Biomedical Signal Processing and Control 26 (2016) 11–22

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

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

Efficient block-sparse model-based algorithm for photoacoustic image reconstruction

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ARTICLE INFO

Article history:
Received 21 July 2015
Received in revised form
16 November 2015
Accepted 7 December 2015

Keywords:
Photoacoustic imaging
Image reconstruction techniques
Medical and biological imaging

ABSTRACT

The model-based algorithm for photoacoustic imaging (PAI) has been proved to be stable and accurate. However, its reconstruction is computationally burdensome which limits its application in the practical PAI. In this paper, we proposed a block-sparse discrete cosine transform (BS-DCT) model-based PAI reconstruction algorithm in order to improve the computational efficiency of the model-based PAI reconstruction. We adopted the discrete cosine transform (DCT) to eliminate the minor coefficients and reduce the data scale. A block-sparse based iterative method was proposed to accomplish the image reconstruction. Due to its block independent nature, we used the CPU-based parallel calculation implementation to accelerate the reconstruction. During the iterative reconstruction, the number of required iterations was reduced by adopting the fast-converging optimization Barzilai–Borwein method. The numerical simulations and *in-vitro* experiments were carried out. The results has shown that the reconstruction quality is equivalent to the state-of-the-art iterative algorithms. Our algorithm requires less number of iterations with a reduced data scale and significant acceleration through the parallel calculation implementation. In conclusion, the BS-DCT algorithm may be an effectively accelerated practical algorithm for the PAI reconstruction.

1. Introduction

Photoacoustic imaging (PAI) is an emerging technique that combines the high contrast of pure optical methods with the high spatial resolution of ultrasound imaging [1–6]. The potential of photoacoustic to image biological tissues has been shown in a variety of imaging applications, from structural imaging [7–9] of tumor detection [10,11], ocular imaging [12] and vascular anatomy [13,14] to functional imaging of blood oxygenation [15] and molecular contrast agents [16].

The physical basis of the PAI is the photoacoustic effect, which converts absorbed optical energy into pressure *via* thermoelastic expansion [2]. In this paper, we focus on the computed-tomographic PAI. In this imaging mode, the PAI is performed by illuminating an optically absorbing object with short high-power laser pulses and the generated photoacoustic signals are detected by ultrasonic transducers placed in multiple positions. The goal of the PAI is to obtain an estimate of the optical absorption distribution within the object from the received photoacoustic signals. To accomplish this, an image reconstruction algorithm is required.

A variety of analytical image reconstructions have been developed. The filtered back-projection (FBP) algorithm is the most popular algorithm [17,18]. Reconstruction algorithms in the time domain [19,20] and frequency domain [21–23] have been proposed in various geometries. The de-convolution reconstruction algorithm proposed by Zhang et al. has specific advantage under the circumstance of limited-angle sampling and heterogeneous acoustic medium [24,25]. These analytical reconstruction algorithms have been widely used for the PAI reconstruction due to their implementation convenience. However, these algorithms generally assume an idealized transducer model and ignore the measurement noises. These drawbacks limit the applications of the analytical algorithms and impair their performance. To overcome the limitation, iterative image reconstruction algorithms are proposed.

The typical PA image reconstruction problem can be considered as a source reconstruction problem. We need to build up a model to describe the relationship between the received ultrasound signals and the optical absorption distribution to solve this problem. So they are also called the model-based algorithms. Most of them calculate iteratively to get the optical absorption image. Previous

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http://dx.doi.org/10.1016/j.bspc.2015.12.003
1746-8094/

works have used least-square QR (LSQR) based decomposition methods in obtaining accurate reconstruction image [26–29]. The compressed sensing (CS) has been involved into the PAI reconstruction [30–34]. Some parameters in the aspect of image processing are also employed to assist the image reconstruction. Some algorithms are proposed by using total variation (TV) minimization to the PAI image reconstruction [35–40]. These TV-based algorithms are reported to be stable and efficient under the sparse-view circumstance for the PAI reconstruction. The iterative algorithms are widely used in the PAI reconstruction for its high-quality performance. However, the computation cost and memory storage required for the PAI reconstruction are excessively burdensome in implementing these algorithms. Acceleration of iterative PAI reconstruction algorithms will facilitate algorithm development and many potential clinical applications [26,41–43].

The structured compressed sensing [44] that exhibit additional structure in the signal recovery problem has been received much attention in the last few years. The block-sparse model [45–47], in which the nonzero elements are appearing in blocks rather than being arbitrarily spread, has been used to solve many compressed sensing recovery problem. It has been proved that when the number of the nonzero elements is fixed, block-sparsity has a better recovery performance than conventional sparsity [48]. During the iteration, the block-sparse model updates the signals block by block and the blocks are independent with each other. This property can be used to implement a parallelization strategies for improving the computational efficiency.

In this paper, we propose a novel efficient iterative algorithm to accelerate the image reconstruction in the PAI. We calculate the discrete cosine transform (DCT) coefficients from the received signals to make the energy of the signals concentrated and choose the relatively significant DCT coefficients for reconstruction to scale down the dataset. We include the block-sparse minimization into the PAI reconstruction for the first time. The block-sparse reconstruction algorithm helps to improve the imaging quality with less information. Due to its block independent nature, this algorithm can be easily implemented for parallelization strategies to accelerate image reconstruction in practical modalities. Our numerical studies and *in-vitro* experiments confirm that the proposed method is able to accelerate effectively and the quality of the reconstruction can be kept in a high level as well.

The remainder of the paper is organized as follows. In Section 2, we briefly introduce the block-sparse model and the procedures of the block-sparse model-based image reconstruction. Numerical studies and experimental results are described in Sections 3 and 4. Finally, a brief discussion and summary of the proposed algorithm is provided in Section 5.

2. Method

2.1. Photoacoustic-theory

We focus on two-dimensional PAI in this paper. Photoacoustic signals are usually generated by excitation of tissue by an ultrashort laser pulse. The heat is subsequently converted into pressure waves, which propagate through tissue. Then these photoacoustic signals are detected by the ultrasound transducer at different positions in the scanning plane. Based on the assumption that the illumination is spatially uniform and the laser pulse is sufficiently short, the relationship between the detected acoustic signals and the laser absorption distribution can be written as

$$\nabla^2 p(\vec{r},t) - \frac{1}{c^2}\frac{\partial^2 p(\vec{r},t)}{\partial t^2} = -\frac{\mu}{C_p}u(\vec{r})\cdot\frac{\partial I(t)}{\partial t} \quad (1)$$

where $p(\vec{r},t)$ is the acoustic pressure measurements at the position $\vec{r}$ and the time t, c is the sound speed, C_p is the specific heat, μ is the isobaric expansion coefficient, $I(t)$ is the temporal profile of the laser pulse and $u(\vec{r})$ is the laser absorption distribution. In our study and many photoacoustic tomography studies, a laser pulse is employed with a very short duration. Its duration is nano seconds. So here we made an approximation to treat the $I(t)$ as a Dirac-delta function.

With assumption that the sound speed remains the same, Eq. (1) can be solved as follows:

$$p(\vec{r}_0,t) = \frac{\mu}{4\pi C_p}\frac{\partial}{\partial t}\oint_{|\vec{r}-\vec{r}_0|=ct}\frac{u(\vec{r})}{t}\mathrm{d}^2\vec{r} \quad (2)$$

where $\vec{r}_0$ is the position of the ultrasound transducer.

While the back-projection algorithms seek to invert Eq. (2) analytically, the iterative model-based algorithms numerically invert a discretized version of Eq. (2). In model-based image reconstructions, a projection matrix A is typically established to connect the acoustic pressure measurements with the reconstructed image. The measurements can be calculated based on the reconstructed image, and then the reconstructed image can be repeatedly corrected by minimizing the difference between the calculated measurements and the real ones. In this way, the optimization method can be used for collaboration and then the iteration reconstruction algorithm can be developed.

2.2. Structured compressed sensing for PAI

In this paper, including the structured compressed sensing, we build up a novel model for the PAI reconstruction. We define a new variable f as:

$$f\left(\vec{r}_0,t\right) = \frac{4\pi C_p}{\mu}\int_0^t p\left(\vec{r}_0,t'\right)\mathrm{d}t'\cdot t \quad (3)$$

where t' is the integration variable.

Then Eq. (2) can be converted as follows:

$$f\left(\vec{r}_0,t\right) = \oint_{|r-r_0|=ct}u(\vec{r})\mathrm{d}^2\vec{r} \quad (4)$$

In practical imaging, the reconstructed image and the measurements are processed discretely, and the image is reshaped into vectors for convenience. If the size of the reconstructed image $u(\vec{r})$ is X pixels $\times$ Y pixels, the total pixel number of the reconstructed image $u(\vec{r})$ is N (N=XY). After vectorization, the reconstructed image $u(\vec{r})$ becomes a vector u with the length of N. If the total number of the detection points is Q, the length of measurement in each detection point is M, Eq. (4) can be expressed as:

$$f_i = A_i^{\mathrm{T}}\cdot u \quad i = 1,2,\ldots,Q \quad (5)$$

where f_i is the integration of the $u(\vec{r})$ along the arc that is centered in ith detection point and with a radius of ct, A_i is the projection matrix of the ith detection point, T is the transpose operation of a matrix. The calculation of the projection matrix is as follows:

(a) Calculate a matrix $A_i(j)$ as:

$$A_i(j) = \max\left\{1-\left|\frac{z\cdot \mathrm{d}x}{c\cdot \mathrm{d}t}-j\right|,0\right\}(1\le j\le M) \quad (6)$$

where $z=\sqrt{(m-m_i)^2+(n-n_i)^2}$, (m, n) is the coordinate of the matrix $A_i(j)$, (m_i, n_i) is the position of the ith detection point, $\mathrm{d}x$ is the actual length between two pixels in the reconstructed image, $\mathrm{d}t$ is the discretized time step and M is the total sampling points at one detection point.

(a) $A_i(j)$ is a $N\times M$ matrix. The value of each point (m, n) in the matrix $A_i(j)$ is calculated by Eq. (6).
(b) Vectorize the matrix $A_i(j)$ as the jth column vector in projection matrix A_i.