



Enhancing Lung Cancer Image Quality Using Advanced Filtering Approaches

Preetha G1^a, S.Nirmala Sugirtha Rajini2^b, Akshaya.V3^c

^a,Department of Computer Science and Applications, SRM Institute of Science and Technology, Ramapuram,
Chennai, TamilNadu, India,

^{b,c,d} Department of Computer Applications,

^b Dr.M.G.R. Educational and Research Institute, Maduravoyal, Chennai -95, TamilNadu, India,

^c,Department of Computer Science and Applications, SRM Institute of Science and Technology, Ramapuram,
Chennai, TamilNadu, India,

^{b,c,d} Department of Computer Applications,

ABSTRACT

Lung cancer detection from medicinal imaging often faces challenges due to noise in CT and PET/CT scans. This paper suggests a noise removal system employing three filtering approaches: Gaussian, Bilateral Filter, and Adaptive Gaussian-Bilateral Filter (AGBF). Each technique is assessed based on performance metrics including NRMSE, UIQI, and FSIM to determine their efficiency in noise reduction while preserving critical image particulars. The Lung-PET-CT-Dx dataset was used to test the suggested filters, and the outcomes show that AGBF consistently outperformed the other filters in all forms. AGBF produced the lowest NRMSE, highest UIQI, and FSIM, demonstrating its superior capability to decrease noise and preserve structural integrity in lung images. This system provides significant advancements for lung cancer diagnosis by refining the quality of medical images, making it easier for healthcare professionals to detect subtle lesions and irregularities. The recommended method offers a reliable solution for automated image enhancement in medical settings.

KEYWORDS

Lung Cancer, Detection, Filters, Performance Metrics, Lung Images, Medical Images

1. INTRODUCTION

In recent years, image-processing techniques have been widely used in the medical area to enhance picture detection (P.R. Katre et al., 2017). The typical medical treatment for lung cancer is chemotherapy, surgical removal, and radiation therapy. To ensure accuracy, preprocessing, feature selection, segmentation, and model training must all be completed in this specific order (M. S. Manavadaria et al., 2024).

Lung cancer remains one of the leading reasons of cancer-related deaths worldwide, with early detection playing a crucial role in improving patient outcomes. Medical imaging, particularly CT and PET/CT scans, is fundamental for diagnosing and staging lung cancer. However, these images often contain noise, which can obscure vital details and affect the accuracy of diagnoses. Noise in medical images can arise from various sources, such as low signal-to-noise ratios, scanning errors, or patient motion. This noise can significantly degrade the image quality, making it challenging for clinicians to detect small tumors or abnormalities.

This paper explores the performance of these filters on Lung-PET-CT-Dx, a publicly available dataset containing CT and PET/CT scans of lung cancer patients. We assess the efficiency of each filter using three key image quality metrics: NRMSE (Normalized Root Mean Square Error), UIQI (Universal Image Quality Index), and FSIM (Feature Similarity Index). These metrics allow for a comprehensive evaluation of the filters in terms of both noise removal and feature preservation. The outcomes demonstrate that AGBF outperforms both Gaussian and Bilateral Filters, achieving the best overall results in these metrics.

2. RELATED WORKS

Lung cancer (LC) is an often dangerous illness that kills people at a young age due to uncontrolled cell development in the lung tissues. The present diagnostic procedures are ineffective for cancer detection. As a result, an automated lesion segmentation approach using CT images was created. However, due to the variability in lesions, it is extremely difficult to accomplish accurate automated detection and segmentation of lung tumors. M Lavanya et al. (2017) report the use of a robust lesion detection and segmentation approach to segment each cell from diseased pictures to retrieve the relevant information. The backpropagation network is used to categorize cancer cells.

LC has a high fatality rate that continues to damage human lives all over the world. Early identification of LC improves human survival and illness prevention. Histopathological examination is a popular approach for diagnosing LC. Visual inspection of histological diagnoses requires more inspection time, and the outcome is based on physicians' subjective perceptions. Anurodh Kumar et al. 2024 used the first-time nonlocal mean (NLM) filter to reduce the influence of noise on histopathology pictures. The NLM filter effectively removed noise while maintaining the edges of pictures. The resultant denoised pictures are then used as input for the proposed multi-headed LC classification CNN. Furthermore, the model quantization approach is used to

minimize the suggested model's size for data storage. Reducing model size takes less memory and accelerates data processing. The suggested model's efficacy is compared to existing state-of-the-art approaches. The data show that the suggested technique can be useful for automatically classifying LC subtypes, perhaps assisting healthcare practitioners in making more precise selections.

LC, a major worldwide health problem, needs excellent early detection and classification methods to enhance patient outcomes. Akanksha Singh et al., 2024 address this difficulty by building a comprehensive system that uses medical imaging data to classify LC more quickly and with better diagnostic findings. The research intends to improve the efficiency of the LC detection system by leveraging sophisticated processing techniques and DL algorithms. The project aims to improve picture quality and extract important information by preparing DICOM image files from lung scans using approaches such as noise reduction, contrast enhancement, and feature extraction.

An image is a two-dimensional matrix of x and y coordinates that serves as a visual representation of reality. Any image is likely to have some level of noise. Image noise is an undesired component that results from the random change of brightness or color information in pictures. Noise may be classified into several categories, including Gaussian and speckle noise. Lung cancer is mostly caused by rapid and uncontrolled cell proliferation in lung tissues. CT scan pictures, which enable comprehensive imaging of tumor development inside the lungs, are routinely employed. However, many noise kinds, such as those indicated above, may be experienced during a CT scan. The removal of these sounds is crucial for medical diagnostics and is accomplished via filters. Filtering is a technique for improving and denoising images. A. Ravishankar et al., 2017 provide an overview of lung cancer and an assessment of numerous sounds and their removal procedures, including the use of various filters.

3. PROPOSED MODEL

Noise and outliers are frequent in all medical images. Various forms of noise, such as salt-and-pepper noise and speckle noise, are introduced to lung CT scans. These noise and outliers obscure several tiny characteristics in a lung CT picture. These sounds decrease the efficacy of the segmentation and feature extraction stages of lung cancer detection, as well as the quality of the lung CT images. Unwanted materials, known as noise, can be introduced into a CT picture during the collection process. The look of low-contrast photos was reduced owing to noise. Radiation exposure has a significant impact on image quality. The amount of damaged pixels determines the degree of noise in a picture (C Shankara et al., 2022).

Filtering plays a crucial role in enhancing image quality by reducing unwanted noise while preserving important details, making it easier to analyze and interpret medical images. By improving the clarity of images, it supports accurate diagnosis and decision-making, particularly in critical fields like medical imaging. Effective filtering

ensures that subtle features, such as tumors or lesions, are visible, which is essential for early detection and treatment planning. Additionally, it enables more consistent and reliable results across varying image qualities.

Gaussian Filter

The Gaussian filter is a smoothing method that reduces noise in photographs while maintaining edges. It operates by convolving the picture using a Gaussian function, which applies weights based on pixel distance from the center. Closer pixels have a greater effect.

Bilateral Filter

The Bilateral Filter smooths an image while keeping its edges by calculating weights that take into account both spatial and intensity differences. It eliminates noise without softening the edges, making it suitable for photographs with fine detail.

Adaptive Gaussian-Bilateral Filter (AGBF).

Pseudo-code for AGBF

1. Load the input lung image.
2. **Apply Gaussian Filtering:**
 - Set the Gaussian filter parameters: Kernel size, Standard deviation
 - Apply the Gaussian filter to the image for global noise reduction.
3. **Apply Bilateral Filtering:**
 - Set the Bilateral filter parameters: Diameter of the pixel neighborhood, and Sigma values for color and space.
 - Apply the Bilateral filter to the Gaussian-filtered image for edge-preserving noise reduction.
4. **Postprocessing:**
 - Save or display the final filtered image.
 - Compare with the original and intermediate results.
5. **Output:**
 1. Return the final filtered image.

The proposed noise removal system was evaluated using a Gaussian Filter, Bilateral Filter, and **AGBF** on the Lung-PET-CT-Dx dataset. The performance metrics—NRMSE, UIQI, and FSIM—demonstrated that the **AGBF** consistently outperformed other filters.

4. RESULTS AND DISCUSSION

AGBF achieved the lowest NRMSE, indicating superior noise reduction, and the highest UIQI and FSIM values, showcasing better preservation of structural and feature integrity. The results confirm AGBF's capability to balance noise removal and detail retention, making it the most effective filter for enhancing lung cancer image quality.

PERFORMANCE METRICS

NRMSE: NRMSE quantifies the difference between the original and processed images relative to the pixel range. A lower NRMSE indicates better quality.

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \hat{x}_i)^2}}{x_{\max} - x_{\min}}$$

Here, x_i and \hat{x}_i are original and processed pixels, x_{\max} and x_{\min} are pixel range bounds.

UIQI : UIQI measures similarity in structure, luminance, and contrast between two images, ranging from -1 to 1 (1 is a perfect similarity).

$$\text{UIQI} = \frac{4\mu_x\mu_y\sigma_{xy}}{(\mu_x^2 + \mu_y^2)(\sigma_x^2 + \sigma_y^2)}$$

Where μ_x, μ_y are means, σ_x, σ_y are variances, and σ_{xy} is covariance.

FSIM: FSIM focuses on preserving essential image features like edges and textures. Values close to 1 indicate high similarity.

$$\text{FSIM} = \frac{\sum_i \text{PC}_i \cdot S_i}{\sum_i \text{PC}_i}$$

Where PC_i (phase congruency) measures structural features, and S_i measures similarity.

Table 1.1 Performance Comparison of Filters for 1000 Lung Images

Filter Name	Average NRMSE	Average UIQI	Average FSIM
Gaussian Filter	0.28	0.83	0.86
Bilateral Filter	0.21	0.89	0.91
AGBF	0.13	0.91	0.95

The performance of the three filters is summarized based on their ability to reduce noise and preserve image quality. The Gaussian Filter demonstrated moderate effectiveness with an NRMSE of 0.28, UIQI of 0.83, and FSIM of 0.86, providing basic smoothing but some loss of structural details. The Bilateral Filter showed improvement, achieving better noise reduction (NRMSE 0.21) and higher image quality metrics (UIQI 0.89, FSIM 0.91). The AGBF outperformed both, with the lowest NRMSE (0.13) and highest UIQI (0.91) and FSIM (0.95), ensuring optimal noise reduction and feature preservation.

5. CONCLUSION

The findings of this study contribute to improving lung cancer diagnosis by providing an enhanced image quality, thereby facilitating better detection of lung abnormalities. Furthermore, this noise reduction framework can be integrated into clinical settings for real-time image processing, assisting healthcare professionals in making more accurate and reliable diagnoses. By enhancing medical images, the proposed system paves the way for improved automated diagnostic tools and potentially better patient outcomes.

Future work can explore further optimization of the **AGBF** by incorporating machine learning techniques to adaptively adjust filter parameters based on the characteristics of the input images. Additionally, the integration of deep learning-based methods for noise reduction could enhance performance, particularly in complex medical images. Another potential avenue is the real-time application of this noise removal system in clinical environments, ensuring efficient processing without compromising diagnostic accuracy. Further evaluation of more diverse datasets could also help assess the generalizability of the proposed method for broader medical imaging applications.

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