Published in final edited form as:

Ultrasound Med Biol. 2010 June ; 36(6): 967–977. doi:10.1016/j.ultrasmedbio.2010.03.002.

Super-Resolution Image Reconstruction Using Diffuse Source Models

Michael A. Ellis¹, Francesco Viola, Ph.D.¹, and William F. Walker, Ph.D.^{1,2}

¹ Department of Biomedical Engineering, University of Virginia, UVa Health System, P.O. Box 800759, Charlottesville, VA 22908

² Department of Electrical and Computer Engineering, University of Virginia, 351 McCormick Rd. P.O. Box 400743, Charlottesville, VA 22904

Abstract

Image reconstruction is central to many scientific fields, from medical ultrasound and sonar to computed tomography and computer vision. While lenses play a critical reconstruction role in these fields, digital sensors enable more sophisticated computational approaches. A variety of computational methods have thus been developed, with the common goal of increasing contrast and resolution to extract the greatest possible information from raw data. This paper describes a new image reconstruction method named the Diffuse Time-domain Optimized Near-field Estimator (dTONE). dTONE represents each hypothetical target in the system model as a diffuse region of targets rather than a single discrete target, which more accurately represents the experimental data that arise from signal sources in continuous space, with no additional computational requirements at the time of image reconstruction. Simulation and experimental ultrasound images of animal tissues show that dTONE achieves image resolution and contrast far superior to those of conventional image reconstruction methods. We also demonstrate the increased robustness of the diffuse target model to major sources of image degradation, through the addition of electronic noise, phase aberration, and magnitude aberration to ultrasound simulations. Using experimental ultrasound data from a tissue-mimicking phantom containing a 3 mm diameter anechoic cyst, the conventionally reconstructed image has a cystic contrast of -6.3 dB whereas the dTONE image has a cystic contrast of -14.4 dB.

Keywords

adaptive; beamforming; super-resolution; ultrasound

Introduction

Image reconstruction methods are used in many scientific fields, to analyze and filter important information from acquired data. While lenses play a critical reconstruction role in optics and some areas of acoustics, the advent of digital sensors has enabled the development of more sophisticated computational approaches to image reconstruction, all sharing the common goal of increasing image contrast and resolution to extract the greatest possible information from

Corresponding Author: Name: Michael Ellis, Mail: UVa Health System, P.O. Box 800759, Charlottesville, VA 22908, Phone: 434.924.9951, Fax: 434.982.3870, mae3x@virginia.edu.

Publisher's Disclaimer: This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final citable form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

the raw data. In medical ultrasound, the received sensor array data is often processed using “delay-and-sum” beamforming. In this approach, the image is reconstructed by summing weighted and time-delayed versions of the received signals. While this method is computationally efficient and easy to implement, it often achieves poor resolution and contrast as compared to more sophisticated approaches because it operates independently from the received data.

By adaptively tuning the image reconstruction algorithm to the received data, the reconstructed image can be optimized for desired attributes. Wiener filter theory, for example, has been applied to array signal processing in RADAR and SONAR to optimize a set of filter weights used in image reconstruction (Capon 1969; Frost 1972; Gabriel 1992; Haykin 2002; Van Veen 1988). By using the information in the received data itself, these reconstruction techniques are able to achieve resolution beyond that predicted by diffraction theory while maintaining excellent clutter reduction. In receive-only systems, such as passive SONAR, many unique statistical looks at the environment can be acquired, allowing estimation of the signal covariance matrix, which provides second order statistical information about the received signal. However, systems that both transmit and receive, such as medical ultrasound, can’t easily acquire enough unique looks at the environment to reliably determine second order statistics and build a covariance matrix. To circumvent this problem, several groups have applied spatial smoothing prior to estimation of the covariance matrix as well as diagonal loading of the covariance matrix estimate itself (Holfort, et al. 2009; Synnevag, et al. 2005; Vignon and Burcher 2008; Wang, et al. 2005). Such techniques increase the robustness of the covariance matrix estimate at the expense of contrast and resolution enhancement. Alternatively, several groups have developed image reconstruction techniques that do not rely on statistical properties of the data, allowing them to be used on a single realization. Such algorithms include techniques based on generalized eigenvalue problems (Ali and Schreiber 1992; Sarkar, et al. 1996), Bayesian approaches (Bethel, et al. 2002; Radich and Buckley 1997; Viberg and Swindlehurst 1994), maximum likelihood estimators (Cekli and Cirpan 2001; Tu, et al. 1997), data-adaptive regularization (Malioutov, et al. 2002), and minimum worst case gain methods (O’Brien and Kiriakidis 2003).

We have previously described a source localization method – named the Time-domain Optimized Near-field Estimator (TONE) – that is well suited for solving highly underdetermined problems given a well-defined system model (Viola, et al. 2008). This algorithm is built upon the Spatial Processing: Optimized and Constrained (SPOC) technique originally described by Van Trees *et al.* for applications in passive SONAR (Bethel, et al. 2002). While SPOC is designed for use with narrowband, far-field data, TONE is designed for use with broadband, near-field data, such as seen in medical ultrasound. Using a maximum *a posteriori* estimation technique with a well-defined system model, TONE can achieve a spatial resolution beyond the diffraction limit – hence, the term super-resolution – and image contrast far superior to that of CIR methods. TONE is particularly useful because it doesn’t require knowledge of second order statistics and is therefore suitable for use with only a single realization of data.

Although TONE has been demonstrated to significantly improve contrast and spatial resolution when applied to medical ultrasound, its discrete target model is ill suited for accurate representation of data arising from signal sources in continuous space. One possible remedy is to increase the spatial sampling rate of the system model, but this comes at an extreme cost in computational complexity, as described later. In this paper we describe an improvement to this algorithm – called Diffuse-TONE, or dTONE – that employs a more well suited system model and subsequently improves the contrast and robustness of TONE with no additional computational cost at the time of image reconstruction. Using a signal model in which each hypothetical target consists of a weighted sum of sources in a finite region rather than a single

discrete target, dTONE is able to more accurately represent a continuous medium. This significantly reduces clutter in the reconstructed image and increases the robustness of the algorithm to sources of image degradation. In addition, the discrete spatial sampling of the TONE system model results in images with a pixelated appearance from which it is difficult for the typical human observer to extract information. dTONE's diffuse source model provides a natural method for reducing pixelation in reconstructed images.

In (Ellis, et al. 2007a) we show preliminary results from the present method, using more sparsely sampled system models. In this paper we briefly present the dTONE algorithm and its diffuse target model. We then validate the performance of dTONE as compared to both TONE and CIR with simulations, experiments on tissue-mimicking phantoms, and experiments on excised animal tissue samples. Finally we offer some discussion of the performance and application of dTONE and some brief conclusions.

Note for the reader: matrices are represented using underlined upper-case italic characters such as $\underline{X}$ while vectors are represented with underlined lower-case italic characters such as $\underline{x}$. Superscripts T and H represent the transpose and conjugate transpose (Hermitian) operations, respectively.

TONE Image Reconstruction

The dTONE algorithm is built upon a simple linear model that has previously been applied to medical ultrasound (Lavarello, et al. 2006; Lingvall 2004; Stoughton and Strait 1993). The region of interest (ROI) – which describes the output image – is first subdivided into a collection of hypothetical targets at arbitrary positions, as shown on the left panel of Fig. 1. While any arbitrary sampling may be applied, a uniform rectangular grid is used here for simplicity and ease of display. Finer grid sampling yields finer resolution but entails higher computational costs. For each hypothetical target in the ROI, we determine the hypothetical signal received by the digital sensor array from a target at that specific point (i.e., the spatial response). The spatial response of each hypothetical target is a matrix of dimensions $T \times N$, where T is the number of samples in temporal dimension and N is the number of elements in the array, regardless of array geometry. After the spatial responses for all of the hypothetical targets have been measured via experiment or calculated via theory, they are reshaped into column vectors and concatenated to form an array manifold matrix, $\underline{V}$, of dimensions $NT \times LP$, where L and P are the numbers of hypothetical targets in two spatial dimensions (Viola, et al. 2008). It should be noted that some modalities do not require sampling in the temporal dimension ($T=1$) and some may require spatial sampling of the hypothetical targets in more than the two dimensions described by L and P . The observation model becomes:

$$\underline{x} = \underline{V} \underline{f} \quad (1)$$

where $\underline{x} = [\underline{x}_1 \ \underline{x}_2 \ \dots \ \underline{x}_N]^T$ is the data received by the N -element array and $\underline{f}$ is the $LP \times 1$ target vector, whose elements are the amplitudes of the hypothetical targets located in the ROI. $\underline{x}$ is the $NT \times 1$ vector obtained by concatenating the $T \times 1$ channel data $\underline{x}_i$. TONE operates on the received data $\underline{x}$ and the array manifold matrix $\underline{V}$ to solve for the position and amplitude of the real targets (i.e., the $\underline{f}$ vector). We solve this under-determined problem using a maximum *a posteriori* estimate of the target vector, as explained below. The maximum posterior estimate of $\underline{f}$ is given by (Scharf 1990):

$$\hat{\underline{f}} = \max_{\underline{f}} p(\underline{f} | \underline{x}) = \max_{\underline{f}} \underline{A} p(\underline{x} | \underline{f}) p(\underline{f}) \quad (2)$$

Where $p(\underline{x}, \underline{f})$ is the joint probability density function (PDF) and A is a normalizing constant that does not affect the maximum *a posteriori* estimate. We assume that the marginal PDF $p(\underline{f})$ is known *a priori* and mathematically expressed as a zero-mean Gaussian function (Levitan and Herman 1987; Wagner, et al. 1983). Furthermore, $p(\underline{x}, \underline{f})$ is equally likely for every $\underline{f}$ that satisfies the observation model in equation (1). Thus, equation (2) reduces to the following:

$$\hat{\underline{f}} = \max_{\underline{f}} p(\underline{f}) \quad (3)$$

which is referred to as the maximum *a posteriori* (MAP) estimate of $\underline{f}$. By substituting the marginal PDF $p(\underline{f})$ in (3) and rearranging terms, the MAP problem becomes:

$$\min_{\underline{f}} \sum_{l=1}^{LP} \ln |f_l|^2 \quad \text{subject to} \quad \underline{x} = \underline{V} \underline{f} \quad (4)$$

where f_l are the elements of $\underline{f}$. A solution for (4) is found using the iterative procedure described in (Viola, et al. 2008).

Diffuse Target Model

dTONE applies a modification to the system model, $\underline{V}$, used in the TONE image reconstruction in order to improve the algorithm's robustness to discrepancies between the data and the model, with no added computational cost at the time of image formation. Whereas each column of the array manifold matrix in TONE represents the system response from a single hypothetical target in a discrete grid, each column in dTONE represents the system response from a weighted collection of hypothetical targets with a finite region of support. Thus, the ROI is sampled with a grid of diffuse hypothetical targets rather than a grid of individual targets. The response from each of these diffuse targets is reshaped into a single column of the array manifold matrix, just as in TONE, as shown in the right panel of Fig. 1. Therefore, assuming equal spatial sampling in both TONE and dTONE, the size of the array manifold matrix does not change, indicating that the computation time required to reconstruct the image will not change.

Although Fig. 1 shows each diffuse target as a 5×5 non-overlapping region, the extent of the region of support for each diffuse target, the spatial sampling rate, and the subsequent weighting applied are each discretionary. It is also possible for these diffuse regions to overlap by any amount desired. By varying the size, weighting, and overlap of these diffuse regions, the performance of the dTONE algorithm can be fine tuned for a specific application. In this paper, we implement 5×5 sample, cubic b-spline (Unser 1999) weighted diffuse regions, overlapping such that the edges of one diffuse target align with the centers of those two targets away. This approach has been empirically determined to provide a reasonably smooth hypothetical target space with improved robustness and a compact region of support.

In the dTONE reconstructed images each sample represents a diffuse region of scatterers rather than a single discrete scatterer. This presents a natural opportunity to reduce the pixelated appearance of the output image by converting the single sample back to the diffuse region that it models. To do so, the output image is first up-sampled appropriately by inserting zeros between each sample and is then convolved with the diffusivity kernel used in the model itself. The result is a smoother final image with improved contrast and robustness to deviations from the system model.

Simulation Methods and Results

A series of ultrasound simulations were performed to compare the performance of dTONE to both TONE and CIR in the presence of electronic noise, phase aberration, and magnitude aberration. All calculations were performed in MATLAB (MathWorks Inc., Natick, MA) and utilized synthetic ultrasound signals generated using the DELFI ultrasound simulation tool (Ellis, et al. 2007b).

Electronic Noise Robustness

A series of point targets with equal scattering coefficient were distributed within a 3 mm $\times$ 5 mm region in range and azimuth, respectively. The positions of the targets were chosen so that none coincided with the positions of the hypothetical targets in the TONE and dTONE models and so that their spacing was near the diffraction limit of a system with the parameters described below. We simulated a 64 element, 300 μ m pitch, linear array operating at 5 MHz with 60% fractional bandwidth. The temporal sampling frequency was set at 40 MHz. A plane wave, parallel to the transducer surface, was used to transmit for both TONE and dTONE in order to simplify the system model and reduce computation cost, while a transmit focus at 22 mm ($f/1.14$) was used for CIR to mimic realistic system performance. 100 realizations of white noise were added to each receive channel then filtered using a 100 tap FIR filter with a pass-band from 3–7 MHz to achieve a post-filtered, per-channel signal-to-noise ratio (SNR) of 40 dB and 30 dB. CIR was applied on the filtered received radio frequency (RF) data using Hanning apodization and dynamic receive focusing. For dTONE and TONE, the ROI was discretized into a rectangular grid of hypothetical targets separated by 24 μ m in range and 38 μ m in azimuth. Elevation slice thickness was not considered. Both variants were applied to the filtered received RF data after complex demodulation to produce an in-phase and quadrature (IQ) pair. The images from a realization of noise with typical performance from all reconstruction methods are shown in Fig 2.

Both TONE and dTONE are non-linear methods, which implies conventional metrics like point spread function (PSF) parameters are not intrinsic characteristics of the imaging system. Thus, the PSF will vary, depending on the target being imaged and the various sources of model error such as aberration and electronic noise. To effectively quantify the resolution and clutter of the reconstructed images, many realizations of the targets must be acquired and analyzed. The full width half maximum (FWHM) was measured for each noise realization using the lateral variation of the single scatterer at a range of 23 mm and the axial variation of the single scatterer at 2 mm in azimuth. The means and standard deviations for these measures are given in Table 1. Both TONE and dTONE provide significant increases in the axial and lateral resolution of the modeled imaging system, although the resolution of both methods degrades with decreasing SNR. dTONE provides increased resolution over TONE for all levels of SNR simulated.

While the clutter in CIR methods is often characterized using side lobe levels, TONE and dTONE do not generate side lobes in the typical sense. Rather, images from these two source localization methods are characterized by false scatterers that clutter the reconstructed images in much the same way as side lobes. Unlike side lobes, which appear in a predictable location, these false scatterers appear randomly throughout the image. To quantitatively assess their effect on image contrast and provide a means of comparison between methods, a 2 mm by 3.5 mm speckle generating region surrounding a 1.2 mm diameter anechoic cyst centered at a range of 22 mm was modeled using the same parameters as the point target simulations. Cystic contrast was measured as the ratio of the energy inside the cyst to that of an equal sized area outside the cyst at an equal depth. The results are given in Table 1. TONE provides around a 5 dB improvement in cystic contrast over CIR for this simulation while dTONE provides about a 15 dB improvement. The standard deviation of cystic contrast for both TONE and dTONE increases with decreasing SNR, while the mean cystic contrast changed very little.

Phase and Magnitude Aberration

The same phantom and system model that was used in the electronic noise robustness simulations was also used to determine the robustness of the beamformers to phase and magnitude aberration. Recent literature suggests that aberrations in the breast and abdominal wall can be modeled as a near-field, thin phase-screen where the magnitude aberrators have a root mean square (RMS) strength of 5 dB and a full-width at half-maximum (FWHM) correlation length of 2.6 mm and the phase aberrators have an RMS strength of 28 ns and a FWHM correlation length 3.6 mm (Fernandez, et al. 2003; Gauss, et al. 1997). Using these statistics, 100 realizations of each aberrator were generated and applied to the data prior to filtering and beamforming.

As with the electronic noise simulations above, the reconstructions from TONE and dTONE vary due to the random nature of the aberrators. The images from a realization with typical performance from both algorithms are shown in Fig. 3. The FWHM and cystic contrast – measured using the methods described above – are shown in Table 2. Again, both TONE and dTONE provide significant increases in the axial and lateral resolution of the modeled imaging system, although the resolution of both methods degrades in the presence of aberration somewhat more than in the presence of electronic noise. This same trend holds true for cystic contrast measurements as well.

Experimental Methods and Results

Anechoic Cyst Phantom

A 3 mm diameter, 7 cm long cylindrical anechoic cyst, surrounded by a $1 \times 1 \times 7$ cm speckle-generating region was formed in 7% acrylamide gel. The $1 \times 1 \times 7$ cm region of acrylamide gel containing Sephadex™ G-50 Superfine scatterers (GE Healthcare) was embedded in a larger block of acrylamide gel containing no scatterers such that the center of the cyst was at a depth of approximately 2 cm from the top of the phantom. An Ultrasonix Sonix RP system employing a 128 channel, 300 μ m pitch, linear array was used to transmit a 6.6 MHz, 60% fractional bandwidth plane wave and obtain single channel RF data. The data was filtered using a 100-tap FIR filter with a pass-band from 3–10 MHz, demodulated to produce an IQ pair, and all but the center 64 channels were removed. The array manifold matrix was constructed by shifting and warping the spatial response from a single 20 μ m diameter stainless steel wire embedded in the same 7% acrylamide gel at a depth of 2 cm. Elevation effects were not modeled for this set of experiments. Hypothetical targets were placed every 95.6 μ m axially and every 120 μ m laterally for both TONE and dTONE. The CIR image was formed using a 64 element, 300 μ m pitch aperture on both transmit and receive, which is the standard configuration for the ultrasound system used. The transmit beam was focused at 2 cm ($f/1.04$) and dynamic receive focusing was applied after band-pass filtering and apodization with a Nuttall window.

The results from this experiment are shown in Fig. 4. The cystic contrast of each reconstructed image was computed as the ratio between the energy within the anechoic cyst and that of an equal sized region of speckle outside the cyst at the same range from the transducer. The CIR image has –6.4 dB of cystic contrast, while the TONE image has –7.4 dB of contrast and the dTONE image has –14.4 dB of contrast. Visual inspection of Fig. 4 agrees with these findings as the CIR image contains significant clutter, reducing the apparent size of the cyst itself. Although the TONE image appears to more accurately delineate the cyst boundaries, it still contains significant clutter within the anechoic cyst, reducing its effective contrast. dTONE reduces this clutter while maintaining excellent delineation of the cyst boundary, increasing the contrast between the echogenic and anechoic regions.

Animal Tissue Phantom

An excised mouse heart was flushed with phosphate-buffered solution (PBS) to remove any remaining blood from the chambers and then embedded at a depth of 2 cm in a block of 7% acrylamide gel. Effort was taken to ensure the chambers of the heart remained in an open state by backfilling them with 7% acrylamide prior to embedding the heart. Additionally, a 3 cm length of aorta was excised from a rabbit, flushed with PBS, and backfilled with 7% acrylamide prior to embedding it in a block of 7% acrylamide at a depth of 2 cm. Both tissue samples were then imaged using the same parameters used for the anechoic cyst phantom. A somewhat more finely sampled array manifold matrix was employed, with hypothetical targets placed every 76.5 μm axially and every 90 μm laterally. Again, elevation slice thickness was not modeled.

Results from the tissue phantoms are shown in Figs. 5 and 6. The CIR image of the mouse heart shows a significant amount of clutter in the two ventricles, making a distinction between the septum and the ventricles very difficult. The TONE and dTONE images show a superior delineation of the boundary between the septum and the anechoic ventricles. The TONE image is, however, degraded by the presence of cloud-like artifacts that are significantly reduced using dTONE. In the top panel of Fig. 6, the inner diameter of the rabbit aorta is difficult to measure accurately due to poor resolution and clutter in the lumen. Using both TONE and dTONE, however, the boundary of the lumen is more clearly delineated, increasing the reliability of such measurements. Once again, the TONE image is degraded by the presence of cloud-like artifacts, which are significantly reduced using the dTONE algorithm.

Discussion

The extraction of information from reconstructed images depends upon the ability to accurately resolve and measure small features within the images. In medical imaging, for example, the ability to resolve finer targets may open the door for new or more accurate diagnoses. Conventional, data-independent, image reconstruction techniques are limited in their ability to resolve small features with good contrast, thereby limiting their efficacy. In this paper we show that dTONE is able to achieve spatial resolutions and image contrasts far superior to those of CIR techniques. This goal is accomplished through the inclusion of information from the data itself in the process of image reconstruction.

Unless the imaged point targets lie exactly on the hypothetical targets, it is not possible to perfectly match the received data to the discrete target based TONE system model. It may seem logical to assume that, when a true target lies between hypothetical targets, TONE would distribute energy to the hypothetical targets directly surrounding that target. However, the coherent nature of the system indicates that a diffuse cloud of hypothetical scatterers around the actual targets may produce a better fit to the TONE model, giving rise to the cloud-like clutter artifacts seen in the TONE images throughout this paper. Altering the system model from a grid of individual hypothetical targets to a grid of weighted, diffuse hypothetical targets allows the system model to fit the data received from those targets that lie between hypothetical targets in a more local manner. This, in turn, reduces the amplitude and extent of the clutter in the final image, resulting in improved image contrast.

Although a reduction in clutter is seen in the dTONE images throughout this paper, there is still a significant amount in both the 30 dB SNR image and the phase aberration image. While this may seem to pose a problem for dTONE, there are various methods that could be used to reduce electronic noise or phase aberration in medical ultrasound. A lower transmit pulse center frequency, for example, would increase the SNR at the expense of some spatial resolution and be less susceptible to phase aberration errors. Additionally, coded excitation (Chiao and Hao 2005; Misaridis and Jensen 2005a, 2005b) could be used to increase the SNR of the received data, ensuring that it remains high enough to avoid additional clutter due to electronic noise.

As only a single plane-wave transmit is needed to acquire the data, relatively long codes could be used with little or no consequences from tissue motion. An ancillary modification that would increase the SNR of the received data is to use a focused transmit beam rather than a plane wave transmit. Doing so would simply require redefining each column of the array manifold matrix.

In addition to reducing clutter, dTONE presents a clear method for reducing the pixelation in the output images. Because each pixel in the output image represents a weighted, diffuse region of hypothetical scatterers, it would be reasonable to display them as such. The output image can be appropriately up-sampled by inserting zeros between the samples and then convolving the image with the same diffusivity kernel used to form the system model. This significantly reduces the pixelated nature of the image, which should improve image interpretation. While it is possible to perform the same procedure on a TONE reconstructed image as well, it would only have the effect of blurring the image and would be a misrepresentation of the output, as each pixel in a TONE image only represents a single hypothetical target. In addition, it would not provide the added robustness and clutter reduction benefits of the dTONE algorithm.

The spatial sampling rate, weighting, and spatial extent of the diffusivity kernel are each discretionary and can be altered to tune dTONE for a specific application. In medical ultrasound for example, if we are most concerned with detecting diffuse lesions in an echogenic background, we may want to sacrifice some resolution for increased contrast, keeping in mind that the resolution is already far superior to that of CIR. In this case we would likely opt for a diffusivity kernel with greater extent to further reduce the presence of clutter. If, however we are most concerned with resolving and detecting micro-calcifications in the liver or breast, we may opt for a more compact diffusivity kernel to achieve finer resolution at the cost of some additional clutter. In this paper, we empirically determined a 5×5 sample, cubic b-spline weighted diffusivity kernel, whose edges are in line with the centers of those hypothetical targets directly surrounding it, to be a good choice for a wide variety of applications. Further work is being done to assess the effect of altering these parameters on the reconstructed image.

One of the main limitations of dTONE not addressed in this paper is the algorithm's high computational complexity. The rate limiting step of the algorithm requires the multiplication of two large matrices, which has a computational complexity on the order of $fix^2(out+fix)$, where fix is the number of non-zero singular values of the system model matrix and out is the number of hypothetical scatterers. For a $1.4 \text{ cm} \times 1.6 \text{ cm}$ image region sampled every $76.5 \mu\text{m} \times 90 \mu\text{m}$, as used for the experimental tissue phantoms in this paper, the array manifold matrix, $\underline{V}$, is on the order of 19K by 30K complex elements, or a total of 570M complex elements, and the reconstruction requires roughly 12×10^{12} calculations. The experimental images in this paper required about 1.5 hours of computation on an Intel Dual-Core XEON EMT 2.66 GHz processor. An increase in the extent of the image region or the spatial sampling rate of the hypothetical targets would significantly increase the size of the array manifold matrix. Although this matrix can be computed in advance and stored for later use, the time required for image reconstruction increases significantly as $\underline{V}$ grows. However, there are several approaches to this problem that may reduce the computational complexity. In one such approach, the image region is divided into smaller sub-regions, each with their own array manifold matrix. dTONE could then be applied in parallel to each of these smaller regions, providing reductions in computation times not only due to parallelization, but also due to the decreased dimensionality of the problem. In addition, it may be possible to alter the cost function currently used in TONE and dTONE to yield a closed form solution that does not require iteration to solve. Such a modification would not only offer computational complexity benefits, but would also provide another means to tune the output image of dTONE to maintain a desired set of characteristics. We are currently investigating these and other approaches.

Although this paper focuses on the application of dTONE to medical ultrasound beamforming, it has a far broader range of applications in fields as diverse as sonar, computed tomography, and computer vision. dTONE and its underlying algorithm present a means of solving any highly under-determined system, given a well-defined system model. In computed tomography (CT), for example, we can model the attenuation coefficient of each voxel in the reconstructed image and its impact on the received signal. While CT image reconstruction is typically over-determined, if the ROI is very finely sampled to achieve super-resolution, the image reconstruction will be highly under-determined, making it an ideal application for dTONE. Alternatively, rather than increasing the spatial sampling to achieve super-resolution in computed tomography, it may be possible to maintain a standard spatial sampling and reduce the number of x-ray projections to decrease the dose of ionizing radiation. This image reconstruction would also be highly under-determined and therefore an ideal application for dTONE. Likewise, dTONE could be used to increase contrast and resolution in any other image reconstruction application involving a highly under-determined system.

Conclusions

In this paper, we presented a maximum *a posteriori* image reconstruction algorithm, named dTONE, which is well suited for solving any highly under-determined problem given a well-defined system model. In both simulation and experiment with animal tissues using medical ultrasound, dTONE reconstructed images displayed improved contrast and resolution when compared to CIR methods. This paper also presented a diffuse target based system model and compared its performance to that of a discrete target based system model. In both simulation and experiment, dTONE reconstructed images displayed greater contrast and robustness to common sources of image degradation than those from TONE, a variant that uses a discrete target based model.

Acknowledgments

This work was supported by the U.S. Army Congressionally Directed Medical Research Program in Breast Cancer under Grant W81XWH-04-1-0590 and NIH grant R01 EB005433.

We acknowledge the technical support from Ultrasonix Medical Corporation, the IBM Shared University Research Program, and the University of Virginia Research Computing Support Group.

References

- Ali M, Schreib F. Adaptive single snapshot beamforming: a new concept for the rejection of nonstationary and coherent interferers. *Signal Processing, IEEE Transactions on* 1992;40:3055–58.
- Bethel, R.; Shapo, B.; Trees, HV. Single Snapshot Spatial Processing: Optimized and Constrained. *Sensor Array and Multichannel Signal Processing Workshop Proceedings*; 2002. p. 508-12.
- Capon J. High-resolution frequency-wavenumber spectrum analysis. *Proceedings of the IEEE* 1969;57:1408–18.
- Cekli, E.; Cirpan, H. Deterministic maximum likelihood method for the localization of near-field sources: algorithm and performance analysis. *Electronics, Circuits and Systems; IEEE International Conference*; 2001; 2001. p. 2
- Chiao RY, Hao X. Coded excitation for diagnostic ultrasound: a system developer's perspective. *Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on* 2005;52:160–70.
- Ellis, M.; Viola, F.; Walker, W. Diffuse Targets for Improved Contrast in Beamforming Adapted to Target. *IEEE Ultrasonics Symposium*; 2007a. p. 216-19.
- Ellis MA, Guenther DA, Walker WF. A Spline-Based Approach for Computing Spatial Impulse Responses. *IEEE Transactions on Ultrasonics Ferroelectrics & Frequency Control* 2007b;54:1045–54.

- Fernandez A, Dahl J, Dumont D, Trahey G. Array elevation requirements in phase aberration correction using an 8×128 1.75 D array. *Proceedings of SPIE* 2003;4687:79.
- Frost OL. An algorithm for linearly constrained adaptive array processing. *Proc IEEE* 1972;60:926–35.
- Gabriel WF. Adaptive Processing Array Systems. *Proceedings of the IEEE* 1992;80:152–62.
- Gauss, RC.; Soo, MS.; Trahey, GE. Wavefront Distortion Measurements in the Human Breast. *Proc. IEEE Ultrason. Symp*; 1997. p. 1547-51.
- Green PJ. Bayesian reconstructions from emission tomography data using a modified EM algorithm. *Medical Imaging, IEEE Transactions on* 1990;9:84–93.
- Haykin, S. *Adaptive Filter Theory*. Upper Saddle River, NJ: Prentice Hall; 2002.
- Holfort IK, Gran F, Jensen JA. Broadband minimum variance beamforming for ultrasound imaging. *Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on* 2009;56:314–25.
- Lavarello R, Kamalabadi F, O'Brien W. A Regularized Inverse Approach to Ultrasonic Pulse-Echo Imaging. *IEEE Trans Med Imag* 2006;25:712–22.
- Levitan E, Herman GT. A Maximum a Posteriori Probability Expectation Maximization Algorithm for Image Reconstruction in Emission Tomography. *Medical Imaging, IEEE Transactions on* 1987;6:185–92.
- Lingvall F. A method of improving overall resolution in ultrasonic array imaging using spatio-temporal deconvolution. *Ultrasonics* 2004;42:961–68. [PubMed: 15047414]
- Malioutov, D.; Cetin, M.; Fisher, J.; Willsky, A. Superresolution source localization through data-adaptive regularization. *Sensor Array and Multichannel Signal Processing Workshop Proceedings*; 2002. p. 194-98.
- Meer P, Mintz D, Rosenfeld A, Kim DY. Robust regression methods for computer vision: a review. *Int J Comput Vision* 1991;6:59–70.
- Misaridis T, Jensen JA. Use of modulated excitation signals in medical ultrasound. Part I: basic concepts and expected benefits *Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on* 2005a;52:177–91.
- Misaridis T, Jensen JA. Use of modulated excitation signals in medical ultrasound. Part II: design and performance for medical imaging applications *Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on* 2005b;52:192–207.
- Noumeir, R.; Mailloux, GE.; Lemieux, R. Bayesian Image Reconstruction: An Application to Emission. *Statistical Signal and Array Processing, IEEE Workshop*; 1994; p. 405-08.
- O'Brien, R.; Kiriakidis, K. Single-snapshot robust direction finding. *IEEE Transactions on Signal Processing*; 2003.
- Radich B, Buckley K. Single-snapshot DOA estimation and source number detection. *Signal Processing Letters, IEEE* 1997;4:109–11.
- Sarkar T, Park S, Koh J, Schneible R. A Deterministic Least Squares Approach to Adaptive Antennas. *Digital Signal Processing* 1996;6:185–94.
- Scharf, LL. *Statistical Signal Processing: Detection, Estimation and Time Series Analysis*. Reading, MA: Addison-Wesley Publishing Company; 1990.
- Stoughton R, Strait S. Source imaging with minimum mean-squared error. *The Journal of the Acoustical Society of America* 1993;94:827.
- Synnevag, J.; Austeng, A.; Holm, S. Minimum variance adaptive beamforming applied to medical ultrasound imaging. *IEEE Ultrasonics Symposium*; 2005; p. 2
- Tu M, Gupta I, Walton E. Application of maximum likelihood estimation to radar imaging. *Antennas and Propagation, IEEE Transactions on* 1997;45:20–27.
- Unser M. Splines: a perfect fit for signal and image processing. *Signal Processing Magazine, IEEE* 1999;16:22–38.
- Van Veen, B. Beamforming: A Versatile Approach to Spatial Filtering. *IEEE ASSP Magazine*; 1988; p. 4-24.
- Vetter, T.; Jones, MJ.; Poggio, T. A bootstrapping algorithm for learning linear models of object classes. *Computer Vision and Pattern Recognition, IEEE Computer Society Conference*; 1997; p. 40-46.
- Viberg M, Swindlehurst A. A Bayesian approach to auto-calibration for parametric array signalprocessing. *Signal Processing, IEEE Transactions on* 1994;42:3495–507.

- Vignon F, Burcher MR. Capon beamforming in medical ultrasound imaging with focused beams. *Ultrasonics, Ferroelectrics and Frequency Control*, IEEE Transactions on 2008;55:619–28.
- Viola F, Ellis M, Walker W. Time-Domain Optimized Near-Field Estimator for Ultrasound Imaging: Initial Development and Results. *Medical Imaging*, IEEE Transactions on 2008;27:99–110.
- Wagner RF, Smith SW, Sandrik JM, Lopez H. Statistics of speckle in ultrasound B-scans. *IEEE Transactions on Sonics and Ultrasonics* 1983;30:156–63.
- Wang Z, Li J, Wu R. Time-delay-and time-reversal-based robust capon beamformers for ultrasound imaging. *Medical Imaging*, IEEE Transactions on 2005;24:1308–22.

Figure 1. Schematic representation of the system model matrix formation for TONE (left) versus dTONE (right). Although the diffusivity kernels for dTONE are shown here as 5×5 non-overlapping regions, they can be of any spatial extent, spatial sampling rate, and weighting.

Figure 2.

Simulated assessment of electronic noise robustness showing the target distribution (top left) and the CIR image (bottom left). The second through fourth columns show the dTONE (top) and TONE images (bottom) for post-filtered single channel SNR levels of infinity, 40 dB, and 30 dB, respectively. All images are log compressed to 50 dB.

Figure 3.

Simulated assessment of aberration robustness showing the target distribution (top left) and the CIR image (bottom left). The second through fourth columns show the dTONE (top) and TONE images (bottom) in the presence of phase aberration, magnitude aberration, and both combined, respectively. The phase aberrators had an RMS magnitude of 28 ns and a FWHM correlation length of 3.6 mm, while the magnitude aberrators had an RMS magnitude of 5 dB and a FWHM correlation length of 2.6 mm. All images are log compressed to 50 dB.

Figure 4.

Experimental images of an anechoic cyst phantom, as beamformed using CIR (top), TONE (middle), and dTONE (bottom). All images are log compressed to 50 dB.

Figure 5. Experimental long-axis images of an excised mouse heart, as beamformed using CIR (top), TONE (middle), and dTONE (bottom). All images are log compressed to 50 dB.

Figure 6.

Experimental images of a cross-section of excised rabbit aorta, as beamformed using CIR (top), TONE (middle), and dTONE (bottom). All images are log compressed to 50 dB.

Table 1

Full Width at Half Maximum (FWHM) for the Reconstructed Images at Range 23 mm and Cystic Contrast for a 1.2 mm Diameter Anechoic Cyst at a Depth of 22 mm.

	Lateral FWHM (um)		Axial FWHM (um)		Cystic Contrast (dB)	
	Mean	St Dev	Mean	St Dev	Mean	St Dev
CIR	453.0	-	230.0	-	-24.8	-
Noise Free						
TONE	93.6	-	85.6	-	-29.2	-
dTONE	75.0	-	61.2	-	-39.9	-
40 dB SNR						
TONE	114.6	3.9	85.0	2.1	-29.2	0.5
dTONE	81.1	1.5	60.9	1.2	-39.8	0.2
30 dB SNR						
TONE	125.6	5.6	85.4	2.6	-29.7	1.4
dTONE	98.5	3.4	64.3	1.4	-39.6	0.6

Table 2

Full Width at Half Maximum (FWHM) for the Reconstructed Images at Range 23 mm and Cystic Contrast for a 1.2 mm Diameter Anechoic Cyst at a Depth of 22 mm.

	Lateral FWHM (um)		Axial FWHM (um)		Cystic Contrast (dB)	
	Mean	St Dev	Mean	St Dev	Mean	St Dev
Aber. Free						
CIR	453.0	-	230.0	-	-24.8	-
TONE	93.6	-	85.6	-	-29.2	-
dTONE	75.9	-	61.2	-	-39.9	-
Mag. Aber.						
CIR	453.0	0.0	230.0	0.0	-23.0	0.4
TONE	131.5	22.7	97.2	34.5	-29.1	4.2
dTONE	124.3	18.9	70.6	33.6	-39.1	3.1
Phase Aber.						
CIR	453.0	0.0	230.0	0.0	-23.4	0.1
TONE	140.2	22.5	96.2	47.2	-27.8	4.1
dTONE	132.1	13.7	71.3	30.5	-38.4	3.6
Combined						
CIR	453.0	0.0	230.0	0.0	-23.0	0.4
TONE	138.5	27.7	98.2	27.6	-25.4	5.1
dTONE	132.1	17.6	72.3	23.0	-37.6	3.6