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New adaptive weighted filter approach for reducing the speckle noise inultrasound images

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ABSTRACT

Ultrasound images are affected by the speckle phenomenon, a multiplicative noise that degrades image quality. A new adaptive weighted filter approach for reducing the speckle noise in ultrasound images is introduced in the proposed method. In existing method high level impulse noise is not removed and PSNR, SSIM is very low. These problems can be overcomed by using adaptive weighted filter approach. Peak signal-to-noise ratio (PSNR) is the ratio between the power of a signal and the power of the disturbing noise. The structural similarity index (SSIM) is a method for measuring the similarity between two images. The new filter achieves good results in reducing the noise without affecting the image content. The performance of the proposed filter has been compared with some of the commonly used denoising filters. We deduce new stochastic distances for a Fisher-Tippett distribution, based on well-known statistical divergences, and use them as distance measures in a modified version of the BM3D algorithm for filtering log-compressed ultrasound images. The proposed filter outperforms the existing filters in terms of quantitative analysis and in edge preservation. The experimental analysis is done using various ultrasound images and obtains high PSNR and SSIM.

KEYWORDS:

SSIM
Peak signal to noise ratio
Ultrasound
BM3D
Fisher-Tippett

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1. INTRODUCTION

Ultrasonography is an important modality of medical imaging since it is non-invasive, harmless, portable, low cost and is conducted in real time. The main issue affecting ultrasound images is a random granular pattern, the speckle, which is a phenomenon arising from the coherent nature of the acquisition system. The speckle, a form of multiplicative noise, affects the interpretability of the image, both by specialists or automated tools, and should be attenuated as much as possible. This kind of noise is also present in other types of coherent imaging systems, such as the laser, sonar, and synthetic aperture radar (SAR).

Ultrasound image despeckling is an important research field since it can improve the interpretability of one of the main categories of medical imaging. Many techniques have been tried over the years for ultrasound despeckling, and more recently, a great deal of attention has been focused on patch-based methods, such as non-local means (NLM) and block-matching collaborative filtering (BM3D). A common idea in these recent methods is the measure of distance between patches, originally proposed as the Euclidean distance, for filtering additive white Gaussian noise. In this work, we derive new stochastic distances for the Fisher-Tippett distribution, based on well-known statistical divergences, and use them as patch distance measures in a modified version of the BM3D algorithm for despeckling log compressed ultrasound images. State-of-the-art results in filtering simulated, synthetic, and real ultrasound images confirm the potential of the proposed approach.

In [1] they consider the adaptive Wiener filtering of noisy images and image sequences. It uses an adaptive weighted averaging (AWA) approach to estimate the second-order statistics required by the Wiener filter. The proposed AWA wavelet Wiener filter is superior to the traditional wavelet Wiener filter by about 0.5dB (PSNR). Different filtration techniques (Wiener and Median) and a proposed novel technique that extends the existing technique by improving the threshold function parameter K which produces results that are based on different noise levels is described in [2]. A signal to mean square error as a measure of the quality of denoising was preferred. Ultrasound is a powerful technique for imaging the internal anatomy. The main disadvantage is the low performance.

A new despeckling technique based on the “nonlocal” denoising filter is presented[4]. The filter has been modified in order to take into account SAR image characteristics. Complexity is very poor comparing to the existing system. [5]The main focus of this paper isto define a general mathematical and experimental methodology to compare and classify classical image denoising algorithms and then to propose an algorithm (Non Local Means) addressing the preservation of structure in a digital image.

In this paper[8] they developed a new method based on the homogeneity level for speckle noise suppression and simultaneously edge and feature preservation. It is very complex while using this method. A new method to reduce speckle by filtering is introduced[9], namely, the double filtering method. A double filtering is an image that filtered two times by using a different combination of the filter. This method is inefficient comparing to others.

To overcome all the disadvantages in the existing system, a new adaptive weighted filter approach for the reduction of speckle noise in ultrasound images is proposed in our method

2. PROPOSED METHOD

A adaptive weighted algorithm is developed by removal of salt and pepper noise. The salt and pepper noise is the impulse noise. It has developed by the two main steps. The first step can be detecting the noise pixel correlation between the image pixels. Then the different method niose levels. The low noise level neighborhood pixels mean method can be adopted, the remove the noise, the high level noise removal the adaptive weighted algorithm used.

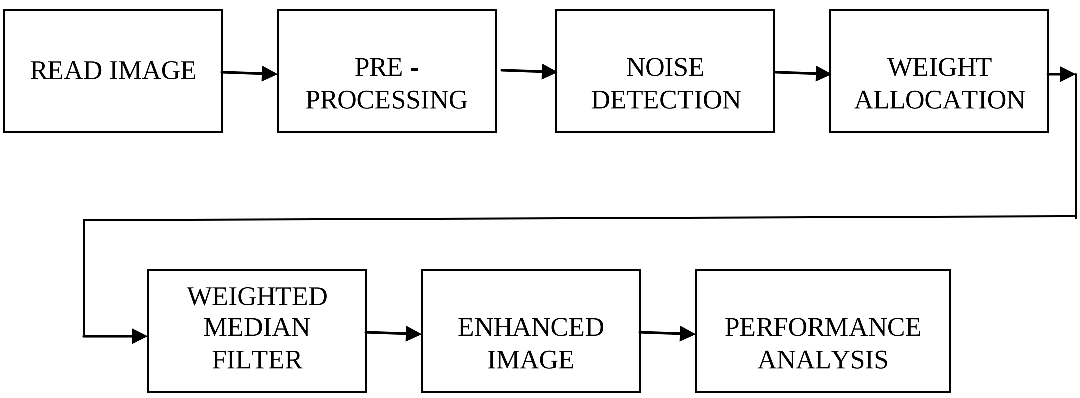

Fig. 1 : Block Diagram

2.1 Preprocessing

The image is first processed in order to extract the features, Resize means change the size of an image to make it more suitable. In images most patches repeat almost identically over and over in the image. In Preprocessing, denoising is performed patch-wise with each patch denoised separately and inserted into the denoised image. Divide overlap block patches.

2.2 Adaptive Weighted Filter

It consists of two major steps, first to detect noise pixels according to the correlations between image pixels, then use different methods based on the various noise levels. For the low noise level, neighborhood signal pixels mean method is adopted to remove the noise, and for the high noise level, an adaptive weight algorithm is used. Several types of noise have been defined. In this paper the impulse noise is considered.

2.3 Stochastic distance

Divergence measures play a major role in statistical inference and discrimination since they are measures of the statistical distance between probability distributions. This distribution has a double exponential or Fisher-Tippett shape, of which the only parameter is the tissue reflectivity.

$$p\left(\frac{x}{\sigma}\right) = \left(\frac{\exp(z)-1}{\sigma^2}\right)\exp\left(\frac{z-(\exp(z)-1)^2}{2\sigma^2}\right)$$

2.4 BM3D filter

The BM3D is known to be one of the state-of-the-art filtering algorithms for AWG noise corrupted images. block-matching, 3D collaborative filtering in a sparse domain, and reconstruction operation . block-matching operation, the image is scanned in overlapping windows, and for each of these windows, a reference patch is compared to all other (overlapping) patches inside the window. All similar patches, according to Euclidean distance, are stacked to form a 3D block. These 3D blocks undergo a linear transformation and are filtered in a sparse domain. After inverse transformation, there are many estimates for the same pixel, and the patch is reconstructed by combining those estimates. The BM3D algorithm executes the core operations twice. In the first step, the 3D blocks are filtered using a sparse coefficient threshold, while in the second step, the 3D blocks are filtered using a Wiener filter with coefficients estimated from the result generated in the first step.

2.5 Performance analysis

In the performance analysis, the efficiency of the proposed approach is compared with the existing method.

3.ALGORITHM DETAILS

3.1 Adaptive weighted Algorithm

A new adaptive weight algorithm is developed for the removal of salt and pepper noise. It consists of two major steps, first to detect noise pixels according to correlations between image pixels, then use different methods based on the various noise levels. For the low noise level, neighborhood signal pixels mean method is adopted to remove the noise, and for the high noise level, an adaptive weight algorithm is used. Several types of noise have been defined. The impulse noise is considered. In case of images corrupted by this kind of noise, intensity of the pixel xij at location (i, j) is described by the probability density function.

It is known that the salt and pepper noise value is the max or min value in the image according to the characteristic of the noise sprinkling on images.

If $fi, j = 0$, it means the pixel is a signal point, else it is a noise one. it means the pixel is a signal point, else it is a noise one. Because the values of some signal pixels are absolutely around 0 or 255, it is needed to further decide whether the pixel is a noise one or not.

3.2 Stochastic distances (Fisher-Tippett distributions)

Divergence play a major role in statistical inference and discrimination since they are measures of the statistical distance between probability distributions. This distribution has a double exponential or Fisher-Tippett shape, of which the only parameter is the tissue reflectivity:

$$\left(\frac{x}{\sigma}\right) = \left(\frac{\exp(z) - 1}{\sigma^2}\right)\exp(\frac{z - (\exp(z) - 1)^2}{2\sigma^2})$$

Let X and Y are two noisy patches of size N x M, whose statistics can be described by the Fisher-Tippett distribution given by equation and the respective reflectivity parameters $\sigma 1$ and σ 2:

$$f_x = \left(\frac{\exp(z)-1}{\sigma_1 2}\right)\exp(\frac{z-\exp(z)-1)}{2\sigma_1 2})^2$$

$$f_y = \left(\frac{\exp(z)-1}{\sigma_2 2}\right)\exp(z-\frac{\exp(z)-1}{2\sigma_2 2})^2$$

In this case, the parameter vectors are $\Theta 1=\{\sigma 1\}$and $\Theta 2=\{\sigma 2\}$. These stochastic distances depend only on the reflectivity parameters $\sigma 1$ and $\sigma 2$that can be estimated from the noisy patches. The smaller the calculated value of the distance, the closer the patches are statistically. For patches with equal parameters ($\sigma 1=\sigma 2$) the stochastic distances will be evaluated to zero.

3.3 Ultrasound image noise

The technique of diagonising the uses of ultasound images are most popular.The segmenting anatomical part from the ultrasound images those the segmentation like the breast,carotid artery.many methods are ultrasound using medical imaging.B mode or 3D mode are linear transducer perform scan through the body produce 2dimensional ultrasound images.The granular noise is the speckle noise.Medical images to database physiology and anatomy to identify abnormalities.

3.4 Image quality matrix

The evaluation of the performance of despeckling filters in ultrasound images is not a trivial task. The first problem is the lack of one or a set of objective quality metrics universally accepted by the research community. Moreover, specialists may not be available to evaluate the image quality for diagnosis. Furthermore, there is no ground truth for comparison when filtering real ultrasound images. In this work, we do not deal directly with the problem of mapping the quality of the filtered images for better diagnosis, measuring the quality of the filters using a set of objective quality metrics and a subjective evaluation by a medical image expert.

The objective quality metrics are chosen to quantify the performance of the filters in smoothing the homogeneous areas, while preserving details and borders. Filtered images with those characteristics may support, when tuned for specific cases, the development of better diagnosis techniques. Consider the following convention for the description of the metrics in the next topics: If denotes the filtered image, In denotes the noisy image, Ig denotes the ground truth noiseless image, M and N are the image dimensions, (i; j) refers to the spatial position of a pixel, and the symbols E[] and VAR[] indicate the expected value and variance operations. The metrics that require Ig are known as full-reference metrics, while the metrics using only are the non-reference metrics.

Speckle smoothing metrics(SSI/SMPI): In a homogeneous region of an RF ultrasound image, the speckle strength, also known as the speckle index, is given by the relation of the standard deviation and mean

$$SI=\frac{\sqrt{VAR[I_n]}}{E[I_n]}$$

If for a specific homogeneous area in the image, one normalizes the speckle index of the filtered image by the speckle index of the original image, we have the speckle suppression index.

$$\text{SSI}=\left(\frac{\sqrt{VAR[I_f]}}{E[I_f]}\right)\left(\frac{E[I_n]}{\sqrt{VAR[I_n]}}\right)$$

When the filter suppresses speckle, SSI < 1, and the lower the SSI is, the stronger suppression abilities the filter has. The SSI may fail to evaluate the despeckling performance if the filter overestimates the filtered image mean. To avoid this effect, Shamsoddini and Trinder (2010) defined the speckle suppression and mean preservation index (SMPI) in

$$\text{SMPI}=(R+[E(I_n)-E(I_f)](\frac{\sqrt{VAR[I_f]}}{\sqrt{VAR[I_n]}}))$$

Lower values of SMPI indicate better filter performance regarding mean preservation and speckle removal. After log compression, the mean is no longer proportional to the standard deviation, and we must calculate the speckle index using the variance, Since SSI and SMPI are based on the speckle index, we should also replace the standard deviation by the variance in their calculations.

We calculate the SSI and SMPI for each individual pixel of the image, in a 7x7 window centered on the pixel. The global SSI and SMPI associated with the image is the mean value of the pixels. Additionally, SSI and SMPI should be calculated only for homogeneous regions of the image. To decide whether a pixel belongs to a homogeneous area, where the speckle index (named coefficient of variation) is used as an edge detector. There, the authors show that the local SI is approximately equal to the global SI for the homogeneous areas of an RF image. The local SI refers to the SI calculated in a patch of the image, and the global (SIglobal) refers to the SI calculated for the whole image. Here, experimentally, we determined that pixels with 0:9 belong to homogeneous areas.

4. RESULT AND DISCUSSION

Fig 3.1 shows the input ultrasound image. This image was preprosessed and in Preprocessing, denoising is performed patch-wise with each patch denoised separately and inserted into the denoised image

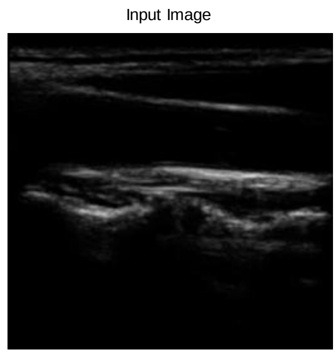

Fig3.1 Input image

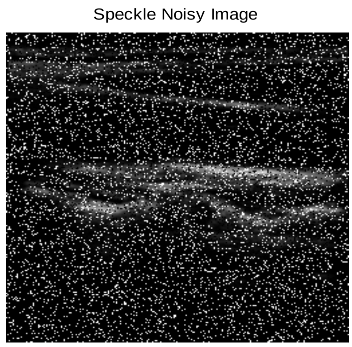

Fig3.2 Speckle noisy image

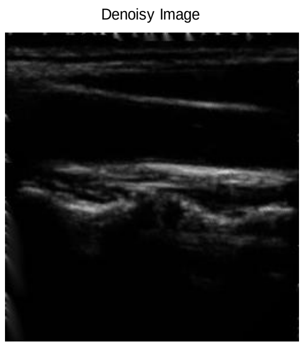

Fig3.3 Denoisy image

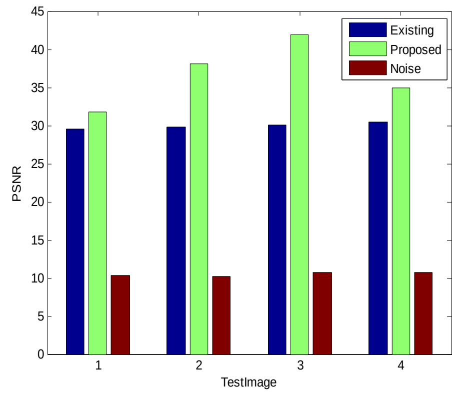

Fig3.4 Comparison chart for PSNR

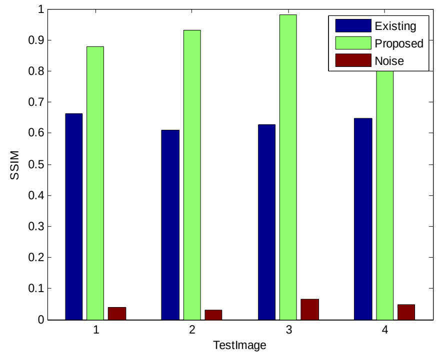

Fig3.5 Comparison chart for SSIM

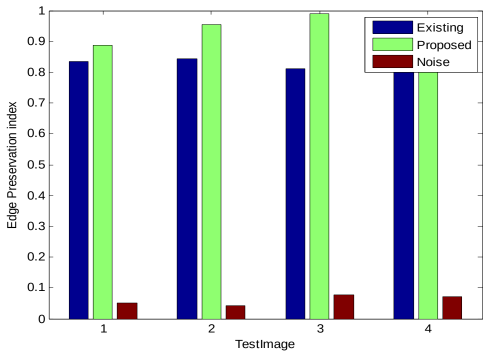

Fig3.6 Comparison chart for EPI

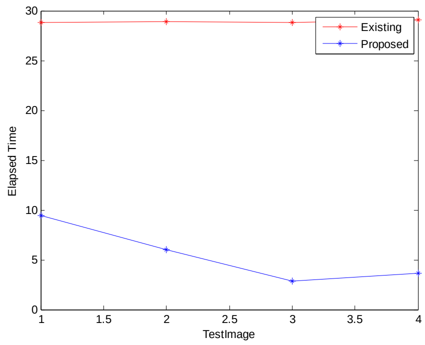

Fig3.7 Comparison chart of elapsed time

Figure 3.4, 3.5 and 3.6 shows the comparison chart for PSNR, SSIM and EPI. Com paring to the existing method the proposed method shows better performance. The time taken by the proposed method is low comparing to the existing system.

5. CONCLUSION

From the experimental and mathematical results it can be concluded that for denoising ultrasound images, the weighted trimmed median filter is optimal compared to traditional median filter. It produces the better PSNR for the output image compared to the traditional filter considered without deteriorating the image content. It is very simple, easy to implement, produces efficient noise suppression and an excellent image detail-preserving capability.

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