Weighted model-based optoacoustic reconstruction in acoustic scattering media

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Received 31 January 2013, in final form 30 April 2013
Published 29 July 2013
Online at stacks.iop.org/PMB/58/5555

Abstract

Model-based optoacoustic inversion methods are capable of eliminating image artefacts associated with the widely adopted back-projection reconstruction algorithms. Yet, significant image artefacts might also occur due to reflections and scattering of optoacoustically-induced waves from strongly acoustically-mismatched areas in tissues. Herein, we modify the model-based reconstruction methodology to incorporate statistically-based weighting in order to minimize these artefacts. The method is compared with another weighting procedure termed half-image reconstruction, yielding generally better results. The statistically-based weighting is subsequently verified experimentally, attaining quality improvement of the optoacoustic image reconstructions in the presence of acoustic mismatches in tissue phantoms and small animals ex-vivo.

(Some figures may appear in colour only in the online journal)

1. Introduction

The majority of the currently utilized optoacoustic inversion schemes are derived by assuming that the imaged sample is acoustically homogeneous and perfectly matched to the coupling medium (water) (Kruger et al 1995, Paltauf et al 2002, Norton and Vo-Dinh 2003, Xu and Wang 2004, Filbir et al 2010). However, the propagation of acoustic waves is generally distorted due to speed of sound or mass density variations and acoustic attenuation, which lead to artefacts in the reconstructed images if the corresponding effects are not corrected. Heterogeneities in soft tissues relate to small changes in the speed of sound (typically below 10% with respect to water). In order to correct for this effect, one could in principle attempt to take into account the time-shift of the signals caused by such speed of sound variations (Xu and Wang 2003, Manohar et al 2007, Modgil et al 2010, Deán-Ben et al 2012c) or to use a first order approximation of the optoacoustic wave equation in the frequency domain (Jiang et al 2006). On the other hand, strong reflections or scattering of the ultrasonic waves, which usually occur in the presence of lungs, bones or other highly mismatch organs, might add more significant artefacts in the reconstructed images (Deán-Ben et al 2011a, 2011b, 2012b).
Finally, acoustic attenuation causes quantification inaccuracies and loss of resolution in the images due to the reduction of amplitude and broadening of optoacoustic signals (Deán-Ben et al 2011c), so that a model for the propagation of the waves in attenuating media must be considered in order to improve the tomographic reconstructions (La Riviere et al 2006, Burgholzer et al 2010).

It has been previously noted that the deterioration in the quality of the acoustic signals is scaled with depth (Anastasio et al 2005). This property was used to improve reconstruction quality by using only the leading half of the acoustic signals collected around the imaged sample. For each projection, the trailing half corresponding to regions in the object that are farther than the object’s centre is neglected, which is equivalent to applying a weighting factor equal to 1 or 0 for different time instants. Although this interesting heuristic approach generally led to improved reconstructions in acoustically heterogeneous objects, the disposal of 50% of projection data is not always justified. Specifically, for regions close to the object’s centre, the difference in data quality between the projections may not be significant. Also, the reconstruction for a given point is done with a limited number of transducer locations, which may not contain enough information to retrieve a satisfactory reconstruction, especially for limited-view cases.

In a recent work (Deán-Ben et al 2011a), we introduced a more general approach to account for acoustic heterogeneities causing acoustic reflections and scattering which was based on statistical principles. The method was demonstrated by modifying the filtered back-projection (FBP) algorithm, and was shown to reduce artefacts caused by acoustic reflections or scattering. Such statistical approach is based on weighting the contribution of the signals employed to make the reconstruction with the probability that they are not distorted by scattered or reflected acoustic waves. Thereby, the signals that more likely correspond to direct wave propagation from the excitation point would generally have a higher contribution to the reconstruction than those for which a reflected or scattered wave is more probable to affect the signal. Then, as the accuracy in the determination of such probability depends on the available structural information of the sample, the quality of the tomographic reconstructions can be further improved for example by taking into account the approximate location of regions with high acoustic scattering (Deán-Ben et al 2011b). However, FBP-based optoacoustic reconstruction algorithms are generally not adequate for quantitatively estimating the optical absorption distribution (Rosenthal et al 2010). Additionally, FBP algorithms cannot fully account for the effect of detector geometry on the reconstruction (Rosenthal et al 2011). By this, the overall efficiency of the aforementioned statistical approach, applied in combination with FBP, is reduced as well. The half-time image methodology, on the other hand, is based on model-based reconstruction and so it may in general overcome the performance of weighted back-projection algorithms.

Herein we apply instead the aforementioned statistical methodology to modify a model-based inversion algorithm, termed interpolated-matrix-model inversion (IMMI) (Rosenthal et al 2010). This algorithm provides a better quantitative reconstruction performance compared to FBP, an important measure for applications that require accurate image analysis, such as evaluation of biomarker distribution in tissue. Additionally, contrary to other model-based reconstruction procedures (Jiang et al 2006, Provost and Lesage 2009), the IMMI enabled regularization-free reconstruction in the case of full-tomographic view, yielding high-resolution images. Thereby, the modification of the IMMI algorithm based on statistically-based weighting is an important issue to address. In such cases both the signals and the model are weighted so that no additional quantification errors are introduced with this procedure, which is very important if the actual distribution of optical energy must be estimated. The weighting of this algorithm based on the half-time methodology was also done, showing in
general noisier results than the statistically-based weighting and strongly distorted images in limited-view cases. The experimental results obtained both in tissue-mimicking phantoms and in small animals post mortem indicate the convenience of weighting the algorithm to avoid artefacts and distortion in the reconstructed images due to acoustic reflections and scattering.

2. Theory

2.1. Interpolated matrix model inversion

In this section we briefly describe the IMMI algorithm. A more comprehensive description can be found in Rosenthal et al (2010). It is based on a discretization of the optoacoustic forward model for short-pulsed illumination, given that thermal confinement conditions are fulfilled. In such a case, the pressure field due to optoacoustic excitation at the initial instant is given by Wang (2009)

\[ p(r, t) = \frac{\Gamma}{4\pi c} \frac{\partial}{\partial t} \int_S \frac{H(r')}{|r - r'|} dS', \tag{1} \]

where \( c \) is the speed of sound, \( H(r') \) is the amount of energy absorbed in the tissue per unit volume and \( \Gamma \) is the dimensionless Grueneisen parameter. \( S' \) is the surface of a sphere centred at \( r \) and with a radius equal to \( ct \). In some practical cases, for instance when cylindrically-focused ultrasonic transducers have been used, an approximation consists in assuming that all the acoustic sources lie in a plane, so that equation (1) can be reduced to a two-dimensional geometry and the integration is performed over a circumference.

In practice, the reconstruction consists of computing the value of \( H(r'_k) \) for the pixel positions \( r'_k \) in the discrete image. Taking this into account, a discrete approximation of equation (1) can be expressed as

\[ p(r_i, t_j) = \sum_{k=1}^{N} a_{ij}^k H(r'_k), \tag{2} \]

with \( N \) being the number of pixels in the image. To calculate the coefficients \( a_{ij}^k \), \( H(r') \) must be calculated in the whole 2D space by means of interpolation from the values of \( H(r'_k) \) at the pixel positions. It has been shown in Rosenthal et al (2010) that the coefficients \( a_{ij}^k \) can be estimated semi-analytically if the interpolation is performed by tiling the \( x-y \) reconstruction plane with right-angle triangles with vertexes on the pixel positions, so that \( H(r') \) is obtained by linear interpolation inside each triangle. A faster method to calculate these coefficients consists in approximating the integration circumference by a set of points with equally-spaced angular positions from the transducer locations (Deán-Ben et al 2012c), which can also be used for three-dimensional reconstructions (Deán-Ben et al 2012a).

The same discretization of equation (1) can be obtained for \( P \) positions of the transducer and for \( I \) instants, in a way that a system of linear equations can be formulated, which is expressed in a matrix form as

\[ \mathbf{p} = \mathbf{A}_M \mathbf{H}. \tag{3} \]

Equation (3) corresponds to the forward model, in which the theoretical pressure for a set of detector positions and instants \( \mathbf{p} \) is calculated as a function of the absorbed energy in the pixel positions \( \mathbf{H} \). \( \mathbf{A}_M \) is the model matrix with dimensions \( PI \times N \). The optoacoustic reconstruction is performed by minimizing the mean square difference between the theoretical pressure \( \mathbf{p} \) and the measured pressure \( \mathbf{p}_m \), i.e.

\[ \mathbf{H}_{sol} = \arg\min_{\mathbf{H}} \| \mathbf{p}_m - \mathbf{A}_M \mathbf{H} \|^2. \tag{4} \]
Figure 1. Principle underlying the statistical weighting approach. The area $A$ is an area containing all the optical absorbers and all the possible acoustic reflectors and acoustic scatterers. The area $A_{ij}$ contains all the points $r'$ in which a reflected or scattered wave may have been generated to be detected at the transducer located in $r_i$ at instant $t_j$.

The solution of equation (4) is calculated by means of the Paige–Saunders iterative least-squares method QR decomposition (LSQR) (Paige and Saunders 1982) algorithm, in which the sparsity of the model matrix is exploited to make a fast reconstruction.

2.2. Probability of signal distortion due to acoustic reflections or scattering

The forward model in equation (3) is derived by assuming a homogeneous medium with constant speed of sound, which is equivalent to considering direct wave propagation between the excitation and measuring points. However, if strong heterogeneities are present, there is a probability that the signal measured at a given detector position and at a given instant is distorted by a reflected or scattered acoustic wave. To estimate such probability, we assume that an area $A$ (grey area in figure 1) containing all the optical absorbers (points in which $H(r') \neq 0$) and all the possible acoustic reflectors and acoustic scatterers can be determined.

The probability $P_{ir}(t_j)$ of detecting a reflected or scattered wave, having unit amplitude (in arbitrary units) at the $i$th position of the transducer $r_i$ and at time $t_j$, is given by Deán-Ben et al (2011a)

$$P_{ir}(t_j) = \int_{A_{ij}} P_{ir}(t_j|r') f_E(r') \, dr'$$

with $f_E(r')$ being the probability density function corresponding to the location at which a differential of energy is absorbed and $P_{ir}(t_j|r')$ the conditional probability that a reflected or scattered wave with unit amplitude is detected at an instant $t_j$, given that all the energy is absorbed at $r'$. The area $A_{ij}$ contains all the points $r'$ in which a reflected or scattered wave may have been generated to be detected at the transducer located in $r_i$ at instant $t_j$. $P_{ir\text{,dist}}(t_j)$ is the probability that the wave, measured with the $i$th transducer at instant $t_j$, is distorted by a reflected or scattered wave (which in practice is the case when the scattered or reflected wave is above the noise level). We consider that $P_{ir\text{,dist}}(t_j)$ is proportional to $P_{ir}(t_j|r')$. In Deán-Ben et al (2011a) it was shown that $P_{ir\text{,dist}}(t_j)$ can be approximated as

$$P_{ir\text{,dist}}(t_j) = \min \left[ 1, \omega \left( \frac{A_{ij}}{A} \right) \right],$$

where $\omega$ is a weighting parameter to be determined heuristically. Then, the probability $P_{ir}(t_j)$ that the signal detected by the $i$th transducer at instant $t_j$ corresponds to a direct propagation,
i.e., that it is not distorted by reflection or scattering events, is given by

\[ P_d(t_j) = 1 - P_{r,\text{dist}}(t_j). \]  

(7)

This statistical analysis provides the basis for the modification of the reconstruction algorithms in the case that acoustic reflections or scattering affect the quality of the reconstructed images. In this way, the reconstruction is done preferably with the optoacoustic signals that more likely correspond to direct wave propagation, so that the signals that are probably distorted by reflected or scattered waves contribute less to the reconstruction. It is important to notice that the accuracy in the estimation of \( P_d(t_j) \) depends on the available information about the sample. For example, if the approximate position of highly scattering regions is known, the quality of the reconstructed image can be further improved (Deán-Ben et al. 2011b, 2012b).

2.3. Weighted interpolated matrix model inversion

The modification of the IMMI algorithm, suggested herein, consists of weighting each equation of the linear system of equation (2) with the probability that the signal for the corresponding instant and transducer position is not distorted by reflection or scattering events, in a way that the reconstruction is made preferably with those equations which are more likely to correspond to direct propagation between the excitation and detection points. Thereby, equation (2) becomes

\[ P_d(t_j) p(r_i, t_j) = P_d(t_j) \sum_{k=1}^{N} a_{ij}^k H(r'_k). \]  

(8)

In this way, the linear system of equations is modified as

\[ W p_m = W A M H, \]  

(9)

with \( W \) being a matrix with dimensions \( PI \times PI \) and with elements \( P_d(t_j) \) in the diagonal and zero otherwise.

The reconstruction is then made by solving a mean square difference minimization problem equivalent to equation (4), given by

\[ H_{\text{sol}} = \arg \min_H \| W p_m - W A M H \|^2. \]  

(10)

3. Materials and methods

Numerical simulations and experimental measurements were done in order to test the performance of the weighted model-based inversion suggested herein.

In a first example, we assessed the effect of the statistical weighting on image quality in an ideal setting where the acoustic medium is homogeneous. The projection data was produced numerically using a two dimensional phantom including four parabolic optical absorbers, for which the optoacoustic signals can be calculated analytically (Rosenthal et al. 2010). Reconstructions were performed using statistically weighted IMMI and FBP with several values of \( \omega \). The analytical signals were computed for 180 equally-spaced angular positions of the transducer located at a distance of 40 mm from the centre and for 500 equally spaced instants covering the region of interest (ROI).

In a second step, the same numerical phantom was used to compare the performance of the IMMI and the weighted IMMI for different angles covered by the transducers locations (full-view or limited-view). In this example, the weighting was also done based on the half-time image reconstruction method, and the results were compared with the statistically-weighted
Figure 2. (a) Actual optical absorption distribution. (b)–(c) Tomographic reconstructions obtained with the weighted IMMI algorithm and with the weighted FBP algorithm for a weighting parameter $\omega = 2$. (d)–(e) Central horizontal profiles of the optical absorption distribution respectively obtained with weighted IMMI algorithm and with the weighted FBP algorithm for a weighting parameter $\omega = 0$ (blue), $\omega = 1$ (red), $\omega = 1.5$ (green), $\omega = 2$ (yellow) and $\omega = 2.5$ (magenta). The theoretical profile is shown in black. The area $A$ was taken as the circle inscribed in the field of view in all cases. For the IMMI reconstructions, significant deterioration in the reconstruction quality was obtained only for $\omega = 2.5$.

IMMI. In all cases, the signals were computed for 180 equally-spaced angular positions of the transducer and for 500 equally spaced instants covering the ROI.

The proposed algorithm was also tested experimentally with tissue-mimicking phantoms and with an adult wild-type zebrafish post mortem. The experimental setup consisted of a short-pulsed laser with tuneable wavelength, whose output beam was adapted to obtain approximately uniform illumination conditions on the surface of the sample. The laser wavelength was set to 605 nm and to 587 nm for phantom and zebrafish measurements, respectively. The generated ultrasonic waves were detected with cylindrically-focused ultrasonic immersion PZT transducers, having 3.5 MHz and 15 MHz central frequencies (approximately 100% bandwidth) for the phantom and zebrafish experiments, respectively. The respective focal lengths of the transducers were 38.1 mm and 19.05 mm. A rotation stage was used to rotate the imaged object over 360° with a rotation step of 2° (180 projections). For each projection, the signal was averaged 64 times and band-pass filtered. More details on the experimental setup can be found in Ma et al (2012).

The tissue-mimicking phantoms were made with an agar solution in which we included black India ink and intralipid to simulate the background optical absorption and scattering of biological tissues (Deán-Ben et al 2011a). Also, regions with a higher concentration of ink (OA in figure 4) were included in the phantoms. Acoustic reflections were effected by introducing straws filled with air in cylindrical cavities of the phantoms (HC in figure 4). The zebrafish was 6 months old and was imaged in a region close to the swim bladder, which contains air gaps and several mismatched tissues. It was embedded in a pure agar phantom for easy handling.
4. Results

The distribution of the optical absorption for the numerical phantom is depicted in figure 2(a). Figure 2(c) shows the tomographic reconstruction obtained with the weighted FBP algorithm considering $\omega = 2$ and an area $A$ corresponding to the circle inscribed in the ROI. It is clearly perceived that the calculated amplitude for the absorbers close to the middle of the image is lower than for those close to the boundaries. For higher values of $\omega$ these quantification inaccuracies are increased, and eventually an area with null absorption appears in the middle of the image as the weighting factor corresponding to those points is zero for all the positions of the transducer. This is shown in figure 2(e), which displays the central horizontal profile of the tomographic reconstructions obtained with the weighted FBP algorithm for different values of $\omega$. On the other hand, figure 2(b) shows the tomographic reconstruction obtained with the weighted IMMI algorithm for $\omega = 2$ and for an area $A$ corresponding to the circle inscribed in the ROI. In this case, the calculated amplitude for the four absorbers is the same. The central horizontal profiles of the tomographic reconstructions obtained with the weighted IMMI algorithm are shown in figure 2(d). It is shown that the reconstructed profiles are not distorted when increasing $\omega$, except when $\omega$ becomes high enough so that a region with
null absorption appears in the middle of the image. Then, the method presented in this work can be used to perform optoacoustic reconstructions in homogeneous acoustic media without introducing further errors in the images.

Figure 3 displays the comparison of the IMMI and the weighted IMMI for different angles covered by the transducer locations. The first column represents the full-view case ($360^\circ$) and the second and third columns correspond, respectively, to view angles of $270^\circ$ (135 transducer locations) and $180^\circ$ (90 transducer locations). The centre of the arc covered by the transducer locations is at the left from the image, i.e., the angular positions range from $-135^\circ$ to $135^\circ$ and from $-90^\circ$ to $90^\circ$ respectively. The first and second rows show, respectively, the tomographic reconstructions obtained with the IMMI and with the statistically-weighted IMMI. It is shown that the quality of the images is reduced due to the weighting, specifically for those positions located farther from the view arc. This is most certainly due to the fact that the available information is reduced with the weighting. Thus, a higher distortion is produced if the weighting is done with the half-time methodology, as shown in the third column of figure 3. In this case, the matrix $W$ in equation (9) is a diagonal matrix with values 1 for the instants corresponding to the leading half of the optoacoustic signals and 0 otherwise. In this case, only a limited number of transducer locations contribute to the reconstruction.
Tomographic reconstructions of the zebrafish obtained with the IMMI algorithm (a)–(c), with the statistically-based weighted IMMI algorithm (d)–(f) and with the half-time weighted IMMI algorithm (g)–(i). The reconstructions are done by considering all the measuring locations in a full-view scenario (a), (d), (g), or for a limited-view case by taking measuring locations along an arc covering an angle of 270° (b), (e), (h) or 180° (c), (f), (i). For the limited-view case, the centre of the detection arc is located above the images. (j) and (k) show a comparison of the reconstructions obtained with the IMMI algorithm and the statistically-based IMMI algorithm for several slices. The area $A$ is taken as the as the area inside the dashed circumferences and the weighting parameter $\omega = 1$ for all cases.

at each point, so that more distortion is produced, especially when the transducer locations cover an angle lower than 360°. It is shown in figure 3 that the reconstructed image is strongly distorted for 270° and even an area with null absorption is retrieved for the 180° case due to the absolute lack of information corresponding to such region. For example, the points located in the vertical centre of the right side of the image are not covered after the trailing part of the signals is removed. It is important to take into account that in general the inversion must be regularized in the limited-view case (Deán-Ben et al. 2012c, Buehler et al. 2011), which may further condition the images retrieved, but in any case the weighted IMMI based on statistical principles behaves better than the weighted IMMI based on the half-time image reconstruction method. Even in the full-view case, the noise in the images (calculated as the standard deviation within the white squares in figure 3) is higher for the half-time methodology than for the statistically-weighted IMMI as indicated in the caption of figure 3.

The tomographic reconstructions corresponding to the tissue-mimicking phantoms obtained with the IMMI algorithm and with the statistically-weighted IMMI algorithm for $\omega = 1$ are shown in the second and third columns of figure 4. A clear reduction of the artefacts is achieved in all cases. The corresponding reconstructions obtained with the weighted IMMI based on the half-time methodology are shown in the fourth column of figure 4. Although the artefacts due to acoustic reflections are also reduced in this case, in general the images produced with half-time weighted IMMI are more noisy and more distortion appears in the central region of the images. It is important to take into account that all the images displayed were obtained with no regularization. Regularization in general may help to reduce the noise but it comes at the expense of some reduction of information in the images, which is not desirable for quantification purposes.

On the other hand, the reconstructed images corresponding to the fish are displayed in figure 5. Specifically, figures 5(a)–(c) show the reconstructions rendered with the IMMI
algorithm, figures 5(d)–(f) show the images retrieved with the statistically-weighted IMMI algorithm for \( \omega = 1 \) (the area covering the sample is limited by the dashed white circumferences) and figures 5(g)–(i) show the reconstructions obtained with the weighted IMMI based on the half-time methodology. The tomographic reconstructions yielded by taking all the measuring locations (full-view case) are showcased in figures 5(a), (d) and (g), whereas the equivalent images obtained by considering only an detection arc covering an angle of 270° and 180° are displayed in figures 5(b), (e), (h) and figures 5(c), (f), (i) respectively. The centre of the arc covered by the transducer locations is above the image. It is shown that whereas both weighted approaches help improving the images for the full view case, the statistically-based weighting generally performs better for limited view scenarios. The full-view reconstructions for several slides obtained with the IMMI algorithm and with the statistically-weighted IMMI algorithm for \( \omega = 1 \) are shown in figures 5(j) and (k) respectively, where a clear reduction of the artefacts is demonstrated.

5. Discussion and conclusions

In this work we have suggested and analysed improvements of optoacoustic reconstructions by using a modified model-based interpolated-matrix-model inversion (IMMI) optoacoustic inversion algorithm for objects with strong acoustic heterogeneities causing reflections and scattering of ultrasonic waves. The application of this algorithm in tissue-mimicking phantoms and a zebrafish post mortem showcases an improvement in the resulting tomographic reconstructions with respect to the case in which a uniform acoustic medium is assumed.

The methodology to reduce the artefacts associated to acoustic reflections or scattering is based on weighting the contribution of the signals to the reconstruction with the probability that they are not affected by such acoustic phenomena. It was introduced in a previous work, where the filtered back-projection algorithm was used. The application of the same methodology to the model-based reconstruction presents important advantages. We have shown in this work that the reconstructions for acoustic homogeneous media obtained with the weighted algorithm are equivalent to those obtained with the standard one, so that quantification errors are not introduced due to the weighting as it is the case for the back-projection algorithm. We have also shown that the statistically-weighted IMMI usually behaves better than another commonly employed weighting-based procedure termed half-time image reconstruction. Although half-time weighting generally reduces the artefacts associated to acoustic wave propagation distortion, artefacts are produced in the central region of the images. Also, in limited-view cases there are regions of the image not covered by any signal when the trailing edge is removed, which limits the applicability of the half-time methodology in these cases. The IMMI algorithm has proven to behave better than the back-projection for a two dimensional geometry in terms of not being affected by sharp or smooth variations in the optical absorption, so overall the images obtained with the weighted IMMI algorithm are expected to be more quantitative than those obtained with weighted back-projection. Recently, we have developed a three-dimensional model-based algorithm applicable to arbitrary detection geometries and arbitrary transducer shapes (Deán-Ben et al 2012a), so that the applicability of the statistically-based weighting methodology to model-based algorithms anticipates its convenience for a quantitative estimation of the optical absorption. This is important as the accuracy in the estimation of the probability of distortion of the signals depends on the available information of the sample; so that an accurate estimation of the optical absorption may help to more accurately estimate at which instants the strong reflections are measured and therefore further improve the reconstructions. These issues will be addressed in future work. Finally, it is also important to notice that the model-based algorithm used in this work can be adapted to samples
Weighted model-based optoacoustic reconstruction in acoustic scattering media with small speed of sound variations (Deán-Ben et al. 2012c), which also helps improving the images in case the acoustic waves propagate through large areas with a speed of sound different than the background.

In conclusion, the statistical weighting of our model-based inversion algorithm has been proven to reduce the artefacts associated to acoustic scattering and reflections, which anticipates its general applicability due to the overall better performance of model-based reconstruction procedures as compared with back-projection formulae.

Acknowledgments

DR acknowledges support from the German Research Foundation (DFG) Research Grant (RA 1848/1) and the ERC Starting Independent Researcher Grant. VN acknowledges support from the ERC Senior Investigator Award and the Medizin Technik BMBF award for excellence in medical innovation.

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