A Novel Despeckling Approach for Ultrasound Images Using Adaptive OBNLM Filter

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Abstract. The Optimize Bayesian Non-Local Mean Filter (OBNLM) provides a very strong tool for despeckling in Ultrasound. However, some parameters of this filter depend on the input (noise) and they are difficult to adjust. This article generates a denoising solution using the adaptive OBNLM filter in combination with the Binary Bat Algorithm (BBA) and on the no-reference Q-Metric (BBA-OBNLM). The proposed filter can despeckle noise without the need for reference images and still keep the image details, edges and textures in good condition. Furthermore, in this article, we have also carried out some simulations with images which are added speckle noise with different variances to demonstrate the performance of the proposed method superior to previous publications.

Keywords: Ultrasound image · Speckle noise · OBNLM filter
Q-Metric · BBA

1 Introduction

Ultrasound is a medical imaging technique that uses high frequency sound waves and reflected waves. This is a widely used clinical diagnostic technique thanks to its mobility, low cost and safety as it does not require ionizing radiation [1]. The biggest downside of medical ultrasound is its poor picture quality, mainly due to the noise in the process of image processing and recovery.

The non-local means filter (NLM) method proposed by Buades et al. [2] is a denoising algorithm that takes the mean value of all pixels within a given region measured by the similarity of adjacent pixels to the target pixel [3]. Compared with conventional filters, NLM exhibits higher clarity while preserving the finer details of the image. This technique is very powerful and well suited for Gaussian noise model [3].

In diagnostic ultrasound, speckle noise is a major component affecting image quality [4]. In the article [5], Coupe et al. proposed a despeckling method named Optimized Bayesian Nonlocal Means (OBNLM) for ultrasonic images, which is inspired by NLM techniques, to remove speckle noise in ultrasound images. The OBNLM filter possesses two major changes. On the one hand, replacing the original image patches with a blockwise approach contributes to lowering the computational level. On the other hand, Pearson distance is used to compare statistical measures between image patches. The results in [5] show that OBNLM performs better

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when compared to conventional noise filters. Parameters for this filter should be selected for each type of input images with different levels of noise. However, according to the presentation of Coupe et al. [5], the selection of parameters for this filter is subjective and experience-based.

Recently, such nature-derived optimization algorithms as Genetic Algorithm-GA, Particle Swarm Optimization-PSO, and Bat Algorithm Optimization-BA have been proven to be more flexible and better than traditional optimization techniques. The Binary Bat algorithm (BBA) [6] presented in 2013 is considered to be one of the most powerful optimization tools, which is proposed based on the BA algorithm to solve other optimization problems in the discrete search space. The paper [7] successfully proposed the BBA-NLM filter adopting the NLM algorithm combined with the BBA optimization algorithm using the Q-Metric.

Objective image quality metrics can be divided into two main categories: full-reference and no-reference. Some full-reference metrics which include the classical mean-squared error (MSE) and the structural similarity (SSIM) have been widely used in the image processing field. However, since these metrics basically measure the similarity between the target and reference images instead of *real* image quality, they can hardly be employed in situations where the reference image is not available. Such problems are what the Q-Metric (Quality Metrics) defines to solve [8, 9].

This article will propose a new filter, BBA-OBNLM, which is created by combining the BBA optimization algorithm with the OBNLM algorithm using the Q-Metric to despeckle ultrasound images. The results show that the proposed filter can eliminate speckle noise without using reference images, while it still achieves the best results. The models and experiment results will be shown in the next section of the article.

2 Proposed Despeckling Approach

2.1 Proposed Despeckling Model

The proposed despeckling model is shown in Fig. 1. Noisy images are directly filtered by OBNLM. Then, Q-metrics of the filtered images are measured and used to optimize the parameters of OBNLM filter based BBA Parameter update block.

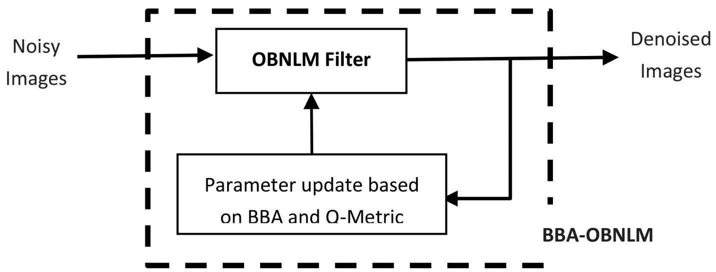

Fig. 1. Proposed despeckling model based on OBNLM, BBA, and Q-Metric

The basic principle of the OBNLM filter has been introduced in [5]. Let us consider a 2D gray-scale noisy image: $u = (u(x_i))_{x_i \in \Omega^2}$ defined over a bounded domain $\Omega^2 \subset \mathbb{R}^2$ and $u(x_i) \in \mathbb{R}_+$ is the noisy observed intensity at pixel $x_i \in \Omega^2$.

The standard NLM filter presented in [2, 10, 11] can be considered as a pixelwise filter, the restored intensity $NL(u)(x_i)$ of pixel x_i, is the weighted average of all the pixel intensities $u(x_i)$ in the image Ω^2.

As presented in [12], a blockwise implementation of the proposed *NLM*-based speckle filter is able to decrease the computational burden. The parameters: k and d are the search window and the patch window size coefficients, h is the degree of the filter.

Firstly, a search area of size $(2k+1)^2$ is formed which is centered at the current pixel x_i. The image is divided into blocks with overlapping supports of size $P = (2d+1)^2$. The block B_{i_k} is restored according to the equations described below:

$$NL(u)(B_{i_k}) = \sum_{B_j \in \Delta_{i_k}} \mathrm{w}(B_{i_k}, B_j) u(B_j) \tag{1}$$

With:

$$\mathrm{w}(B_{i_k}, B_j) = \frac{1}{Z_{i_k}} \exp\left(- \frac{\left\| u(B_{i_k}) - u(B_j) \right\|_2^2}{h^2} \right) \tag{2}$$

Where $u(B_i) = \left(u^{(1)}(B_i), \ldots, u^{(P)}(B_i)\right)^T$ is an image patch gathering the intensities of the block B_i, Z_{i_k} is a normalization constant ensuring $\sum_{B_j \in \Delta_{i_k}} \mathrm{w}(B_{i_k}, B_j) = 1$.

The construction of the BBA optimization algorithm using the no-reference Q-Metric objective function has been described in details in [7]. Initializing bat population: pulse rate $r_i = 0.5$, loudness $A_i = 0.5$, pulse frequency is in the range of $[0, 2]$, the number of array elements $n = 10$ and maximum number of iterations $k_{\max} = 100$.

2.2 Simulation Scenarios

Simulation model was constructed with two different input images which were taken into the proposed filter model. First, image 1 (Fig. 3) is a Phantom-sized simulation image (256 × 256) which was created from a Matlab function. Image 2 (Fig. 4) is a “Liver” clinical liver ultrasound image (256 × 256) which was taken from the website ‘google.com’. Speckle Noise was randomly added to these images with the variance of 0.2, 0.4 and 0.8 respectively. Then, these images with added speckle noise were applied to the BBA-OBNLM filter, where the parameters of the filter are optimized by the BBA optimization algorithm using the Q-Metric. The image quality of restoration is proportional to the objective function, the larger the Q, the better the position of the bat. The Monte Carlo simulation method is used to evaluate the convergence of the objective function. To assess the effectiveness of the non-reference method using the Q-index, the MSE value of the recovery images from the filters was also calculated to compare with the non-interfering input images of the traditional reference image quality assessment methods. In addition, different spatial filters were also utilized to compare the results with the proposed filter.

The parameters for the fixed filter are chosen according to the description in article [5], specifically, corresponding to $\sigma = \{0.2, 0.4, 0.8\}$, we choose $h = \{12, 14, 16\}$ for the OBNLM filter and $h = \{13, 25, 30\}$ for the standard NLM filter. The window parameters with $k = 6$, $d = 5$ or $d = 11$ are also well chosen for each input image.

2.3 Convergence of BBA-OBNLM

The convergence curve of BBA-OBNLM filter is shown in Fig. 2. As can be seen clearly, BBA-OBNLM nearly converges after 30 iterations. In other words, Q does not change much after 30 iterations); even from the 20th repeat, the increase in Q-Metric value is negligible. Therefore, the use of Monte Carlo strategies for selecting and setting parameter values which are listed above in the experiments is reasonable.

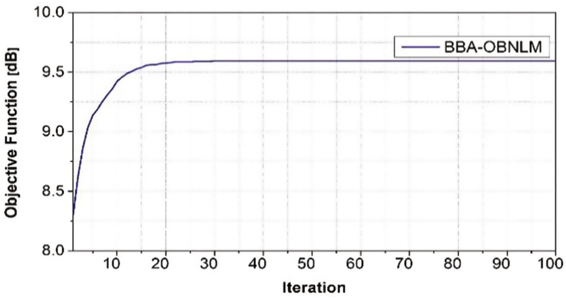

Fig. 2. Objective curve of BBA-OBNLM

2.4 Capability of the Proposed Filter

Figures 3 and 4 visually show the "Phantom" and "Liver" images with the proposed BBA-OBNLM filter. Among the images, Image (a) is the original image without noise, Image (b) shows the image after noise which is randomly added at 03 different levels of noise $\sigma = \{0.2, 0.4, 0.8\}$. Image (c) is the image after being filtered by the proposed filter. The results show that the images after being filtered have better results than noisy images and they are nearly the same as the original image. These results will be evidenced by the specific data in the next section.

2.5 Comparison of the Proposed Filter and Others

Table 1 lists the MSE values of the different filters with the input images as clinical ultrasound images with 0.2, 0.4 and 0.8 noise variances. Simulation results show that, with the same input image, the output image quality of the OBNLM filter using the proposed parameter sets is much better than using this filter. The fixed numbers were proposed by Coupe et al. [5]. Compared with conventional filters, the filter efficiency of images using the BBA-OBNLM technique also shows a clear difference.

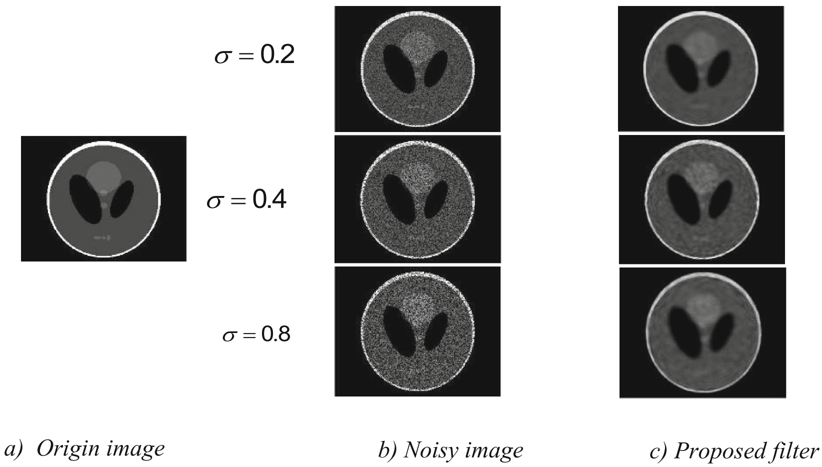

Fig. 3. Despeckling results for simulation “Phantom” in Matlab

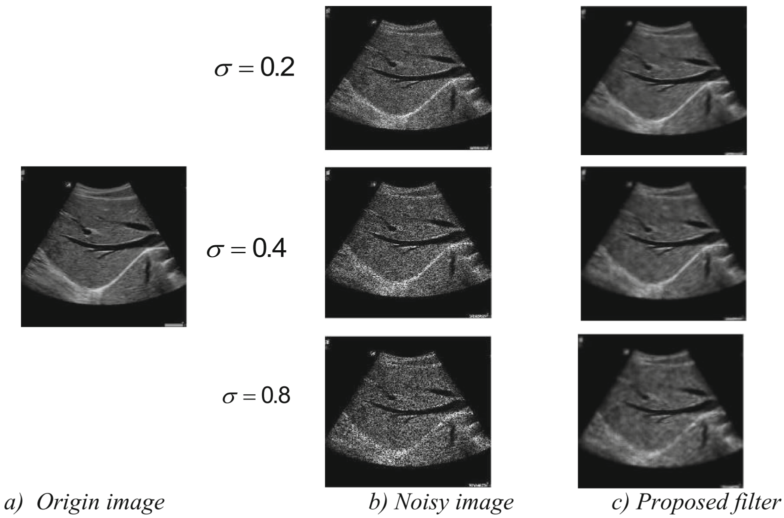

Fig. 4. Despeckling results for clinical ultrasonography images “Liver”

2.6 Q-Metric and MSE Value of BBA-OBNLM

Table 2 illustrates the correlation between the maximum value of the Q-Metric achieved and the MSE corresponding to the clinical ultrasonic images of the Liver after the first 20 repeats. The results show that Q-Metric values accurately reflect the filter efficiency when compared to MSE. Note that the Q-Metric value is as high as possible and MSE value is as low as possible. This confirms that the use of the Q-Metric index as the objective for the optimizer is greatly significant in real time image processing but the results are still accurate compared to other norms.

Table 1. Comparison of Q-Metric and MSE of liver ultrasonography with different variances of speckle and repeats.

TT	$\sigma = 0.2$		$\sigma = 0.4$		$\sigma = 0.8$	
	MSE	Q	MSE	Q	MSE	Q
1	58.774	9.6056	84.514	7.6662	110.3038	6.3954
2	58.5825	9.7146	84.514	7.6662	110.9005	6.3928
3	58.5825	9.7146	86.2595	7.5344	110.3038	6.3954
4	58.774	9.6056	84.514	7.6662	110.9005	6.3928
5	60.0151	9.4742	84.514	7.6662	110.3038	6.3954
6	64.7431	9.0979	86.2595	7.5344	110.3038	6.3954
7	60.1795	9.5895	84.514	7.6662	110.9005	6.3928
8	58.774	9.6056	86.2595	7.5344	110.3038	6.3954
9	60.1795	9.5895	84.514	7.6662	110.3038	6.3954
10	59.2146	9.5388	84.514	7.6662	110.3038	6.3954

Table 2. Compares the MSE of the proposed filter with other spatial filters of each input image type

Images/Filters	Phantom			Liver		
	$\sigma = 0.2$	$\sigma = 0.4$	$\sigma = 0.8$	$\sigma = 0.2$	$\sigma = 0.4$	$\sigma = 0.8$
None	506.5069	1014.5351	1570.1275	399.4280	774.4193	1324.9017
Gauss	466.8221	677.2061	874.9475	141.1692	235.0573	375.9500
Mean	414.8427	577.7806	725.8308	78.7999	120.9072	183.7127
Median	326.7304	635.0758	982.4875	137.1829	233.6147	433.1374
Adp Median	438.3760	605.708	917.7133	147.7121	184.4294	249.7403
Lee	414.7970	577.7900	725.7935	78.7537	120.8690	183.6366
Kuan	414.8427	577.7806	728.8074	79.0805	120.8827	184.2796
Wiener	408.8918	577.7806	725.8308	80.6594	121.1346	188.9100
NLM	293.3523	465.8922	767.2844	133.9355	144.5427	167.4009
OBNLM	285.1389	429.9685	726.8359	104.9164	111.3376	121.4800
Proposal	**256.3811**	**403.9809**	**630.4527**	**56.8342**	**81.1162**	**109.48**

3 Conclusion

This paper aims to propose a despeckling approach for ultrasound images. The proposal is based on adaptive OBNLM, in which its parameters have been adaptively adjusted by BBA optimization algorithm and Q-metric fitness function. The proposed filter is able to despeckle the ultrasound images without reference. In order to show the performance of the proposal, two simulation scenarios have been carried out. The results show that the proposed filter is capable of despeckling while preserving the edge of the ultrasound images. In addition, compared with various traditional filters as well as OBNLM filter, the proposed filter is more efficient in terms of Q-metric and MSE value.

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