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Simultaneous dictionary learning and reconstruction from subsampled data in photoacoustic microscopy

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Abstract— **Photoacoustic microscopy acquires volumetric RF data to obtain high resolution, high contrast, images of the microvasculature but is associated with slow acquisition of data due to mechanical raster scanning across the image plane. Recent work has shown that the acquisition speed can be increased using compressive sampling methods and subsequent reconstruction. These methods use bases (dictionaries) learned from prior fully sampled acquisitions, or classical bases such as the Fourier or wavelet bases. In this study, we present the simultaneous learning of bases, and reconstruction using only subsampled data. The algorithm was validated at two different subsampling levels 50% and 75% downsampling, and compared to the ground truth reconstruction with fully sampled data by estimating the peak signal to noise ratio (PSNR). No significant difference in performance was observed between the fully sampled (20.0±3.0 dB), 50% (19.9±2.1 dB) and 75% (19.1±2.6 dB) subsampled data.**

Keywords—Photoacoustic Microscopy, Dictionary learning, compressed sensing

I. Introduction

Photoacoustic microscopy (PAM) constructs high resolution and high contrast images of the microvasculature [1]. PAM acquires volumetric RF data by mechanically raster scanning the specimen under test with coaxially and confocally aligned ultrasound detection and optical excitation [2][3]. The slow speed of the mechanical raster scan limits its application and translation to other microvascular imaging applications.

Recent work to reduce the acquisition time includes the use of additional hardware, such as mirror galvanometers [4], or digital micromirror devices [5][6], to reduce the scanning time by electronic steering of the optical excitation which increases the scan speed. A complimentary strategy, used in other imaging modalities such as MRI or ultrasound is to acquire fewer samples and perform a non-linear offline reconstruction using compressive sensing (CS)[7][8].

Recovery of the unknown data in CS is predicated on the data being sparse, or at least compressible in a basis, which is approximately incoherent with the sampling basis [8]. In this work, we apply dictionary learning (DL) methods to simultaneously learn the basis in which the data are sparse and perform signal recovery from incomplete/undersampled data in PAM. Throughout the paper, matrices are in boldface and italicized, vectors are in boldface, while scalars are italicized.

II. Compressive sensing

In compressive sensing the data (b) are constrained to have has few non-zero coefficients compared to its dimensionality in the transform domain (A), while undersampling in the data domain (multiplication by Φ) leads to sampling over a wide swath of the transform domain (incoherence) [7]–[9].

$$\min \|\mathbf{x}\|_0 \text{ subject to } \|\boldsymbol{\Phi A}\mathbf{x} - \mathbf{b}\|_2^2 \leq \varepsilon \quad (2.1)$$

The sparsity constraint is enforced by the l0 'norm' ($\| \ \|_0$) or its convex relaxation, the L1 norm [9]. Accurate sparse coding requires *a-priori* knowledge that the signal is sparse in a given domain, or the use of a dictionary (union of several bases) with more bases than the dimensionality of the data (overcomplete). Pioneering work by Engan et al. [10][11] , Aharon et al.[12], and several others [13]–[15] led to powerful algorithms which could generate data adaptive dictionaries from training data capable of representing data sparsely.

III. Dictionary learning

Dictionary learning (DL) methods have led to state of the art results in denoising, super-resolution, compressive sensing, in a multitude of applications [16]–[19]. Most DL algorithms [10]–[15] proceed using an alternating minimization approach. The approach begins a sparse coding stage, where the data are sparsely coded with the dictionary. Subsequently, the dictionary is updated to minimize the representation error. The updated dictionary is then used for the next sparse coding stage. This sequence is repeated until a specified number of iterations elapse or a tolerance in the error with respect to the data is reached.

DL has also found extensive application in PAM and photoacoustic tomography [19]–[23]. Liu et al. [24] have used learned dictionaries to reconstruct data using compressive sensing in PAM. In this work, dictionaries are learned from fully data acquired earlier, and the learned dictionary is used to reconstruct undersampled data. However, several authors, [25]–[27] have demonstrated methods to learn the dictionaries directly from incomplete or under sampled data, which does not need a basis trained from previously acquired fully sampled data.

In this work, we use the method developed by Mairal et al.[26] to obtain a basis and reconstruct undersampled PAM data. The method uses the K-SVD DL algorithm with a revised update method, based on a weighted rank 1 approximation. For fully sampled training data ($\boldsymbol{T}$), the K-SVD follows the following sequence of iterations, first, sparse coding, holding the dictionary $\boldsymbol{D}$ fixed, at a sparsity of K.

$$\underset{\mathbf{x_i}}{argmin}\ ||\boldsymbol{D}\mathbf{x_i} - \mathbf{T}_i||_2^2 \leq \varepsilon \text{ subject to } ||\mathbf{x_i}||_0 \leq K \quad (3.1)$$

Followed by the dictionary update stage for the i'th atom

$$\boldsymbol{E} = \boldsymbol{T} - \sum_{j \neq i} \boldsymbol{d}_j\, \mathbf{x}_j^T \quad (3.2)$$

where $\mathbf{x}^\mathbf{T}$ denotes the sparse coefficient vectors of the training samples that use the i'th atom.

$$\text{Rank 1 SVD } \boldsymbol{(E)} = \mathbf{U\Sigma V'} \quad (3.3)$$

$$\mathbf{d_j}^{\boldsymbol{u}} = \mathbf{U} \quad (3.4)$$

Where $\mathbf{d_j}^{\boldsymbol{u}}$ denotes the updated basis vector $\mathbf{d_j}$. The iterations (2.1)-(2.3) are performed until suitable convergence criterion is achieved or a fixed number of iterations has elapsed.
However, for subsampled data, we have

$$\underset{\mathbf{x_i}}{argmin}\ ||\boldsymbol{\Phi D}\mathbf{x_i} - \mathbf{T}_i||_2^2 \leq \varepsilon \text{ subject to } ||\mathbf{x_i}||_0 \leq K \quad (3.5)$$

and the update stage (2.3)-(2.4) is modified to perform iterative weighted rank 1 approximation as follows

$$\text{Rank 1 SVD } (\boldsymbol{\Phi T} + (\mathbf{1} - \boldsymbol{\Phi})\mathbf{d_j}^{\boldsymbol{old}}\mathbf{x_j}^{\boldsymbol{old}}) \quad (3.6)$$

For each atom, (2.6) is repeated for a fixed number of iterations.

IV. Methods

This method was validated using PAM data acquired from the brain of a male CD-1 mouse (300 B-scans, 3600 A-lines each). The data were retrospectively subsampled by randomly dropping A-lines (Fig.2 (c)). Twenty five thousand randomly chosen voxels (100 µm x 25 µm x 50 µm) from the focal plane were used to train the dictionary and reconstruct the image from subsampled data using the proposed method (Fig.3 (d)). We also reconstruct an image using a dictionary trained from fully sampled data for comparison (Fig.2 (b)) with the same parameters of the algorithm as shown in table 1. To avoid ambiguity, we refer to the number of times the K-SVD alternating minimization is executed as outer iterations. The dictionary learning parameters were chosen so as to reconstruct the data faithfully

TABLE 1. ALGORITHM PARAMETER VALUES

Parameter	Value
Dictionary size	1024
Sparsity	20
Outer iterations	5
Weighted rank 1 SVD iterations	5

V. Results

The data were reconstructed at two different subsampling levels (50% and 75%) subsampling. Fig. 1(a) Depicts a portion of the ground truth single B-scan data, after envelope detection, indicated by the green line in Fig. 3. The same portion of the B-scan is shown in Fig. 1(b) after reconstruction using fully sampled data.

Fig. 1 (c) depicts a B-scan with 50% of the A-lines discarded and Fig.1(d) shows the B-scan in Fig 1(c) reconstructed using the dictionary learned from 50% subsampled data. The algorithm's performance was quantified by measuring the peak signal to noise ratio (PSNR) of the reconstructed data with respect to the ground truth data as illustrated in Fig. 2.

Fig. 3 shows the reconstruction of 50 % subsampled data.

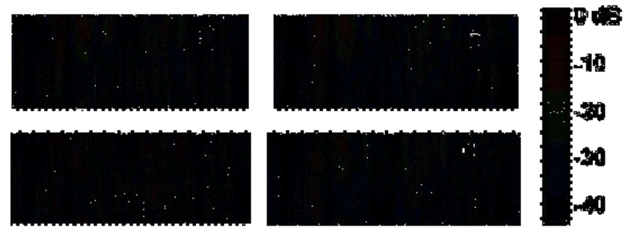

Fig. 1(a) Ground truth B-scan (b) MIP of B-scan reconstructed with fully sampled dictionary (c) 50% subsampled B-scan (d) Reconstructed data from (c).

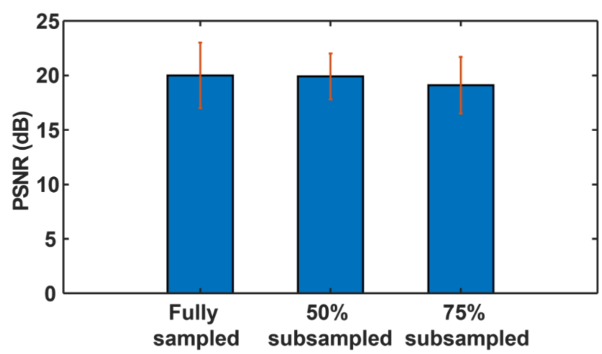

Fig 2. PSNR evaluated with respect to ground truth data for N=300 B-scans, each consisting of 3600 A-lines.

Fig. 3(a) shows the ground truth MIP, Fig. 3 (b) shows the MIP of the data reconstructed using a dictionary learned from fully sampled data. Fig. 3 (c) shows MIP of the 50% subsampled data and Fig. 3(d) shows the MIP reconstructed from 50% subsampled data. No significant difference was observed between the PSNR evaluated for the fully sampled reconstruction, and the reconstruction estimated for the 50% and 75% subsampled data.

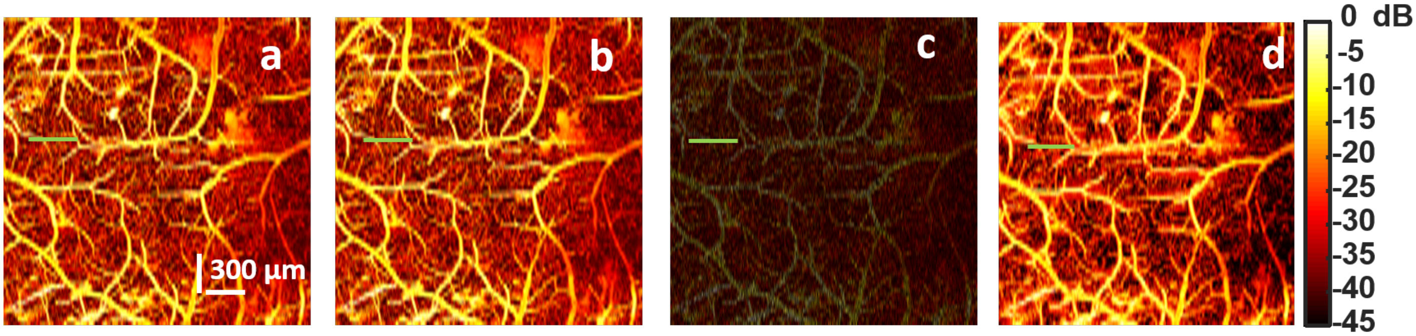

Fig. 3. (a) Ground truth MIP of brain data (b) MIP of Reconstructed data with fully sampled data (c) 50% subsampled data (d) Reconstructed data from (c).

VI. Discussion

In this work, an algorithm to learn a dictionary from incomplete PAM data with simultaneous reconstruction was presented. The algorithm is able to reconstruct the data with negligible difference as is seen from Fig.1 and Fig. 3. No statistically significant difference is observed with respect to the reconstructed data as seen from the PSNR results 19.9±2.1 dB (50%) and 19.1±2.6 dB (75%) Fig. 2.

The approach potentially has the ability to speed up PAM scans by at least four times. In future work, this dictionary learning method can be extended to deal with more structured subsampling patterns, rather than random downsampling.

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