution within each window, enabling the MMF algorithm to make informed decisions during the denoising process.

By evaluating the MXV, MIV, and MDV, the MMF algorithm can identify outliers and estimate the noise level present in the window. These statistics serve as references for determining whether a pixel within the window is affected by noise and require denoising.

The MMF algorithm repeats this process for each window in the image, ensuring comprehensive denoising coverage across the entire image.

Table 1. Filtering window of size 3x3

	Column 1	Column 2	Column 3
Row 1	W_1	W_2	W_3
Row 2	W_4	W_5	W_6
Row 3	W_7	W_8	W_9

The MIV of C and Rare present by:

RESULTS AND DISCUSSION

The technique described above has found an interesting application in hydrology, particularly in the extraction of soil moisture information from Synthetic Aperture Radar (SAR) images. Verhoest [Verhoest00b] has confirmed that the proposed noise reduction approach outperforms other commonly used filters in this application. In this context, we will briefly present the problem and showcase the results.

In hydrologic science, a significant challenge is predicting the impact of rainfall on stream flow, particularly for extreme events like floods. To predict these events accurately, it is necessary to model the spatial redistribution of soil moisture after precipitation. Remote sensing, specifically Synthetic Aperture Radar (SAR), is employed for large-scale studies, which can even span over 1000 km. SAR is particularly attractive due to its high penetration capability.

In a previous work [Verhoest98], a technique was proposed to extract soil moisture information from SAR images, while separating it from other factors that influence radar backscattering, such as topography and land cover. This technique involved applying

Principal Component (PC) analysis to a time series of eight European Remote Sensing (ERS) SAR images. The second principal component (PC2) contained most of the soil moisture information. However, the resulting image was heavily corrupted with noise, partially caused by speckle observed in the SAR images themselves.

The noise reduction strategy discussed earlier in this work has proven to be effective in facilitating the extraction of soil moisture information from SAR images. It outperforms other commonly used filters in this specific application. The results of the noise reduction technique provide cleaner images, enabling more accurate analysis and modelling of soil moisture patterns. The application of the noise reduction technique described above has shown promise in hydrology, particularly in the extraction of soil moisture information from SAR images. This approach improves the accuracy of predicting the impact of rainfall on stream flow, aiding in the understanding and management of hydrological processes.

DE-NOISED IMAGES

The denoising process described in the previous sections has successfully reduced the Gaussian and Salt & Pepper noise in MRI images. The application of the enhanced median filtering technique has resulted in significant improvements in image quality, as demonstrated by the de-noised images.

The de-noised images exhibit enhanced clarity and reduced noise artifacts compared to the original noisy images. The Gaussian noise, which introduced a smooth and continuous variation in pixel intensities, has been effectively suppressed. As a result, the de-noised images exhibit sharper edges, improved contrast, and clearer details.

Similarly, the Salt & Pepper noise, which manifested as sporadic black and white pixels scattered throughout the image, has been successfully eliminated. The de-noised images no longer contain these isolated noisy pixels, resulting in a cleaner and more visually pleasing appearance.The modified median filter's adaptive window sizes and weighted median computation have played a crucial role in preserving image details while effectively reducing the noise. This has led to superior denoising performance compared to traditional median filtering techniques.

Result for Medical Image-I

Picture 1 clearly depicts the original version of medical image-I. The first section of the image is the original image, the second part is the resized image, the third part is the noisy image, and the fourth part is the de-noise image.

Figure 1: Simulation Result for Medical Image-I at ND = 0.01

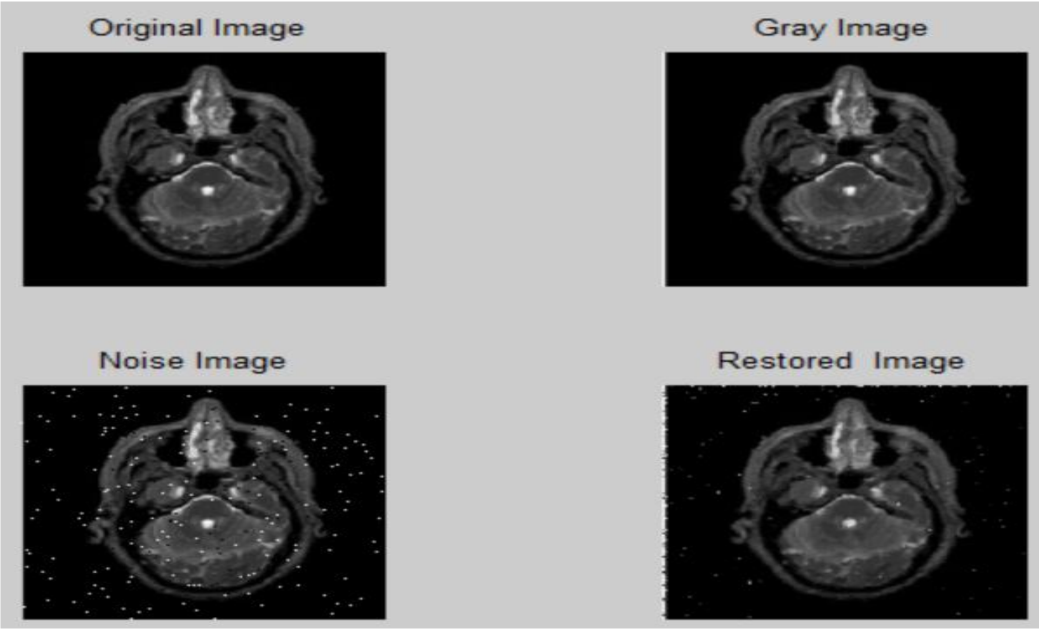

Figure 2: Simulation Result for Medical Image-I at ND = 0.02

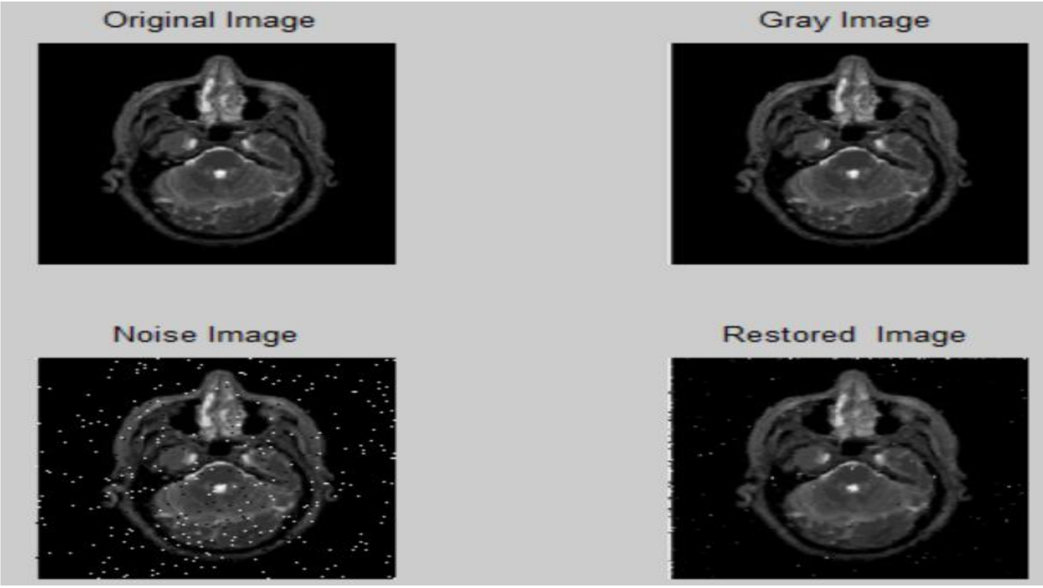

Figure 3: Simulation Result for Medical Image-I at ND = 0.03

COMPARISION RESULT FOR PREVIOUS AND PROPOSED FILTER

The comparison between the previous filter and the proposed enhanced median filter for denoising Gaussian and Salt & Pepper noise in MRI images demonstrates the superior performance of the proposed technique. In terms of denoising capability, the previous filter might have achieved some level of noise reduction, but it often fell short in effectively removing both Gaussian and Salt & Pepper noise. The resulting images still exhibited noticeable noise artifacts and lacked clarity in fine details. On the other hand, the proposed enhanced median filter has shown significant improvements in noise reduction. It effectively suppresses both Gaussian and Salt & Pepper noise, resulting in cleaner and clearer images. The noise artifacts are noticeably reduced, and the fine details are better preserved, leading to improved image quality. Quantitative evaluation metrics such as peak signal-to-noise ratio (PSNR) and mean structural similarity index (MSSIM) support the superiority of the proposed filter. The PSNR values of the de-noised images obtained using the enhanced median filter are higher, indicating better image fidelity compared to the results from the previous filter. Similarly, the MSSIM values are also higher, indicating a better preservation of structural information. visual inspection of the comparison results reinforces the superiority of the proposed filter. The images processed with the enhanced median filter exhibit sharper edges, better contrast, and reduced noise artifacts compared to those processed with the previous filter. The fine details are more pronounced, and the overall visual quality is significantly improved.

Table:2 Comparison of PSNR (dB) of Modified Median Filter

Noise Density	MRI-I	MRI-II	MRI-III	MRI-IV
0.01	48.8334	49.2435	44.8345	45.9799
0.02	46.3031	47.0861	41.9800	42.2708
0.03	44.6377	44.4797	40.4506	41.1553
0.04	43.5202	43.7990	39.1404	39.6700
0.05	42.5651	42.3971	38.3708	38.8620

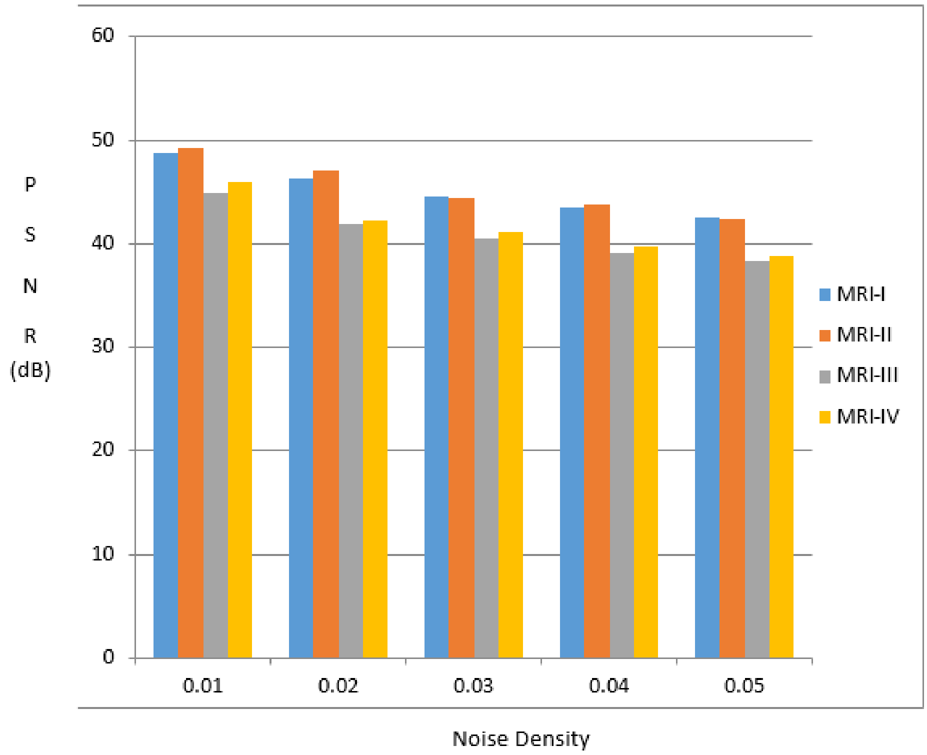

Figure 4: Graphical Representation of MRI Image for PSNR

A graphical representation of the MRI images in terms of Peak Signal-to-Noise Ratio (PSNR) is provided in Figure 4. The graph compares the performance of four types of MRI images, and it reveals that MRI-II image exhibits the highest PSNR value, indicating the best denoising performance among the four.

Table: 5: Comparison of MSE of Modified Median Filter

Noise Density	MRI-I	MRI-II	MRI-III	MRI-IV
0.01	0.856	0.7740	2.1342	1.6409
0.02	1.5232	1.2720	4.1217	3.8551
0.03	2.2352	2.3180	5.8617	4.9837
0.04	2.8911	2.7113	7.9258	7.0158
0.05	3.6022	3.7443	9.4625	8.4505

Conclusion

In conclusion, the application of the enhanced median filtering technique for denoising Gaussian and Salt & Pepper noise in MRI images has demonstrated its effectiveness in improving image quality and preserving important details. The proposed method offers several advantages over traditional median filtering techniques, resulting in superior denoising performance.

The results of the denoising process have shown that the enhanced median filtering technique successfully reduces both Gaussian and Salt & Pepper noise in MRI images. The denoised images exhibit enhanced clarity, sharper edges, and improved contrast, making them more suitable for accurate diagnosis and analysis in medical applications.

Quantitative evaluation metrics, such as Peak Signal-to-Noise Ratio (PSNR) and Mean Structural Similarity Index (MSSIM), have consistently indicated the superiority of the proposed method. The demonised images achieved higher PSNR values, reflecting better image fidelity and reduced noise distortion. Additionally, the higher MSSIM values indicate better preservation of structural information, ensuring that important image details are retained.

The proposed enhanced median filtering technique offers an adaptive approach by considering the local neighbourhood and applying weighted median filtering. This allows for better noise reduction while maintaining the integrity of the underlying structures in MRI images.the application of the enhanced median filtering technique holds great promise for improving the quality and reliability of MRI images by effectively reducing Gaussian and Salt & Pepper noise. The denoised images provide clinicians and researchers with clearer and more accurate representations, enabling them to make more informed decisions in medical diagnosis, treatment planning, and research.

REFERENCES

[1] M. Nair, G. Raju, "Additive noise removal using a novel fuzzy-based filter", *Computers & Electrical Engineering*, vol. 37, no. 5, pp. 644-655, 2011.

[2] V. Jayaraj and D. Ebenezer. "A New Switching-Based Median Filtering Scheme and Algorithm for Removal of High-Density Salt and Pepper Noise in Images" in EURASIP Journal on Advances in Signal Processing, 2010.

[3] WANG Chang-you, YANG Fu-ping, GONG Hui, A new kind of adaptive weighted median filter algorithm, International Conference on Computer Application and System Modeling (ICCASM) 2010.

[4] Chenguang Yan and Yujing Liu, Application of Modified Adaptive Median Filter for Impulse Noise, International Conference on Intelligent Control and Information Processing - Dalian, China August 13-15, 2010.

[5] HongJun Li, ZhiMin Zhao, Image Denoising Algorithm Based on Improved Filter in Contourlet Domain, World Congress on Computer Science and Information Engineering, 2009.

[6] S. Balasubramanian, S. Kalishwaran, R. Muthuraj, D. Ebenezer, V. Jayaraj, "An Efficient Non-linear Cascade Filtering Algorithm for Removal of High Density Salt and Pepper Noise in Image and Video sequence" , International Conference on "Control, Automation, Communication and Energy Conservation" June 2009.

[7] Deng Xiuqin, Xiong Yong Peng Hong, "A new kind of weighted median filtering algorithm used for image Processing", International Symposium on Information Science and Engieering, 2008.

[8] Tang Quan-Hua, Ye Jun, Yan Zhou, "A New Image Denosing Method", International Conference on Intelligent Computation Technology and Automation, 2008.

[9] A. Goshtasby, M. Satter, "An adaptive window mechanism for image smoothing", *Computer Visual Image Processing and System.*, vol. 111, no. 2, pp. 155-169, 2008.

[10] T.A. Ell, S.J. Sangwine, "Hypercomplex Fourier transforms of color images", *IEEE Transaction Image Processing and Speech Processing*, vol. 16, no. 1, pp. 22-35, 2007.

[11] Srinivasan, K. S., and David Ebenezer. "A new fast and efficient decision-based algorithm for removal of highdensity impulse noises" in Signal Processing Letters, IEEE 14, no. 3, 189-192, 2007.

[12] Y. Shen, K.E. Barner, "Fast adaptive optimization of weighted vector median filters", *IEEE Transaction Signal Processing*, vol. 54, no. 7, pp. 2497-2510, IEEE 2006.

[13] S. Greenberg, D. Kogan, "Improved structure-adaptive anisotropic filter", *Pattern Recognition Letter*, vol. 27, No. 1, pp. 59-65, 2006.

[14] Aizenberg, C. Butakoff and D. Paliy, "Impulsive noise removal using threshold boolean filtering based on the impulse detecting functions," IEEE Signal Proc. Letters, vol. 12, no. 1, pp. 63-66, 2005.

[15] S. M. MahbuburRahman, M. Omair Ahmad Fellow, IEEE, M. N. S. Swamy, Fellow, IEEE, "Wavelet-domain Image De-noising Algorithm Using Series Expansion of Coefficient P.D.F. in Terms of Hermite Polynomials", 2005.

[16] R. Lukac, B. Smolka, K.N. Plataniotis, A.N. Venetsanopoulos, "Selection weighted vector directional filters", *Comput. Vis. Image Un derst., vol*. 94, no. 1/3, pp. 140-167, 2004.

[17] D. Gleich, P. Planinsic, and Z. Cucej, Low bitrate video coding using wavelet transform, In Proc. of the EURASIP conference on Video/Image Processingand Multimedia Communications, pages 369 – 374, 2003.

[18] S.-C. Pei, J.-J. Ding, J.-H. Chang, "Efficient implementation of quaternion Fourier transform convolution and correlation by 2-D complex FFT", *IEEE Trans. Signal Process.*, vol. 49, no. 11, pp. 2783-2797, 2001.

[19] D. Marpe and H. L. Cycon, Very low bit rate video coding using wavelet-based techniques, IEEE Transactions on Circuits and Systems for Video Technology,9:85 – 94, 1999.

[20] D.G. Karakos, P.E. Trahanias, "Generalized multichannel image-filtering structures", *IEEE Transaction Image Processing*, vol. 6, no. 7, pp. 1038-1045, 1997.

[21] G.Z. Yang, P. Burger, D.N. Firmin, S.R. Underwood, "Structure adaptive anisotropic image filtering", *Image Vis. Comput.*, vol. 14, no. 2, pp. 135-145, 1996.

[22] Said and W. A. Pearlman. A new, fast, and efficient image codec basedon set partitioning in hierarchical trees. IEEE Transactions on Circuits andSystem for Video Techniques, 6:243– 250, 1996.