A NEW RESTORATION METHOD AND ITS APPLICATION TO SPECKLE IMAGES

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ABSTRACT

The visual interpretation of ultrasound brain images is a proven method to detect the White Matter Damage at an early stage. A problem, common to all medical ultrasound images, is the presence of speckle noise, which not only complicates the visual interpretation of images, but also quantitative measurements. This paper proposes a new filter that removes a significant amount of speckle noise from ultrasound images, while preserving details very well. The filter is based on a new cleaning technique that operates on the detail images of a wavelet decomposition. The papers illustrates that the proposed technique has some advantages over other popular techniques, i.e., the ones proposed by Lee, Frost, Malfait and Roose, and Sattar et al.

1. INTRODUCTION

In this article we address the problem of noise suppression. Although image acquisition techniques yield an ever improving quality, there is always a need for post-processing methods to remove noise from obtained images. This is especially difficult in the case of image dependant noise, e.g., speckle noise. The problem is not just to remove noise but to preserve valuable image data as well. Reduction of speckle noise is a very important post-processing step in medical imaging, including ultrasound imaging for purposes of segmentation and visual interpretation.

Ultrasound imaging is the perfect means for morphological investigation of the neonatal brain [1]. With real time ultrasound waves, most of the diseases can be discovered and followed, and this with a harmless non-invasive technique. In particular post-asphyctic damage, white matter damage and matrix-bleedings, injuries that determine the future of many matured and pre-terminal neonaties, can be investigated well with ultrasound. Many techniques have been proposed for noise reduction in general and speckle noise in particular. Two classes of techniques are especially successful at reducing speckle noise:

1. Techniques that are applied directly in the original image domain like the Lee [2] and Frost [3] filters.

2. Techniques that are applied in the wavelet domain like the technique developed by Malfait and Roose [4], which is a universal filter, and the technique proposed by Sattar, Floreby, Salomonsson and Lövström [5], designed especially for speckle noise reduction.

In this paper we propose a new method for noise reduction in the wavelet domain. Originally, we developed the method for suppression of Gaussian noise. However, the results in this paper indicate that this method also removes speckle noise efficiently.

The purpose of this paper is to introduce the new technique and to demonstrate that it performs well on speckle noise of ultrasound images of the neonatal brain. The results show that the new technique performs favorably compared to some state-of-the-art techniques.

X0	X1	X2
X3	X4	X5
X6	X7	X8

Fig. 1. The neighboorhood mask.

2. THE NEW METHOD

The method proposed in this paper is based on the analysis of the detail images, obtained from the wavelet decomposition of the original image. The goal of the analysis is to determine the position of real edges in the image so that false edges and noise can be removed.

The wavelet decomposition in our method is based on a discrete redundant wavelet decomposition with *spline* wavelets [6].

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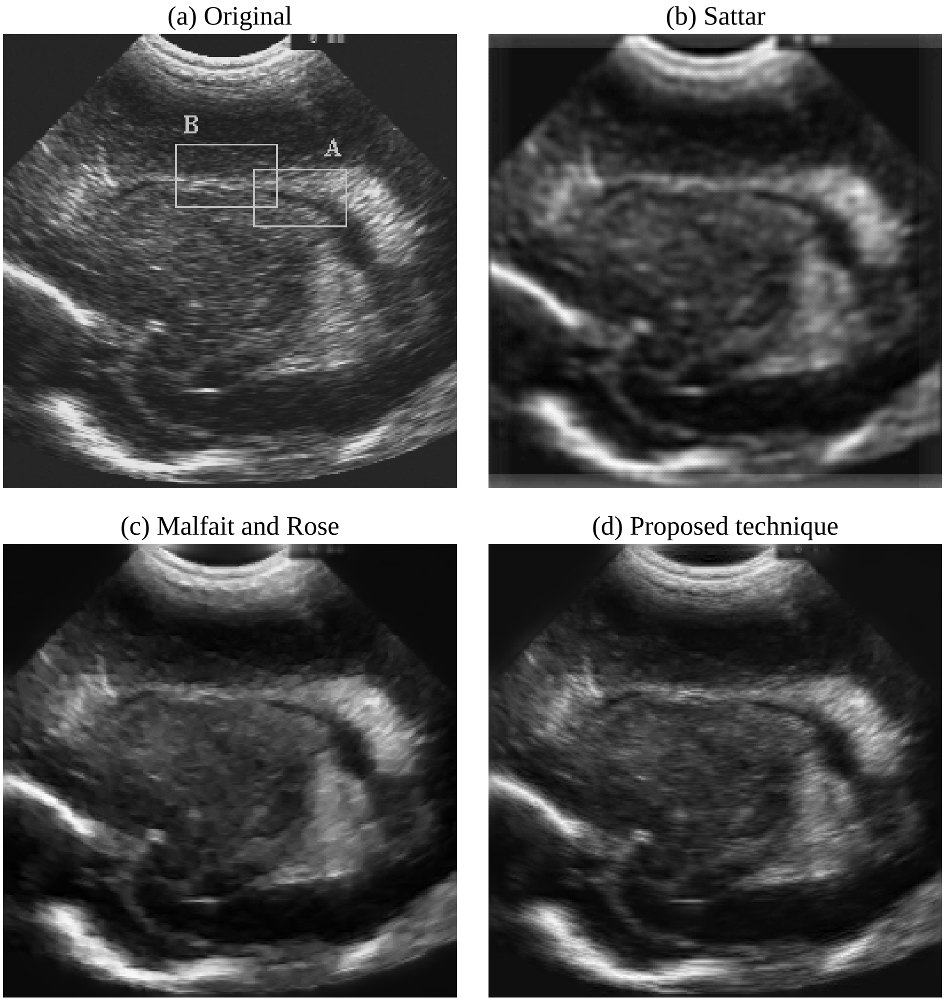

Fig. 2. Results obtained on an ultrasound image of a neonatal brain.

This decomposition produces at each resolution scale one set of scaling coefficients (low pass image) and two sets of wavelet coefficients containing the band pass information in horizontal and vertical directions.

Each pixel in the detail images can have a positive, zero or negative value. Ideally, an edge pixel should have a non-zero value, while other pixels should have zero value. In practice, the non-edge coefficients are non-zero due to noise. Our method tries to find such coefficients and correct them, by setting them to zero. In our method we use wavelet based filtering combined with simple spatial rules. We now explain the filtering rules in more detail.

Each of the detail images is split into two images, each containing only the positive values and the negative values, respectively (the missing coefficients in each image are set to zero). The images are then re-scaled to the gray scale interval [0, 255]; for the negative image, this is done after taking the absolute value of each pixel. We call the re-scaled images the 'P' and the 'N' image, respectively.

To determine the presence of an edge in the neighborhood of a given pixel, we use a spatial rule that is applied to 8 “neighborhoods” of the pixel. These neighborhoods are located within a 3×3 window and are given by:

$$\begin{array}{ll} R_0 = \{X_0, X_1, X_2, X_5\}, & R_1 = \{X_0, X_1, X_2, X_3\}, \\ R_2 = \{X_1, X_2, X_5, X_8\}, & R_3 = \{X_2, X_5, X_7, X_8\}, \\ R_4 = \{X_5, X_6, X_7, X_8\}, & R_5 = \{X_3, X_6, X_7, X_8\}, \\ R_6 = \{X_0, X_3, X_6, X_7\}, & R_7 = \{X_0, X_1, X_3, X_6\}, \end{array}$$

where the meaning of the symbols X_i is clarified in figure 1.

We perform recursive filtering of the detail images, using a threshold decomposition of the P and N images. We start with a threshold t=255, and clean the P and N images, which results in new images that we will call P(254) and N(254). Next this process is repeated for t=254...1, resulting in images $P(t)$ and $N(t)$. We now describe one of the cleaning steps in detail:

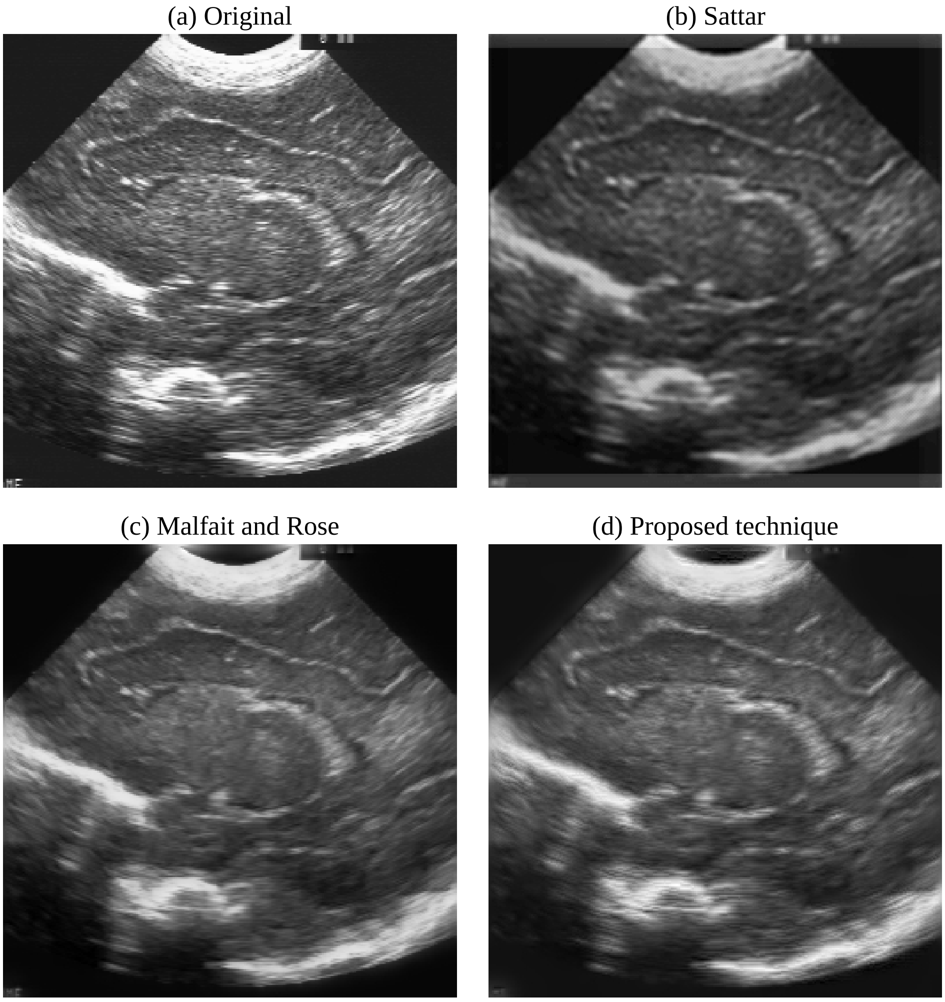

Fig. 3. Results obtained on an ultrasound image of a neonatal brain.

1. first we create a binary image from, e.g., $P(t)$ by replacing all pixel values less than t with 0 and all others with 1;

2. next we scan the binary image with the 3x3 mask, and apply the following rule

$$\textit{value} = \max\left\{\min_{R_j}\{V(X_i) \mid i \in R_j\}, 0 \leq j < 8\right\},$$

to compute a binary number *value*, which equals 1 if an edge is detected. In this equation, $V(X)$, denotes the value of a pixel in the $P(t)$ or $N(t)$ image at spatial position X.

3. we now compute $P(t-1)$ and $N(t-1)$ as follows (we only explain this for $P(t)$ but the computation of $N(t)$ is similar):

   - If the central pixel value at the thresholded image equals *value*, then $P(t-1) = P(t)$;
   - else if *value* = 0 then $P(t-1) = P(t) - 1$;
   - else if *value* = 1 then $P(t-1) = t$.

In this way, we finally obtain $P(1)$ and $N(1)$, the cleaned P and N images. These images are first used to reconstruct a cleaned version of the corresponding detail image: for this we first re-scale $P(1)$ and $N(1)$ to within their original range; next we combine the re-scaled images into one cleaned detail image. The images $P(1)$ and $N(1)$ are also used to perform an initial cleaning on the detail images on the next scale: whenever $P(1) = N(1) = 0$, the wavelet coefficients at the same position are set to zero in all detail images.

For the final filtering of the second and third scale detail images, we use a simpler method than for the first scale detail images: again, we apply rules R_0-R_7 on the images obtained from the horizontal and vertical detail images. For each rule we are looking for a minimum value of all pixels, and at the end we take the maximum value for all rules. Positive central pixel in the detail image is set to

$$V(X_4) = M \max\{\min_{R_j}\{V(X_i) \,|\, i \in R_j\}, 0 \leq j < 8\}/255,$$

where M is the value of the largest coefficient in the detail image, or if they are negative, they are set to

$$V(X_4) = m \max\{\min_{R_j}\{V(X_i) \,|\, i \in R_j\}, 0 \leq j < 8\}/255,$$

where m is the value of the smallest coefficient in the detail image.

Our method tries to estimate noisy coefficients and adjust their values to the neighbouring coefficients in the way shown above. If the neighbouring coefficients belong to an edge, the difference between the coefficients will be small. It means that the minimum value obtained for each rule, will not differ a lot from the value of each coefficient. If there is an edge in the neighbourhood of the central pixel, we assume that the central pixel belongs to the edge. Then we assign the maximum of obtained minimum values to the central pixel. It is obvious that in this way, the central pixel will receive a value consistent with the presence of an edge. The same logic we apply for the finest scale, but here we are looking for the edges in the binary images, obtained in the way described above. We adjust coefficients according to the detection of the edges at a certain gray level. We decrease the value of the central coefficient through levels (as described above) until we detect an edge in its neighbourhood. After we detect an edge we adjust the value of the coefficient to the value of the current gray level.

3. EXPERIMENTAL RESULTS

We compare our results to those obtained by two multi-scale methods. The first multi-scale method was proposed by Sattar, Flöreby, Salomonsson and Lövström [5] and the second one was proposed by Malfait and Roose [4]. In order to have a fair comparison, we optimized the parameters of all filters to achieve the optimal visual compromise between edge sharpness and amount of noise. Remark that in our filter there are no parameters that should be adjusted.

When we compare our method to the method proposed in [5] we can notice that in general, the Sattar image is blurred much more than the image obtained with our method. Also, the texture in the regions that should be smooth is rather irregular in nature.

After comparing the image obtained by our method to the image obtained by method proposed in [4] we can conclude that results obtained by both methods are comparable in preserving details and removing noise. The method proposed in [4] removes noise better in some regions, but in some areas it produces of patchy texture. The sharpness of the edges is comparable for both methods.

The problem in general with removing speckle noise from medical images is absence of ground truth (there is no ideal image to compare the results to). In future research we will attempt to develop criteria for estimating the efficiency of the speckle filters applied to medical images. In particular we will apply filters to artificial images as well as real images with the known content. Both types of images are corrupted by speckle noise.

In conclusion, the first results obtained with our method are promising, even though the proposed filter was not originally designed for removing speckle noise.

4. CONCLUSIONS AND FURTHER WORK

We proposed a new method based on multi-scale spatial filtering. The method successfully reduces speckle noise in ultrasound images. We compared it to other techniques and we got favorable results. The method might be useful as a pre-processing step in segmentation or for visual interpretation. More research is needed to verify, whether it gives diagnostic advantages.

5. REFERENCES

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