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Original Article

Semi-Blind Ultrasound Image Deconvolution from Compressed Measurements

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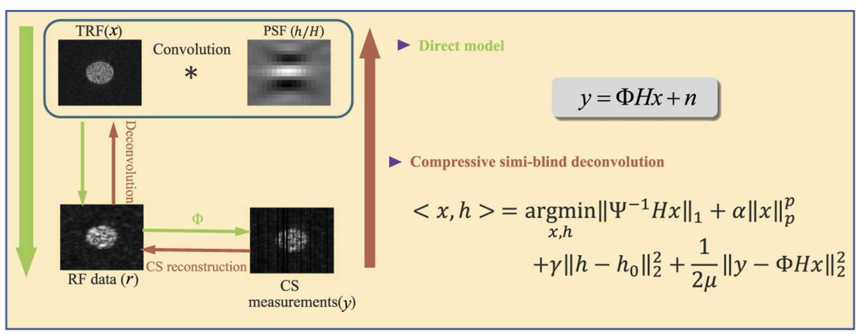
Received 28 July 2017; received in revised form 18 November 2017; accepted 20 November 2017

Highlights

- Estimating the PSF at the same time in the recently proposed compressive deconvolution framework for ultrasound imaging.
- Taking fully advantage of the existing method of PSF estimation.
- Presenting an analytical solution to the sub-problem of PSF.

Graphical abstract



Abstract

The recently proposed framework of ultrasound compressive deconvolution offers the possibility of decreasing the acquired data while improving the image spatial resolution. By combining compressive sampling and image deconvolution, the direct model of compressive deconvolution combines random projections and 2D convolution with a spatially invariant point spread function. Considering the point spread function known, existing algorithms have shown the ability of this framework to reconstruct enhanced ultrasound images from compressed measurements by inverting the forward linear model. In this paper, we propose an extension of the previous approach for compressive blind deconvolution, whose aim is to jointly estimate the ultrasound image and the system point spread function. The performance of the method is evaluated on both simulated and *in vivo* ultrasound data.

Keywords: Ultrasound imaging; Compressive sampling; Blind deconvolution

1. Introduction

Despite its intrinsic rapidity of acquisition, several ultrasound (US) applications such as duplex Doppler or 3D imaging may require higher frame rates than those provided by conventional acquisition schemes or may suffer from the high amount of acquired data. In this context, compressive sampling (CS) framework appears as an appealing solution to overcome these issues. Since the first works in compressive US imaging published in 2010 [1–4], there have been several studies devoted to this topic to date [5–11]. Conventional approach to sample sig-

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https://doi.org/10.1016/j.irbm.2017.11.002
1959-0318/

Please cite this article in press as: Chen Z, et al. Semi-Blind Ultrasound Image Deconvolution from Compressed Measurements. IRBM (2017), https://doi.org/10.1016/j.irbm.2017.11.002

nals or images follows the Shannon–Nyquist theorem. According to the Shannon–Nyquist sampling theorem, the sampling rate must be at least twice the maximum frequency contained by the signal. However, the theory of CS makes it possible to go against the common knowledge in data acquisition. It allows to recover, via non linear optimization routines, an image from few linear measurements (below the limit standardly imposed by the Shannon–Nyquist theorem) provided two conditions: i) the image must be sparse in a known basis or frame and ii) the measurement matrix must be incoherent with the sparsifying basis [12]. Existing works focused on these two aspects, *i.e.* the sparsity study and the incoherent acquisition, have shown that it is possible to recover US radio-frequency (RF) images based on their sparsity in basis such as 2D Fourier transform [13], wavelets [14], waveatoms [15], or learning dictionaries [6], using various acquisition schemes such as projections on Gaussian [4] or Bernoulli random vectors [13], plane-wave emissions [14] or Xampling [5].

However, despite the promising results, there are still two remaining problems regarding the application of CS in US imaging. i) Since perfect sparsity is almost never reachable due to the presence of noise and the incoherence between measurement matrix and sparse basis cannot be easily satisfied in practical situations, the images reconstructed from compressed measurements tend to be less good compared to standard acquisitions, especially for a low number of measurements. ii) In the case where an exact CS recovery is possible, *i.e.*, the quality in terms of resolution of the recovered US images is equivalent to those acquired using standard schemes, whereas it is widely accepted that image quality is one of the open challenges in US imaging. The signal-to-noise ratio, the spatial resolution and the contrast of standard US images are affected by the physical phenomenons related to US wave propagation and limited by the bandwidth of the transducer of imaging system.

Image deconvolution represents a valuable tool that can be used for improving image quality without requiring complicated calibrations of the real-time image acquisition and processing systems. US image deconvolution has been extensively studied in the literature, showing very promising results [16–18]. Motivated by the interest of CS and deconvolution, we have recently proposed a framework called compressive deconvolution (CD) in US imaging [19]. The objective was to reconstruct enhanced RF images from compressed linear measurements, aiming to obtain a higher frame rate or less data volume and to enhance the image contrast at the same time. The main idea behind CD is to combine CS and deconvolution, leading to the following linear direct model:

$$\boldsymbol{y} = \Phi H \boldsymbol{x} + \boldsymbol{n} \tag{1}$$

where $\boldsymbol{y} \in \mathbb{R}^M$ stands for the M linear compressed measurements obtained for one RF image $H\boldsymbol{x}$ and $\Phi \in \mathbb{R}^{M\times N}$ ($M << N$) corresponds to the CS acquisition matrix. The RF image $H\boldsymbol{x}$ models that the tissue reflectivity function (TRF) $\boldsymbol{x} \in \mathbb{R}^N$ is degraded by $H \in \mathbb{R}^{N\times N}$, which is a block circulant with circulant block (BCCB) matrix related to the 2D PSF of the US system. Finally, $\boldsymbol{n} \in \mathbb{R}^M$ represents a zero-mean additive white Gaussian noise. We emphasize that all the images in (1) are expressed in the standard lexicographical order.

Inverting the model in (1) will allow us to estimate the TRF $\boldsymbol{x}$, which is considered as a higher resolved US image, from the compressed RF measurements $\boldsymbol{y}$. Though similar models have been recently proposed for general image processing purpose [20–23] including a theoretical derivation of RIP for random mask imaging [24], we formulated in [19] the reconstruction process into a constrained optimization problem exploiting the relationship between CS recovery and deconvolution:

$$\begin{aligned} &\underset{\boldsymbol{x}\in\mathbb{R}^N,\boldsymbol{a}\in\mathbb{R}^N}{min} \ \| \boldsymbol{a} \|_1 + \alpha\|\boldsymbol{x}\|_p^p + \frac{1}{2\mu} \| \boldsymbol{y} - \Phi\Psi\boldsymbol{a} \|_2^2 \\ &\quad s.t. \quad H\boldsymbol{x} = \Psi\boldsymbol{a} \end{aligned} \tag{2}$$

where $\boldsymbol{a}$ is the sparse representation of the US RF image $H\boldsymbol{x}$ in the transformed domain Ψ. It enables the reconstruction of the RF image and the TRF at the same time. α and μ are hyperparameters balancing the weight of each term in the cost function to minimize. The optimization problem above includes three terms: i) the ℓ_1-norm term aiming at imposing the sparsity of the RF image in the sparse basis Ψ, ii) the ℓ_p-norm term modeling the *a priori* of the target image $\boldsymbol{x}$, where the shape parameter p related to the Generalized Gaussian Distribution (GGD) is ranging from 1 to 2 ($1 \le p \le 2$), allowing us to generalize the existing works in US image deconvolution mainly based on Laplacian or Gaussian statistics [25,26], iii) the data fidelity term.

In order to solve this problem, an algorithm based on the Alternative Direction Method of Multipliers (ADMM) was initially proposed in [19] and was further improved with faster convergence based on Simultaneous Direction Method of Multipliers (SDMM) in [27]. Both algorithms have achieved promising results with the assumption that the PSF was known or could be estimated in a pre-processing step. However, the PSF cannot be perfectly known in practical situations. An initial investigation to jointly estimate the PSF has been recently published in [28] to show the possibility of recovering RF image, TRF and PSF at the same time.

In this paper, following the previous work and exploiting the prior information on the PSF, we propose and detail a compressive semi-blind deconvolution (CSBD) algorithm. The results on simulated and experimental images show improved performance compared to the non-blind approach. The remainder of this paper is organized as follows. In Section 2 we formulate the compressive semi-blind deconvolution problem. Section 3 details our proposed CSBD algorithm and simulation results are shown in Section 4 before drawing the conclusions in Section 5.

2. Methods

2.1. Problem formulation

Given the commutativity of the 2D convolution product, let us write the CD direct model in a different form, that includes the PSF kernel $\boldsymbol{h}$ instead of the associated BCCB matrix H:

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