Speckle reduction based on Wiener filter in ultrasound images

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***Abstract*— In this manuscript, a technique for speckle noise reduction in ultrasound images is presented. The method exploits Wiener filter and is able to take into account spatial correlation among noise samples. With respect to classical Wiener filter approach developed in independence hypothesis, the methodology is able to sensibly improve filtering performances, at the cost of no computational time increase. Results on realistic simulated datasets are reported, showing the effectiveness of the approach.**

I. INTRODUCTION

Noise reduction in Ultra-Sound (US) imaging is a significant and challenging task, mainly due to the nature of involved noise. This kind of multiplicative noise, referred to as speckle, produces artifacts that can hardly be modeled, mainly because they are tissue-dependent. As in radar domain, speckle is due to multi-path reflections that occurs in each resolution cell due to different acoustic impedances of involved tissues [1]. An effective way to handle the problem is to describe speckle by using its statistical distribution [2]. Usually, a logarithmic transformation is applied to US images, in order to compress the dynamic range and make more effective the visual inspection. Of course, this modifies the speckle statistical description, making it an additive noise.

In last decades, several speckle filtering algorithms have been proposed in literature with the main purpose of reducing speckle noise while preserving any atomic information that could be necessary to reliably and accurately delineate the regions of interest [3], [4], [5]. Existing methods can be classified in four main classes: adaptive filters, Partial Differential Equations (PDE)-based approaches, multi-scale methods and hybrid approaches [6]. Adaptive filters are widely adopted as they are easy to be implemented [7], [8], [9]. They do not make any assumption on the characteristics of speckle and of data, excepting the multiplicative nature of noise. Differently from adaptive filters, PDE-based approaches are iterative and are characterized by good smoothing properties while preserving edges. Multi-scale approaches, such as wavelet thresholding [10], commonly apply a logarithm compression in order to achieve an additive noise model. Hybrid methods combine two ore more approaches for reaching better filtering results [11].

Clearly, the most effective filtering approaches takes into account the nature of the whole acquired signals, instead of considering exclusively the noise. Among them, we recall methodologies based on image patches, which proved to be robust filters in case of US images [6]. The main limitation of such approaches is the computational burden, which generally is not minimal.

Within this manuscript, we present the application of Wiener filter for speckle reduction in US images. Such approach, which is applied in the frequency domain, has proven to be very fast to be applied, being able to produce almost real time results. By considering the filtering quality, the main novelty consists in taking into account the speckle spatial correlation, i.e. the noise autocorrelation function. In the following we prove that this kind of filter, although computationally light, is characterized by better performances with respect to classical approaches that assumes spatially uncorrelated multiplicative noise.

II. METHODOLOGY

The signal $z(x,r)$ acquired by an US scanner and corrupted by multiplicative noise can be modeled as:

$$z(x,r) = y(x,r)n(x,r) \tag{1}$$

where $y(.)$ is the noise-free signal $n(.)$ is the speckle noise and (x,r) are the acquisition geometry indexes. Noise of coherent imaging systems is commonly modeled as an exponential random variable, whose probability density function is:

$$f_N(n) = exp(-n)u(n) \tag{2}$$

where $u(.)$ is the unit step.

In order to work with an additive noise model, a logarithm transformation is applied, achieving:

$$\begin{aligned} s'(x,r) = \log[z(x,r)] &= \log[y(x,r)] + \log[n(x,r)] \\ &= y'(x,r) + n'(x,r) \end{aligned} \tag{3}$$

Depending on the acquisition system, the noise random process exhibits a specific auto-correlation function, and consequently is characterized by a power density function $W_{n'}(\zeta,\eta)$, with (ζ,η) the spatial frequencies in a 2D spectrum.

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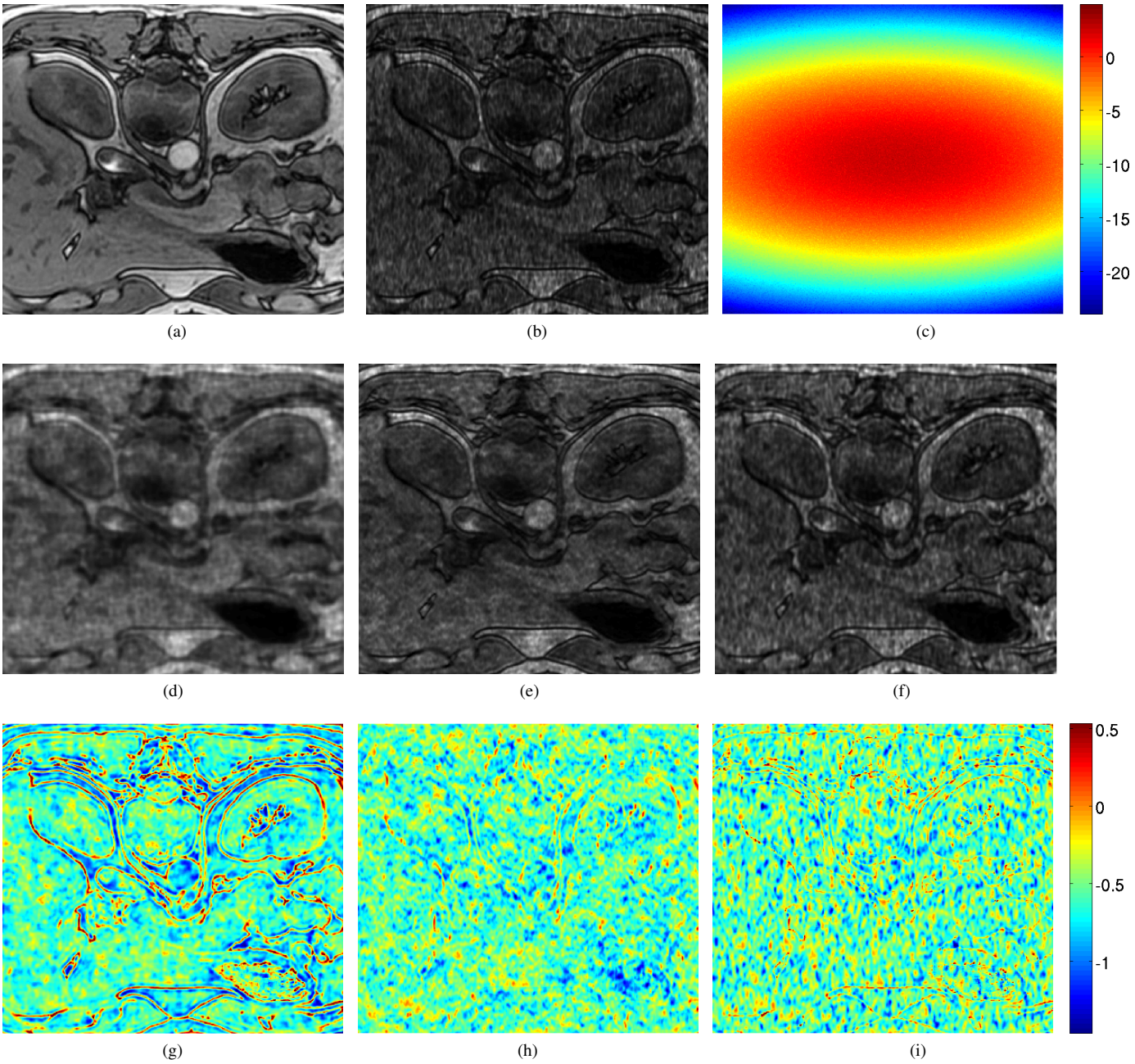


(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig. 1: First row, simulated dataset: noise free image (a), image corrupted by speckle (b) and noise power spectral density (logarithmic scale) (c). Second row, filtering results: image filtered via Wiener filter under uncorrelated noise hypothesis (d), image filtered via Wiener filter taking into account correlation (e) and image filtered via Lee approach (f). Third row: reconstruction error in case of uncorrelated Wiener filter (g), correlated Wiener filter (hb) and Lee filter (i).

Wiener filter can be formulated as [12]:

$$H_W(\zeta,\eta) = \frac{P_{y'}(\zeta,\eta)}{P_{y'}(\zeta,\eta) + W_{n'}(\zeta,\eta)} \quad (4)$$

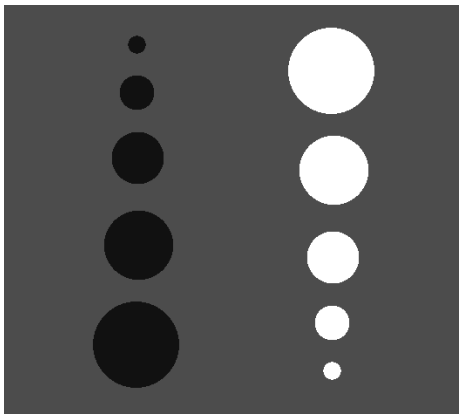
where $P_{y'}(\zeta,\eta) = |Y'(\zeta,\eta)|^2$ is the power spectrum of the noise-free signal in the logarithmic domain $y'(x,r)$. By computing the inverse Fourier transform of Eq. (4), we obtain the filter impulse response, commonly referred to as point spread function.
The output of the filter, i.e. the estimated noise free image $\hat{y}'(x,r)$, can be written as:

$$\hat{y}'(x,r) = s'(x,r) \otimes h_W(x,r) \quad (5)$$

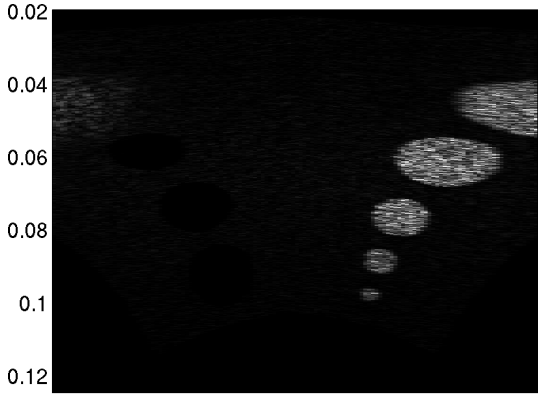
where $\otimes$ is the 2D convolution operator. Generally, the numerator of Eq. (4) is unknown, as it is directly related to the noise-free signal, and has to be estimated. As first approximation, it can be considered equal to the power spectrum of the noisy image $P_{s'}(\zeta,\eta) = |S'(\zeta,\eta)|^2$.
Concerning the noise power density function, it is generally considered as constant, i.e. uncorrelated noise samples. As it will be evident in the next section, by correctly taking into account the correlation between noise samples, i.e. by estimating $W_{n'}(\zeta,\eta)$, it is possible to improve the performances of Wiener filter. As future work, an iterative procedure for the determination of noise and signal power spectra will be investigated.

III. RESULTS

The proposed methodology has been tested on different simulated datasets. An MRI image of the abdomen, reported in Figure 1a, has been considered as ground truth. The image geometry of MR images, which is horizontal/vertical, has not been converter to US systems acquisition geometry azimuth/range as it is irrelevant for the approach. An exponential multiplicative noise has been generated, according to Eq. 2. A spatial correlation has been considered, different for the two dimensions. The power spectral density function $W_{n'}(\zeta,\eta)$ of a noise realization is shown in Figure 1c in logarithmic scale. The obtained noisy image is reported in Figure 1b.
Initially, a Wiener filter assuming uncorrelated noise, i.e. constant power spectral density, has been considered. Such hypothesis is commonly done in the community [13]. The filtering result is shown in Figure 1d. It can be noted that, although the noise level is sensibly low, edges are not correctly retrieved, as high frequencies are excessively reduced by the Wiener filter.
Subsequently, the hypothesis about the knowledge of the noise power spectral density has been done. This assumption is not unrealistic, as noise spatial correlation is mainly related to the acquisition system, thus the function $W_{n'}(\zeta,\eta)$ can be evaluated during scanner calibration. From an image processing point of view, such consideration allows better preserving signal frequencies in the Fourier domain where noise intensity is lower. From Figure 1c, it is clear that such spectrum sections are related to higher frequencies. This assumption is expected to assure better edge retrieval in the



(a)



(b)

Fig. 2: Second dataset. Reference phantom (a) and US image simulated via Field II software (b) in azimuth-range coordinates.

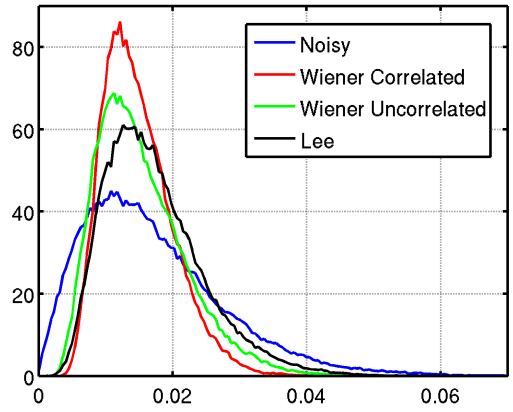
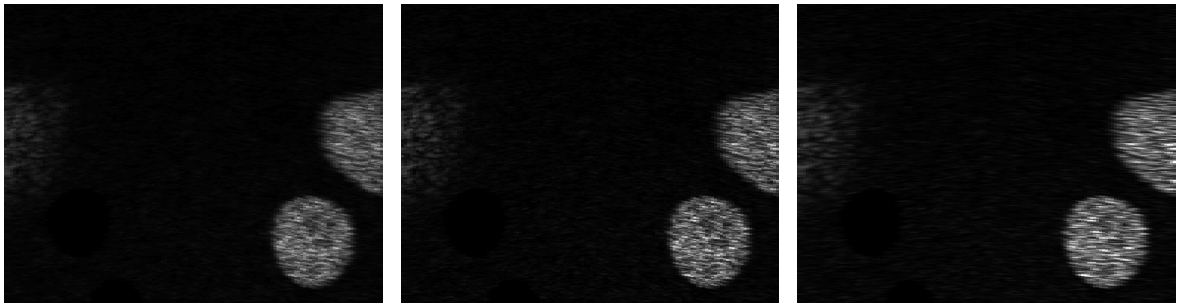


Fig. 3: Histogram of a constant region in case of different filters. As expected, the proposed Wiener correlated approach is the very effective in reducing noise.



(a) (b) (c)

Fig. 4: Second dataset, filtering results: image filtered via Wiener filter under correlated noise hypothesis (a), image filtered via uncorrelated Wiener filter (b) and image filtered via Lee approach (c).

filtered image. Filtering results are reported in Figure 1e, where it is clear that the expectations are met. Globally, the quality of the image is much higher with respect to Figure 1d, as the picture appear crisp and with more small details. In order to give a reference, the noisy image has also been processed with Lee filter [14] (see Figure 1f). With respect to correlated Wiener filter, edges are still well retrieved but the noise smoothing effectiveness is lower, with smooth areas characterized by higher variability.

Reconstruction errors, i.e. the difference between original noise-free image and filtered images, have also been reported in Figures 1g, 1h and 1i for the three considered filters. Such figures confirm what has previously been noticed: errors in the Wiener uncorrelated filtered image are mainly concentrated on the edges, while Lee filter result has a globally higher error level.

In order to verify the performances in a more realistic dataset, Field II ultrasound image simulator has been used [15], [16]. A synthetic image with several circles has been considered (Figure 2a). The noisy image obtained by the simulator is reported in Figure 2b. We focused on the top part of the scene, in order to better appreciate filtering results. The three approaches, i.e. Wiener correlated, Wiener uncorrelated and Lee, have been applied, producing results in Figure 4. Globally, trends previously described are confirmed, with Wiener correlated filter as the best trade-off between smoothing characteristics and edge preservation.

IV. CONCLUSIONS

Within this manuscript, a speckle filter for ultrasound images is proposed. The method exploits Wiener filter and it is able to take into account the power density spectrum of involved noise. In other words, the approach does not make the common assumption of uncorrelated noise by filtering the images in an optimal way with respect to noise autocorrelation function. In comparison with Wiener filter for uncorrelated noise and Lee speckle filter, the algorithm as shown interesting performances, being able to both smoothing noise and preserving edges. That said, further validations on real datasets are required and will be done in the future.

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