Coping with Noise in Ultrasound Images: A review

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Abstract

Ultrasound is notorious for having significant noise with a low signal-to-noise ratio. This inhibits the performance of segmentation and causes difficulty for clinical evaluation, thus noise reduction is paramount to achieving adequate segmentation in ultrasound images. Consequently, the modeling and handling of noise is a significant area of research. In this review paper we introduce the typical characteristics of noise in B-mode ultrasound and analyse th performance of multiple state-of-the-art methodologies for dealing with such noise. A similar paper was written by by Coupé et al. [8] when they introduced OBNLM; though we provide an independent review and generalised description of the problem area. We also discuss the issue of typical image quality assessment methods and consider the impact speckle noise could have on ultrasound image analysis.

Three state-of-the-art denoising algorithms (SRAD, SBF, and OBNLM) are evaluated using three different image quality assessment methods (SSIM, MSE and USDSAI) in comparison with traditional filters such as Lee's. We worked with simulated phantom images, as well as prostate ultrasound images to assess these methods. SRAD and OBNLM seem to be the most effective algorithms and in our discussion we contemplate ways in which they might be further expanded.

1 Introduction

Ultrasound is notorious for having pervasive noise with a low signal-to-noise ratio which inhibits the performance of segmentation algorithms and causes difficulty for clinical evaluation. Consequently, the modeling and handling of noise is a significant and continuing area of research. We are primarily concerned with speckle, due to its prevalence in ultrasound and the fact that it may be considered noise or a source of information.

2 Types of Noise and Their Cause

There are two basic models for noise behaviour [5]. The first, **additive** noise is generally more common. It is independent of image data - thermal noise and noise caused by quantisation are common examples. Secondly, **multiplicative** noise is related to image data and is often found in coherent imaging systems (such as ultrasound) whilst uncommon in other modalities; the typical example is speckle noise which occurs due to variation in the surface being imaged. For the purpose of this paper, and ultrasound in general, we focus on speckle noise, though the most relevant varieties of noise are:

Gaussian noise can frequently be observed as the result of thermal agitation (a.k.a Johnson-Nyquist noise), film grain (sometimes modelled as Poisson noise) and photon counting. It is indicative of the physical characteristics of the imaging methodology. **Speckle** is present in coherent imaging systems; the backscatter waves from a surface may constructively or destructively interfere causing modulation in phase and amplitude observed as variation of high and low intensities known as speckle. It is therefore characteristic of the surface being imaged and inherently multiplicative. Speckle is a significant component of ultrasound and other noise may be considered negligible. **Quantisation noise** arises from the process of transforming continuous data into discrete values (quantisation) and is a mandatory component of digital acquisition. The result is a uniform degradation in resolution characterised by a blocky appearance. Sufficiently high resolution data acquisition can mitigate this.

Year	Author	Technique	Dataset Used
2009	Coupé et al. [8]	Optimised Bayesian NL-means (OBNLM)	2D intraoperative brain images and 3D liver images
2006	Yue et al. [33]	Non-linear Multiscale Wavelet Diffusion (NMWD)	Echocardiographic images
2006	Acton et al. [27]	Squeeze Box Filter (SBF)	Field II simulation
2002	Yu and Acton [32]	Speckle Reducing Anisotropic Diffusion (SRAD)	Carotid artery ultrasound images
2001	Achim et al. [2]	Bayesian Multiscale Estimator (wavelet)	Simulated speckled images
1990	Perona and Malik [22]	Anisotropic Diffusion	Not originally applied to ultrasound, but has been adapted by [32] and others
1989	Loupas et al. [18]	Adaptive weighted median filter (AWMF)	Various images, including liver and gallbladder
1987	Kuan et al. [17]	Non-linear MSE minimisation	Not originally applied to ultrasound
1980	Lee et al. [15]	MSE minimisation	Not originally applied to ultrasound

Table 1: Trends in ultrasound specific denoising

3 Noise Reduction

Ultrasound preprocessing typically involves a significant noise reduction stage to mitigate the presence of speckle and improve segmentation. Conventional image processing filters such as median [18], Lee's [15] and Kuan [17] have traditionally being used to this end. Current analysis of the efficacy of noise filters has been conducted by the original authors, and as such, we felt an independent assessment of major techniques would be of value to the community.

Table 1 provides an overview of both traditional and state-of-the-art filters. Recent developments have been based around anisotropic diffusion and non-local means. Anisotropic diffusion techniques essentially convolve the image with a Gaussian kernel and are superior to traditional techniques at edge preservation. Non-local means (NL-means) [7] filters generate a weighted average based on similarity between pixel neighbourhoods; this prevents unncessary averaging with non-similar regions. NL-means is increasingly popular, and has been adapted to the CUDA platform for real-time ultrasound [9].

In the following subsections we present an overview of typical image quality metrics, as well as the results of performing vairous denoising algorithms on real and simulated ultrasound data.

3.1 Assessing Image Enhancement

A variety of metrics can be used in order to quantify the quality of signals and the efficacy of filters. A long favoured and reliable measure is the mean squared error (MSE) [3] and the related peak signal-to-noise ratio (PSNR) [13]. The output from these methods do not necessarily correlate with human perception of quality and results may be inconsistent across content, most significantly they do not discern structure in images [29]. Whilst all of these metrics are easily implemented and performed, they have particularly obtuse view on what makes a "good" quality image. MSE and PSNR have prevailed as a popular indicators of signal quality due to simplicity in implementation and ease of understanding.

Interest has grown in more sophisticated indicators of signal fidelity. The structural similarity index (SSIM) [30] is a metric targeted at quality assessment based on a reference image with consistency in structural information being an indicator of quality. A SSIM approaching 1 indicates similarity, whilst a SSIM approaching -1 represents dissimilarity, a value of 1 itself would occur in the event of identical images. One study has indicated a link between PSNR and SSIM [12], from which we infer MSE, PSNR or SSIM may be analogous and adequate for the majority of cases although some differences in sensitivity should be noted.

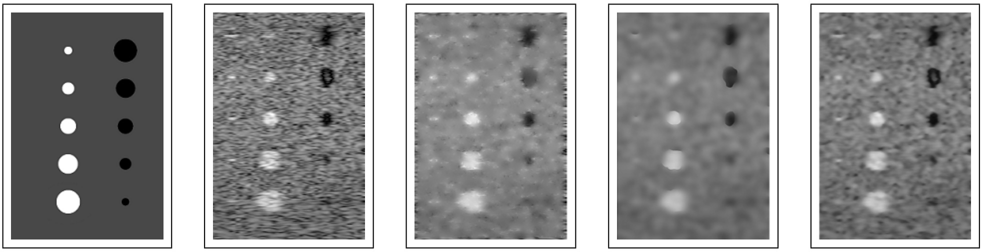
In the context of ultrasound imaging Tay et al. introduced a modified Fisher discriminant contrast metric referred to as the ultrasound despeckling assessment index (USDAI), a ‘large USDSAI would indicate that [the algorithm] produces desirable restoration or enhancement results’ [27], this metric is used to demonstrate the superiority of SBF to SRAD and traditional filters. Coupé et al. have used the same framework to demonstrate superiority of OBNLM to SRAD, SBF and conventional NL-means[8].

Although USDSAI is freely available, no independent evaluation has yet been carried out. Therefore we chose to compare and contrast the MSE, SSIM and USDSAI metrics. Perhaps in the future a well defined solution to the problem of image quality assessment will be available. USDSAI is a good step in this direction given its specificify to homogeneous classes whilst being sensitive to changes across regions.

4 Experiment and Results

Regardless of the evaluation framework, it is important to have a reference image to which image enhancements can be compared. As ultrasound data is of poor quality due to acquisition technology, the best source for such a data set is simulated phantom images. These images should contain structural features of different contrasts, for example Figure 1.

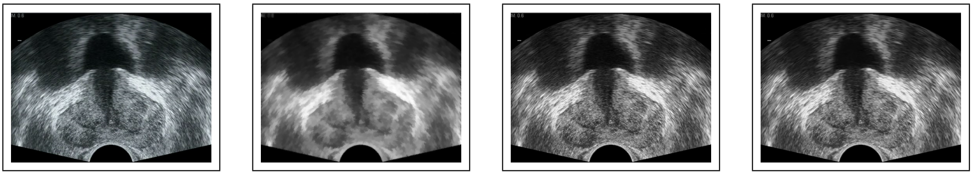
Many techniques for simulation of B-mode images have been published [14, 19, 23, 33]. Whilst these methods may vary in their ability to precisely mimic speckle, they do possess statistically significant characteristics that make them suitable. In Figure 1 we demonstrate the visual appearance of various state-of-the-art denoising approaches applied to a Field [14] simulated ultrasound image (shown in Figure 1a). We compared four filters: SRAD. SBF, OBNLM and median. Each was run multiple times - with a variety of parameters. The effect of filters can be difficult to appreciate visually, and assessment was carried out using MSE, SSIM and USDSAI. The best results from each evaluation method (not limited to a single set of parameters) are listed in Table 2.



(a) (b) (c) (d) (e)

Figure 1: Comparison of denoising methods applied to phantom generated with Field II. These images all have the best USDAI score for the specific denoising method. (a) Template image used as ground truth (b) Field II simulated image. Effects of denoising with (c) SBF (d) SRAD(e) OBNLM.

Figure 2 shows the algorithms performed on a real prostate ultrasound image. It is extremely difficult to perform image enhancement quality assessment on clinical data as there is no true ground truth. The output of each algorithm at various parameters was compared with the original image using SSIM and MSE metrics to assess the amount of degradation resulting from each. It was not possible to use USDSAI for this adata due to the unkown classes present in the image. Interestingly, regardless of the distance between metric results; generally the best result using one metric will be the same for the other.



(a) (b) (c) (d)

Figure 2: Comparison of denoising methods applied to real prostate ultrasound images. Note that the better algorithms (SRAD, OBNLM) preserve detail much more effectively. These images all have the best SSIM score for the specific denoising method. (a) Original (b) SBF MSE: 280, SSIM: 0.65(c) SRAD MSE: 5.68, SSIM: 0.99 (d) OBNLM MSE: 12.9, SSIM: 0.98.

This experiment highlights an important point - evaluation methods can only account for certain specific features of an image and may not accurately assess image quality. In the results, MSE would suggest SRAD is superior, whilst SSIM and USDSAI suggest SBF. It is also apparent that this contradicts the work by [8] - most likely due to the subjectivity of both denoising and evaluation methodologies and differences between data sets. Arguably, SBF, SRAD and OBNLM are all similarly effective, adjustments to their parameters (iterations, smoothing, etc.) can be made repeatedly in order to improve one metric such as USDSAI, but this can lead to reduction in SSIM.

Method	MSE		SSIM		USDSAI	
	Best	Avg.	Best	Avg.	Best	Avg.
SBF	3.47	3.69	0.68	0.59	1.94	1.52
SRAD	2.77	2.82	0.81	0.75	2.01	1.72
OBNLM	2.83	3.10	0.69	0.43	1.42	1.15
Median	3.11	3.15	0.60	0.46	1.23	1.13

Table 2: Evaluation of various denoising algorithms.

5 Discussion

Noise is a prevalent issue in ultrasound, however there are a number of effective state-of-the-art methodologies for denoising, as well as techniques for evaluating them. Anisotropic and NL-means based algorithms are the most effective and recently developed methods for denoising in ultrasound are better suited to speckle compared to traditional approaches.

The term ‘noise’ for ultrasound often implies speckle exclusively. However, contrary to the typical desire to remove noise, statistical analysis of speckle has the potential for classifying regions correlating to anatomical structure. This could be used to segment regions or identify potential seed points for further processing. Raeth [24] observed that for ultrasound, computer analysis was superior to human observers and whilst speckle may seem to degrade an ultrasound image visually, it may provide useful information.

5.1 Inference from Speckle

Typically treated as noise, speckle might be a source of data and research has been conducted into characteristics of speckle distribution as a means for tissue differentiation [28] as it is the deterministic behaviour of waves in a particular environment. In a coherent system (such as ultrasound) images are formed through constructive and destructive interference of waves which results in fluctuation of amplitude (characterised in ultrasound by change in brightness). Ultrasound waves are scattered by surfaces or features in the field of view, the interference of these scattered waves manifests itself as speckle.

With appropriate analysis, speckle patterns may provide a means of inferring structure and other anatomical information; this has been demonstrated for a number of applications. One major research area is speckle tracking [4, 20] such as the clinically applied Laser Speckle Contrast Analysis (LASCA), which monitors change in speckle over time to determine blood flow [25]. Marti et al. [19] present a technique based upon an ellipsoid discriminant function to classify patches and generate speckle probability images, showing a clear correlation of speckle with anatomical structure. Correlation between speckle and intramuscular fat was visually observed in cattle during the 1980s [6] and tissue classification may be achieved with a number of methods such as wavelet-based filters, which have been applied to prostate images [10]. These analysis techniques typically utilise *speckle extraction* algorithms; these aim to separate an ultrasound mage into diffuse and coherent components. One such example is the Wold decomposition that thresholds an ultrasound signal [11] that has been applied to breast images for classification of normal and diseased tissue [11].

With this information in mind, it would be prudent for any researcher attempting to reduce the appearance of speckle to consider the application of speckle classification and probability estimation as a part of their processing pipeline.

6 Conclusions

We have reviewed a variety of major topics pertaining to ultrasound noise; specifically denoising but but we have also introduced the importance of speckle. Density maps would be useful to perfect as a means of selecting seed points for boundary delineating algorithms as well as providing visual clues to clinicians in real time. Work in ultrasound elastography has typically used speckle tracking [21, 26] whilst an entirely separate piece of research used variation in speckle to allow adaptive processing [1], increasing efficiency and reducing the need for unnecessary denoising in highly speckled areas. Deriving information from speckle is challenging, but could yield useful results in a variety of unexpected applications.

In conclusion, there are clearly superior two state-of-the-art algorithms (SRAD and OBNLM) for denoising though it is difficult to assess their efficacy. Before we can perform a truly conclusive evaluation, new metrics for assessing image enhancement must be developed as inconsistencies in the techniques of SSIM, MSE, etc demonstrate they cannot be relied upon. However, it seems that non-local techniques and anisotropic-diffusion are key areas for future work relating to denoising. A combinatory approach may be most appropriate, and indeed, non-local anisotropic diffusion has been applied somewhat recently by Yu [31] to restore conventional images whilst Krissian and Aja-Fernandez [16] have performed extended SRAD to incorporate local statistics.

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