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Acquisition and Processing of Medical Ultrasonic Video Images

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Abstract: With the maturing of ultrasonic imaging technology, medical ultrasonic imaging equipment with real-time, nondestructive, and cheap, the advantages of sensitivity, medical clinical researchers often think of medical ultrasound images as an important basis for clinical diagnosis, however, coherent characteristics of medical ultrasonic images inevitably caused the ultrasonic image speckle noise. The purpose of this study is to collect and process medical ultrasonic video images. In this paper, several typical and efficient filtering methods are analyzed, and a denoising model based on anisotropic diffusion algorithm is proposed. Considering the centrality of wavelet transform coefficient, an effective ultrasonic image denoising algorithm for anisotropic diffusion based on wavelet domain is formed by improving SARD algorithm and adding fidelity term into the algorithm. The experimental results show that the anisotropic diffusion based on wavelet domain of medical ultrasound image denoising algorithm is used to suppress speckle noise in medical ultrasound images has a good effect, not only effectively suppress the speckle noise, at the same time to keep the details of useful edge character and purpose, the processed images meet the requirements of the doctor diagnosed 85%.

1. Introduction

In ancient times, doctors used to assess a patient's physiological information by looking, smelling, asking and cutting. With the development of modern science and technology, medical personnel usually use clinical diagnostic medical equipment, using sound, light, electricity, radiation and other examinations to obtain various physiological information from the human body. Medical ultrasound images have developed rapidly in the field of medical diagnosis technology, and they can timely feed back the information such as video images produced by medical video devices in clinical application to medical staff, who can better analyze the pathological status of patients, find problems as soon as possible and adopt correct treatment methods for treatment. Ultrasonic imaging technology has the following characteristics: first, it is a non-invasive imaging method that will not cause harm to the diagnostic objects during the imaging process, and the diagnostic results can be used repeatedly; Second: Ultrasonic imaging technology has strong real-time performance and low price, and is more convenient for clinical diagnosis. More and more ultrasonic diagnostic equipment is used in medical diagnosis. At present, medical ultrasonic diagnostic equipment has become an indispensable tool for medical diagnosis.

The observation and analysis of ultrasound medical (US) images is sometimes visually complex because of speckle noise resulting from multiple reflections of ultrasound signals from hard tissue in the body. Kishore P V V proposes an American method of improving image visual quality based on Daubechies (DB2) wavelet transform fusion. The active contour line is used to segment the ultrasonic medical image and generate the edge map of the object. The wavelet image with edge is fused with the wavelet de-noised image to improve the visibility and restore the edge and texture of the image. Simulation results show that the improved algorithm has good clinical application performance. The quality indexes calculated for performance estimation include peak signal-to-noise ratio (PSNR), normalized cross correlation (NCC), edge strength (ES), image quality index (IQI) and structure similarity index (SSI). American image filters compete from literature with proposed dual techniques to measure visual performance [1-2].

In order to eliminate the block effect, which causes the traditional speckle image's fuzzy details to reduce anisotropic diffusion, an improved anisotropic diffusion algorithm is proposed in which a new diffusion coefficient by hyperbolic tangent function is used to replace the original diffusion coefficient so that the block effect can be removed from the uniform region of the image. The damping factor is used to guide the attenuation velocity in the non-uniform region, thus preserving the detail and weak edge of the image. At the same time, the relative smooth increment is introduced to automatically monitor the filtering degree, and the iterative process of pDES can be adaptively stopped. The experimental results show that the proposed method can not only filter speckle noise effectively, but also eliminate the block effect caused by traditional anisotropic diffusion method. In addition, it can improve the ability to retain details of the image and improve the structural similarity between the filter image and the original image [3].

In this study, the study was based on the imaging principle of medical ultrasound images and the denoising speckle noise is presented, and analysis of the existing ultrasonic image denoising method, based on the anisotropic diffusion algorithm is improved, and eliminate noise effectively, and try to keep the image edge details and features, has strong practical significance and research value.

2. Medical Ultrasound Image

2.1. Imaging Principle and Speckle Noise of Medical Ultrasound

Ultrasound imaging has been widely used in modern medicine, and the principle of pulse-echo in ultrasonic instruments is usually used to generate ultrasonic images [3-4]. The structure diagram of ultrasonic imaging is shown in Figure 1. In general, organs in the human body have specific acoustic properties, that is, tissues are reflected and scattered out of the body. When the ultrasonic pulse from the sensor passes through the organ in the human body, different counter-wave signals will be produced, which is the continuity of the scattered signals. And the tissues and organs in the human body, according to the normal and pathological conditions, have different reflex characteristics. Therefore, when the ultrasonic detector and instrument receive this signal, an ultrasonic picture will be formed and appear on the picture [5-6].

The acoustic resistance distribution of human soft tissue is random and the scattered particles generated in the ultrasonic pulse are clustered together with the scattering waves. When these scattered waves meet, associated interference occurs. The signals generated by these interferences overlap with the scattering of ultrasonic waves, forming distinctive spots of light and shade and speckle noise of ultrasonic images [7]. Therefore, the ultrasonic information line not only produces unnecessary noise in the formation process, but also can form speckle noise in medical ultrasonic images when the ultrasonic wave passes through the non-uniform medium. Therefore, multiplicative noise exists in medical ultrasound images.

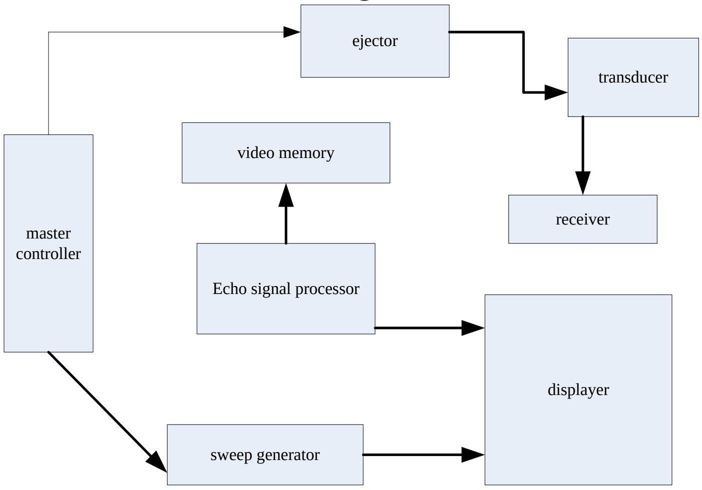


Figure 1. Ultrasonic imaging structure diagram

After the ultrasonic wave enters the human body tissue, the reflected and scattered waves are received by the ultrasonic detector and displayed as ultrasonic images by the instrument analysis. In clinical ultrasonic examination, due to the imbalance of acoustic resistance and the irregular spatial distribution of human soft tissue, a large number of randomly distributed scatterers are formed, and these scatterers produce interrelated scattered waves. When the scattering space is emitted from a certain point to the west, there will be interference and repulsive interference, and the scattered particles and the ultrasonic reflected signal will interfere with each other. As well as the signal emitted by ultrasonic reflection, the unstable signal with amplitude cannot show light and shade in ultrasonic images, which is also the speckle of ultrasonic images, generally known as the speckle noise of medical ultrasonic images [8].

As can be seen from the above introduction, the unbalanced surface of the medium has special microstructure characteristics, scattering phenomenon will occur, and a series of coherent waves will be formed. The noise caused by the interference of these coherent waves is speckle noise. Due to the arbitrary distribution of diffuse reflector in the splitting unit, its backward reflection energy is also accidental, so this echo signal has certain statistical characteristics. Speckle noise is a kind of granular artifact in medical ultrasound images. It has caused serious problems and hindered the development of automated diagnostic techniques. The excellent wavelet domain anisotropic diffusion medical ultrasonic image denoising algorithm has been used and studied by many engineering application experts and mathematics.

The principle of Fourier transform

Fourier transform is one of the commonly used tools in image processing. It can transform the signal phase between time domain and frequency domain. However, the Fourier transform can only get the information of the whole image, but not the information of the local image. To solve this problem, et al. proposed the SHORT-time Fourier transform. It is mainly to segment the signal into a time interval and add a time window to the image to get the local features of the image. However, this method also exists that the size of the time window does not change with frequency, and the signal has only a single multi-resolution ratio analysis. On this basis, wavelet transform is developed gradually. It can realize the local part of STFT and retain the information in time domain and frequency domain flexibly.

The basic principle of wavelet transform is to expand and shift a base wavelet (also known as a parent wavelet), and then inner product with image signals at different scales [9]. The formula for the expansion and translation of the base wavelet is as follows:

$$WT_f(x,y) = \frac{1}{\sqrt{x}}\psi(\frac{t-y}{x}) \quad (1)$$

$\psi(t)$ is the mother wavelet, x and y are the contraction and translation factors respectively. Normally, the $\psi(t)$ and $WT_f(x,y)$ energy is concentrated at the origin. If $\psi(t)$ represents the base wavelet, $\hat{\psi}(\omega)$ is the Fourier transform of $\psi(a)$ [10]. The formula of $\hat{\psi}(\omega)$ is as follows:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{\left|\hat{\psi}(\omega)\right|}{|\omega|} d\omega < +\infty \quad (2)$$

In the formula, ω is the allowable wavelet and C_ψ is the admissible condition.

Let $f(t)$ be the square integrable function $f(t) \in L^2(R)$. $\psi_{x,y}(t)$ represents the continuous wavelet function, then the continuous wavelet change formula is:

$$WT_f(x,y) = \frac{1}{\sqrt{x}}\int_{-\infty}^{+\infty} f(t)\psi^*(\frac{t-y}{x})dt \quad (3)$$

Where $x \neq 0$, y and t are all continuous variables, and $\psi^*(t)$ is the complex conjugate form of $\psi(t)$.

If $\psi(t)$ meets the allowable conditions of wavelet transform, there is its inverse transformation, which is expressed as follows:

$$f(t) = \frac{1}{C_\psi}\int_0^{+\infty}\frac{dx}{x^2}\int_{-\infty}^{+\infty} WT_f(x,y)\psi_{x,y}(t)dy$$

$$= \frac{1}{C_\psi}\int_0^{+\infty}\frac{dx}{x^2}\int_{-\infty}^{+\infty} WT_f(x,y)\frac{1}{\sqrt{a}}\psi(\frac{t-y}{x})dy \quad (4)$$

(2)Anisotropic diffusion algorithm

SRAD can be considered an improved version of traditional anisotropic diffusion, specifically for noise removal. It can not only preserve the edge of the image, but also improve the edge of the image by suppressing the diffusion of the boundary and allowing the diffusion of both sides of the boundary. SARD is adaptive and does not require hard thresholds to control its performance in homogeneous and heterogeneous regions. In fact, the SARD can be seen as a boundary sensitive filter and frost filter. Just as traditional anisotropic diffusion can be regarded as an average filter sensitive to boundaries. But both methods have obvious drawbacks. For anisotropic diffusion, the excessive smoothness of image details is obvious. Point noise is suppressed at the expense of image detail. Although the image after noise reduction can obtain a higher SNR, the loss of image texture will have a negative impact on clinical diagnosis.

In 1990, Perona and MaliC proposed a filtering algorithm based on partial differential equation, which allowed the filtering algorithm based on partial differential equation to effectively suppress noise while preserving edge features and details to the maximum extent [11-12]. The formula is as follows:

$$\begin{cases} \frac{\partial I}{\partial i} = div\left[c(|\nabla I|) \cdot \nabla I\right] \\ I(i=0) = I_0 \end{cases} \quad (5)$$

Where ∇ is the gradient operator, I_0 is the initial image, $|\nabla I|$ is the amplitude, div is the divergence operator, $c(x)$ is the diffusion coefficient. The diffusion coefficients of the two forms are respectively:

$$c(x) = \frac{1}{1+(x+j)^2} \quad (6)$$

$$\text{Or} \quad c(x) = \exp\left[-(x/j)^2\right] \quad (7)$$

Where j is the boundary amplitude parameter. In the anisotropic diffusion equation, the gradient amplitude as the gray discontinuity is used to detect the edge or boundary of the image. It can be seen from (6) and (7) that, since the amplitude of gradient in the image is non-negative, the diffusion coefficient $c(x)$ is a smooth decreasing function within $[0,+\infty)$, when $|\nabla I| >> j$, then $c(|\nabla I|) \to 0$.

In practice, the equation of anisotropic algorithm generally adopts the following discrete form:

$$\begin{aligned} I_{t,k}^{i+\Delta i} &= I_{t,k}^{i} + \lambda(c_N \cdot \nabla_N I + c_S \cdot \nabla_S I + c_E \cdot \nabla_E I + c_W \cdot \nabla_W I)_{t,k}^{t} \\ &= I_{t,k}^{i}\left[1-\lambda(c_N + c_S + c_E + c_W)\right] + \lambda(c_N \cdot I_N + c_S \cdot I_S + c_E \cdot I_E + c_W \cdot I_W)_{t,k}^{t} \end{aligned} \quad (8)$$

$I_{t,k}^{i}$ is the discrete ultrasonic image, λ is theweighted coefficient, Δi is the time step,and t,k is the pixel position. Generally, the gradient operator USES the pixel points in the neighborhood of the four directions. c_N, c_S, c_E, c_W represents the diffusion coefficient of each pixel point in the neighborhood of the four directions respectively. During each iteration, when the gradient value changes, its value also changes accordingly. In the above equation, the $\nabla_N I, \nabla_S I, \nabla_E I, \nabla_W I$ values are the gradient values in the four neighborhood directions of each pixel point.

(3)Lee filter

The Lee filter has a good denoising effect and can effectively remove the noise in SAR images when combined with various wavelets. Lee filtering is one of the typical methods of image speckle filtering using local statistics. It is based on a fully developed speckle noise model. Lee filtering is to obtain enhanced pixel points by calculating the pixel field. The formula is as follows:

$$\overset{\nabla}{I}_x = \overline{I_x} + k_x(I_x - \overline{I_x}) \quad (9)$$

Where $\overline{I_x}$ is the average intensity in the filtering window η_x; k_x is an adaptive filter coefficient, and the formula is as follows:

$$k_x = 1 - C_u^2 / C_x^2 \quad (10)$$

Among them,

$$C_x^2 = \left|1/\left|\bar{\eta}\right|\right| \sum_{y \in \eta} (I_y - \overline{I_x})^2 / \overline{I_x}^2 \quad (11)$$

C_u is a constant determined by the image itself. The formula is as follows:

$$C_u^2 = \frac{\operatorname{var}(z)}{(\bar{z})^2} \quad (12)$$

$\operatorname{var}(z)$ and $(\bar{z})^2$ here are the square of the variance and the mean, ,they are calculated by selecting the local area of a certain length window.

The Lee filter and the Kuan Filter have the same form, although they differ in signal modeling and filter derivation. Essentially, the Lee filter and the Kuan Filter linearly combine the center pixel value of the filter window function with the average of all pixels in the window function to input the filtered image. Therefore, the filter can be converted between the mean filter and the all-pass filter to achieve a balance between noise filtering and boundary preserving. The adjustment of the balance is achieved by the value of the fluctuation coefficient in the sliding window.

(4)Gaussian filtering

In the field of image processing, using sliding mean filter is one of the simplest methods to remove image noise. The idea of this filter is to replace one pixel in the image with a weighted average of some pixels in its surrounding neighborhood (for example, 3 times 3). The sliding mean filter can effectively remove the multiplicative Gaussian noise in image processing. However, they are not very useful in some detail-oriented and textured images, because during processing, they blur the details, resulting in the loss of texture and some details in the image [16]. The formula is as follows:

$$Mask_\sigma = (2\pi\sigma^2)^{-1} e^{\frac{-(x^2+y^2)}{2\sigma^2}} \quad (13)$$

Where x, y and a are the distance from the center pixel in the direction of b and the direction of σ respectively, and 6σ is the size of the filter template core and the standard deviation of gaussian distribution. When the template is out of the range of about the weight coefficient tends to 0.Compared with the sliding average filter, the Gaussian filter has more advantages and can better retain edge, detail, texture and other information. But in practical application, in order to achieve better denoising effect, a larger filtering kernel must be used, which will also make the edge appear more fuzzy. When the ultrasonic image is filtered by Gaussian filter, the resolution of ultrasonic image is improved and the correlation is reduced. At the same time, the multiplicative noise is converted into additive noise by homomorphism change and noise Gaussian, and its statistical characteristics are treated as Gaussian distribution. Therefore, all additive random Gaussian noise denoising methods can be used to remove ultrasonic speckle noise. Thus, the problem that local correlation points cannot be suppressed by traditional denoising methods is solved fundamentally. The formula is as follows:

$$Mask_{\sigma(a+x,b+y)} = (2\pi\sigma(a,b)\sigma(a,b))^{-1} e^{-\frac{x^2}{2\sigma(a,b)^2}-\frac{y^2}{2\sigma(a,b)^2}} \quad (14)$$

Where, $\sigma_{\mathrm{a}}(a,b)$ is the standard deviation that changes longitudinally at positions a and b, and $\sigma_{\mathrm{b}}(a,b)$ is the standard deviation that changes laterally at positions a and b.

2.2 Medical Ultrasound Imaging Based on Edge Segmentation Method

Edge is the important visual information contained in the image, it contains most of the information of the image. Edge detection is a key step in image processing and machine vision. The effect of edge detection is very important for image analysis and understanding. Images contain a lot of information, but not all of it. By edge detection, not only the structural attributes of the image are preserved, but also the information irrelevant to the image processing target is eliminated, greatly reducing the amount of data contained in the image, and finally the edge information we need is obtained. The edge-based segmentation method is used to detect the gray change of the discontinuous position image in terms of texture, gray level and color, and reflect the gray level gradient, represented by $\nabla f(a,b) = \frac{\partial f}{\partial f} i + \frac{\partial f}{\partial f} j$ [17]. The edge detection operator $e(a,b) = \sqrt{f_a^2(a,b) + f_b^2(a,b)}$ is defined, which is the amplitude of $\nabla f(a,b)$. To simplify the calculation, it can also be defined as the sum of the absolute values of the partial derivatives f_a, f_b:

$$e(a,b) = \left| f_a(a+b) \right| + \left| f_b(a+b) \right| \quad (15)$$

(1)Sobel operator

Sobel operator image a point as the center, in the neighborhood of 3 * 3D direction and the partial derivative of the direction. The formula of Sobel operator is as follows:

In the vertical direction:

$$S_1(x,y) = \begin{vmatrix} f(x-1,y-1) + 2f(x,y-1) + f(x+1,y-1) \\ -(f(x-1,y+1) + 2f(x,y+1) + f(x+1,y+1)) \end{vmatrix} \quad (16)$$

In the horizontal direction:

$$S_2(x,y) = \begin{vmatrix} f(x-1,y-1) + 2f(x-1,y) + f(x-1,y+1) \\ -(f(x+1,y-1) + 2f(x+1,y) + f(x+1,y+1)) \end{vmatrix} \quad (17)$$

The vertical and horizontal templates are respectively expressed as:

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (18)$$

Select a threshold T, if $S_1(x,y) > T$, it means there is edge passing in the vertical direction of (x,y), and (x,y) is edge point; In the same way, if $S(x,y) > T$, also means edge point in (x,y). If I don't care about direction,

(2)Roberts operator

The gradient in the Roberts algorithm can be seen as the difference between two pixels in any vertical direction [21-22]. The Roberts operator, on the other hand, takes the difference between two adjacent pixels in the diagonal direction:

$$\Delta_i f = f(x,y) - f(x+1,y+1) \quad (19)$$

$$\Delta_j f = f(x,y+1) - f(x+1,y) \quad (20)$$

Its gradient amplitude value is:

$$R(x,y)=\left|\Delta_i f\right|+\left|\Delta_j f\right| \quad (21)$$

or

$$R(x,y)=\sqrt{\Delta_i^2 f+\Delta_j^2 f} \quad (22)$$

The convolution operator is expressed as:

$$\Delta_i f=\begin{vmatrix}1 & 0\\ 0 & -1\end{vmatrix} \qquad \Delta_j f=\begin{vmatrix}0 & 1\\ -1 & 0\end{vmatrix} \quad (23)$$

Select the close value T appropriately, if $R(x,y)>T$, then (x,y) is the edge point.

(3)Laplace operator

Laplace operator is a second derivative operator, whose center of function is zero in the frequency domain is symmetric, so it has rotation invariance[23-24]. This graph is processed by Laplace operator and the pixel has the feature of zero gray mean[25]. The Laplace transform of a two-dimensional graph function is the isotropic second derivative. The formula is as follows:

$$\nabla^2 f(a,b)=\frac{\partial^2 f(a,b)}{\partial a^2}+\frac{\partial^2 f(a,b)}{\partial b^2} \quad (24)$$

Let's write it as a difference:

$$\nabla^2 f(x,y)=f(x-1,y)+f(x,y+1)+f(x+1,y)+f(x,y-1)-4f(x,y) \quad (25)$$

The Laplace operator can also be expressed as a template form, convolving with the original image to extract the edge of the image [24-25]. The following are several Laplace convolution templates with varying degrees of approximation:

$$\begin{vmatrix}0 & -1 & 0\\ -1 & 4 & -1\\ 0 & -1 & 0\end{vmatrix} \quad \begin{vmatrix}-1 & -1 & -1\\ -1 & 4 & -1\\ -1 & -1 & -1\end{vmatrix} \quad \begin{vmatrix}2 & -4 & 2\\ -4 & 8 & -4\\ 2 & -2 & 1\end{vmatrix} \quad (26)$$

3. Experiment Design

3.1. Experimental Database Chart Design

Speckle noise is inevitable in the process of ultrasound imaging. The presence of speckle noise in medical ultrasound image reduces the resolution and contrast of the image, conceals the edge of some details, and thus reduces the quality of the image. Therefore, effective suppression of speckle noise will become an important preprocessing step for medical ultrasonic image acquisition and processing. The aim of medical ultrasonic image denoising is not only to eliminate noise, but also to preserve the original details of the image as much as possible. Detailed features are an important basis for the diagnosis of organ lesions. At present, the ultrasonic image denoising algorithm based on orthogonal wavelet transform has achieved good results. Its disadvantage is that ultrasonic image signal is represented by the detail coefficient after decomposition by orthogonal wavelet transform, which is easy to produce ringing effect and edge effect in image reconstruction, resulting in edge blurring. Using the stationary wavelet transform can eliminate the blurring of image edge to a great extent. In this paper, based on the results of quantitative analysis and the visual effects of images, the anisotropic diffusion algorithm proposed in this paper is applied to medical ultrasonic images, and a systematic comparative study is carried out. The flowchart of the algorithm is described as follows:

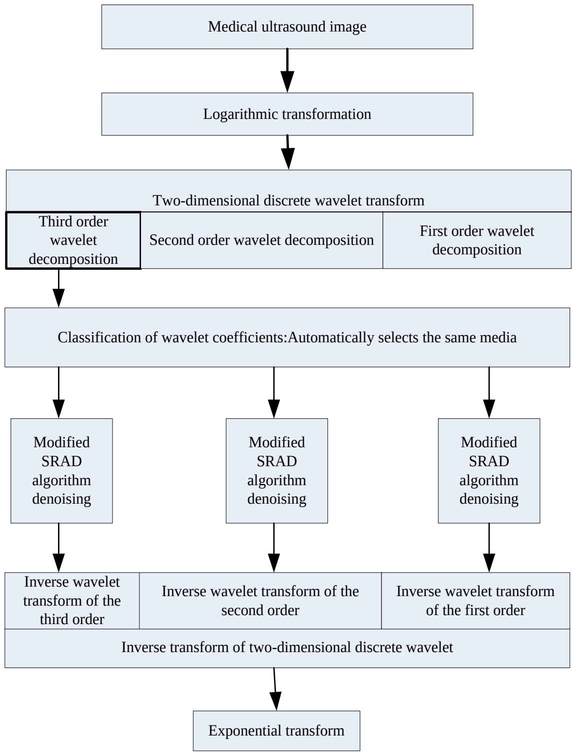


Figure 2. Flow chart of wood text algorithm

3.2. Steps of the Anisotropic Diffusion Algorithm

An anisotropic diffusion algorithm based on wavelet decomposition is presented in this paper. Its main purpose is to remove speckle noise in medical ultrasound images while preserving local details and edge information as much as possible. The following is a brief description of the algorithm process:

Step1:The ultrasonic images in the spatial domain are transformed into the logarithmic domain by logarithmic transformation;

Step2:After logarithmic transformation of the image, the third order wavelet decomposition is carried out. Speckle noise and important feature details are given in each subband;

Step3:In order to calculate the scale function $p_0(x)$, the uniform region is automatically selected by using the wavelet coefficient classification method:

1)Prior probabilities and detailed images acquired and binary mask are used,

2)The probability density is $q(m_t\,|\,0)$ and $q(m_t\,|\,1)$,

3)The compression factor is applied to each wavelet coefficient;

Step4:The improved SARD algorithm is used to remove the spots in ultrasonic images while preserving the edge and detail information;

1)Select a diffusion coefficient with high robustness;

2)Diagonal gradient is added to the calculation of the Laplace operator and the gradient operator.

3)Add a fidelity term to the algorithm;

Step5:After image reconstruction, the coefficients after wavelet transform are transformed into two-dimensional discrete inverse wavelet transform.

Step6:The exponential operation of the reconstructed coefficients.

4. Analysis of Experimental Results of Medical Ultrasound Imaging Simulation Images

4.1. Analysis of Anisotropic Diffusion Ultrasonic Image Denoising Algorithm

The algorithm proposed in this paper divides homogeneous regions and USES the improved SRAD algorithm to denoise, which improves the performance of the denoising algorithm.

In the process of image processing, the grayscale value of pixels is represented by integers, and integers are more convenient for storage and encoding than floating point Numbers. However, in the previous wavelet transform, because the coefficients of the wavelet filter are mostly floating point Numbers, when performing filtering operation, even if the input is an integer, the result is still a floating point number. If the scale-up method is used, integer results can also be obtained, but the dynamic range of data is expanded, which may cause numerical overflow. From the perspective of computer rounding error, wavelet transform is a lossless process. Using the lifting scheme, a kind of integer wavelet transform can be obtained with a little modification, which makes the original data reconstructed accurately. This change is to add the integer operation to the lifting step, so that the wavelet transform process becomes nonlinear. The integer lifting wavelet is based on the lifting algorithm, and the transformation is realized by rounding the predicted and updated values, that is, after each promotion, the coefficient is rounded. This transformation can realize the wavelet transform from integer set to integer set, and the coefficients after transformation are all integers, which brings benefits to the digital image processing. Since there is no need to quantify the coefficients after transformation, it provides the possibility of lossless recovery.

Actual images are generally defined as medical ultrasound images obtained by ultrasonic equipment, which usually contain speckle noise. Relatively clean ultrasound images are generally difficult to obtain. In this paper, simulation images are mainly used to analyze the performance of the drying algorithm from the perspective of visual effects and quantitative analysis results. The denoising process of speckle noise adopts the more classical method proposed by Achim :First, we average the Gaussian noise of the random complex number through the low-pass filter, and then we take the amplitude for the output of the filter. The resulting noise is speckle noise obeying Rayleigh distribution, which we regard as speckle multiplication noise in medical ultrasound images.

The validity of the algorithm presented in this paper is verified. For speckle noise σ of 4 ultrasonic images with different intensity, when σ is 0.1-0.3, the effect of adding noise is not very obvious. Therefore, σ of speckle noise in this paper ranges from 0.6 to 0.8. The values of $RMSE$ and S/MSE of various denoising methods in medical ultrasonic images at different levels of speckle noise are shown in Table 1 and Figure 3,Figure 4,Figure 5 .

Table 1. σ =0.6 $RMSE$ and S/MSE values of various denoising methods at speckle noise level

σ =0.6		Noisy	Lee	Frost	SARD	this paper
U01	RMSE	10.5536	9.5402	9.6923	8.0371	7.8345
	S/MSE	17.2518	18.7818	19.2518	19.3528	20.1500
U02	RMSE	9.0392	7.8392	7.5392	7.1592	6.7535
	S/MSE	17.2566	21.6042	21.8513	21.6692	23.2350
U03	RMSE	10.1382	8.8382	8.7621	8.0563	7.6578
	S/MSE	17.4568	19.7201	19.8534	19.7714	20.8914
U04	RMSE	10.1382	9.9144	9.9081	8.3255	7.6710
	S/MSE	17.2566	19.6512	19.5218	18.1158	20.3715

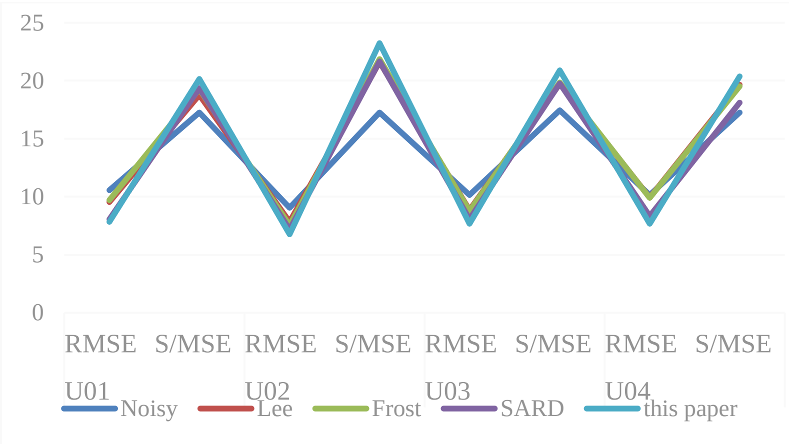


Figure 3. σ *=0.6 the value curves of* $RMSE$ *and* S/MSE *of various denoising methods under speckle noise level*

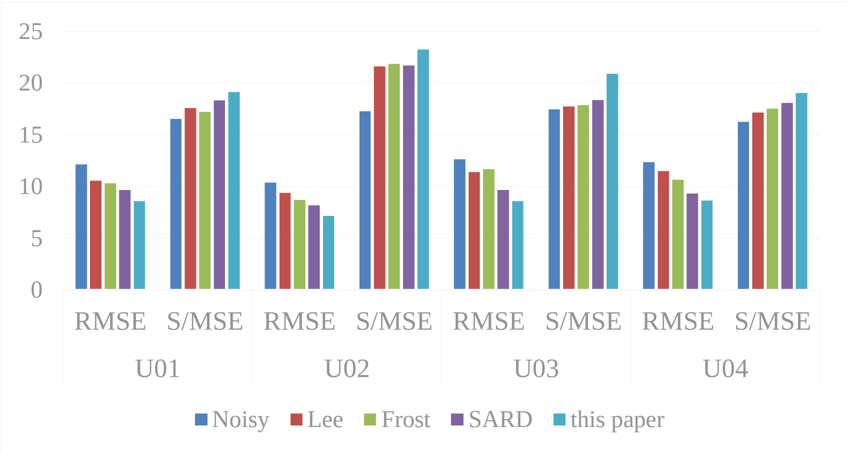


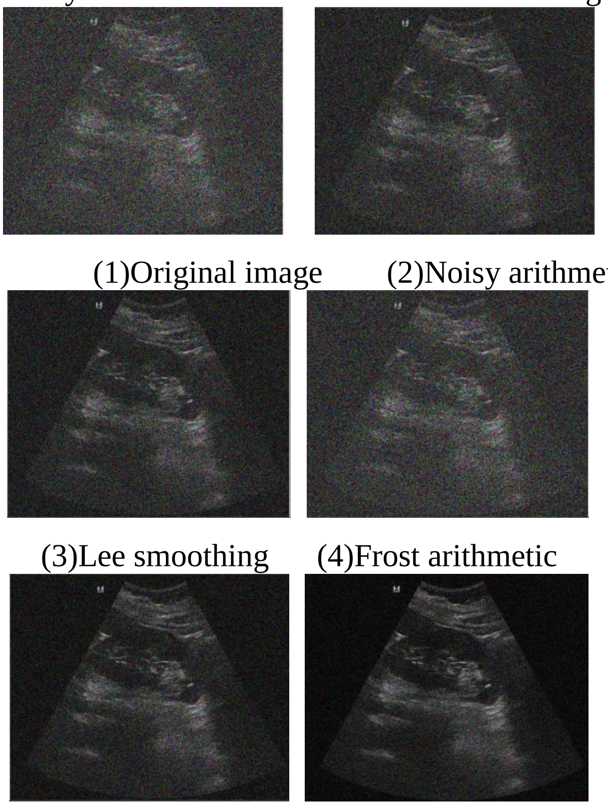
Figure 4. σ *=0.7 Histogram of values of* $RMSE$ *and* S/MSE *of various denoising methods under speckle noise level*

Figure 5. σ *=0.8 Histogram of values of* $RMSE$ *and* S/MSE *of various denoising methods under speckle noise level*

To sum up, while suppressing speckle noise, the anisodamy diffusion algorithm based on wavelet decomposition retains important details and edge features, achieves the best values of RMS and RMS ratio at any noise level, and presents the optimal visual effect.

4.2. Analysis of Simulation Image Experiment Results

In order to analyze the effectiveness of this algorithm more comprehensively and systematically, the real medical ultrasound images in this paper are clinical images provided by Nanjing Forensic Medical Examination Hospital, which have relatively strong research value. As clean ultrasonic images are difficult to obtain, real ultrasonic images of the kidney are used as experimental images in this paper for qualitative analysis from the de-noised visual effect images, as shown in Figure 6:



(1)Original image (2)Noisy arithmetic

(3)Lee smoothing (4)Frost arithmetic

(5)SARD arithmetic (6)In this paper arithmetic

Figure 6 Visual image denoising of real ultrasound image of kidney

The experimental results show that the traditional denoising method Lee filtering is based on the linear speckle noise model and the design method of the minimum mean square error, and damping convolution kernel Frost filtering is to use the index to keep the boundary of the region, the two algorithms are their respective defects, lead to $RMSE$ and S/MSE didn't reach the ideal value, the denoising effects are not obvious. SRAD is a filtering algorithm based on diffusion equation, while compared with the traditional spatial filtering has a better coherence plaque inhibition effect, but the defects existing in the algorithm the model itself, a diffusion equation cannot ensure existence and uniqueness to the choice of homogenous area with randomness, it seriously affected the noise reduction after image edges and details remain. The algorithm shows good denoising performance, which fully shows that the anisotropic diffusion algorithm based on wavelet decomposition can effectively suppress ultrasonic image speckle noise. Compared with other algorithms, the algorithm presented in this paper is always superior in terms of stability and denoising performance, and is an effective medical ultrasonic image denoising algorithm.

5. Conclusion

Compared with other imaging technologies, medical ultrasound imaging has been widely used in the field of medical diagnosis due to its advantages of relatively low cost, non-destructive and real-time imaging. Speckle noise is inevitably introduced in the acquisition of ultrasonic image data, which is caused by the influence of equipment or surrounding environmental factors during the formation of ultrasonic information. Noise will cause the quality of ultrasound image to decline, affecting the doctor's correct diagnosis and treatment. In order to improve the signal-to-noise ratio and stabilize the follow-up processing, it is necessary to denoise ultrasonic images. The detailed features of ultrasound images are important basis for doctors to diagnose and treat lesions. The algorithm proposed in this paper divides homogeneous regions and USES the improved SRAD algorithm to denoise, which improves the performance of the denoising algorithm.

In the acquisition and processing of medical ultrasonic images, the principle of wavelet transform, anisotropic diffusion denoising algorithm of wavelet decomposition and edge detection method are introduced. There are also Roberts edge detection operator, Canny edge detection operator, Sobel edge detection operator, Laplace edge detection operator and a variety of different diffusion algorithms. Aiming at the characteristic of medical ultrasonic image noise approximating gaussian distribution in logarithmic domain and introducing partial differential equation on the basis of wavelet transform, this paper presents an algorithm of ultrasonic image denoising based on anisotropic diffusion. The algorithm proposed in this paper divides homogeneous regions and USES the improved SRAD algorithm to denoise, which improves the performance of the denoising algorithm. Then the improved anisotropic diffusion algorithm is used to deal with the noise to improve the performance of the denoising algorithm. Finally, the two-dimensional discrete wavelet inverse transform and exponential transformation are carried out. Experimental results show that the algorithm proposed in this paper is always superior in both stability and performance of denoising algorithm, and it is an effective algorithm for medical ultrasonic image denoising.

The development of medical imaging technology promotes the improvement of clinical diagnosis in modern medicine. Among them, ultrasonic scanning has been widely used in the medical field for its advantages of cheap, simple, fast, non-invasive, non-radioactive, accurate, continuous dynamic and repeated scanning. The results of this paper can be used to improve the contrast between tissues and the overall sex noise ratio of the image, thus improving the image quality. In this paper, the study of anisovolumous diffusion denoising algorithm based on wavelet decomposition is still in the preparatory stage, and there is still a great room for improvement. Although this paper adopts a fidelity term in the algorithm to reduce the influence of iteration times on the algorithm, the influence of iteration times still exists, leading to the low speed of denoising algorithm! The next research content: how to improve the speed of denoising algorithm.

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