PROCEEDINGS OF VIPIMAGE 2013 – IV ECCOMAS THEMATIC CONFERENCE ON COMPUTATIONAL VISION AND MEDICAL IMAGE PROCESSING, FUNCHAL, PORTUGAL, 14–16 OCTOBER 2013

Computational Vision and Medical Image Processing IV

Editors

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CRC Press
Taylor & Francis Group
Boca Raton London New York Leiden

CRC Press is an imprint of the
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A BALKEMA BOOK

CRC Press/Balkema is an imprint of the Taylor & Francis Group, an informa business

Typeset by V Publishing Solutions Pvt Ltd., Chennai, India
Printed and bound in Great Britain by CPI Group (UK) Ltd, Croydon, CR0 4YY

Published by: CRC Press/Balkema
P.O. Box 11320, 2301 EH Leiden, The Netherlands
e-mail: Pub.NL@taylorandfrancis.com
www.crcpress.com – www.taylorandfrancis.com

ISBN: 978-1-138-00081-0 (Hbk)
ISBN: 978-1-135-81292-2 (eBook PDF)

Computational Vision and Medical Image Processing IV – João Tavares & Natal Jorge (eds)
© 2014 Taylor & Francis Group, London, ISBN 978-1-138-00081-0

Table of contents

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Speckle ultrasound image filtering: Performance analysis and comparison

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ABSTRACT: This paper compiles and compares well-known techniques mostly used in the smoothing or suppression of speckle noise in ultrasound images. A comparison of the methods studied is done based on an experiment, using quality metrics, texture analysisand interpretation of row profiles to evaluate their performance and show the benefits each one can contribute to denoising and feature preservation. To test the methods, a noise-free image of a kidney is used and then the Field II program simulates a B-mode ultrasound image. This way, the smoothing techniques can be compared using numeric metrics, taking the noise-free image as a reference. In this study, a total of seventeen different speckle reduction algorithms have been documented based on spatial filtering, diffusion filtering and wavelet filtering, with fifteen qualitative metrics estimation. We use the tendencies observed in our study in real images. This work was carried out in collaboration with S. Teotónio—Viseu (Portugal) Hospital. A new evaluation metric is proposed to evaluate the despeckling results.

1 INTRODUCTION

Medical ultrasound imaging is a technique that has become much more widespread than other medical imaging techniques since this technique is more accessible, less expensive, safe, simpler to use and produces images in real-time. However, ultrasound imagesare degraded by an intrinsic artifact called 'speckle', which is the result of the constructive and destructive coherent summation of ultrasound echoes (Loizou and Pattichis 2008).

Speckle is a random granular pattern produced mainly by multiplicative noise that degrades the visual evaluation in ultrasound imaging (Wagner et al. 1983) as shown in Figure 1. It is generated by the fact that there are a number of elementary scatterers within each resolution cell of the image that reflect the incident wave back towards the ultrasound sensor. The backscattered coherent waves with different phases undergo constructive and destructive interferences in a random manner.

Removing noise from the original image is still a challenging research in image processing. The presence of speckle noise severely degrades the signal-to-noise ratio (SNR) and contrast resolution of the image, making human interpretation and computer assisted detection techniques difficult and inconsistent. Therefore, a speckle reduction process is quite necessary in low SNR, low contrast ultrasound images for enhancing visualization of organ anatomy and improving the accuracy of object detection (Yu et al. 2010).

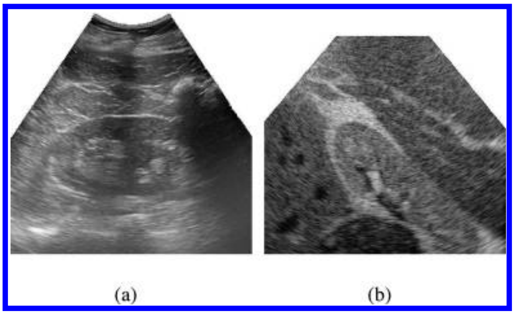

Figure 1. Speckle noise. (a) Real ultrasound image. (b) Simulated ultrasound image.

A smoothing of speckle and preservation of edges are in a general sense divergent. A trade-off between noise reduction and the preservation of the actual image features and contrast has to be made in order to enhance the relevant image content for diagnostic purposes. Best contrast is meant in the sense of decreasing the variance in a homogeneous region while distinct regions are well defined.

Thakur and Anand (2005) presented a comparative study of various wavelet filter based denoising methods according to different thresholding values applied to ultrasound images. In a recent paper (Mateo and Fernández-Caballero 2009) investigates some of the techniques mostlyused in the smoothing or suppression of speckle noise in ultrasound images.

This article investigates and compiles well-known techniques used in the smoothing or suppression of speckle noise in ultrasound images. A comparison of the methods studied is done based on real ultrasound images and computer simulated images, using quality metrics to test their performance and show the benefits each one can contribute.

2 SPECKLE FILTERING TECHNIQUES

Several denoising techniques have been proposed to address the problem of speckle noise including local adaptive statistics filtering, wavelet filtering and anisotropic diffusion methods.

2.1 *Adaptive local filters*

Adaptive filters take a moving filter window and estimate the statistical characteristics of the image inside the filter region, such as the local mean and the local Lee (1980), Frost et al. (1982) and Kuan et al. (1985) filters assume that the speckle noise is essentially a multiplicative noise. Wiener filter (Jin et al. 2003) performs smoothing of the image based on the computation of local image variance. Ideal Fourier and Butterworth filtering performs image enhancement by applying the filter function and inverse FFT on the image (Loizou and Pattichis 2008). Bilateral filtering technique (Tomasi and Manduchi 1998), basically is a combination of a spatial and range filter, where each output pixel value is a Gaussian weighted average of its neighbours in both space and intensity range. This non-linear combination of nearby pixel values, gives the well-known good performance of this filter in smoothing while preserving edges.

2.2 *Anisotropic diffusion filters*

Diffusion filters remove noise from an image by modifying the image via solving a partial differential equation. Speckle reducing filters based on anisotropic diffusion algorithms were introduced by Perona and Malik (1990) (PMAD). Weickert (1999) introduced the coherence enhancing diffusion (CED), that allows the level of smoothing to vary directionally by a tensor-valued diffusion function. Yu and Acton (2002) first introduced partial differential equation by integrating the spatially adaptive Lee (1980) filter and the Perona-Malik diffusion (Perona and Malik 1990), which they called Speckle Reducing Anisotropic Diffusion (SRAD). SRAD provides significant improvement in speckle suppression and edge preservation when compared to traditional methods like Lee, Frost and Kuan filters. In (Fu et al. 2005) is proposed the edge enhanced anisotropic diffusion (EEAD) method that includes anisotropic diffusion and edge enhancement. Krissian et al. (2007) proposed the oriented speckle reducing anisotropicdiffusion (OSRAD) filter which allows different levels of filtering across the image contours and in the principal curvature directions.

2.3 *Wavelet filters*

Wavelet transform, unlike Fourier transform, shows localization in both time and frequency and it has proved itself to be an efficient tool for noise removal. One widespread method exploited for speckle reduction is wavelet shrinkage, including VisuShrink (Donoho and Johnstone 1994), SureShrink (Donoho and Johnstone 1995) and BayeShrink (Chang et al. 2000). A wavelet-based multiscale linear minimum mean square-error estimation (LMMSE) is proposed in (Zhang et al. 2005), where an interscale model, the wavelet coefficients with the same spatial location across adjacent scales, was combined as a vector, to which the LMMSE in then applied.

3 IMAGE QUALITY EVALUATION METRICS

Objective image quality measurement plays important roles in image processing application. A classical procedure for denoising filtering validation uses the measurement of quality indices. However, the measurement of ultrasound image enhancement is difficult and there is no unique algorithm available to measure enhancement of ultrasound image (Wang et al. 2004).

Images were evaluated using several quality evaluation metrics such as average difference (AD), figure of merit (FOM), root mean square error (RMSE), signal to noise ratio (SNR), peak signal to noise ratio (PSNR), maximum difference (MD), normalized absolute error (NAE), normalized cross-correlation (NK), structural content (SC), coefficient of correlation (CoC), universal quality index(UQI), quality index based on local variance (QILV), laplacian mean squared error (LMSE), mean structural similarity quality index (MSSIM) (Loizou and Pattichis 2008). This last metric is not just an index, as it includes a visibility error map for viewing areas where both original image and distorted image are different. We also propose a new metric which combines the LMSE and MSSIM to obtain the Speckle Reduction Score (SRS).

All the metrics are self explanatory and hence a separate explanation for each and every metrics is not included in the discussion due to page limitation.

4 IMPLEMENTATION OF DESPECKLED ALGORITHMS AND RESULTS

In this section we present the results of the 17 despeckle filters described in Section 2.

4.1 *Experiments with synthetic images*

To evaluate the effects of denoising filters on noisy images it is necessary to have reference images (without noise or with low noise level) used to compare the output of filtering and quantify the improvement in image quality. Usually both noisy and reference images might be obtained with the same scanner and under the same running conditions. This is very difficult because of the highly operator dependence of the ultrasound exams and the random variation of scattering and speckle phenomena in each acquisition. In this case, conventional metrics cannot be used to indicate the quality obtained with filtering. For this, it is useful to use synthetic images obtained for example by means of anatomic phantoms or by computer simulations. In our study, Field II (Jensen 2004) is used to simulate a B-mode ultrasound image (Figure 2b) of an MRI noise-free image of a kidney as the reference image for filtering evaluation (Figure 2a).

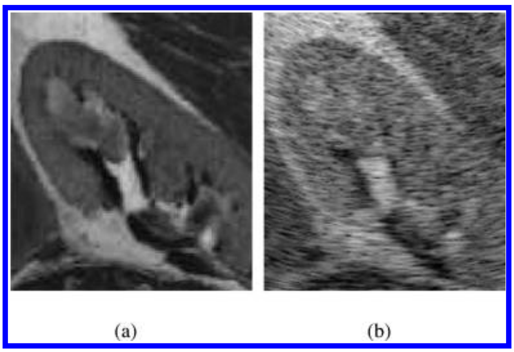

Figure 2. Simulated speckle noise. (a) Reference MRI image. (b) Noisy Field II image.

Table 2 summarizes the performance of the speckle filters, applied to the simulated image, through the calculation of several performance metrics. The best value for each metric is showed in bold. The resulting images are shown in Figure 2.

Although most of the metrics used in this study produce different scores for different levels of despeckling, the variability of the results is very low. The exceptions are LMSE, FOM and MSSIM. However, as FOM is based only in a quantitative comparison ofedge detection results it doesn't evaluate the speckle reduction inside the regions.

To obtain a final score for the speckling filters we propose the Speckle Reduction Score (SRS), a metric that combines the LMSE and MSSIM. The SRS values exhibit high consistency with the qualitative visual appearance of the smoothed images.

The values obtained for the performance metric, indicate that the best despeckling filters are LMMSE, SureShrink, Bilateral, BayeShrink, PMAD and Frost. Filters OSRAD and Lee have the poorer results.

4.2 *Application to real images*

Performance of a despeckling algorithm can also be subjectively measured by visual inspection

Table 1. Image quality evaluation metrics computed for the 17 despeckled filters.

Metrics	RMSE	SNR	PSNR	LMSE	MD	AD	NK	CoC	NAE	UQI	Qilv	FOM	SC	MSSIM	SRS
Noise	38.82	10.84	16.35	1.14	154	22.23	0.77	0.67	0.32	0.09	0.73	0.21	1.49	0.20	0.22
Median	34.46	11.80	17.38	3.61	139	22.37	0.79	0.76	0.29	0.15	0.74	0.44	1.45	0.47	1.68
Lee	37.06	11.21	16.75	1.32	139	22.15	0.78	0.70	0.31	0.11	0.73	0.24	1.47	0.26	0.34
Frost	33.37	12.03	17.66	43.32	**120**	22.08	0.80	0.79	0.29	0.16	0.75	0.48	1.42	0.53	23.09
Kuan	34.06	11.86	17.49	2.65	121	21.82	0.79	0.76	0.29	0.14	0.75	0.38	1.43	0.44	1.17
Wiener	34.12	11.85	17.47	2.53	128	21.84	0.79	0.76	0.29	0.15	0.75	0.33	1.43	0.47	1.18
Fourier	34.96	11.65	17.26	15.57	138	21.51	0.79	0.74	0.30	0.14	0.73	0.45	1.44	0.42	6.47
Butterworth	34.29	11.80	17.43	14.76	131	21.43	0.79	0.75	0.29	0.15	0.74	0.45	1.43	0.45	6.69
Bilateral	33.42	12.02	17.65	47.20	122	22.25	0.80	**0.79**	0.29	0.17	0.75	**0.55**	1.43	**0.54**	25.38
PMAD	**33.19**	**12.06**	17.71	44.29	122	21.70	**0.80**	0.78	0.29	0.16	0.75	0.36	**1.42**	0.54	23.69
CED	35.72	11.50	17.07	2.33	130	22.22	0.78	0.73	0.30	0.12	0.74	0.24	1.46	0.33	0.76
SRAD	38.35	11.18	16.46	41.31	134	28.88	0.75	0.78	0.31	0.16	0.72	0.33	1.63	0.50	20.62
EEAD	34.09	11.84	17.48	2.80	131	**21.32**	0.80	0.75	0.29	0.15	0.75	0.44	1.42	0.45	1.25
OSRAD	41.34	10.57	15.80	1.26	150	27.72	0.73	0.70	0.33	0.13	0.69	0.04	1.66	0.33	0.42
Visu	35.63	11.52	17.10	1.48	133	22.23	0.78	0.73	0.30	0.12	0.74	0.29	1.46	0.33	0.48
Sure	33.65	11.99	17.59	48.63	139	22.20	0.79	0.78	0.29	**0.18**	0.75	0.47	1.44	0.52	25.39
Bayes	33.65	11.99	**18.71**	47.06	137	22.21	0.79	0.78	0.29	0.18	0.75	0.46	1.44	0.52	24.52
LMMSE	33.42	12.04	17.65	**60.98**	123	22.23	0.80	0.79	**0.29**	0.17	**0.76**	0.54	1.43	0.53	**32.52**

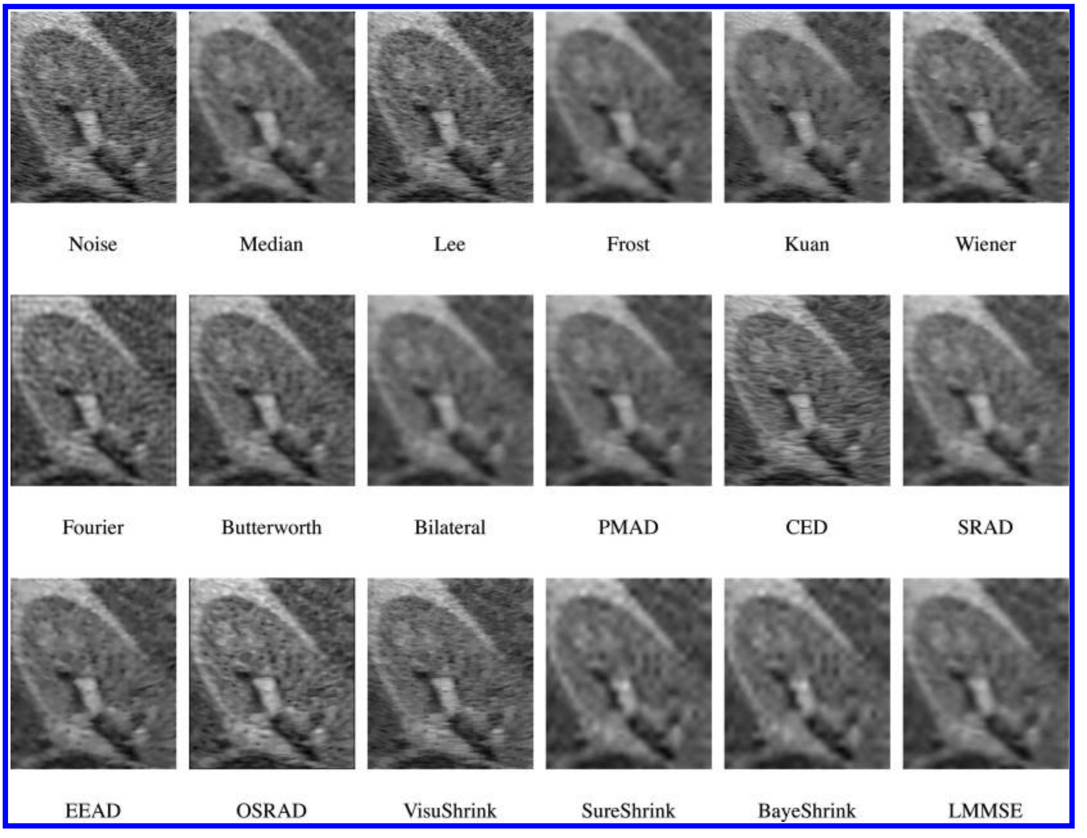

Figure 3. Images after applying the despeckle filters described in Section 2.

of enhanced images by experts. For that we also applied the different filters evaluated in the previous sections to real ultrasound images. The results are shownin Figure 4.

5 CONCLUSION

This paper compares some of the different algorithms and methods currently used to smooth the speckle noise in medical images obtained through ultrasound images. A new evaluation metric is proposed to evaluate the despeckling results. The comparative study of noise suppression methods in ultrasound images was carried out on a noise-free synthetic image of a kidney. We have used the Field II software to corrupt the image, adding the typical noise in ultrasound images. Afterwards we have shown some of the most common smoothing techniques over this image using numeric metrics, taking the noise-free image as a reference. In this study, a total of seventeen different speckle reduction algorithms have been documented based on spatial filtering, diffusion filtering and wavelet filtering, with fifteen qualitative metrics estimation. At the second stage the effects of applying the speckle filtering techniques were tested on data acquired in real ultrasound images obtained from S. Teotónio—Hospital, Portugal.

REFERENCES

Chang, S., B. Yu, & M. Vetterli (2000). Adaptive wavelet thresholding for image denoising and compression. *IEEE Transactions on Image Processing 9*(9), 1532–1546.

Donoho, D. & I. Johnstone (1994). Ideal spatial adaptation via wavelet shrinkage. *Biometrika 81*, 425–455.

Donoho, D. & I. Johnstone (1995). Adapting to unknown smoothness via wavelet shrinkage. *Journal of the American Statistical Association 90*(432), 1200–1224.

Frost, V., J. Stiles, K. Shanmugan, & J. Holtzman (1982). A model for radar images and its application to adaptive digital filtering of multiplicative noise. *IEEE Transactions on Pattern Analysis and Machine Intelligence 4*(2), 157–166.

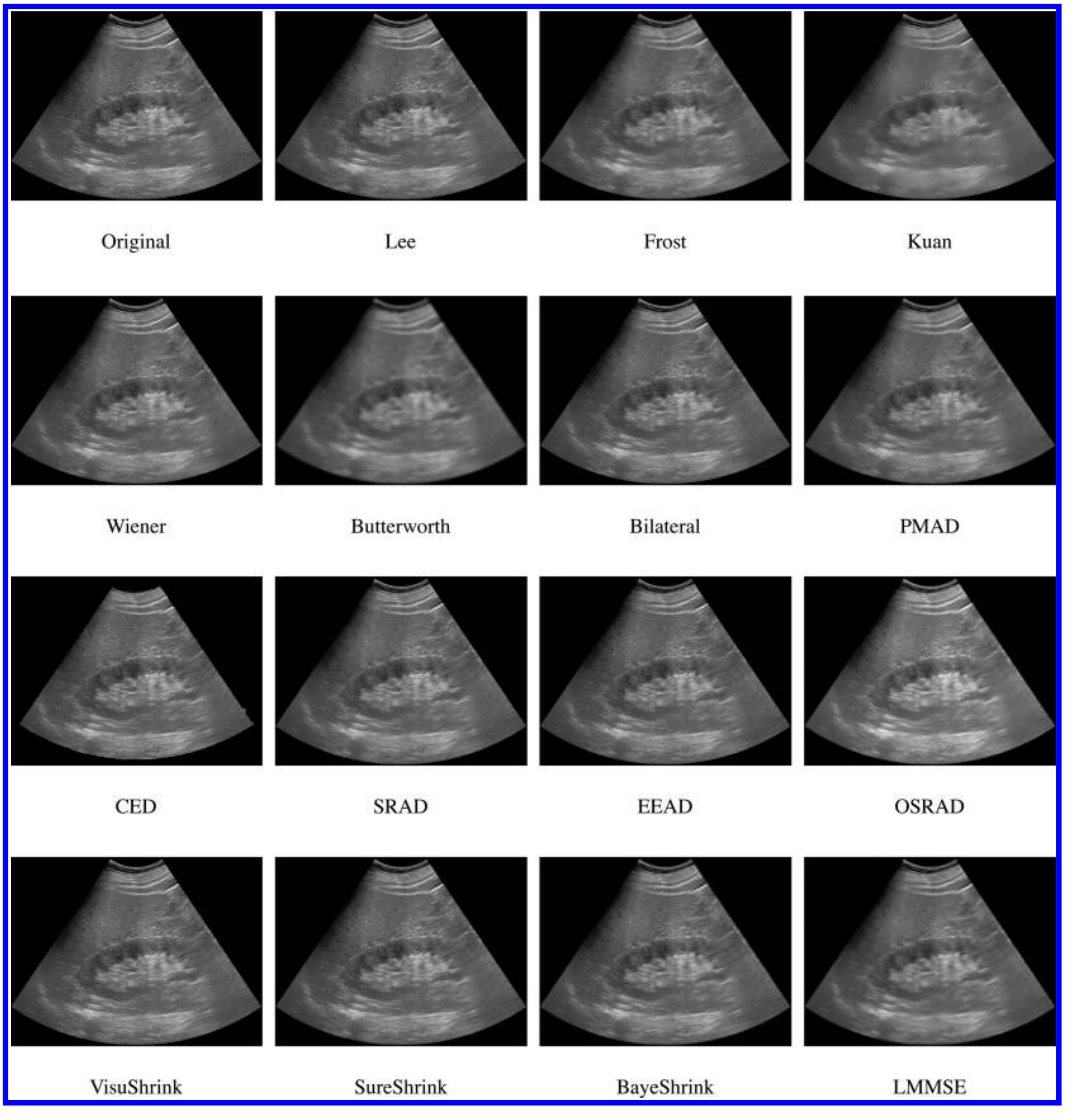

Figure 4. Original ultrasound image and the despeckled filtered images.

Fu, S., Q. Ruan, S. Fu, W. Wang, & Y. Li (2005). A compound anisotropic diffusion for ultrasonic image denoising and edge enhancement. In *IEEE International Symposium on Circuits and Systems*, Volume 3, pp. 2779–2782.

Jensen, J. (2004). Simulation of advanced ultrasound systems using Field II. In *IEEE International Symposium on Biomedical Imaging*, pp. 636–639.

Jin, F., P. Fieguth, L. Winger, & E. Jernigan (2003). Adaptive Wiener filtering of noisy images and image sequences. In *Int. Conference on Image Processing*, Volume 3, pp. 349–352.

Krissian, K., C. Westin, R. Kikinis, & K. Vosburgh (2007). Oriented speckle reducing anisotropic diffusion. *IEEE Trans. on Image Processing 16*(5), 1412–1424.

Kuan, D., A. Sawchuk, T. Strand, & P. Chavel (1985). Adaptive noise smoothing filter for images with signal-dependent noise. *IEEE Transactions on Pattern Analysis and Machine Intelligence 7*(2), 165–177.