SVD–based normalized–transformed scheme for real–time DC optical tomography

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Abstract: An SVD–based normalized–transformed reconstruction scheme is described as a means to achieve real–time recovery of images from time–series DC intensity data. Results from numerical and experimental studies will be presented.
OCIS codes: (100.2960) Image analysis; (170.3010) Image reconstruction techniques; (170.6960) Tomography.

1. Introduction

Recently we have put forward the hypothesis that optical tomography, adopted to provide a time series of image data, can allow for the examination of an entirely new class of information involving tissue function – the spatiotemporal dynamics of the vascular response [1]. As a practical matter, it can be anticipated that the study of dynamic phenomena associated with the vascular response will require the collection of data sets comprising hundreds to thousands of time points. This need brings into consideration of the anticipated computing times, especially if 3D reconstructions are sought.

Much of the algorithm development work addressing image recovery in the area of optical tomography has focused on the use of recursive iterative methods (usually Newton–type) [2]. While the details of these methods vary, common to all is the realization that to achieve acceptable image quality, the computational effort needed is often substantial, especially for 3D problems. Whereas these efforts remain tractable when the recovery of only a few images is sought, it is mainly infeasible in cases where analysis of a typical time series is considered. Compounding this concern is the expectation that the nature of dynamic studies often requires feedback in real time. Certainly such capabilities are common in the case of ultrasound imaging. Here we describe an SVD–based normalized–transformed algorithm as a means to provide real–time analysis of time–series data.

2. Methods

The method used for real–time imaging of time–series data is a four–step process. The first step generates a set of time–dependent inverse system equations based on a recently described normalized–difference formulation that considers the evaluation of differential measurement data [3]. The second step scales the weight matrix by normalizing the row vectors to their respective mean values. This makes the weight matrix more uniform and better conditioned. The third step involves representing the unknowns as a linear combination of a set of independent basis functions. In principle almost any function could be considered, but we have chosen to use the weight functions themselves as the basis functions, thereby permitting transformation of the normally large $M \times N$ *weight* matrix to a much smaller $M \times M$ one. The fourth step employs SVD method for solution for all of the time–dependent system equations. In this step, the singular vector decomposition of the weight matrix is only done once (i.e., the first time point). After that, all reconstruction solutions related to the sequential time points can be obtained by doing simple substitution, which only performs an N^2 computation, for each new set of detector data.

3. Simulation conditions

The target medium examined was a geometrically simple 2–D structure (8 cm diameter circle) containing eight embedded inclusions, each 0.6 cm in diameter. The optical properties of the background medium were μ_a = 0.06 cm^{-1}, μ_s' = 10 cm^{-1}. The absorption contrast for each inclusion was assigned one of four different aperiodic functions representative of the types of temporal behavior reported associated with vascular reactivity (quasiperiodic, stochastic and chaotic). The mean value of the functions was twice the value of the background absorption coefficient and was modulated by 20%. The scattering contrast for the inclusions was 50% greater than the background, but time–invariant. In this manner, four different aperiodic fluctuations were occuring in the medium simultaneously, one for each designated pair of inclusions. Figure 1 shows a schematic of the target medium. Table 1 lists the ranges of absorption coefficient values and the types of temporal fluctuation modeled.

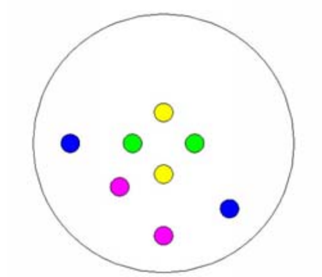

Figure 1. Test medium with inclusions.

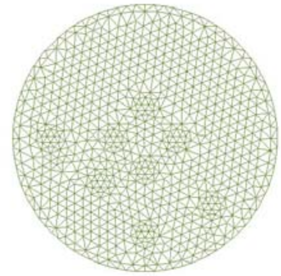

Figure 2. FEM mesh of test medium.

Table 1. Properties of temporal fluctuations assigned to inclusions' optical absorption coefficient

Range (cm^{-1})	Dynamics Functions			
	$\mu_a(g,t)$	$\mu_a(y,t)$	$\mu_a(b,t)$	$\mu_a(p,t)$
0.096 – 0.144	Chaotic 1	Quasiperiodic	Chaotic 2	Stochastic

The details regarding these temporal fluctuation functions have been described in Ref. 4. Simulated tomographic measurements (16 sources × 16 detectors, uniformly spaced) were obtained by computing solutions to the diffusion equation for a DC source for each of the 1000 time points considered. The FEM grid used is shown in Figure 2. The mesh contains 789 nodes and 1488 elements. Recovery of the image time series was performed using the basic scheme outlined above.

Several test parameters were examined with the aim of identifying the dependence of positional and temporal accuracy of the recovered objects on the optical properties of the reference medium and details of algorithm used. The latter involved computing solutions based on the SVD method itself, SVD plus row scaling, and SVD plus row scaling and the weight transform. Inverse solutions were obtained using a mesh containing 408 nodes and 733 elements.

4. Results

Figure 3 shows a typical reconstruction result using the SVD method. Here we considered the static case wherein the inclusion contrast was made equal to the temporal mean value of the assigned time series. Inspection shows that whereas the inclusions located nearer the surface are well resolved, those located more interior are not, and appear as an aggregate. The computing time for this solution was ~54 seconds using a SGI RISC 10000 processor. This compares to a computing time of 4.6 seconds when the SVD + weight transform + row scaling method described above is used. The corresponding result using this method is shown in Figure 4. Comparison shows the two results are comparable, with the latter possibly having improved object resolution. This improved computing time can in turn be greatly enhanced by pre-calculating the singular values and singular vectors of the weight matrix. In this case the complete image time series requires only 99 seconds to compute for all 1000 images. It is obvious that even larger time savings can be expected for solutions of 3D problems.

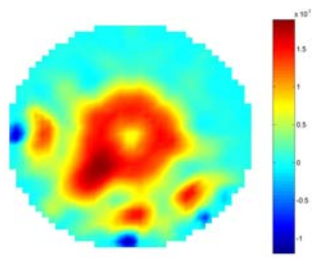

Figure 3. SVD–only solution.

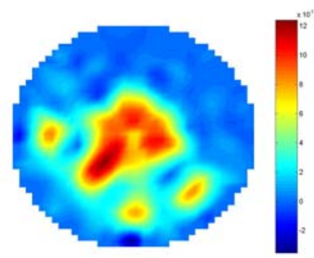

Figure 4. SVD + weight Transform and scaling.

As we have recently emphasized and documented [1], improved resolution of the target medium can be obtained by post–processing the image time series to extract different temporal measures of the system. An example of this is shown in Figure 5. Here we have computed spatial covariance maps for each of the assigned time functions. Inspection reveals that nearly complete isolation of the each inclusion from the others is achieved. These results show that methods adopted provide for computationally efficient solutions that have good–to–excellent spatial resolution. Similar results modeled from 3D media and results on laboratory phantoms will be presented.

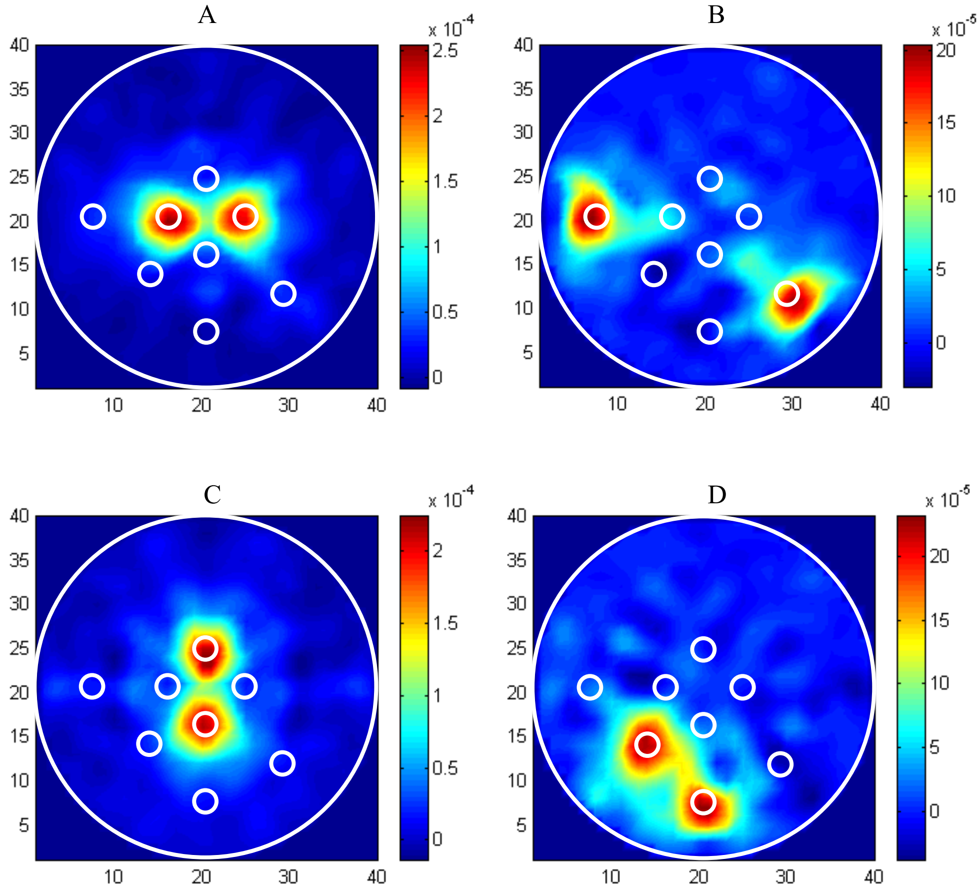

Figure 5. Covariance maps of image time series. Panel A, Chaotic 1; Panel B, Chaotic 2; Panel C, Quasiperiodic; Panel D, Stochastic.

4. Conclusion

The SVD based reconstruction method described provides for fast image recovery and improved spatial resolution The method is well suited for 3D problems because computing times will scale by N^2.

5. References

[1] R. L. Barbour, H. L. Graber, Y. Pei, S. Zhong, and C. H. Schmitz, "Optical tomographic imaging of dynamic features of dense–scattering media," J. Opt. Soc. Am. A **18**, 3018–3036 (2001).

[2] S. R. Arridge, "Optical Tomography in Medical Imaging," *Inverse Problems* **15**, R41–R93 (1999).

[3] Y. Pei, H. L. Graber, and R. L. Barbour, "Influence of systematic errors in reference states on image quality and on stability of derived information for DC optical imaging," Appl. Opt. **40** 5755–5769 (2001).

[4] H. L. Graber, C. H. Schmitz, Y. Pei, S. Zhong, S.-L. S. Barbour, S. Blattman, T. Panetta, and R. L. Barbour, "Spatio–temporal imaging of vascular reactivity," in Physiology and Function from Multidimensional Imaging, A. V. Clough, C.–T. Chen, eds., Proc. SPIE 3978, 32–43 (2000).

6. Acknowledgement

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