Sparse signal representation at the service of quantitative optoacoustic tomography

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ABSTRACT

We report on a new method for extraction of quantified optical absorption maps of scattering and absorbing media using sparse representation, a relatively recent and fast emerging technique in the field of signal processing. The tomographic reconstruction is facilitated by assuming slow spatial variations of illuminating optical field along with relatively sharp changes in optical absorption coefficient. As opposed to previous approaches that utilize photon transport equation in order to correct images for inhomogeneous light distribution within the imaged object, the method herein provides an estimate for photon fluence directly from the recorded optoacoustic signals. In this way a robust quantitative performance is achieved without prior knowledge of illumination geometry and optical properties of the object.

Keywords: Sparse signal representation, optoacoustics, blind deconvolution, quantitative imaging

I. INTRODUCTION

Although the enormous potential of optoacoustic imaging is well recognized, certain limitations currently hinder its effective implementation in many realistic imaging scenarios. Typically, simple photon propagation patterns are assumed or the issue of nonuniform distribution of illuminating photon field is completely disregarded. This in turn imposes variety of limitations on practical application, e.g. with respect to ability for accurate and quantitative imaging of endogenous tissue contrast and distribution of bio-markers and contrast agents [1]. A common assumption is that broad illumination will result in a plane-wise uniform photon distribution in tissue, which is a very inaccurate assumption that has so far resulted in mostly superficial blood vessel images. Naturally, as light propagates in tissue, heterogeneous intrinsic tissue absorption and overall light propagation characteristics alter the propagation pattern, by creating a heterogenous deposition of energy in the various tissue elements [2]. Herein we describe and implement a method to perform high-fidelity opto-acoustic imaging, offering true quantitative imaging not only of superficial but also of deeper seated contrast. Instead of indirect photon propagation modeling, it is assumed that the photon fluence in tissue can be directly extracted from the recorded optoacoustic signals. Since the latter represent a product between the local light fluence and the local absorption coefficient, in most practical cases, it can be assumed that the fluence exhibits much slower spatial dependence as compared to more rapid absorption coefficient variations. We utilize this fact in order to effectively decompose these two contributions using sparse representation methods. This makes the final tomographic reconstruction independent from the particular experimental geometry and measurement conditions.

II. THEORY

Typical quantification challenge arises from the fact that optoacoustic signals do not directly convey information on the underlining optical absorption coefficient (μ_a) but rather on the local energy absorption ψ in tissue. The raw images therefore represent the product between absorption and the local light fluence U, i.e.

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$$\psi = \mu_a U \quad (1)$$

In cases of uniform sample illumination, e.g. in cases of superficial imaging, where the light intensity is uniformly distributed over the object's surface, the optoacoustic tomography (OAT) image is approximately proportional to the optical absorption coefficient. In practice, biological tissues present a highly heterogeneous environment with unknown optical properties therefore sample illumination is rarely uniform. For instance, when absorbing targets deeper in tissue are to be imaged, as in whole-body animal or organ imaging, the photon fluence is significantly attenuated as a function of depth and is also significantly affected by tissue optical heterogeneity. Optoacoustic images that are obtained using the assumption of uniform illumination will therefore be biased in favor of targets closer to the surface. Thus, in order to accurately reconstruct the object's absorption coefficient map, the light intensity within the tissue should be known so that it can be corrected for. However, the light distribution depends on the precise map of tissue optical properties, which cannot be easily measured or calculated.

III. IMAGE QUANTIFICATION

There are several possible approaches that can tackle this imaging problem. In the most straightforward (iterative) approach, the optical absorption coefficient, obtained at each reconstruction iteration, can be used to calculate the fluence in the succeeding iteration using finite-element solution of the light diffusion equation. In this way, the absorption coefficient μ_a^i map for the current iteration is calculated using the following equation:

$$\mu_a^i = \frac{\psi'}{U_i + \sigma}, \quad (2)$$

where $\psi' = \psi \cdot \mu_a^{surf} / h^{surf}$, h^{surf} and μ_a^{surf} are the values of the optoacoustic image and absorption coefficient averaged on the boundary of the imaged object, U_i is normalized to accept the value of one on the boundary of the object, and σ is a dimensionless regularization parameter. The regularization parameter is added to prevent possible divergence in the solution. Fig. 1 presents experimental results where this method was used to correct optoacoustic images from a tissue mimicking phantom containing highly absorbing insertion [3].

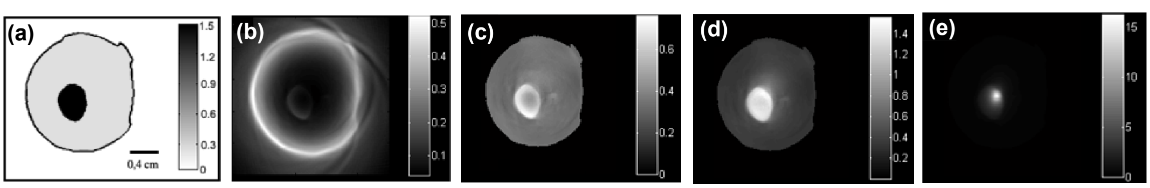

Figure 1. (a) Cross-sectional geometry of tissue-mimicking phantom, the black is the insertion with an absorption coefficient of 1.5 cm^{-1} and the gray area is the background with an absorption coefficient of 0.32 cm^{-1}, reduced scattering coefficient was set to 20 cm^{-1}(b) Raw OAT image, (c) OAT image normalized by fluence within a hypothesized homogeneous medium. First correction iteration is presented in (c); Iteration # 4 and 9 are shown in (d) and (e), respectively.

In order to minimize the sensitivity of the algorithm to noise or to modeling errors a regularizing term was added to the equation to ensure convergence, albeit on the expense of reducing overall accuracy. Under ideal conditions, the algorithm theoretically should converge and accurately recover the absorption coefficient. Indeed, the experimental findings indicate that the implementation of iterative inversion opto-acoustic schemes can potentially improve image quality in optoacoustic tomographic imaging. But in practice, due to large number of unknown parameters, e.g. scattering coefficient or other experimentally-related model inaccuracies, the improvements made by this kind of iterative scheme are only valid for the first few iterations while after this the algorithm quickly diverges (Fig. 1(e)) [3].

IV. SPARSE SIGNAL REPRESENTATION

The more advanced method for light attenuation correction relies on the general properties of the optical fluence, rather than specific and multiple parameter dependant light-propagation model. The method sparsely decomposes the optoacoustic image into two components: a slowly varying global component attributed to the diffusive photon fluence in the medium and a localized high spatial frequency component representing variations of the absorption coefficient. This decomposition is based on the assumption that, owing to light diffusion, the photon fluence exhibits a slowly varying spatial dependence in contrast to fast spatial variations of the absorption coefficient, more typically associated with variations in structures that have well-defined boundaries that introduce high spatial frequency components. The decomposition in these two components relies on sparse representation, a relatively new and fast emerging area in the field of signal and image processing which assumes that natural images can be approximated by a sum of a small number of elementary functions [4]. In order to exploit this approximation, one needs to find a suitable set of these functions, often referred to as a library, and perform the decomposition numerically. Sparse representation has played an important role in the development of denoising and compression algorithms as well as in the field of compressive sensing.

For optoacoustic image representation in a logarithmic form, a simple library is suggested that is composed of two bases, the wavelet-based functions f_n that sparsely describes the fast variations of the absorption coefficient and Fourier-based functions g_m sparsely describing the slow-varying light fluence, i.e.

$$\log\psi = \log\mu_a + \log U = \sum_n a_n f_n + \sum_m b_m g_m \tag{3}$$

In order to perform the decomposition, the problem will first be discretized on a uniform grid. Once two libraries that fulfill the sparsity condition are chosen, the decomposition problem is to find the minimum number of coefficients a_n and b_n that fulfill Eq. (3). We use orthogonal matching pursuit (OMP) method [5] to solve this optimization problem. Eventually, the sparse representation of the optoacoustic image in the library directly yields both the absorption coefficient and the light fluence.

Figure 2. (a) A map of optical absorption in a heterogeneous turbid phantom; (b) the corresponding tomographically-reconstructed optoacoustic image showing the effects of nonuniform light distribution in the object; (c) Corrected reconstruction of the absorption coefficient of the object obtained by the sparse decomposition algorithm.

The algorithm was initially tested in numerical simulations. Typical optoacoustic images were simulated by solving the diffusion equation in turbid cylindrical-shape tissue phantoms having optical heterogeneities with a varying optical absorption coefficient. The background absorption and scattering coefficients were 0.3 cm^{-1} and 10 cm^{-1}, respectively. All the numerical calculations were performed on a100 x 100 grid. In the decomposition, the absorption coefficient was represented by the 2-level Haar basis. Figure 2 depicts the results obtained from the simulation example of a relatively complex-shape phantom. The cross-sectional absorption coefficient distribution in the phantom and the resulting optoacoustic image are shown in Fig. 2a and 2b, respectively. Because of the increased complexity of the image, the number of iterations in the decomposition algorithm was increased to 650. The reconstruction of the absorption coefficient is shown in Fig. 2c. The maximum error in the reconstructed image over the simulated image was 20% and the average error across the insertion was 10%.

The algorithm was similarly tested in tissue-mimicking phantom yielding good quantification capacity and robust performance in the presence of optical heterogeneities (Fig. 3).

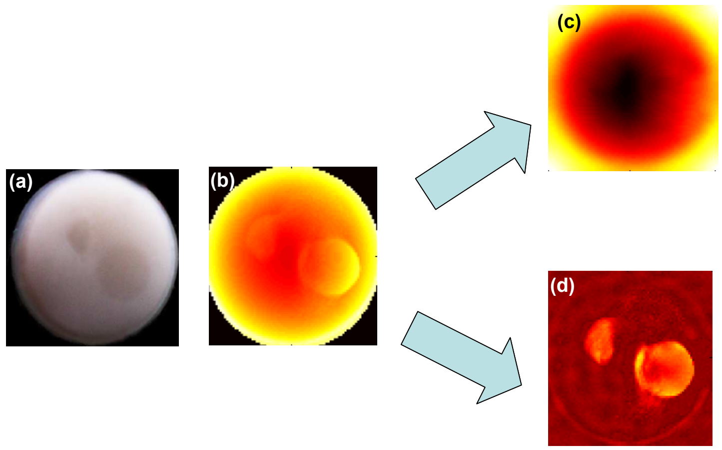

Figure 3. Sparse decomposition of optoacoustic tomographic image (b) of a cylindrical tissue-mimicking phantom (cross-sectional photograph is shown in (a)) yields two separate images of light distribution in the phantom (c) and the map of underlying optical absorption coefficient (d).

IV. DISCUSSION AND CONCLUSIONS

Quantification of optoacoustic images is a complicated long-standing challenge. One possible solution considers light propagation modeling approaches however its implementation always needs to take into account certain poorly defined experimental and modeling factors that relate to the ability to accurately calculating the photon fluence distribution in the imaged object. In particular, knowledge of the absorption and reduced scattering coefficient is not always straightforward. While the absorption coefficient can be directly linked to the optoacoustic signals, determination of the scattering coefficient is problematic as no accurate method exists to volumetrically determine its distribution, especially when it is spatially varying within tissue. In particular, we have found that, even with exact knowledge of the optical properties, the iterative method based on light diffusion equation did not yield convergence at long iterations for experimental data. It was rather influenced by different inconsistencies between experiment and theory, including noise and artifacts that can also be amplified. Therefore, for best performance in realistic imaging scenarios, the iterative algorithm should preferably be used with some approximate or a-priori information on the imaged object, including a well defined convergence criterion and a good estimate of the background optical properties.

Alternatively, by avoiding the use of a parameter-based physical model, the sparse decomposition approach does not propagate modeling errors into the reconstruction of the absorption coefficient and, thus, offers a robust performance under measurement uncertainties. The underlying assumption of the algorithm is that whereas the fluence is smooth and global, the absorption coefficient normally has more localized and often sharp spatial transients. The method was successfully tested in both numerical simulations and in an experiment with a tissue-mimicking phantom, resembling typical small-animal whole-body imaging configuration and the corresponding tissue properties and other experimental parameters.

REFERENCES

[1] D. Razansky, M. Distel, C. Vinegoni, R. Ma, N. Perrimon, R. W. Köster, and V. Ntziachristos, "Multi-spectral optoacoustic tomography of deep-seated fluorescent proteins *in-vivo,*" *Nature Phot.* 3(7), 412-417 (2009).
[2] B. T. Cox, S. R. Arridge, and P. C. Beard, " Gradient-Based Quantitative Photoacoustic Image reconstruction for Molecular Imaging," *Proc SPIE* **6437**, 64371T-1-10 (2007).
[3] T. Jetzfellner, D. Razansky, A. Rosenthal, R. Schulz, K-H. Englmeier, and V. Ntziachristos, "Performance of iterative optoacoustic tomography with experimental data," *Appl. Phys. Lett.* 95 (2009).

[4] A. Rosenthal, D. Razansky, and V. Ntziachristos, “Quantitative optoacoustic tomography using sparse signal representation”, *IEEE Trans. Med. Imag.,* 28(12), 1997-2006 (2009).
[5] Y. C. Pati, R. Rezaiifar, P. S. Krishnaprasad, “Orthogonal matching pursuit: recursive function approximation withapplications to wavelet decomposition,” *Conference Record of The Twenty-Seventh Asilomar Conference on Signals, Systems and Computers*, (1993).