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Enhanced Wiener filter for ultrasound image restoration

Fabio Baselice[a,*], Giampaolo Ferraioli[b], Michele Ambrosanio[a], Vito Pascazio[a], Gilda Schirinzi[a]

[a] Dipartimento di Ingegneria, Università degli Studi di Napoli Parthenope, Napoli, Italy
[b] Dipartimento di Scienze e Tecnologie, Università degli Studi di Napoli Parthenope, Napoli, Italy

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ABSTRACT

Background and Objective: Speckle phenomenon strongly affects UltraSound (US) images. In the last years, several efforts have been done in order to provide an effective denoising methodology. Although good results have been achieved in terms of noise reduction effectiveness, most of the proposed approaches are not characterized by low computational burden and require the supervision of an external operator for tuning the input parameters.
Methods: Within this manuscript, a novel approach is investigated, based on Wiener filter. Working in the frequency domain, it is characterized by high computational efficiency. With respect to classical Wiener filter, the proposed Enhanced Wiener filter is able to locally adapt itself by tuning its kernel in order to combine edges and details preservation with effective noise reduction. This characteristic is achieved by implementing a Local Gaussian Markov Random Field for modeling the image. Due to its intrinsic characteristics, the computational burden of the algorithm is sensibly low compared to other widely adopted filters and the parameter tuning effort is minimal, being well suited for quasi real time applications.
Results: The approach has been tested on both simulated and real datasets, showing interesting performances compared to other state of art methods.
Conclusions: A novel denoising method for UltraSound images is proposed. The approach is able to combine low computational burden with interesting denoising performances and details preservation.

1. Introduction

Ultrasound (US) systems works by transmitting within the patient body a low energy sound pulse with frequency in the range of 3 - 30MHz using an US probe. Pulses travel through tissues and find different acoustic impedances, and thus they are attenuated and partially scattered back to the US probe. Once the echoes are acquired, the system processes them to form a 2D image, also known as sonogram, or B-mode (brightness) images [1].

US scanners are commonly used in clinical diagnosis due to their many advantages such as lack of radiation risk, cheapness, noninvasive nature and high portability. Such features have made US systems widely adopted despite the availability of more sophisticated imaging techniques such as CT scan, MRI or PET. With respect to previously cited clinical imaging techniques, US systems generally generate lower quality image, with a higher amount of noise. This is mainly a consequence of the acquisition system, which acts as a radar, i.e. sending signals and receiving echoes. Due to multipath reflections that occur within the medium, the received signal is not constant and exhibits a specific pattern, commonly referred to as speckle. This phenomenon gives to the acquired images a granular appearance, with several bright and dark spots caused by random constructive and destructive interference of echoes. Speckle phenomenon mainly reduces the contrast of the acquired images, degrades the details and the overall quality, negatively affecting the diagnostic value of the ultrasound imaging. For these reasons it is commonly considered as noise. Therefore, speckle reduction is important for ultrasound image processing tasks [2]. The main drawback of the process is due to the multiplicative nature and to the dependency of speckle from the imaged volume.

The suppression of speckle is mainly performed in two ways. According to the moment the speckle reduction is performed, it is possible to distinguish between compounding approach and post-processing approach, [3–5]. The former method works modifying the data acquisition procedure in order to acquire several images of the same region and combine them to form a single image. The post-processing approach exploits the B-mode images after they

* Corresponding author.
E-mail addresses: fabio.baselice@uniparthenope.it (F. Baselice), giampaolo.ferraioli@uniparthenope.it (G. Ferraioli), michele.ambrosanio@uniparthenope.it (M. Ambrosanio), vito.pascazio@uniparthenope.it (V. Pascazio), gilda.schirinzi@uniparthenope.it (G. Schirinzi).

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have been generated, applying different type of filters. In the following, we will focus on the post-processing approach.

Several speckle filters have been proposed in literature, related to different research fields. The main goal consists in achieving a regularized image, i.e. a filtered image, with edges and small details preserved, with high computational efficiency [6–9]. Five main classes can be defined for describing existing approaches: linear and non-linear filters, adaptive speckle filters, wavelet-based filters and Partial Differential Equation (PDE) approaches.

Linear filtering techniques require an additive noise model, thus an homomorphic transformation (generally logarithmic) is applied. A classical approach consists in applying the Wiener filter in the transformed domain in order to reject the resultant additive noise. After this step, the homomorphic transformation is inverted, e.g. by computing the exponential in case the logarithm was adopted in the first step [10]. The Wiener filter is one of the first approaches to denoising application, and it is able to minimize the Mean Square Error (MSE) of the regularized image.

Among the nonlinear approaches, the median filter is one of the most used. It has the advantage of preserving edges and is well suited in case of impulsive noise (salt and pepper). The main drawback is that some tiny details could be completely removed.

Adaptive speckle filters assumes the multiplicative model for the speckle noise. Among them, we recall Lee, Kuan and Frost algorithms [11–13]. These kinds of approaches assume the statistical independence between the noise free image and the speckle noise and a constant ratio of noise standard deviation to image mean value, the latter assumption being only valid in homogeneous regions. The spatial filtering is applied in a square-moving window, known as kernel, exploiting the statistical relationship between pixels. The main drawback of such approaches is that the window dimension will greatly affects the quality of the filtered image, and a proper value should be manually set. In recent years, some more sophisticated methodologies which adopt non-smooth regularization (such as Total Variation) have been proposed [14].

Wavelet-based techniques project the image in the wavelet domain before filtering the speckle [15–18]. The advantage is that in this domain the noise is uniformly spread, while most of the image information is concentrated in a few significant coefficients. In the transformed domain, a shrinkage function is applied for reducing the noise coefficients. Finally, the inverse wavelet transformation is applied. The most critical step is the weighting of the coefficients in the transformed domain. The main difference among wavelet-based denoising methods is related to this operation.

One of the most adopted denoising filter related to the PDE family was proposed in [19], namely the Anisotropic Diffusion (AD) filter. This method, which is a nonlinear PDE, exploits the gradient magnitude to detect an image edge or boundary. Its peculiarity is a good trade off between intra-region smoothing and edge preservation [20]. Anisotropic diffusion is well suited for additive noise. As for linear filter family, in cases of multiplicative speckle, a homomorphic transformation is required.

Most of the techniques proposed in the last years are evolutions and refinements of the previously defined approaches, e.g. [20–22]. Recently, methodologies based on the joint analysis of image patches have shown high filtering effectiveness [23]. In particular, such method consists in finding similarities among regions in order to compute the mean between image patches with similar details, i.e. preserving edges [24,25]. In this case, which is commonly referred to as the Non-Local Mean (NLM) approach, the main drawback is the non minimal computational burden, due to the large amount of information that has to be processed. This is a limitation common to most of methods recently proposed and characterized by good performance. Another factor limiting their applicability is the number of parameters to be tuned in order to achieve effective image regularization, as the operator is asked to spend time in searching the optimal configuration. Following that, a methodology able to combine good performance, low computational load and minimal supervision would be desirable.

In this manuscript, an evolution of the Wiener filter for speckle reduction in US images, namely Enhanced Wiener (EW) filter, is proposed. The methodology, which implements an adaptive filter, has been developed in order to overcome one of the main limitations of the Wiener filter: working in the frequency domain, it cannot take into account the local behavior of the image properly [26]. Proposed methodology adopts Markov Random Field (MRF) theory for modeling the noise free image, and subsequently for tuning the filtering intensity. This enhancement allows the filter to adapt its behavior to the local characteristics of the image, producing better edges and detail preservation and data regularization with respect to the standard Wiener filter. In brief, a modified version of the Wiener filter is implemented, with a parameter for controlling the regularization intensity. When MRF suggests the presence of edges or details, the solution is achieved by adopting the Wiener filter with a low regularization parameter. On the contrary, in case of smooth areas stronger regularization is enforced. This technique guarantees a high computational efficiency due to the exploitation of the Fast Fourier Transform (FFT), good denoising performance due to its adaptive approach and only one parameter to be set, providing a useful instrument for quasi real time applications.

The manuscript is organized as follows: in Section 2 the methodology is presented, while Section 3 and 4 compare its performance with other state-of-art approaches in case of simulated and real datasets. In the final Section conclusions are drawn.

2. Methods

2.1. The acquisition model

Let us consider the following multiplicative noise model for the amplitude signal $z(x, r)$ acquired by an US scanner [27]:

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

where $y(.)$ is the noise-free signal, $n(.)$ is the speckle noise and (x, r) are the space indexes defined with according to the acquisition geometry. The noise $n(.)$ is commonly modeled as a random variable with Rayleigh probability density function [11,28,29].

By applying a homomorphic transformation, the multiplicative model is converted into additive. The idea is to apply the filtering step in this transformed domain, and subsequently come back to the original one via an inverse transformation. If a logarithmic transformation is applied, the acquisition model becomes:

$$\begin{aligned} z'(x,r) &= \log[z(x,r)] = \log[y(x,r)] + \log[n(x,r)] \\ &= y'(x,r) + n'(x,r) \end{aligned} \tag{2}$$

where $y'(x, r)$ and $n'(x, r)$ are the signal and the noise in the logarithmic domain, respectively.

Wiener Filter can be applies on the new acquisition model. The WF is a linear time invariant filter with the 2D frequency response function defined as [30,31]:

$$H_W(\zeta,\eta) = \frac{P_{y'}(\zeta,\eta)}{P_{y'}(\zeta,\eta) + \alpha W_{n'}(\zeta,\eta)} \tag{3}$$

where $P_{y'}(\zeta,\eta) = |Y'(\zeta,\eta)|^2$ is the power spectrum of the noise-free signal $y'(x, r)$, with (ζ, η) the spatial frequencies in the 2D spectrum. Such filter is optimal in the sense that it minimizes the Mean Square Error (MSE) of the filtered image [32]. Depending on the acquisition system, the noise random process exhibits a specific auto-correlation function, and consequently is characterized by a power density function $W_{n'}(\zeta,\eta)$. The details on the computation of $W_{n'}(\zeta,\eta)$ in the considered case are provided in the Appendix. The parameter α is a scalar value adopted for tuning