



Image Enhancement by Linear Spatial Deconvolution: Recent Developments



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Introduction

Diffuse optical tomography (DOT) is a functional imaging modality capable of studying blood flow in normal and pathological tissues in real time. DOT employs harmless near infrared radiation to obtain measurements of absorption and scattering coefficients (μ_a and μ_s) within tissue, which can be used to extract images of physiological parameters such as hemoglobin concentrations. The advantages of DOT, when compared to PET imaging or MRI, include its low cost, superior temporal resolution, and fewer physical constraints on the subject. Potential drawbacks to DOT include its low spatial resolution and, consequently, lower quality images. Most strategies for improving image quality incorporate computation-intensive algorithms, which eliminate the possibility of studying tissue dynamics in a physiologically relevant time frame.

In an effort to improve image quality, a spatial deconvolution algorithm based on temporal encoding of spatial information was developed. This algorithm was shown to significantly improve qualitative and quantitative image accuracy, with a computational effort far lower than that required for recursive iterative reconstruction techniques [1]. Furthermore, it was shown that the tradeoff between enhancement of spatial resolution and degradation of temporal accuracy can be contained within acceptable bounds [2]. Subsequent refinements of the deconvolution algorithm are capable of performing equally well for 3-D imaging problems [3] and in restricted-view cases [4]. Previous characterizations of this approach were constrained by the use of a homogeneous background, and by the modeling of only temporally varying μ_a in the inclusions. To explore an image enhancement scheme systematically, we have investigated the effect of target medium complexity on the fidelity of the method and the method's ability to improve the quality of recovered images of the diffusion coefficient D ($\sim 1/\mu_a$). Most recently, we conducted pilot solid-state dynamic phantom studies for validating the linear spatial deconvolution algorithm.

Influence of Background Medium Heterogeneity

The starting point for the geometrical model used was a 3D T1-weighted structural MRI image of the human head. As shown in Figure 1, six principal tissue types—scalp, muscle, skull, cerebrospinal fluid (CSF), gray matter, and white matter—were identified within the selected area. The corresponding finite element model and the source/detector configuration are depicted in Figure 2.

All surface detector data and internal photon intensities were obtained by performing finite element method (FEM) computations to numerically solve the diffusion equation with Robin boundary conditions [5]. Each forward problem computation was performed four times, once for each of the four values of μ_a assigned to the CSF (Table 1).

Sinusoidal time-varying absorption coefficients in the inclusion volume and the gray matter of the model tissue compartments were used to evaluate the method's ability to recover dynamic information. In addition, images were reconstructed from data that were either noise-free or contaminated with white Gaussian additive noise (see Fig. 6). To assess the extent to which the effects of noise are reversible, elementary temporal and spatial low-pass filtering techniques were applied after the reconstruction and deconvolution steps [2].

Deconvolution operators and detector-readings time series were computed for four combinations of time-averaged optical parameters (Table 1). To examine the sensitivity of the image enhancement algorithm to a spatially complex mismatch between the optical parameters of the filter-generating and target media, every deconvolution operator was applied to the images reconstructed from each medium's detector data. Spatial and temporal correlations (SC and TC, respectively) were computed between the true properties of each target medium and all corresponding image time series.

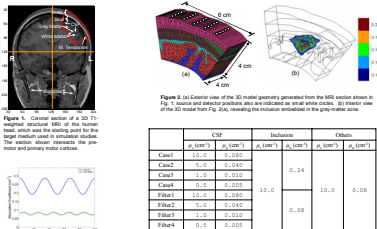


Figure 3. (a) 3D slice of the head showing the location of the CSF region. (b) Finite element model of the head. (c) Source/detector configuration. (d) Table 1: Optical coefficients used for the four CSF regions. (e) Plot of the time series of the CSF region.

Spatially convolved images are shown in Fig. 4(a),(c); the Fig. 4(a) result, Case1/Filter2, is computed using a weight function that under-estimates the CSF optical coefficients, while the Case3/Filter2 image (Fig. 4(c)) is obtained when weight functions are used that over-estimate the CSF optical coefficients. The noteworthy features of Fig. 4(a),(c) are that they are qualitatively very similar; there is substantial depth location error, with the recovered μ_a perturbation apparently located within the skull; the size of the inclusion is over-estimated in all cases; the magnitude of the μ_a perturbation is over-estimated in all cases.

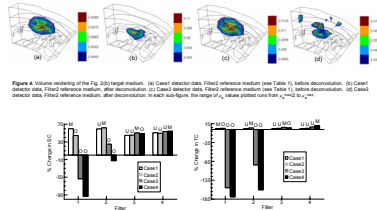


Figure 4. (a) Spatially convolved images for Case1/Filter2. (b) Reference image. (c) Spatially convolved images for Case3/Filter2. (d) Reference image.

Even though qualitative image accuracy is more variable after spatial deconvolution than before, the result obtained for the Case1/Filter2 pairing after deconvolution [Fig. 4(b)], compare with Fig. 4(a)] is superior in depth location, inclusion size, and quantitative perturbation magnitude. In stark contrast, when the direction of the mismatch is reversed and the CSF optical coefficients are over-estimated [Fig. 4(c)], the high-absorption region of the deconvolved image splits into two parts: one at the correct location and the other consisting of superficial artifacts. Increasing the magnitude of the mismatch leads to a completely erroneous result (not shown) that consists almost exclusively of the superficial artifacts. Comparison of imaging results for all 16 Case/Filter pairings and all 100 time frame shows that the type of trend seen in Fig. 4 turns up consistently.

The effect of deconvolution on the target image was quantified by computing the percent differences in the SC and TC before and after the procedure, for all 16 Case/Filter pairings [Figure 5(a) (spatial) and 5(b) (temporal)]. The white bars in Figure 5 represent data for the Case1 medium, where the CSF optical coefficients are never over-estimated, while the black bars include data for the Case2 medium, where CSF optical coefficients are never under-estimated. It can be seen that deconvolution for the Case1 medium always brings about an increase in SC and TC, while for the Case2 medium, the effect of deconvolution ranges from significant degradation of image quality to substantial improvement. Results for the other Cases are in between those for the preceding two.

Figure 6 shows the percent changes in SC [Fig. 6(a)] and TC [Fig. 6(b)], for all four Case/Filter pairings and all three noise levels. As in Fig. 5, positive/negative values indicate that the correlation is higher/lower after deconvolution than before. By inspection, it can be observed that at the lowest noise level of data collected in DOT brain measurements: 1) the SC invariably increases upon deconvolution; 2) the loss of TC associated with deconvolution can be minimized by using sLPF and tLPF in combination.

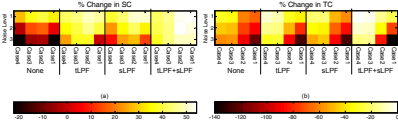


Figure 6. (a) Bar chart of relative percent change in image spatial correlation, comparing the image-target SC before and after spatial deconvolution, for the four Case/Filter pairings. (b) Bar chart of relative percent change in image temporal correlation, comparing the image-target TC before and after temporal deconvolution, for the four Case/Filter pairings. The white bars represent Case1 medium, where the CSF optical coefficients are never over-estimated, while the black bars include data for the Case2 medium, where CSF optical coefficients are never under-estimated. The bars represent the mean values of the percent change in SC and TC, with the error bars showing the standard deviation.

Recovery of Diffusion Coefficient Distributions

All of the simulations reported in this section used circular, 4-cm radius, 2D media. The modeled heterogeneities consisted of either one or two circular inclusions wherein D was approximately half that of the background region (i.e. μ_a of the inclusion is approximately twice that of the background).

Two types of two-inclusion studies were performed, and in every case the inclusion diameter was fixed at 0.6 cm, with one centered at (x_0, y_0) and the other at (x_1, y_1) . For the first study, y_0 was fixed at 0 and x_0 was adjusted, in 0.1-cm increments, from a minimum of 0.3 cm (i.e., inclusions have a point of contact) to a maximum of 1.0 cm. For the second, x_0 was fixed at 0.5 cm and y_0 was adjusted, in 0.2-cm increments, from a minimum of 0.2 cm to a maximum of 3.0 cm. The particular case illustrated in Fig. 7 is $D(x,y)$ for inclusions centered at (1,0).

In every simulation, the absorption coefficient was fixed at $\mu_a = 0.06 \text{ cm}^{-1}$ throughout the medium, while the background scattering coefficient was $\mu_{s, \text{bg}} = 10 \text{ cm}^{-1}$, which, according to the relation $D = 1/(3\mu_a + \mu_s)$, corresponds to a background diffusion coefficient of $D_{\text{bg}} = 0.0331 \text{ cm}^2/\text{s}$. Within the inclusions, the time-averaged scattering coefficient was $\mu_{s, \text{inc}} = 20 \text{ cm}^{-1}$, which corresponds to a diffusion coefficient of $D_{\text{inc}} = 0.0166 \text{ cm}^2/\text{s}$. All forward-problem and inverse-problem computations were carried out in the manner specified in Ref. 5. Reconstructed images (e.g., Fig. 9(a),(e)) were post-processed by applying the spatial deconvolution algorithm that was the subject of Refs. 1-4. The key distinction between these studies and the previous ones is that here μ_a , rather than μ_s , was modulated in each reference-medium pixel. All modeled $\mu_a(x,y)$ states were converted to the corresponding spatial distributions of D and the deconvolution operator was generated by comparing the latter to the recovered D images, as explained in Refs. 1-4. To examine the effect of random error on the accuracy of recovered images, computations were conducted three times, with noise-free detector data used in the first instance, and with data to which Gaussian white noise was added in the remainder. The noise levels were 1% and 2%, where the noise level for the k^{th} D channel is defined as $\epsilon_k = 100s_k/m_{k0}$, where s_k is the standard deviation of the k^{th} -channel noise distribution, and m_{k0} is the time-averaged noise-free detector reading.

Recovered images were subsequently treated with a noise-suppression scheme consisting of a combination of temporal low-pass filtering (tLPF) and spatial "softbox" filtering (sLPF) [2]. Comparisons between the target medium and reconstructed images, including the spatial and temporal correlation coefficients (SC and TC, respectively), and spatial and temporal root mean squared error (sRMSE and tRMSE, respectively), are used here as global indices of spatial and temporal accuracy of recovered images [5]. Several "local" measures of image quality also were computed (see Fig. 10). The parameters from which the latter were computed are defined in Figure 8.

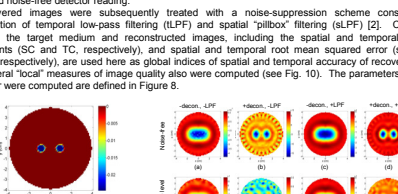


Figure 7. Heat map of the diffusion coefficient $D(x,y)$ showing two inclusions.

Recovered images of the target medium (shown in Fig. 8(a)) detector data are noise contaminated. The noise levels were 1% and 2%, where the noise level for the k^{th} D channel is defined as $\epsilon_k = 100s_k/m_{k0}$, where s_k is the standard deviation of the k^{th} -channel noise distribution, and m_{k0} is the time-averaged noise-free detector reading.

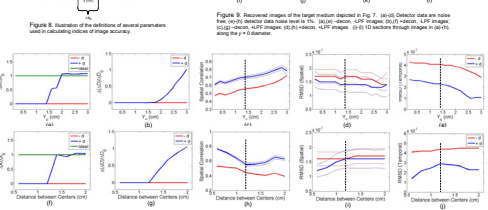


Figure 8. Reconstructed images of the target medium (shown in Fig. 8(a)) detector data are noise contaminated. The noise levels were 1% and 2%, where the noise level for the k^{th} D channel is defined as $\epsilon_k = 100s_k/m_{k0}$, where s_k is the standard deviation of the k^{th} -channel noise distribution, and m_{k0} is the time-averaged noise-free detector reading.

Representative images and 10 summary ratios of two-inclusion target medium, time frame and inclusion location $(x_0, y_0) = (0.5, 0)$, are shown in Figure 9. Qualitatively, the trends seen in these results agree with those previously reported for target media containing μ_a perturbations [4]. Overall, the results demonstrate that the spatial deconvolution yields significantly improved images, in terms of spatial resolving power and quantitative accuracy. However, deconvolution tends to amplify any background artifacts, whether they originate from systematic factors or from random errors. Consequently, when the detector data are noisy, the inclusions continue to be recovered with fair accuracy, but the amplitudes of noise artifacts can become comparable to those of the inclusions. By using the tLPF and sLPF in combination [2], the background artifacts are substantially reduced, at the cost of some reduction in quantitative accuracy.

Various scalar indices of image accuracy are plotted in Figure 10. Results for the variable- y_0 study are in Fig. 10(a)-(e), and those for a complementary variable- x_0 (y_0 fixed at 0) are in Fig. 10(f)-(j). Neither of the resolving-power indices [Fig. 10(a),(b),(f),(g)] rises above zero for the spatially convolved images. For the deconvolved images, partial resolution is seen when $y_0 > 1.4 \text{ cm}$ in Fig. 10(a). It can be observed from the other quantities plotted in Fig. 10 (the SC, sRMSE and tRMSE) that after deconvolution, the SC is significantly higher, while the sRMSE and tRMSE are substantially lower, than before deconvolution. The vertical dashed lines in Fig. 10 are located at the values of y_0 or x_0 at which the inclusions begin to be resolved.

Preliminary Results of Dynamic Phantom Studies

Recently, we have developed a dynamic calibrating phantom system [6] that employs electrochromic (EC) technology as a basis for electronically modulating the optical properties of an inclusion within a scattering medium. Fig. 11(a) shows the tissue-like brain-shaped phantom, with an EC cell embedded up to a depth of ~2cm below the surface of the plastic skull. Figure 11(b) illustrates the finite element model used in the image reconstruction, as well as the location of EC cell embedded in gray matter. The variation of the optical properties of the EC cell, which mimics a blood volume change, is plotted in Fig. 11(c). In our dynamic phantom experiment, a 5x5 array of illumination-detection fibers, located at the surface of the skull, is used as illustrated in Fig. 11(a). The experimental data sets are measured by our DYNODT imager.

Figure 12 demonstrates recovered results obtained by using our linear spatial deconvolution method. Shown in panels (a) and (b) of Figure 12 are GLM coefficient maps wherein the EC cell input function (see Fig. 11c) was used as the modeled response. Inspection reveals that in the absence of deconvolution, the inclusion is localized in the more superficial regions of the tissue, and not where it is truly located (i.e. motor cortex) – a result that resembles findings seen with the MR simulated brain (Figure 4). A notably improved result is seen in Panel (b), where the recovered location overlaps with estimates of the true location as judged by CT imaging. It can also be observed that the recovered GLM coefficients following deconvolution are now ten-fold greater than those seen in the unprocessed image. The last column of Figure 12 shows a comparison at the pixel level, where the blue traces within the region of maximal GLM values and the green is outside. Notice the correlation evident between the two pixels in the unprocessed image [Panel (a)], which we take as evidence of spatial blurring, and its absence following application of the deconvolution operator.

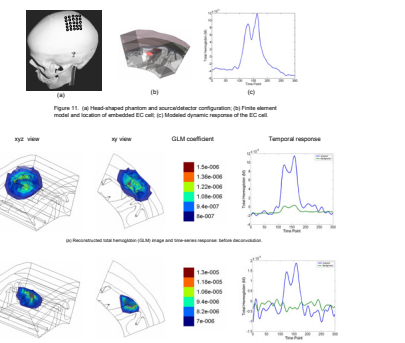


Figure 11. (a) Head-shaped phantom and source/detector configuration. (b) Finite element model. (c) Time-varying absorption coefficient. (d) Reconstructed images of the target medium. (e) Detector data with noise. (f) Detector data with noise. (g) Detector data with noise. (h) Detector data with noise. (i) Detector data with noise. (j) Detector data with noise.

Conclusions

1. The image-enhancing effects of spatial deconvolution are not degraded by static or dynamic background heterogeneity, irregular external boundaries, or irregular, non-convex, interior region interfaces.
2. Performance is not degraded by levels of noise typically associated with DOT brain imaging studies.
3. A large mismatch between the background optical coefficients of the target and reference media may yield highly artificial images, especially if the absorption and scattering of the reference media are over-estimated. Qualitatively similar artifacts can occur if the measurement data are excessively noisy.
4. The linear deconvolution algorithm has been extended to enhance the accuracy of DOT images to include spatial maps of the scattering coefficient. The types and magnitudes of image-enhancing effects obtained here are similar to those found in the previous studies on μ_a perturbations.
5. The linear spatial deconvolution method has been experimentally validated by a dynamic head phantom.

In summary, we have developed a highly efficient linear spatial deconvolution technique that is capable of improving image quality of linear reconstructions in a broad array of tested media containing multiple inclusions, with either absorption or scattering contrast, capable of simple or complex dynamic behaviors. We have also shown that the technique is equally effective in the case of media having complex backgrounds and have experimentally validated this finding in a dynamic phantom modeling a sudden change in blood volume. A corollary to these findings is the inescapable conclusion that much of the image blurring seen in first-order solutions to the DOT inverse problem is not due to neglect of higher order, nonlinear, effects. The effects present are a linear convolution, seemingly brought about by the mathematical operations inherent to linear algebraic techniques.

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