Biomedical Signal Processing and Control 39 (2018) 336–350

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Research Paper

The complex data denoising in MR images based on the directional extension for the undecimated wavelet transform

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ARTICLE INFO

Article history:
Received 17 January 2017
Received in revised form 1 July 2017
Accepted 3 August 2017
Available online 30 August 2017

Keywords:
Magnetic resonance imaging
Wavelet transform
DEUWT
Translation-invariant
Complex denoising

ABSTRACT

Magnetic resonance (MR) images are commonly affected by noises. Denoising is an important issue that has been frequently discussed in recent years. In this paper, an interesting phenomenon is found that the directional information is abundant in MR images. Therefore, high-quality reconstructed MR images could be obtained if the related directional information is considered. To address the issue, the directional extension for the undecimated wavelet transform (DEUWT), an effective tool that is able to handle the directional information and provides the translation-invariant (TI) property as well, is employed to process MR images. Based on the DEUWT, we present a novel and fast wavelet domain complex data denoising algorithm for MR images. In the presented algorithm, we combine the DEUWT with the stein's unbiased risk estimator (SURE) thresholding, and treat the real and imaginary components of the MR image as a single complex entity. The experimental results show that the proposed algorithm outperforms existing state-of-the-art methods on both simulated complex images and complex phantoms.

1. Introduction

Magnetic resonance imaging (MRI) has become a powerful diagnostic technique since it provides highly detailed images of tissues and organs [1]. MR images acquired with high temporal resolution often display large noise artifacts, which arise from physiological sources as well as the acquisition hardware [2]. These noise artifacts degrade human interpretation or computer-aided diagnosis of images [1]. Time averaging of image sequences which aiming at the improvement of signal-to-noise rate (SNR) would require additional acquisition time, and thus reduces the temporal resolution [3]. The limitation of acquisition time is also a problem due to practical constraints (such as patient comfort and system throughput), and physiological constraints arising in dynamic applications (such as lung and cardiac imaging). Therefore, reconstruction techniques for the acquisition of higher-quality MR images are very important. One of the significant techniques is MR image denoising [4–8]. Naturally, MR image denoising can apply the ideas from general image denoising, but it is well known that magnitude MR images obey a Rician distribution [9]. Rician noise, which is different from additive Gaussian noise, is signal-dependent. Therefore, it is difficult to separate signal from noise.

The discrete wavelet transform (DWT) which is widely used for time-frequency localization, multi-resolution analysis, edge detection and decorrelation, has been successfully used in the MR image denoising [2,3,10–24]. Weaver et al. [10] put forward the application of the soft threshold in the wavelet domain to reduce the noise in MR images. Subsequently, several wavelet domain noise reduction schemes have emerged in references [11–15]. Most of them consider the incorporated noise as additive Gaussian noise and do not realize the Rician distribution of magnitude MR images [2].

Nowak [16] proposed a method that takes the Rician distribution of noise in magnitude MR images into consideration. He squared the magnitude MR image and applied a scaled noncentral chi-square distribution to model the square of the Rician random variable. One of the disadvantages is that this method is time-consuming. In MRI, the k-space data of MR images is complex data. The contributions of the noise arising from the scanner electronics to each of the real and imaginary parts of the k-space data are additive and can be assumed to characterized by a zero-mean Gaussian probability density function [17]. Consequently, before reconstructing the magnitude images, it is also available to denoise the real and imaginary parts of the complex images independently (with algorithms designed to remove Gaussian noise), rather than the magnitude images. Zaroubi et al. [18] suggested that this method not only

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http://dx.doi.org/10.1016/j.bspc.2017.08.014
1746-8094/

displays better performance, but also saves computing cost compared with the Nowak's magnitude method. Bao and Zhang [3] proposed an adaptive multiscale products thresholding algorithm that is applied to the real and imaginary components of the complex MR image respectively, retrieving more marginal information. However, because of the independent filtering of the real and imaginary parts, the distortions of phase and amplitude may occur in the denoised outputs, resulting in image artifacts. To handle this problem, Alexander et al. [17] developed a wavelet domain Wiener-type denoising algorithm that denoises the real and imaginary components of the complex signal as a single complex entity rather than as two independent parts. In this way, the distortions would not appear and the simulated results suggest that the proposed algorithm might provide a better recovery of the contrast than Nowak's method.

Anand and Sahambi in [19] proposed a wavelet based bilateral filtering method for noise removal in MR images. They used the undecimated wavelet transform to provide effective representation of the noisy coefficients. Yang and Fei [20] proposed a wavelet multiscale denoising method for MR data. In order to denoise the images, they used a translation-invariant (TI) wavelet transform to decompose the MR sinogram into multiscales. Luisier et al. [21] developed the Chi-square unbiased risk estimation (CURE) method for noise reduction in MR images. Firstly, a linear expansion of thresholds (LET) estimator is applied to the coefficients of an arbitrary undecimated filter bank transform. Secondly, consider the special case of the unnormalized Harr wavelet transform, a multiscale orthogonal transform is allowed for the derivation of subband-dependent CURE denoising strategies. Fernandez and Villullas [22] proposed a denoising method in MR images through shrinkage of wavelet coefficients by the conditioned probability of being noise or details. The parameters are computed by means of the expectation maximization (EM) algorithm to avoid the estimation of noise variance. Wirestam et al. [23] proposed a Wiener-like filtering in wavelet domain for complex MR image denoising. In their method, one hard-thresholding filter and two Wiener-like filters are combined to provide effective noise reduction in magnitude MR images. Hu et al. [24] proposed a wavelet domain translation-invariant Wiener-like filtering method for complex MR data denoising. Compared with Wirestam's method, Hu et al. firstly introduced TI property into the denoising algorithm to suppress artifacts caused by translations of the signal, and then used one stein's unbiased risk estimator (SURE) thresholding with two Wiener-like filters to make the hard-thresholding scale adaptive.

In recent years, the importance of the directional information has received increased attention in many image processing applications such as image denoising. In the wavelet domain, as a result of a separable extension from one-dimensional (1-D) cases, multidimensional wavelet transforms have limited directionality and cannot reserve enough directional information. There are a series of methods in providing directional information such as the directional filter bank [25], complex wavelets [26,27], curvelets [28], contourlets [29], etc. Lu and Minh [30–32] proposed a simple directional extension for wavelets (DEW), the building block of which is a two-channel 2-D filter bank with a checkerboard-shaped frequency partition. The DEW works with both the critically sampled wavelet transform as well as the undecimated wavelet transform (UWT), and the latter can fix the subband mixing problem effectively and improve the directionality markedly. In addition, UWT can obtain translation-invariant, an important property required in signal processing.

We demonstrate that the directional information is abundant in MR images. The performance of the denoising algorithm may be improved if the directional information of MR images is taken into account. For MR image denoising methods considering directional information, Latha and Subramanian in [33] used a curvelet transform based denoising algorithm for noise reduction in MR images. A hybrid MR image denoising method based on curvelet shrinkage and nonlinear diffusion using a combination of a tight frame of curvelets with a nonlinear diffusion scheme is proposed by Ma and Plonka [34]. Another transform based method contourlet transform is also employed by Latha and Subramanian in [33] for MRI denoising. However, we find that few studies have been done on applying DEW to MR images in the literature.

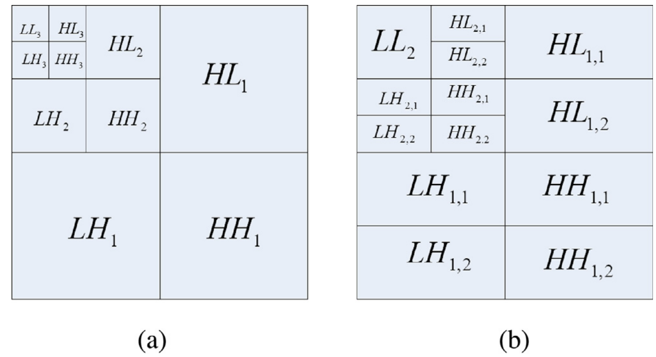

Fig. 1. Decomposition of (a) wavelet transform (level = 3) and (b) DEW (level = 2).

Therefore, a novel denoising algorithm for the complex data of the k-square in MR images based on the directional extension for the undecimated wavelet transform (DEUWT) is proposed in this paper. The presented algorithm effectively combines the extension directional information with TI property when denoising the real and imaginary components of complex MR image together as a single complex entity. The results indicate that the proposed algorithm can effectively reduce the Rician noise and obtain the high-quality MR images.

The paper is organized as follows. Section 2 gives an introduction to the DEUWT and briefly analyzes the directional information of MR images. In Section 3, the proposed denoising algorithm is described in detail. The experimental results and discussion are presented in Section 4 and we conclude the paper in Section 5.

2. Preliminaries

2.1. The directional extension for the undecimated wavelet transform

Wavelet transform can be implemented in image denoising by separable filter banks to decompose the input image (see Fig. 1(a)). It produces a lowpass subband LL_J (J is the largest decomposition level) and three highpass subband serials LH_j,HL_jandHH_j which correspond to vertical, horizontal and diagonal directions respectively. Fig. 2(a) shows its frequency decomposition. The advantage of this transform is the simple and separable implementation. However, it also imposes serious limits on the directionality of the resulting frequency partitioning and the diagonal subbands mix the directional information oriented at 45° and 135° [31].

To handle the subband mixing problem and improve the directionality, Lu and Minh [30–32] designed the checkerboard filter bank based on a parameterization of the polyphase matrices to further divide the three highpass subbands at each scale in the wavelet transform into six finer directional subbands. The decomposed result is shown in Fig. 1(b) and the frequency partitioning is shown in Fig. 2(b) [31]. In the other words, the new transform system contains six directional subbands roughly oriented at 15°, 45°, 75°, 105°, 135° and 165°. The DEW will not increase the redundancy of the overall transform due to its critically-sampled property. Though nonseparable in essence, the proposed DEW has an efficient implementation based on 1-D operations and can be