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Enhanced Switching Median Filter For Denoising Ultrasound

J. Alavandan*
Associate Professor & Head,
Dept of Computer Science & Applications,
Jawahar Science College,
Neyveli, Tamilnadu, India
alaneyveli@gmail.com

Lt.Dr.S.Santhosh Baboo
Reader,
Postgraduate & Research Department of Computer Science, Dwaraka Doss Goverdhan Doss Vaishnav College,
Chennai, India
santhos2001@sify.com

Abstract: Sonar imaging technology is a field that is used in the study of seafloor through the study of high resolution images provided by sonar devices. 2D imaging sonar also referred to as Acoustic cameras, which can be operated from both moving and stationary positions, are used to capture the oceanic images. Imperfect acquisition and transmission errors often distort the signals obtained and as a result, distortion, commonly referred to as "noise", appears. These unwanted signals have to be removed to improve the quality of the image. Sonar images are often affected by 'Salt-and-Pepper' noise. In this paper, a 2-step procedure is used during denoising. The first stage detects noisy regions and the second stage uses enhanced switching median filter to remove the noise. The proposed algorithm was evaluated using metrics like Peak Signal to Noise Ratio, Figure of Merit, Mean Structural Similarity Index and Speed of denoising. The various experiments showed that the performance of the proposed algorithm is efficient in terms of speed of denoising, removal of noise, preservation of edge and structural details.

Keywords: Pre-processing, Salt and Pepper Noise, Sonar Image, Switching Median Filter.

I. INTRODUCTION

Sonar imaging technology is a field that is used in the study of seafloor through the study of high resolution images provided by sonar devices. The two-dimensional imaging sonar also referred to as Acoustic cameras, which can be operated from both moving and stationary positions, are used to capture the oceanic images. As underwater environments are dynamic and complex, obtaining a clear picture of the obstacles and movements of objects in this environment is critical and challenging. The study of sonar images are performed by Sonar imaging systems and consist of techniques for efficient analysis and understanding of the water surface of the Earth. However, imperfect acquisition and transmission errors often distort the signals obtained and as a result, distortion, commonly referred to as "noise", appears. These unwanted signals have to be removed to improve the quality of the image. The techniques used to remove noise are termed as "Image Denoising", which is a well-studied problem in computer vision for natural images. The field is still in infantry stage where sonar imaging is concerned. It is the most sought after tool by the image analysts in the fast-growing field, as noisy images often lead to incorrect interpretation.

Sonar images suffer from a special kind of noise called Salt and Pepper noise [1]. Salt and pepper represents itself as randomly occurring white and black pixels. Salt and pepper noise creeps into images in situations where quick transients, such as faulty switching, take place. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. An effective noise reduction method for this type of noise involves the usage of a median filter, morphological filter or a contra harmonic mean filter. Presence of noise degrades spatial and contrast resolution and obscures the underlying structure of an image. Further, it has a negative impact on sonar imaging whose presence shows a reduction of surface detectability of approximately a factor of eight [2]. This radical reduction in contrast resolution prevents automatic object recognition and texture analysis algorithm to perform efficiently and gives the image a grainy appearance. Hence, despeckling is considered as a critical pre-processing step by many sonar imaging systems and underwater detection systems.

The main objective of this paper is to remove the salt and noise in sonar images. To achieve this objective, a directional switching median filter [3] is considered. This model, referred to as 'Base Model' in this paper, has the drawback of excessive smoothening while removing noise. In order to solve this problem and to improve the visual quality of the image this paper modifies the Base Model to use an adaptive switching concept which switches to removal of noise only when noisy regions are encountered. The proposed method has the advantage of being fast while maintaining the significant details of the original image. The rest of the paper is organized as follows. Section II provides a brief study on the existing denoising methods. Section III presents the proposed methodology and the results of the various experiments are presented in Section IV. The conclusion along with future research directions are presented in Section V.

II. LITERATURE STUDY

Denoising algorithms for salt and pepper noise detection and removal is an area of research work that has attracted many researchers [4], [5] and [6]. Among the various proposed methods, the median filter [1] is one of the most commonly used non-linear filters. It has already been established that median filters are more efficient in removing salt and pepper noise and are computationally inexpensive algorithms. However, it also has the drawback of smearing detailed regions like edges of the original image. Several methods have been proposed to solve this problem and they include adaptive filter [7] and [8], multistate median filter [9], weighted median filter [10] and switching median filters [11]. Vector directional filters uses directional image vectors during denoising [12]. Variations to vector directional filters are the weighted vector direction filter which implement a tracking algorithm to identify the varying signal and noise statistics. Peer Group Filters (PGF) that uses statistical properties of accumulated distances for vector median filtering has also been proposed [13]. This algorithm switches between vector median and the original central pixel. [14] and [15] proposed methods which first identified the noisy pixels and then replaced them by using the median filters or its variants. The other pixels are left unchanged.

This method had the disadvantage that the noise pixel replacement procedure only considered its neighbouring pixels and did not consider the presence of edges. To avoid smearing in detailed regions, the Switching median filter was modified to include a center weighted median filter [1] which used two thresholds to make the decision of replacement. The work of [16] improved the work of center weighted median filter by including more threshold values. Similarly, [17] used a Laplacian edge detector and the detected edges were preserved during noise removal.[3] proposed a rank-order based switching median filter to solve the problems posed by threshold selection. This work is enhanced in this paper to include an adaptive center-weighted median filter, edge preservation step and using a noise detection algorithm to improve visual quality.

III. PROPOSED METHODOLOGY

The proposed denoising method consists of two major steps, namely,

(i) Noise detection

(ii) Removal of Noise

The procedures used by both these steps are detailed below.

A. Noise Detection:

The noise detection procedure first separates the input image into two segments. The first segment has all noise pixels and the second segment has all noise free pixels. Let I be the input image. Divide the image into equal sized blocks (3 x 3 considered in this paper). For each block, with the centre pixel as focus, calculate Pixel Strength and angular measures using the 8 surrounding pixels. These values combined to two threshold values (T1 and T2) calculated using the method proposed by [18] are used during the identification of noise and noise free pixels. Let B be the current block with C_{ij} as centre pixel. Create a vector, P_B using the intensity values of the 8 surrounding pixels. The eight surround pixels are identified as NW (NorthWest), N (North), NE (NorthEast), W (West), E (East), SW (SouthWest), S (South), SE (SouthEast) (Figure 1).

NW	N	NE
W	C	E
SW	S	SE

Figure 1: 3 x 3 Block with 8 pixel positions

Using the vector P_B, the Pixel Strength Measure is calculated as follows:

$$\text{Pixel Strength Measure } (PSM_{\mathbf{B}}) = |\text{Intensity}(C_{ij}) - \text{Intensity}(P_{ij})| \quad (1)$$

where B is the current block and P_k is the k^{th} element in vector P having the 7 brightness values of the surrounding pixels.

Similarly, the Pixel Angular Distance Measure ($PADM_{\mathbf{B}}$) is calculated using Equation (2).

$$\text{Pixel Angular Distance Measure } (PADM_{\mathbf{B}}) = \arccos\left(\frac{C_{ij}P_{ij}}{\sqrt{C_{ij}^{2}}\sqrt{P_{ij}^{2}}}\right) \quad (2)$$

The next step identifies the minimum of PSM_B and $PADM_B$. Let this be Min_PSM_B and Min_PADM_B. A pixel is considered noisy or noise free according to Equation (3).

$$= \begin{cases} Noisy & if\ \text{Min\_PSM}_{B} < T_1 \ \&\&\ \text{Min\_PADM}_{B} < T2 \\ Noise\ \text{Free} & Otherwise \end{cases} \quad (3)$$

Using the above result, a binary image is created where a value 0 identifies noise free pixel and 1 identifies a noisy pixel.

B. Removal of Noise:

Using the binary image constructed in the above step, a Switching Median Filter (SMF) is enhanced to remove salt and pepper noise in the sonar images. In this paper, an Adaptive SMF (ASMF) is used. The steps in AMSF are given below.

Step 1: Determine initial window size, L, using Equation (4) where ND is the noise density.

$$L = \begin{cases} ND \le 40 & 1 \\ 41 \le ND < 60 & 2 \\ ND \ge 61 & 3 \end{cases} \quad (4)$$

Step 2: This step starts by dividing both the noisy image X and its corresponding binary image B into (2L+1 x 2L+1) sliding windows

Step 3: Calculate the total number of pixels (N) number of noisy pixels (NN) and number of noise free pixels (NF) in the current filtering window of X using the binary image created in previous section.

Step 4: Repeat Step 4a until NF > ½(L x L)

Step 4a : Extend window size by 1 on all the four sides.

Step 5: Replace noisy pixel with the median of noiseless pixels.

IV. EXPERIMENTAL RESULTS

Several experiments were conducted to evaluate the proposed model. The performance metrics used are (i) Peak Signal to Noise Ratio (PSNR) (ii) Figure of Merit (FoM) and (iii) Fusion Speed. PSNR is a quality measurement between the original and the fused image. The higher the PSNR the better the quality of the reconstructed image. To compute PSNR, the block first calculates the Mean-Squared Error (MSE) and then the PSNR (Equation 5).

$$\text{PSNR} = 10\log_{10}\left[\frac{R^2}{\text{MSE}}\right] \qquad (5)$$

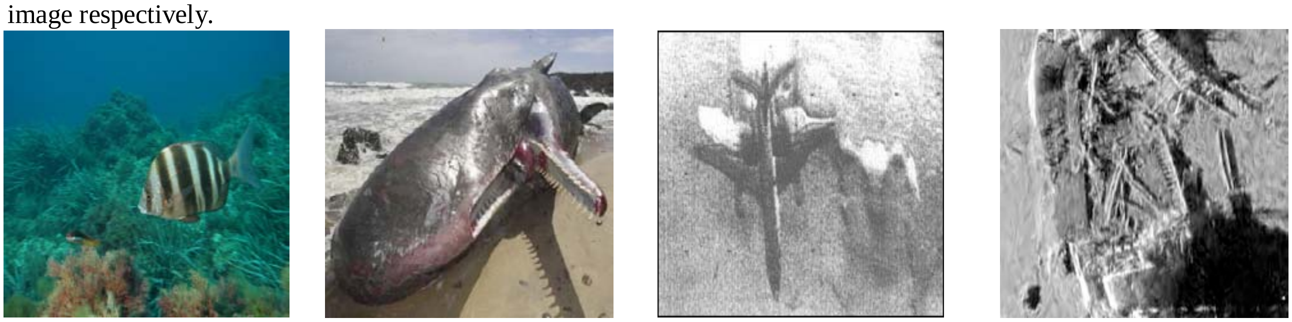
where $\text{MSE} = \dfrac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M*N}$ where M and N, m and n are number of rows and columns in the input and output image respectively.

To compare edge preservation performances of different denoising schemes, the Pratt's Figure of Merit (FoM) [19] is adopted and is defined by Equation 6.

$$FoM = \frac{1}{\max\{\hat{N}, N_{ideal}\}} \sum_{i=1}^{\hat{N}} \frac{1}{1 + d_i^2 \alpha} \qquad (6)$$

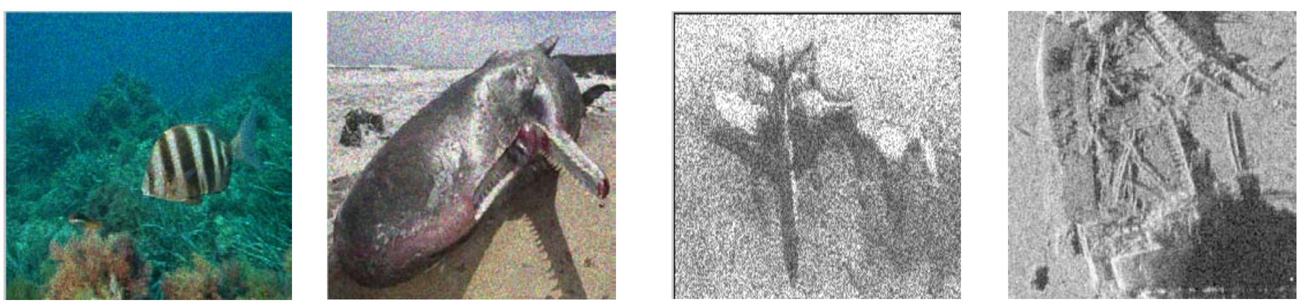
where $\hat{N}$ and N_{ideal} are the number of detected and ideal edge pixels, respectively, d_i is the Euclidean distance between the i^{th} detected edge pixel and the nearest ideal edge pixel, and α is a constant typically set to 1/9. FoM ranges between 0 and 1, with unity for ideal edge detection.

Denoising speed denotes the time taken for the algorithm to perform the fusion procedure and construct the enhanced version of the image. Several images were used to test the proposed model. The results projected in this section use the four test images shown in Figure 2.



Sonar 1 **Sonar 2** **Sonar 3** **Sonar 4**

(a) Original Images



NS1 **NS2** **NS3** **NS4**

(b) Noisy Images

Figure 2: Test Images

The PSNR values obtained for the proposed and Base Models are shown in Table I. The proposed algorithm is also compared with its traditional counterpart SMF.

Table I: PSNR (dB)

Algorithm Used	**NS1**	**NS2**	**NS3**	**NS4**
SMF	35.91	37.43	36.64	34.26
Base Model	37.66	39.23	36.98	36.22
Proposed Model	41.23	43.51	40.67	40.06

According to the report of [20], a PSNR value in the range 30-45 indicates that the resultant image is a very good match to the original image. In accordance with this report, the results of all the three algorithms produce PSNR values in the range 34-45dB proving that all produce good quality images. However, comparing the performance of the three algorithms, the PSNR of the proposed model is higher than the traditional SMF and base models, indicating that it is an improved version of the base and traditional models. On average, SMF produced images with 36.06dB, Base model produced images with 37.52dB and the proposed model produced images with 41.37dB. The proposed model that shows a performance gain of 9.29% and 12.83% with Base and SMF models respectively.

The Pratt's Figure of Merit (FoM) obtained for the test images are shown in Table II.

Table II: FoM

Algorithm Used	NS1	NS2	NS3	NS4
SMF	0.8623	0.8955	0.8790	0.8503
Base Model	0.9156	0.9346	0.9278	0.9111
Proposed Model	0.9452	0.9528	0.9499	0.9410

The near to unity values produced by the proposed model indicates that the algorithm has better edge preserving capability than the base and traditional model.

Speed of denoising algorithm is used to determine the time complexity of the proposed algorithms. Speed is determined as the difference between the starting time and the time taken by the algorithm to produce the fused result. The results obtained for the test images are presented in Figure 3.

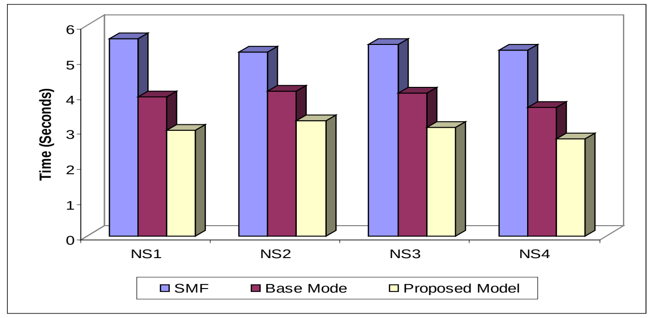


Figure 3: Speed of the Denoising Algorithms

Again from the results, it could be seen that the proposed algorithm is the fastest among the three algorithms. The average time taken by the proposed denoising model is <3.03 seconds while it is <3.95 seconds for base model and <5.39 seconds for the traditional SMF algorithm. This shows that the proposed algorithm is fast.

Figure 4 shows the visual comparison of the experimental results.

NS1 **NS2** **NS3** **NS4**

Figure 4: Visual Comparison

Thus, from the various results, it can be concluded that the proposed algorithm that used an enhanced noise detector and adaptive switching median filter for salt and noise removal from sonar images, achieves improved results with respect to restored image quality, edge preservation capacity and speed.

V. CONCLUSION

The need for efficient image restoration methods has grown with the massive production of images produced by the state-of-the-art acoustic cameras using in sonar technology. These cameras capture huge amount of images of sea floor and has multiplied the need for efficient denoising algorithms that can help researchers during analysis. In spite of various solutions being proposed, an efficient technique that meets all the demands of sonar imaging systems is still a very active research area. In this paper, a modified version of switching median filter that used adaptiveness and a preprocessing step that identified noise and noise free pixels was introduced. Experimental evaluation was performed using three performance metrics, namely, PSNR, FoM and speed of denoising time. All the experimental results showed that the proposed model is efficient in removing salt and pepper noise while preserving significant and edge details. The present model can further be enhanced to detect other type of impulse noise like speckle noise and uniform noise and a unified filtering mechanism for each of these can be implemented as a single model.

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