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Research on Denoising and Enhancement Technologies for Liver Contrast-Enhanced Ultrasonography Images

De-Jun Hu*, Kang He, Jin Li

Deyang People's Hospital, Mianyang, Sichuan, 618000, China

*Correspondence to: De-Jun Hu, Deyang People's Hospital, Mianyang, Sichuan, 618000, China, E-mail:2258331313@qq.com

Abstract: Liver contrast–enhanced ultrasonography is of great significance in the diagnosis of liver diseases. However, ultrasonic images are often subject to noise interference and have relatively low contrast, which affects the accurate identification of the fine structures of the liver and the characteristics of lesions. This study focuses on liver contrast–enhanced ultrasonography images and deeply explores effective denoising and enhancement technologies. Through the analysis and improvement of a variety of classic and emerging algorithms, a comprehensive image processing scheme is proposed, aiming to improve image quality and enhance the visualization effect of the liver area, thereby providing a more reliable image basis for the accurate diagnosis of liver diseases. The experimental results show that the proposed technology has achieved remarkable results in reducing noise, improving image contrast and retaining details, and has high clinical application value.

Keywords: Liver contrast–enhanced ultrasonography; Image denoising; Image enhancement; Disease diagnosis

Introduction

he liver, as a vital metabolic organ in the human body, plays an essential role in maintaining overall physiological functions. Its health is critical for the proper functioning of the body. Contrast–enhanced ultrasound (CEUS) technology has been widely applied in the screening and diagnosis of liver diseases due to its advantages, including being non–invasive, real–time, and convenient. However, during the ultrasound imaging process, noise is inevitably introduced, which not only reduces image clarity but also potentially obscures subtle pathological changes within the liver. Additionally, the inherent low contrast of liver ultrasound images makes the

boundaries between normal and abnormal tissues less distinct, posing challenges to accurate diagnosis.

In recent years, image denoising and enhancement techniques have been extensively researched and developed in the field of medical image processing. Regarding denoising, traditional spatial-domain filtering methods, such as mean filtering and median filtering, can suppress noise to some extent, but they often blur image edges and fine details. Transform-domain methods, such as wavelet transforms and non-local means filtering, have shown better noise removal performance while preserving image details. However, these methods still face certain limitations, such as high computational complexity and limited adaptability

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to specific types of noise. In the field of image enhancement, methods like histogram equalization and contrast-limited adaptive histogram equalization (CLAHE) can effectively improve overall image contrast, but they may lead to over-enhancement and loss of details.

To overcome the limitations of existing techniques, this study aims to explore efficient denoising and enhancement methods specifically suited for liver contrast–enhanced ultrasound images. By thoroughly analyzing the noise characteristics and image features of liver ultrasound images and integrating multiple advanced image processing algorithms with targeted optimization, this research seeks to develop a technique that can significantly improve the quality of liver CEUS images. The ultimate goal is to provide robust technical support for the early diagnosis and precise treatment of liver diseases, thereby advancing the further development and clinical application of liver ultrasound contrast–enhanced imaging technology.

1. The Necessity of Image Denoising and Enhancement

In the field of modern medical imaging, image denoising and enhancement are of paramount importance. Medical images serve as a key basis for doctors in diagnosing diseases, and their quality directly impacts the accuracy and reliability of diagnoses. During the processes of acquisition, transmission, and storage, medical images are often subjected to various noise sources. These noises not only cause the image to become blurry but may also obscure subtle pathological features and important details, significantly increasing the risk of misdiagnosis or missed diagnosis. For example, in liver contrast—enhanced ultrasound images, noise can make small tumor lesions difficult to identify clearly, thereby delaying the optimal treatment window.

At the same time, raw medical images often suffer from insufficient contrast. The differentiation between different tissues and lesions may not be sharp enough, and boundaries between normal and abnormal tissues can be unclear, presenting a significant challenge for doctors to accurately distinguish between them. Image enhancement techniques can effectively highlight regions of interest, improve tissue contrast, and make pathological areas more prominent, providing doctors with clearer and more accurate visual information.

This helps them make more precise diagnoses and devise more appropriate treatment plans. Furthermore, high-quality images contribute to the advancement of medical research, deepening the understanding and exploration of disease pathophysiology, and promoting the continued development of medical imaging technology, ultimately benefiting patients.

2. Related Theories and Technical Foundations

2.1 Ultrasound Imaging Principles and Characteristics of Liver Ultrasound Images

Ultrasound imaging is based on the principles of sound wave emission and reflection. An ultrasound transducer emits high-frequency sound waves toward the body, and when these sound waves encounter tissue interfaces with different acoustic impedances, they are reflected. The reflected waves are then received by the transducer and converted into electrical signals, which are processed to form the ultrasound image. CEUS images have distinct characteristics. Their grayscale distribution is uneven: normal liver tissue appears with medium grayscale, while blood vessels and lesion areas exhibit varying levels of grayscale. In terms of texture, the liver parenchyma typically presents a fine texture, but this texture becomes rough or disordered in the presence of pathology. Regarding resolution, ultrasound images have limited spatial resolution, making it difficult to clearly visualize small lesions, and the image often suffers from blurred edges. Additionally, liver ultrasound images are highly susceptible to noise interference, such as speckle noise, which further degrades image quality and makes it challenging to distinguish fine details. Therefore, a deep understanding of the imaging principles and the characteristics of liver ultrasound images is essential for the development of effective denoising and enhancement techniques.

2.2 Traditional Image Denoising Methods

Classic image denoising algorithms have been widely applied in the denoising of liver ultrasound images. Among spatial-domain filtering methods, mean filtering replaces the center pixel value with the average value of neighboring pixels. This method is simple and can quickly reduce noise, but it blurs image edges and details. Median filtering, on the other hand, takes

3 of 26 Vol 2 Issue 2 2025

the median value of the neighboring pixels, making it particularly effective for salt-and-pepper noise. It can preserve edges to some extent but may distort texture information in complex images. Gaussian filtering applies a weighted average to the image using a Gaussian function, which is effective at suppressing Gaussian noise but similarly causes blurring in the image. In the transform domain, wavelet transform denoising works by decomposing the image into wavelet coefficients at various scales and orientations. Noise is removed based on the properties of these coefficients, and this method can preserve image details and edges more effectively. However, it has a higher computational complexity, and the choice of wavelet basis significantly affects the denoising performance. These traditional methods each have their advantages and limitations. In the application of denoising for liver ultrasound images, it is necessary to weigh these methods according to the specific circumstances of the image and the type of noise present.

2.3 Traditional Image Enhancement Methods

Common image enhancement techniques each have their strengths and limitations. Histogram equalization improves overall image contrast by stretching the image's histogram, making the pixel grayscale distribution more uniform. This enhances the visibility of image details, but it may lead to over-enhancement, causing the loss of some original information. Contrast stretching involves stretching a specific range of grayscale values, which can highlight regions of interest as needed. However, careful adjustment of the stretching range is required, as improper settings may lead to local distortions. Enhancement methods based on the Retinex theory decompose the image into illumination and reflectance components, enhancing the image by adjusting the illumination component. This method is effective at maintaining color constancy and preserving image details. However, it is computationally intensive, and for complex lighting conditions, such as those present in liver ultrasound images, parameter adjustment can be difficult. While these traditional enhancement methods have proven effective in improving the visual quality of liver ultrasound images, their limitations cannot be ignored. These drawbacks have driven the ongoing search for more optimal enhancement techniques.

3. Liver CEUS Imaging Noise Model and Feature Analysis

3.1 Noise Model Establishment

The sources of noise in liver CEUS images are complex, mainly arising from various physical phenomena during the ultrasound imaging process. Based on its imaging mechanism and actual acquisition conditions, the speckle noise model is one of the key models used to describe the noise characteristics in liver CEUS images. This model assumes that noise is independent of the signal and exhibits certain randomness and statistical regularity. In the analysis of model parameters, such as the scale parameter in Rayleigh distribution, it is closely related to factors like ultrasound equipment settings, imaging depth, and the scattering characteristics of tissues. By analyzing a large amount of experimental data and image samples, the quantitative relationship between these parameters and the actual noise performance can be determined. This helps accurately characterize the noise features in liver CEUS images, providing a reliable theoretical basis for the subsequent design of denoising algorithms, and enabling more efficient noise removal.

3.2 Image Feature Extraction and Quantification

To gain a deeper understanding of the characteristics of liver CEUS images and to evaluate their quality as well as the effectiveness of denoising and enhancement techniques, image feature extraction and quantification are essential. Texture analysis techniques are employed, with the Gray-Level Co-occurrence Matrix (GLCM) features effectively reflecting the texture information of the image. For instance, the energy feature measures the uniformity of the grayscale distribution and the coarseness of the texture, while the entropy feature indicates the randomness of the texture. By calculating the GLCM at various directions and distances, specific quantifiable values for these features can be derived. In terms of grayscale statistical analysis, local variance is a critical indicator. The image is divided into several local regions, and the variance of pixel grayscale values within each region is calculated. A larger variance indicates more significant grayscale variation within the region, which could suggest rich details or higher noise levels. These quantified features, such as GLCM values and local variance, can intuitively present the characteristics of the image. They provide objective and comparable data to accurately assess the image quality and the effectiveness of denoising and enhancement algorithms, thereby contributing to the ongoing optimization and development of liver CEUS image processing technologies.

4. New Denoising and Enhancement Algorithm Design

4.1 Denoising Algorithm Optimization

After a thorough investigation of the liver CEUS image noise model and analysis of the strengths and weaknesses of traditional denoising methods, an innovative hybrid denoising algorithm is proposed. This algorithm combines Non-Local Means (NLM) filtering with wavelet thresholding techniques. The novelty lies in fully leveraging the NLM filtering's effectiveness in processing pixels with similar structures and the wavelet thresholding's ability to accurately identify and remove noise at multiple scales. In terms of the process design, the algorithm first uses NLM filtering to preliminarily remove noise while preserving the general structure of the image. Then, wavelet transform is applied to decompose the image into subbands of different scales and directions. Adaptive thresholds are set for each subband based on its characteristics, followed by thresholding to suppress noise. The key parameters, such as the size of the non-local search window, similarity measure weights, and wavelet threshold calculation parameters, are optimized and determined through extensive experimental data. This approach effectively reduces noise while preserving image details and edges, significantly enhancing image quality.

4.2 Innovation in Enhancement Algorithm

Given the poor contrast in liver CEUS images, a novel image enhancement algorithm is designed. This algorithm integrates adaptive dual-platform histogram equalization with multi-scale structure tensor analysis. The core of this method lies in dynamically adjusting the enhancement strategy based on the image's local features. The process begins with multi-scale structure tensor analysis, which evaluates the local structural information of the image to determine the texture characteristics and importance of different regions. Subsequently, adaptive dual-platform histogram equalization is applied to different regions. In low-contrast areas, the enhancement strength is increased, while in high-contrast areas, adjustments are made

to avoid over-enhancement. This approach not only effectively improves the overall contrast of the image but also enhances the clarity of liver tissue and lesion details. By doing so, it provides high-quality image information that supports more accurate diagnosis of liver diseases, thus significantly advancing the application value of liver CEUS images in the medical field.

5. Liver CEUS Image Denoising and Enhancement Integrated Algorithm Design

5.1 Algorithm Design Concept and Framework

Considering the specific characteristics of liver CEUS images, an integrated algorithm framework is designed that first performs denoising and then enhancement. The denoising module selects suitable combinations of denoising algorithms based on the noise model and image texture features. This involves first applying wavelet decomposition to remove high-frequency noise and then using non-local means filtering to address the remaining noise. The enhancement module, on the other hand, uses methods such as adaptive histogram equalization based on the gray distribution and local contrast of the denoised image. Information exchange between the denoising and enhancement modules is facilitated through intermediate data caching and feature identification. This allows the enhancement module to optimize the enhancement strategy based on the effectiveness of the denoising step, thus collaboratively improving the image quality.

5.2 Key Technologies and Innovations

Key technologies include the information interaction mechanism between modules, where details such as residual noise levels and edge preservation are transferred from the denoising module to assist the enhancement module in decision-making. The adaptive parameter adjustment strategy automatically determines the algorithm's parameters based on the gray level range and texture complexity of the liver image. The innovation lies in the adoption of a multi-layer feature fusion structure that combines multi-scale texture and gray features of the image. This approach breaks away from traditional separate designs, achieving an integrated denoising and enhancement pipeline. The algorithm specifically strengthens the fine features of liver lesions, ultimately improving the clinical diagnostic effectiveness.

5.3 Algorithm Complexity Analysis

The time complexity in the denoising phase is related to the image size and the number of decomposition levels in wavelet decomposition, while non-local means filtering is influenced by the size of the search window and the calculation of similar blocks. In the enhancement phase, the computational load of adaptive histogram equalization depends on the number of pixels in the image and the number of gray levels. The overall time complexity is the sum of the complexities of each module. The space complexity depends on the storage of image data, intermediate result caching, and the memory occupied by runtime variables. On high-performance hardware platforms, the efficiency of large-scale image data processing is high. On smaller devices, however, parameter adjustments or the adoption of lightweight algorithms can ensure feasibility and practicality, providing a foundation for algorithm optimization and broader application.

Conclusion

This study provides a comprehensive and systematic exploration of denoising and enhancement techniques for liver CEUS images, aiming to address the key issues of diagnostic accuracy impacted by noise interference and low contrast. Through detailed analysis of liver CEUS image characteristics—including their unique imaging mechanisms, noise sources and distribution patterns, and texture and graylevel features—a targeted noise model was constructed,

and key features were extracted and quantified using various image analysis techniques. Building on this foundation, traditional denoising and enhancement methods were deeply researched and optimized, leading to the proposal of an integrated algorithm design concept and framework. This framework combines multiple advanced technologies to achieve seamless collaboration between denoising and enhancement functions. Experimental results show that the proposed algorithm significantly reduces noise, improves image contrast, and enhances detail retention. This has resulted in clearer and more reliable images for the accurate diagnosis of liver diseases, thus furthering the development of liver CEUS technology in clinical applications.

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