Comparison of Noise Removal Techniques for Ultrasound Images

Jia Wan, Yingnan Ma, Yizhou Zhao and Anup Basu
Department of Computing Science
University of Alberta, Canada

Abstract— **Ultrasound scanning is a very useful tool for medical diagnosis and treatments. However, it takes a long time to make appointments for ultrasound scanning in the hospital. This may result in unacceptable delays and missing the best time for treatments. To address this problem, portable ultrasound scanning devices have recently been introduced. Portable handheld ultrasound devices can promote widespread use of ultrasound scanning. However, the images scanned by a portable ultrasound scanner is relatively poor compared to standard ultrasound scanning systems. To improve the quality of the ultrasound images obtained from these portable ultrasound devices, we implement and compare four different methods to remove the noise in these ultrasound images. We also compared the performances to see which approach is more effective for different organs of the human body.**

Clinical relevance— **By implementing denoising techniques, the organs can be easily recognized from the ultrasound images, which can improve the accuracy for diagnosis.**

I. INTRODUCTION

Ultrasound scanning is a useful tool for medical diagnosis and treatments. However, the scanned images from a portable scanner is relatively poor in comparison to standard ultrasound scanning systems. Narrow vision [1] and relatively low penetration are two main factors causing this problem.

In recent years, different approaches have been implemented to solve the denoising problem in ultrasound images, such as filtering methods, decomposition methods and neural network. In our article, we implement both filtering methods and decomposition methods to solve the noise removal task for ultrasound images. We mainly focus on two parts of the human body, namely knuckles and heart.

In the next section we review related work. Following this,the proposed methods for noise reduction are outlined. Experimental results are described in Section 4, before future work and conclusions.

II. RELATED WORK

A. Filtering Methods

In recent years, different approaches have been implemented to solve the denoising problem in ultrasound images. Adaptive median filter [2] proposed by Loupas et al. [3] uses the ratio of mean to variance as a measure of how nearly uniform in value the pixels in an area are. Compared with the standard median filtering, the adaptive median filter performs better in preserving detail and smoothing non-impulsive noise.

In addition to the adaptive median filter, Bayes filtering can also solve the noise removal problem for medical ultrasound images. Achim [4] proposed a method based on Bayes filtering. The Bayesian rule [5] can be used for Bayesian signal estimation. First, they use a multi-resolution analysis employing the 2-D wavelet transform to decompose the logarithm of the image into several scales. Then, they decompose the image using the dyadic wavelet transform (DWT). The decomposed signal and noise components are respectively modelled as symmetric alpha-stable and Gaussian processes. Finally, a Bayesian processor is built at each scale for statistically optimal signal feature extraction and speckle suppression. Following the abovementioned steps, on each scale we can achieve a more accurate signal reconstruction.

B. Decomposition Method

In addition to the filter methods, the noise removal task in ultrasound images can also be solved by decomposition methods. Decomposition is an effective technique for image processing and video processing, which can be achieved by many methods, such as independent component analysis (ICA). To implement this approach, we need to assume that the signal follows the non-Gaussian distribution. Chawla [6] proposed a method that utilize the independent component analysis (ICA) method to separate noise from Electrocardiogram (ECG) [7] complex signals. In their algorithm they model noise as the independent component. The ICA method is also based on the PCA method. They utilize PCA to reduce the dimensions and feature extraction. PCA can analyze the sensitivity of the different ECG components so that the ICA algorithm can separate noise as an independent component from the principal component.

C. Neural Network Method

In addition to the filtering methods and decomposition methods, neural networks can also address the noise removal task. Sun [8] proposed an approach that combine ResNet with feature matching technique to denoise dual-stage images. First, they use residual learning denoising to obtain a denoised reference image. Then, by utilizing a multi-scale feature selection layer, the ResNet can be spread out to recover the image details based on the reference image and the original image. The feature matching step can promise the framework to generalize different collections of image content. This method can obtain promising results compared to state-of-the-art approaches.

III. PROPOSED METHODS

A. Median Filtering

The median filter is one of the most fundamental filters to achieve noise removal in ultrasound images. It is a nonlinear statistical method widely used to remove noise from images. It uses a 'sliding window' (mask) moving through the image pixel by pixel. The pixels of the mask are ranked by their gray levels, and the median value of the group is used to replace the center pixel value of the mask. The formula [9] of the median filter can be shown as:

$$g(x,y)\& = med\{f(x-i,y-j), i,j \in W\} \tag{1}$$

In this formula, g(x,y) represents the output image, and f(x,y) represents the original image. W is the 2-dimensional mask with size n x n. This n can be 3 or 5 or any other number; but it is usually an odd number. There are many choices for the shape of the mask. It can be a square, a rectangle, a circle or any other shape. We select median filtering as one of our proposed methods and use the denoised images generated from it as a reference.

B. Fuzzy Image Filter Method

The fuzzy image filter [10] is a smoothing technique that depends on local image characteristics. It is a low pass filter since the general idea is to average a pixel using its neighbouring pixels. While processing each pixel on the image, it first estimates the "fuzzy derivatives", which are 8 derivatives for 1 pixel. Then, it uses 16 rules to compute the correction term, which is eventually added to the pixel being processed. There are two rules for each fuzzy derivative. To perform the above computations, three fuzzy sets are used to represent the derivative's properties: small, positive, and negative. We assume that large derivatives are due to image structures such as edges. And small derivatives are due to noise. Therefore, we use a small fuzzy set to represent how "small" this derivative is.

We use derivatives to determine changes between pixels. However, it is difficult to determine if a change in an image is due to noise or due to image structures such as edges. The fuzzy image filter is proposed to take local image structure into account. For each pixel, we compute the derivatives w.r.t each direction as shown in Fig.1, this gives us 8 directions in total.

NW	*N*	*NE*
W	*(x,y)*	*E*
SW	*S*	*SE*

Fig. 1: Directions of derivatives.

As an example, for pixel (x,y), we need to compute the derivatives w.r.t to all its neighbours. For direction NE, which is at the location $(x+1,y-1)$, the derivative would be given by the difference:

$$\nabla_{NE}(x,y)\& = I(x+1,y-1) - I(x,y) \tag{2}$$

Here, we will need to use a fuzzy set small enough to determine if this derivative is "small". The membership function of small is:

$$m_K(u) = \begin{cases} 1 - \frac{|u|}{K}, \&0 \leq | u | \leq K \\ 0\& \mid u \mid \geq K \end{cases} \tag{3}$$

Where K is an adaptive parameter. To compute the fuzzy derivative of pixel (x, y) w.r.t direction NE, $\nabla^F_{NE}(x,y)$, we apply the rules:

- if $\nabla_{NE}(x,y)$ is small AND $\nabla_{NE}(x-1,y-1)$ is small, then $\nabla^F_{NE}(x,y)$ is small.
- if $\nabla_{NE}(x,y)$ is small AND $\nabla_{NE}(x+1,y+1)$ is small, then $\nabla^F_{NE}(x,y)$ is small.
- if $\nabla_{NE}(x+1,y+1)$ is small AND $\nabla_{NE}(x-1,y-1)$ is small, then $\nabla^F_{NE}(x,y)$ is small.

To smooth out noise, we compute the correction term using the fuzzy derivatives we have computed. The idea is that if the fuzzy derivative is small (no edges presented), then we will use the crisp derivative $\nabla_{NE}(x,y)$ to compute the correction term. Two fuzzy rules are applied:

- λ^+_{NW} : if $\nabla^F_{NW}(x,y)$ is small AND $\nabla_{NW}(x,y)$ is positive, then c is positive.
- λ^-_{NW} : if $\nabla^F_{NW}(x,y)$ is small AND $\nabla_{NW}(x,y)$ is negative, then c is negative.

Finally, the correction term is given by the sum of derivatives in all eight directions.

C. PCA Method

In addition to the above filtering methods, we can also implement decomposition methods to solve the noise removal task for ultrasound images. In this work, we implement the principal component analysis (PCA) method to achieve noise removal. We employ an adaptation of PCA for Gaussian noise by calculating eigenvalues and eigenvectors. After obtaining the sparse and low-rank information, we implement decomposition. Mathematically, the decomposition step [11] can be shown as :

$$F = L + S \tag{4}$$

In this formula, F represents the entire information of the images. L stands for low-rank information, which is the principal component of the image. S represents the sparse component, which is the noise in the image.

D. RPCA Method

Similar to the PCA method, robust principal component analysis (RPCA) decomposes the ultrasound images into two components, a low-rank component (L) and a sparse component (S). In ultrasound images, important image features are modelled as low-rank information because important image features correspond to large singular values so that their magnitude can be maintained after the decomposition. The noise refers to the granular patterns that occur in ultrasound images due to wave interference, and noise is modelled as sparse information because the noise corresponds to the smallest singular values [12] and should be removed simply. To capture L and S, RPCA is utilized [13], [14], [15], which focuses on minimizing the nuclear norm $\|L\|_*$ of the low-rank matrix and the $\ell 1$-norm $\|S\|_1$ of the sparse matrix. Mathematically, the objective function is represented as:

$$\arg\min_{L,S} \|L\|_* + \lambda \|S\|_1 \qquad (\text{subject to } F = L + S) \tag{5}$$

For completeness, we briefly introduced the procedure to estimate L and S. The minimizing procedure is devised as an iterative process, which can be shown as:

$$L_{k+1} = \mathscr{D}_{1/\mu}(M - S_k + \mu^{-1} G_k) \tag{6}$$

$$S_{k+1} = \mathscr{S}_{\lambda/\mu}(M - L_k + \mu^{-1} G_k) \tag{7}$$

where $\mathscr{D}_{1/\mu}$ denotes the singular value thresholding operator and $\mathscr{S}_{\lambda/\mu}$ denotes the shrinkage operator [**?**]. Following the ALM algorithm, we update the Lagrange multiplier matrix G using:

$$G_{k+1} = G_k + \mu(M - L_{k+1} - S_{k+1}). \tag{8}$$

With the iterations of updating low-rank matrix, sparse matrix and Lagrange multiplier matrix, the penalty function can converge to some tolerance threshold or reach the maximum number iterations, in which case the final low-rank matrix is captured.

IV. Experimental Results

A. Data

The image data we used were collected using the Clarius L7-Linear Portable Ultrasound Scanner. We selected ultrasound images from different parts of the human body; namely, the human heart and knuckles. Due to the limitation of the scanner, the quality of the ultrasound images was poor, and contained plenty of noise.

B. Evaluation

Since there was no ground truth for the ultrasound images we collected, we evaluated the performance of our proposed methods utilizing a user study. For the user study, we randomly picked 25 computing science students from the university with background knowledge in denoising techniques. Each student ranked four methods with scores ranging from 1 to 4. Specifically, the best performance was evaluated as 4, the worst performance was given a score of 1. We took the sum of all the marks from 25 students as the overall score for each method in the subjective evaluation.

The key point of the evaluation is that we need to observe both denoising performance and the preservation of the key features in an image to decide the overall performance of different proposed approaches.

C. Performance and Comparison

In this work, we implemented two kinds of methods to achieve noise removal for ultrasound images. We separately demonstrate the performance of our proposed methods for ultrasound images with different body parts in Fig.2. The differences among the proposed methods can be clearly observed.

We also compared the performance of our proposed methods according to the user study described above. The evaluation results of the user study is summarized in TABLE 1.

TABLE I: User Study Results for Comparison

Data	**Median Filter**	**Fuzzy Image Filter**	**PCA**	**RPCA**
Knuckles	77	51	31	91
Heart	68	67	26	89

By observing the results, we can see that the RPCA method has the best performance when processing knuckle ultrasound images. The RPCA denoised image looks most smooth among the four proposed methods, especially around the middle area of the image. Due to the iterations of the RPCA method, the final converged result is much more convincing than the PCA method. Observing the PCA result image, it is hard to recognize the difference between the PCA results and the original image. Therefore, the PCA method has the worst denoising performance among four proposed methods. In addition to the decomposition methods, some filtering methods also obtain acceptable performance. According to the results, the fuzzy image filter method can remove noise in the ultrasound image and maintain the important features of the image. However, the median filtering method achieves better denoising performance than fuzzy image filtering because the results appear more smooth.

For human heart ultrasound images, the RPCA method again performs the best among the four proposed methods. The result of the RPCA method looks smooth and important features of the image are mostly preserved. Compared to the RPCA method, the fuzzy image filtering method also performs acceptably with the removal of the noise and the preservation of the key image features. The result of the median filter method is more smooth than the fuzzy image filter. However, the median filter obscures certain pixels, which leads to the loss of some image key features. Therefore, the overall results of user study for both filter results are similar. PCA method performs the worst among these proposed approaches. It is still hard to observe the difference between the original image and the PCA denoised image.

Future Work

Due to the limitation of the setup used in capturing ultrasound images, we could not obtain the ground truth for testing denoising performances. Therefore, we compared the performances of the proposed methods utilizing subjective evaluations. In the future, we will work on the measurement

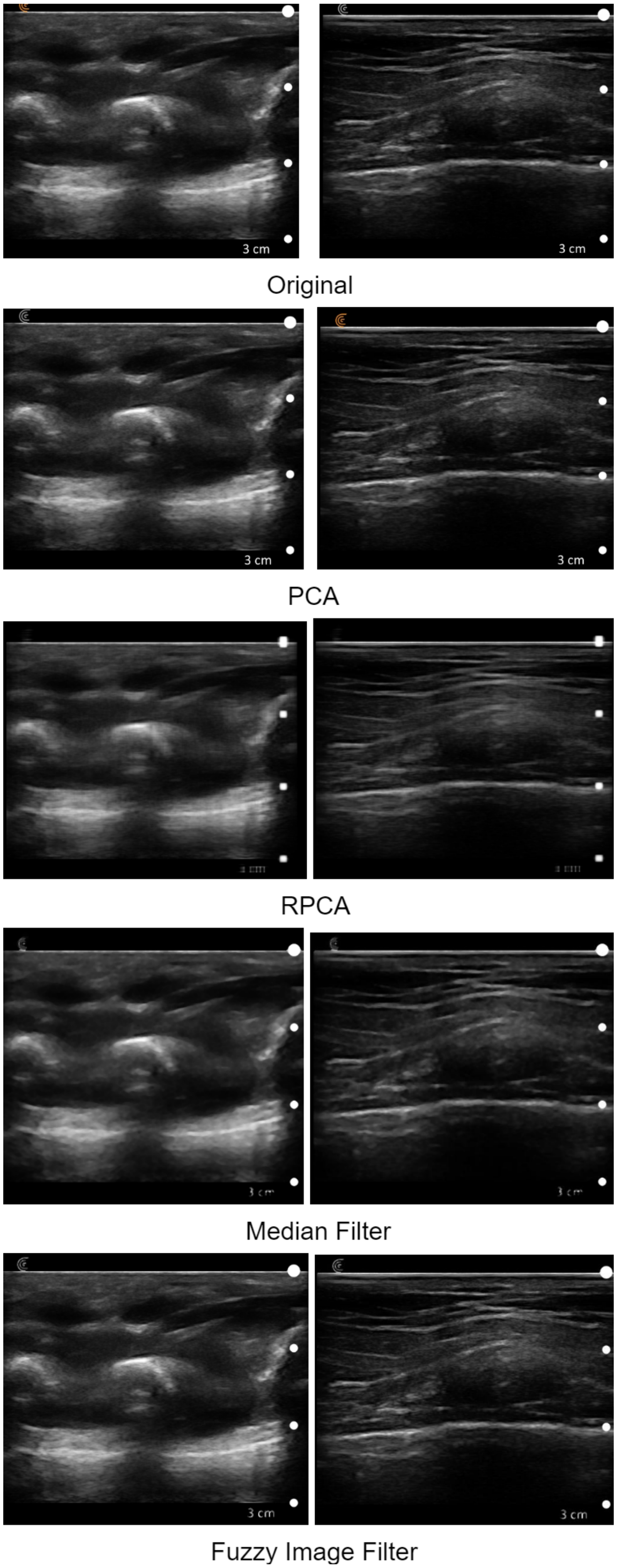

Fig. 2: Images for knuckles (left) and heart (right) for different noise removal methods.

of the denoising task for ultrasound images without ground truth so that the evaluation of performances would be more accurate.

Conclusion

In this paper, we proposed using median filtering, fuzzy image filtering, the PCA and RPCA methods for noise removal on poor quality ultrasound images related to knuckles and hearts. We compared these four different methods for ultrasound image noise removal for a portable device. We found that the RPCA method has better performance than the other three methods in most cases.

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