Deep Learning Solution for Frequency Domain Diffuse Optic Tomography (FDDOT)

Huseyin Ozgur Kazanci (ozgurkazanci@gmail.com)
Akdeniz University Faculty of Engineering https://orcid.org/0000-0003-0036-7657

Okan ORAL
Akdeniz Üniversitesi: Akdeniz Universitesi

Research Article

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Abstract

In this work, deep learning neural network architecture was applied to the well-known diffuse optic tomography problem. Frequency Domain Diffuse Optic Tomography (FDDOT) modality was selected as reference simulation system. Sources and detectors were placed on tissue imaging geometry. Back-reflection geometry has 8 sources and 8 detectors on tissue imaging geometry. Background phantom tissue absorption coefficient m_a=0.3 cm^{-1}, scattering coefficient m_s=100 cm^{-1}. One inclusion which its absorption coefficient m_a=0.7 cm^{-1} was embedded in two different location in 20×20×20 grid sized tomographic cube. These two different scenarios were tested to reconstruct the inclusion image by using Matlab™ deep learning functions. Two different inclusion images were successfully reconstructed with the similar shape of original inclusion in the same 3d location. In deep learning structure, Matlab's convolution layer, cross channel normalization layer, fully connected layer, regression layer was used. In training network options, stochastic gradient descent with momentum method with validation data was selected. In this work, instead of using classical inverse problem solution algorithms deep learning method was used.

I. Introduction

Diffuse optical tomography is biomedical optic imaging modality. It uses hemoglobin sensitive laser source and photodetector units. Main purpose of DOT modality is to investigate the hemoglobin concentration differences over background tissue especially for breast tumor detection. Photon transport is modeled by using diffusion equation inside the imaging tissue. Between each source and detector positions weight functions are calculated in forward problem diffusion equation model. Scattering nature of low energy photons create photon migration paths between source and detector positions depend on the back-reflected or transmission through geometry. Major DOT problem concerns to calculate the absorption coefficient differences over background tissue. Especially for breast tumor imaging these optic absorption coefficient differences constitute hemoglobin inclusion concentrations. In classical manner, inverse problem solution methods investigate these unknown absorption coefficients. Simplest mathematical method is using pseudoinverse solution. Since DOT problem is ill-posed matrix problem, some regularization and iterative methods can also be applied such as Tikhonov-Morozov, Conjugated-Gradient, algebraic reconstruction technique. All these inverse problem solution methods cover classical manner. Nowadays deep learning or machine learning techniques are popular. Scientists started to apply deep learning method to DOT problem. Recently photon scattering inside the heterogenous tissue was modeled by using deep learning technique. Optic differences or abnormalities were learned by using deep learning technique [1]. They used novel deep learning deep convolutional frame layers [1]. In another work, deep learning tutorial was given for DOT problem. Deep learning algorithms and inverse problem solution techniques were given in that work [2]. According to the authors, deep learning techniques might be the best alternative to the ill-posed iterative or regularization problem solution methods [2]. According to the authors, deep learning techniques can give increased efficiency, higher accuracy, and high speed. One of the deep learning methods which is convolutional neural network (CNN) was applied to

investigate the optical properties of heterogenous tissue medium [3]. They compared the traditional classic inverse problem solution methods with CNN method, and they observed superior differences over classical problem solution methods. In similar works, simulation data was prepared, and inverse problem was solved by using deep learning neural network [4–7].

I I. Methods

In this work, simulation data was prepared in the back-reflected diffuse optical tomography (DOT) modality. Source and detector optodes were placed based on the back-reflected imaging geometry. In Fig. 1, 8 sources (red circles) and 8 detectors (blue squares) were demonstrated on the back-reflected imaging geometry. 5 mm × 5 mm xy grid size and 20 × 20 × 20 xyz volume elements were selected for tissue model.

Between each source and detector positions forward model weight functions were calculated. Frequency domain radiative transport diffusion equation was used. Top view of the 8th source-detector coupling photon fluencies at 100 MHz modulation frequency was demonstrated at the Fig. 2. Forward model problem is important step to distribute the photon fluencies inside the imaging tissue phantom background. Each source-detector match perturbation data was calculated by simply matrix multiplication of forward model weight functions and bulk optic absorption coefficient differences over tissue background. In classical manner, these perturbations were given to iterative or regularization inverse problem solution algorithms. Since the increasing popularity of deep learning neural networks, perturbation data was given to the deep learning neural network structure in this work.

I I I. Results

In Matlab program environment deep learning neural network layers were embedded inside the neural network structure. Since there were 8 source and 8 detector couplings which has 64 matches, input layer has 64 elements. Next layer is convolution 2d layer which has 8000 filters. Next layer is cross channel normalization layer which has 16 window channel sizes. Next layer is fully connected layer with 8000 outputs. Since our unknowns are bulk optic absorption coefficients inside the tissue imaging geometry, it has 20 × 20 × 20 = 8000 voxel dimension. These 8000 outputs have linked to the regression layer, finally. Below, layers and training options were given.

```
layers = [ ...
imageInputLayer([1 1 64]);
    convolution2dLayer(1,8000,'Padding','same','Stride',2)
    crossChannelNormalizationLayer(16)
fullyConnectedLayer(8000);
regressionLayer];

maxEpochs = 6;
miniBatchSize = 27;

options = trainingOptions('sgdm', ...
    'ExecutionEnvironment','gpu', ...
    'GradientThreshold',1, ...
    'LearnRateDropFactor',0.2,...
    'LearnRateDropPeriod',5,...
    'MaxEpochs',maxEpochs, ...
    'SequenceLength','longest', ...
    'MiniBatchSize',miniBatchSize, ...
    'Shuffle','never', ...
    'ValidationData',{XValidation,YValidation}, ...
    'ValidationFrequency',30, ...
    'Verbose',0, ...
    'Plots','training-progress');
```

Deep learning training progress plot was shown in Figure 3. 6 epochs with 1776 iterations were done in deep learning training.

Two different scenarios were tested and shown in Figure 4 and Figure 5. In the first scenario, original inclusion was embedded inside the imaging tissue media shown in Figure 4A., Figure 4B. Deep learning network solved the inverse problem and reconstructed the inclusion image which was shown in Figure 4C., Figure 4D. In this scenario inclusion image is at (1.2, 2.2, 2.2) (z, x, y) mm coordinates. In the second scenario, original inclusion was embedded inside the imaging tissue media shown in Figure 5A., Figure 5B. Deep learning network solved the inverse problem and reconstructed the inclusion image which was shown in Figure 5C., Figure 5D. In this scenario inclusion image is at (1.2, 4.5, 4.5) (z, x, y) mm coordinates.

I V. Discussion

In this work, deep learning neural network structure was constructed to solve the inverse problem for DOT modality. Bulk optical absorption coefficient parameters were calculated by using deep learning neural network structure successfully. In Fig. 4, and Fig. 5 original and reconstructed inclusion images can be seen for different inclusion coordinate locations. It can be easily seen that inclusion images were successfully reconstructed. Reconstructed inclusion images are close to the original locations and their

shapes are like the original inclusions. Fast and high accuracy inverse problem solution algorithm by using deep learning neural network structure was demonstrated. In the future, constructing the deep learning neural network structures will be high demanding solution method for DOT modality. Since the DOT modality is ill-posed mathematical problem, novel deep learning neural network approaches can predict the unknown space with the minimum effort and high solution speed. Classical iterative and regularization inverse problem solution methods are cumbersome and slow methods against deep learning neural network method. In this work, one simple deep learning neural network topology was constructed in Matlab programming environment and two different scenarios were tested in network algorithm successfully.

V. Conclusion

In this work, we applied deep learning neural network structure to the well-known diffuse optical tomography problem. We used Matlab's deep learning neural network layers. Classical and traditional inverse problem solution algorithms of the diffuse optical tomography are mathematically ill-posed. Inverse problem solution of the ill-posed problems is usually using iterative and regularization methods. Hence, it is restricting the necessary solution space in 3d volumetric tissue background. Consequently, classical methods suffer for low-resolution. It has also high level of noise since scattering nature of photons in heterogenous tissue medium. Another factor is photon hot spots are superficial, thus unknown solution space is also superficial. For these reasons, another fast and high accuracy diagnostic method is necessary for diffuse optical tomography systems. In this work, deep learning method was applied to the diffuse optical tomography. 8000 different training scenario was given for different inclusion locations. Each scenario has 64 inputs (source-detector matches) and 8000 (voxels) outputs. Finally, 2 different scenarios were tested to predict the solution space. The deep learning neural network structure successfully solved the problem and reconstructed the inclusion images at the correct location. This work gave us courage for future deep learning applications in diffuse optical tomography method.

References

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Figures

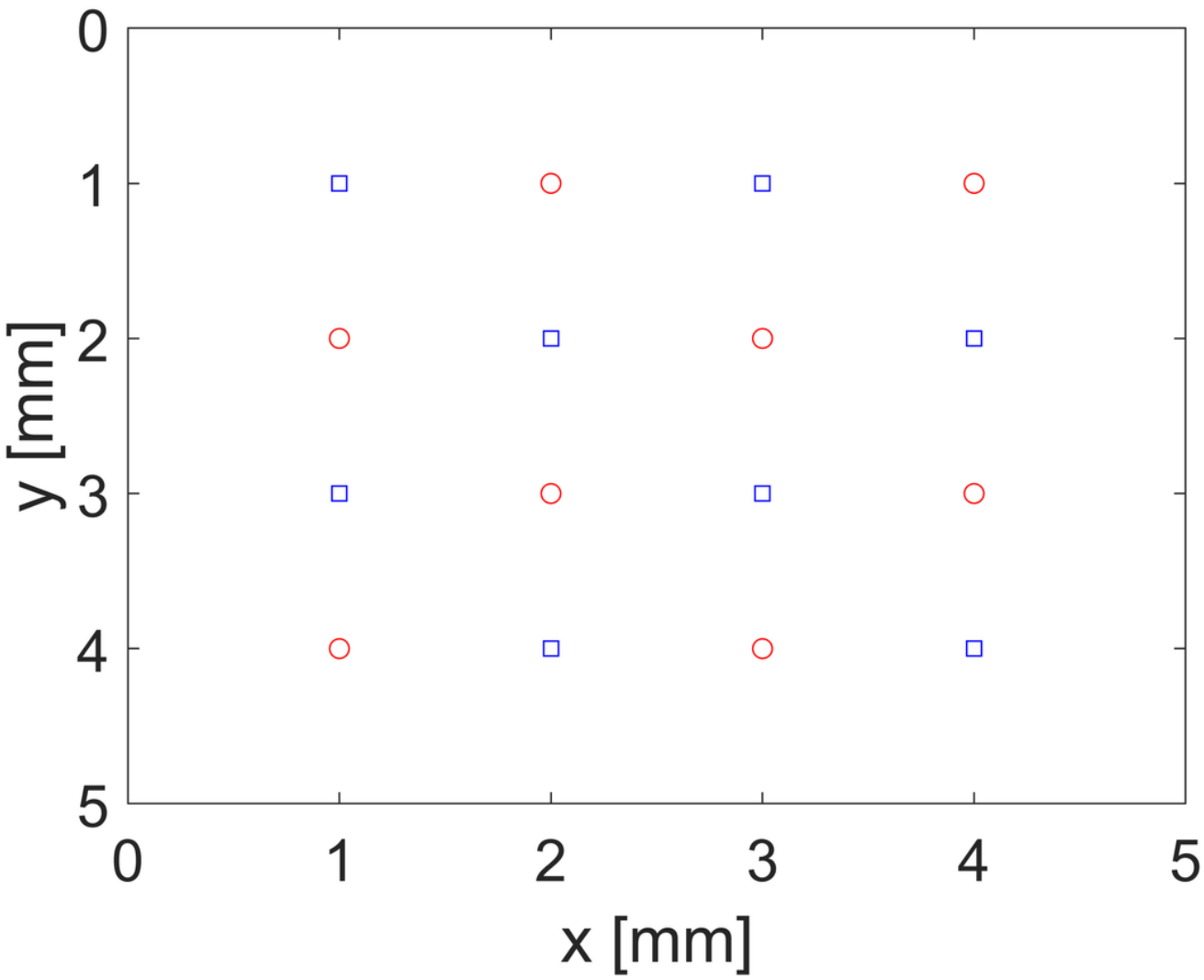

Figure 1

Eight laser sources (red circles) and eight detectors (blue squares) top view.

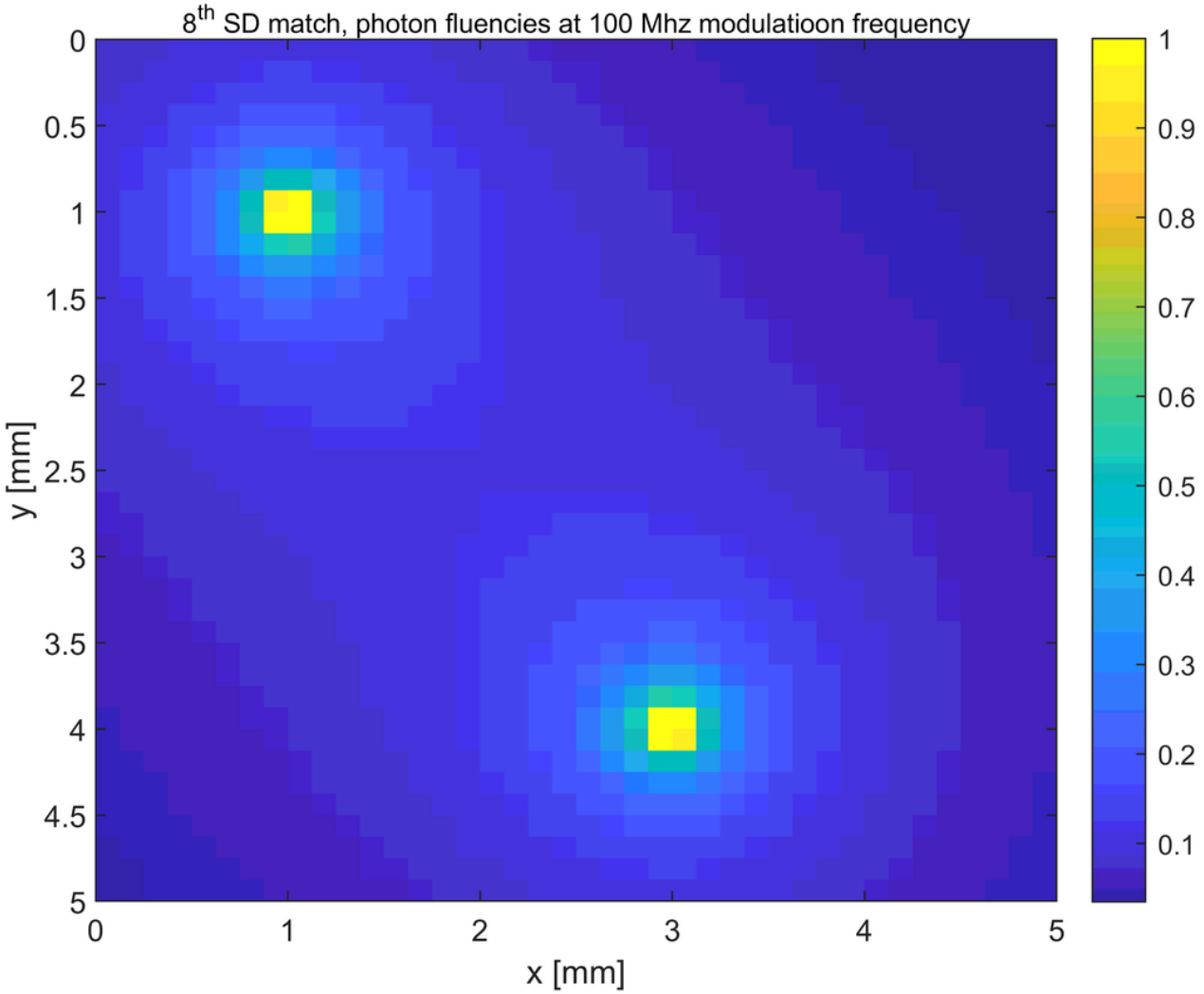

Figure 2

8th source-detector (SD) match photon fluencies at 100 MHz modulation frequency.

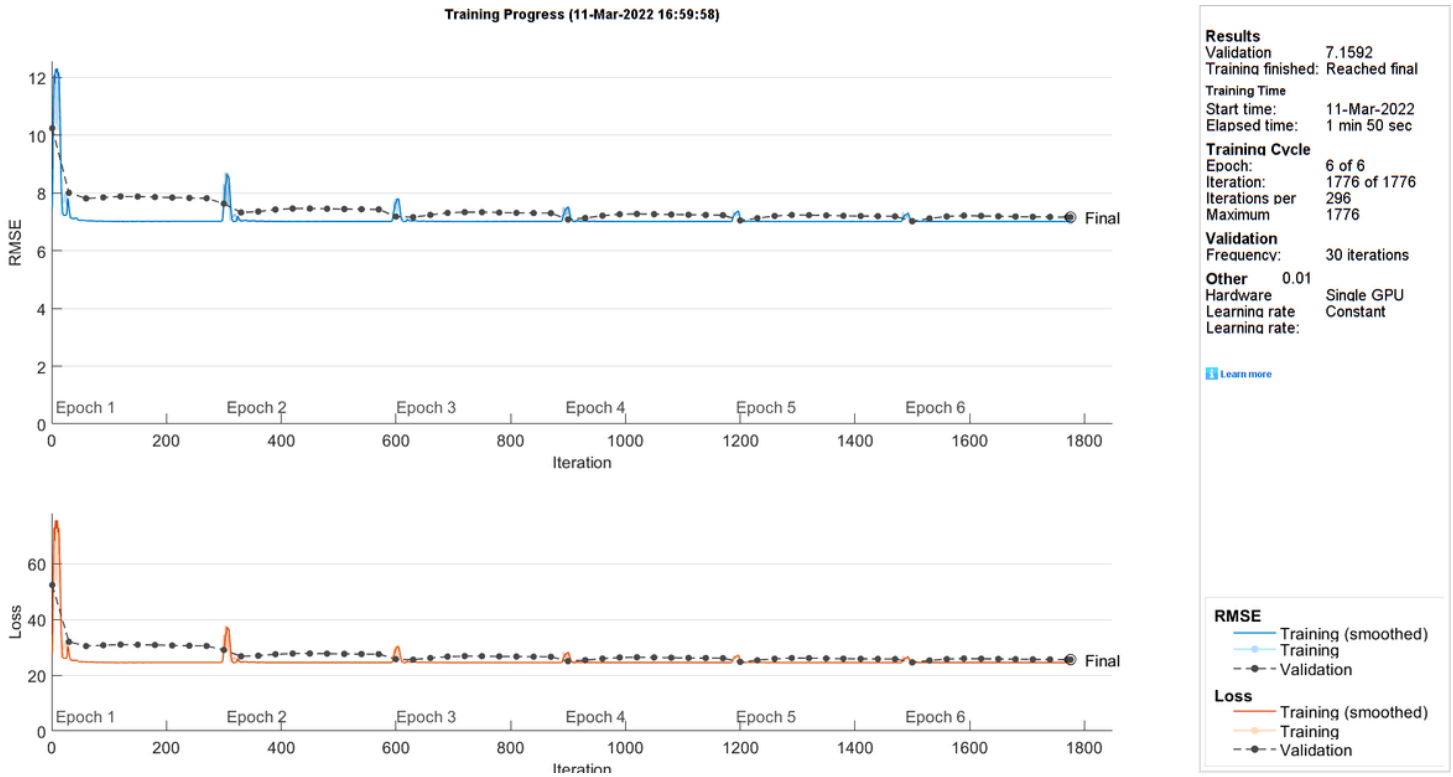

Figure 3

Deep learning training progress plot.

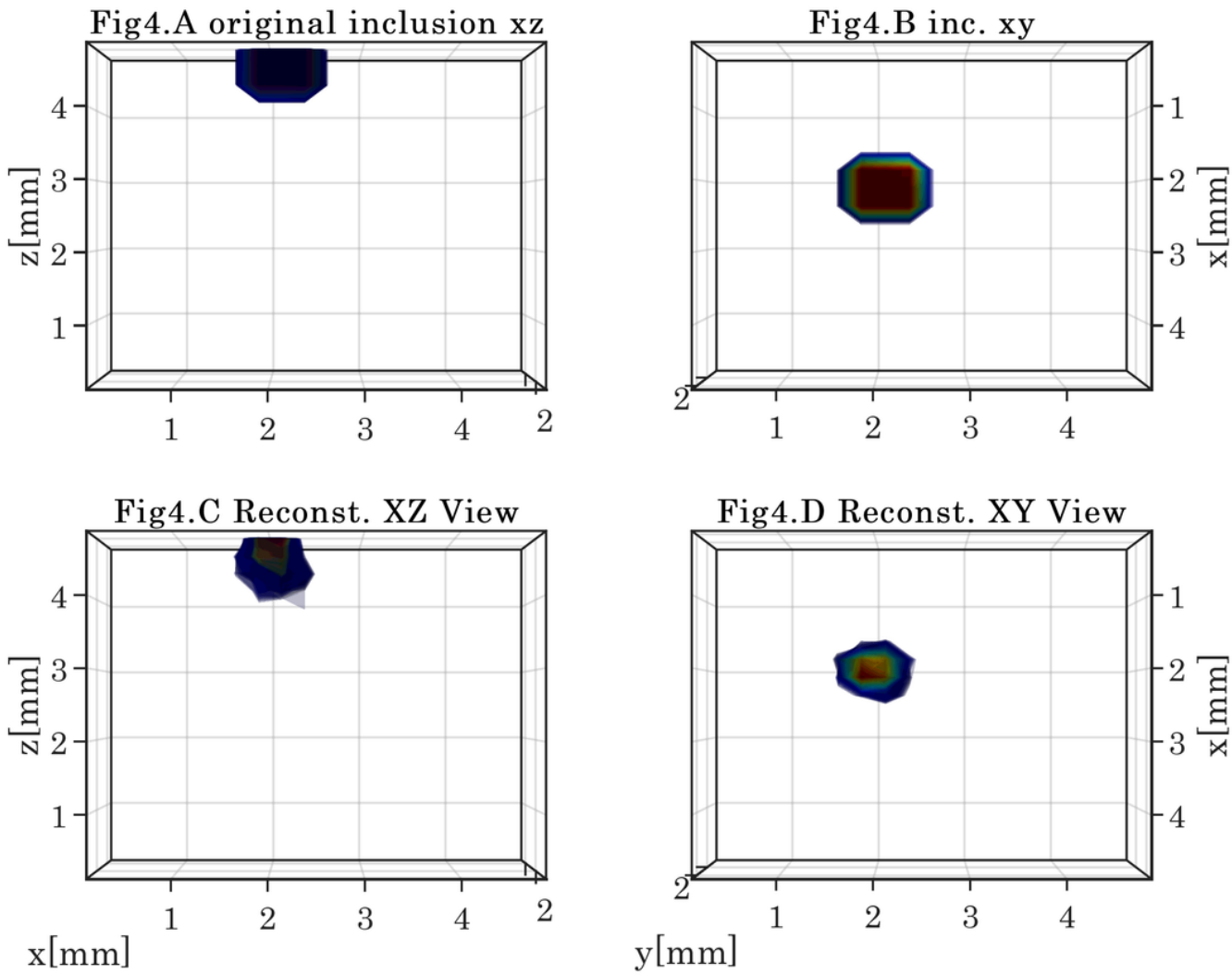

Figure 4

Original Fig.4A., Fig.4B. and reconstructed Fig. 4C., Fig. 4D. inclusion image at (1.2, 2.2, 2.2) (z, x, y) mm coordinates.

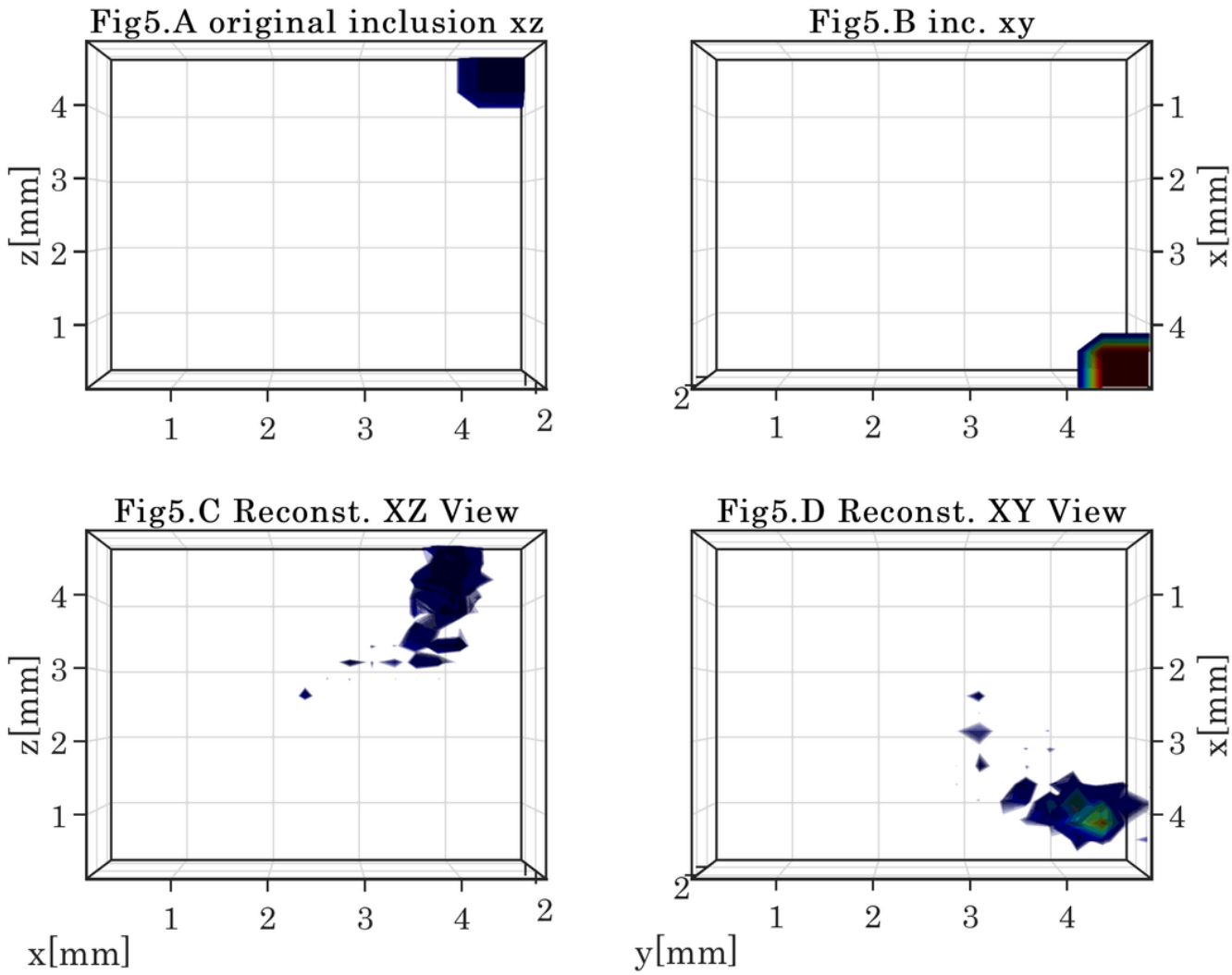

Figure 5

Original Fig.5A., Fig.5B. and reconstructed Fig. 5C., Fig. 5D. inclusion image at (1.2, 4.5, 4.5) (z, x, y) mm coordinates.