Speckle Reduction for Automated Breast Ultrasound

A Comparison of Three Filtering Methods

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Abstract. This paper compares filtering methods for automated breast ultrasound images. The Perona-Malik diffusion filter, the diffusion stick filter and a simple median filter are evaluated as preprocessing methods for segmentation and characterization of lesions in breast ultrasound. In particular, preservation of small relevant image features, edge enhancement characteristics, and computational costs are considered.

1 Introduction

Compared to other common modalities used in medical imaging, the strong signal to noise ratio of ultrasound is affecting its imaging quality to a large extent. Typical ultrasound images are often described as coarse-grained and diffuse due to multiplicative noise called speckle [1, 2]. Although the speckle pattern is characteristic for the imaged tissue, it makes image processing more complicated. Frequently, methods used for computer aided detection (CAD), segmentation, registration, feature extraction or classification of medical data require preprocessing steps for speckle reduction and/or edge enhancement. Among the commonly used methods are simple median filtering, methods based on wavelets [3], nonlinear diffusion [4, 5, 6], stick filter [7] and others [8]. As these methods differ largely in terms of filtering quality and computational costs, none of them can be said to be the dominant technique for all applications. The goal of this paper is to compare a set of filters for (automated) breast ultrasound.

2 Materials and Methods

The SomoVu automated breast ultrasound system from U-Systems Inc. (San Jose, CA, USA; EC Representative: Siemens, Erlangen, Germany) generates three-dimensional ultrasound datasets acquired by an automatic sweep over the slightly compressed breast in supine position. This allows for the reconstruction of coronal and sagittal views in addition to the generic transversal view. The selection of a filter for preprocession is always dependent of the following application. In the context of lesion segmentation an edge enhancement of the lesion border is desired, while smoothing speckle and texture. Features to be preserved are an irregular margin of the lesion, which is used as indication of malignancy, as well as the architectural distortion and (although rarely seen) microcalcifications inside a lesion. One unique feature found in the coronal view is the star like retraction phenomenon which can appear around malignant lesions. In the context of automated detection, the conservation of this feature is an important requirement for a suitable speckle filter. We have chosen 10 datasets featuring breast lesions differing in size, shape, margin and image quality to compare the filter methods against.

The set of filters we compare here comprise the median filter, the Perona-Malik diffusion filter [4] and the diffusion stick filter [7]. We included a two dimensional (3×3) and three dimensional ($3\times3\times3$) median filter to evaluate the effect of the neighboring slices on the filter result. The well known Perona-Malik diffusion filter [4] is a nonlinear diffusion filter, where the strength of the diffusion is controlled by an diffusity function which acts as an 'edge detection' function. In our implementation we chose the edge parameter $\lambda = 2$, the smoothing value $\sigma = 0.1$, a time step of $\Delta t = 1$ and 10 iterations. The idea behind this method is to eliminate small gray value differences which are due to noise and to retain large differences due to signal. In the presence of speckle noise however, gray values differences due to noise can be larger than those due to signal, which can hamper the filter result.

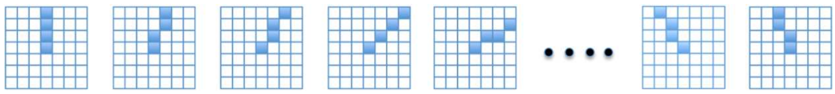
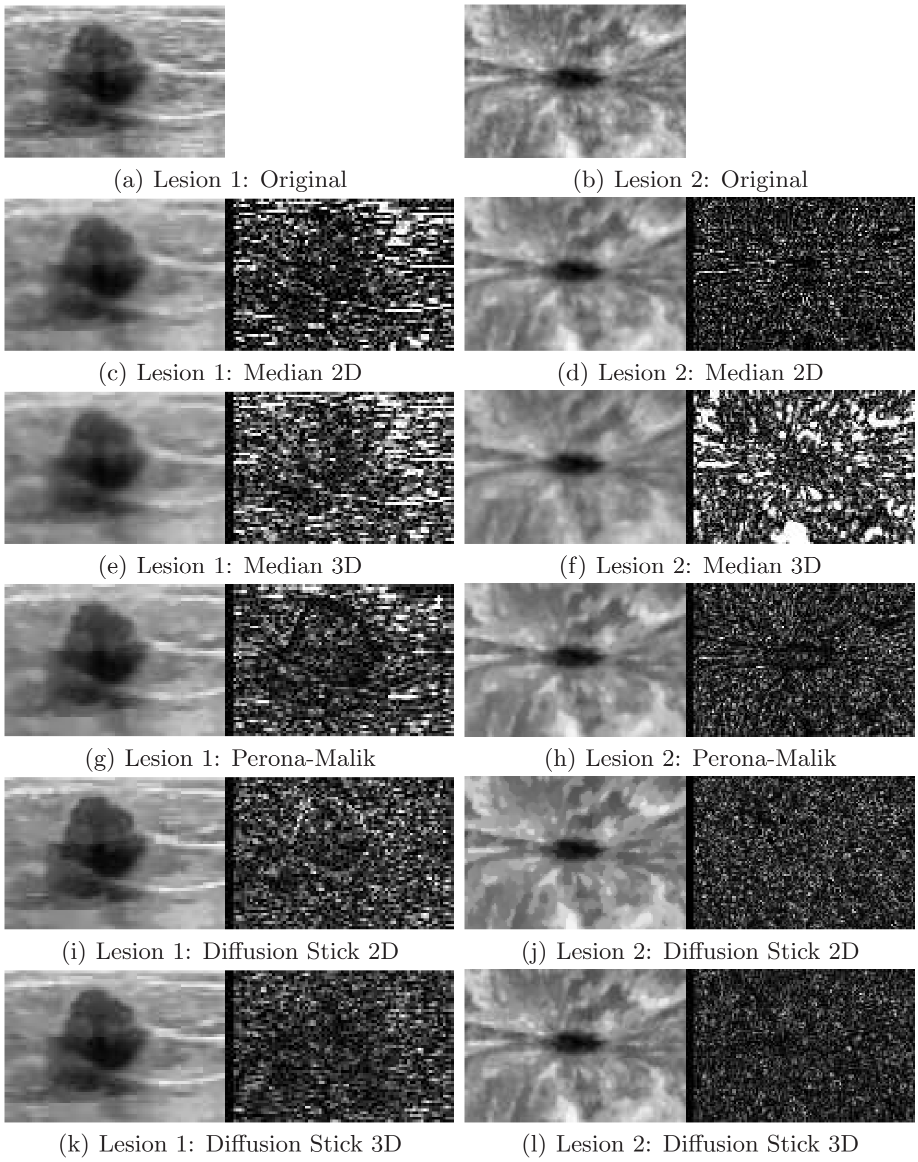


Fig. 1. This image shows 7 examples of the 24 sticks for a 7×7 kernel.

The diffusion stick method [4] is less well known and shall be briefly explained here. It combines the anisotropic diffusion with the works of Czerwinski et al. [9]. A kernel of size $N\times N$ (N must be odd) can be split into $4N-4$ radial sticks each with the length $(N+1)/2$. Each stick starts at the kernel center and ends at one of the $4N-4$ boundary voxels (Fig. 1). Variance and mean along each stick are calculated. The variance acts as edge detection function and controls the degree of diffusion of the mean voxel value. This way, voxel values along lines and edges are preserved while smoothing homogeneous regions. Additionally, a stopping function σ_2 manually set is included to control the overall smoothing (eq. (13) in [7] for details). As we chose a kernel of 7×7, there will be 24 sticks with the size 4. We also included a three-dimensional diffusion stick method with 218 sticks inside a $7 \times 7 \times 7$ kernel. The stopping function σ_2 is set to 100. The algorithms mentioned above have been implemented in MeVisLab 2.1a and were tested on a 2.8 GHz Quad-Core Intel Xeon Mac (Snow Leopard) with 8 GB RAM.

3 Results

We evaluated each filter on 10 lesions with differing characteristics. Two of these lesions are shown in Fig. 2(a, b). The result of all evaluated filters are shown in



(a) Lesion 1: Original
(b) Lesion 2: Original
(c) Lesion 1: Median 2D
(d) Lesion 2: Median 2D
(e) Lesion 1: Median 3D
(f) Lesion 2: Median 3D
(g) Lesion 1: Perona-Malik
(h) Lesion 2: Perona-Malik
(i) Lesion 1: Diffusion Stick 2D
(j) Lesion 2: Diffusion Stick 2D
(k) Lesion 1: Diffusion Stick 3D
(l) Lesion 2: Diffusion Stick 3D

Fig. 2. (a) Lesion 1 features a lobulated shape and possible calcification inside shown in transversal view. (b) Lesion 2 features a retraction the shown in the coronal view. (c-l) The result of each evaluated filter to the respective original lesion images above is shown on the left hand of each subfigure together with the absolute difference to the corresponding original image on the right hand. The difference images visualizes the effect of each filter.

Table 1. Computation time of filters. The whole data block containes 330 slices.

Filter	single slice in [ms]	data block in [s]
Median 2D	3.4	1.1
Median 3D	13.8	4.6
Perona-Malik	82.0	27.1
Diffusion Stick 2D	36.8	12.3
Diffusion Stick 3D	158.2	52.2

the Fig. 2(c-l) below the respective original image. To make the effect of a filter easier visible, each Fig. 2(c-l) shows the difference image of the filter results to the original image on the right hand.

Additionally to the qualitative filter result we compared the computational costs of each filter type in our implementation for a three-dimensional ultrasound dataset of $326 \times 99 \times 330$ voxels. Tab. 1 shows the computation time for a single slice and the whole dataset. The two-dimensional implementation of the median filter needed 1.1 seconds for completion, while the three-dimensional version needed 4.6 seconds. The computation for the Perona-Malik diffusion filter took 27.1 seconds. The two-dimensional diffusion stick algorithm computed the dataset in 12.3 seconds while the three-dimensional implementation needed 52.2 seconds due to the large amount of sticks.

4 Conclusions

The median filter has the lowest computational costs, but its edge preserving capabilities are much weaker compared to the other methods. Moreover, the microcalcifications are almost lost in the filter process as can be seen in Fig. 2(c). Median filtering also appears to thicken or even eliminate linear image features. This is best observed through the respective difference images in the Fig. 2(c, d) and is especially strong in the three-dimensional implementation (Fig.2(e. f)).

With our chosen parameters Perona-Malik diffusion showed better results than the median filter, but (as can be seen in the difference images in Fig. 2(g, h)) there seems to be less filter effect at the position of the lesion borders. This means that the lesion edges do not get smeared while smoothing speckle, but they also do not get enhanced much. Additionally the Perona-Malik diffusion filter appeared to be rather sensitive on the chosen parameters in our experiments and getting pleasing results often needed fixing of the parameters when changing between different datasets of the same quality.

The diffusion stick filter is not as fast as the median filter but as a whole it showed the best results for preserving the features described above and for enhancing the edges of the lesions. Compared to the two-dimensional version, the three-dimensional implementation of the diffusion stick method does not seem to have an improving effect on the filter result, which would compensate for its large computational time. Edges seemed not to get as much enhanced compared to the two-dimensional implementation which is best seen in Fig. 2(i).

Due to the combination of the good results and its comparable low computational costs we chose the two-dimensional diffusion stick filter as our preprocessing filter of choice.

Future work will concentrate on an evaluation of different speckle reduction techniques with respect to specific image analysis tasks in breast ultrasound, such as segmentation of lesions and anatomical structures, feature extraction and classification, and image registration.

References

1. Burckhardt CB. Speckle in ultrasound B-mode scans. IEEE Trans Sonics Ultrasonics. 1978;25(1):1–6.
2. Wagner RF, Smith SW, et al. Statistics of speckle in ultrasound B-scans. IEEE Trans Sonics Ultrasonics. 1983;30(3):156–63.
3. Vue Y, Croitoru MM, et al. Nonlinear multiscale wavelet diffusion for speckle suppression and edge enhancement in ultrasound images. IEEE Trans Med Imag. 2006;25(3):297–311.
4. Perona P, Malik J. Scale space and edge detection using anisotropic diffusion. IEEE Trans Pattern Anal Mach Intell. 1990;12(7):629–39.
5. Yu Y, Acton ST. Speckle reducing anisotropic diffusion. IEEE Trans Image Processing. 2002;11:1260–70.
6. Tauber C, Batatia H, Ayache A. A robust speckle reducing anisotropic diffusion. IEEE Int Conf Image Process. 2004;1:247–50.
7. Xiao CY, Zhang S, Chen YC. A diffusion stick method for speckle suppression in ultrasonic images. Pattern Recognit Lett. 2004;25(16):1867–77.
8. Avianto E, Ito M. Speckle reduction for ultrasonic images using fuzzy morphology. Trans Inf Syst. 2001;84(4):502–10.
9. Czerwinski RN, Jones DL, OBrien WD. Detection of lines and boundaries in speckle images- application to medical ultrasound. IEEE Trans Med Imaging. 1999;18(2):126–36.