

# Influence of hyperparameters on the redistribution index in an electrical impedance tomography algorithm using discrete cosine transformation

R. Chen<sup>1,2\*</sup>, E. Stein<sup>1</sup>, A. Battistel<sup>1</sup>, S. Krueger-Ziolek<sup>1</sup>, S.J. Rupitsch<sup>2</sup>, and K. Moeller<sup>1</sup>

<sup>1</sup> Institute for Technical Medicine (ITeM), Hochschule Furtwangen, Villingen-Schwenningen, Germany

<sup>2</sup> Faculty of Engineering, University of Freiburg, Freiburg, Germany

\* Corresponding author, email: [rongqing.chen@hs-furtwangen.de](mailto:rongqing.chen@hs-furtwangen.de)

*Abstract:* With the introduction of a structural prior, the images of electrical impedance tomography (EIT) benefit from the improvement of interpretability in clinical settings. However, the improvement comes with the risk of the outdated structural prior, which does not comply with the current patient status, therefore resulting in a misleading reconstruction then compromising the clinical decision. The redistribution index can detect an outdated structural prior by quantitatively analyzing EIT reconstructions. The choice of hyperparameter  $\lambda$  in the DCT-based EIT algorithm influences the EIT reconstructions in addition to the structural priors. In this contribution, the influence of the hyperparameters on the redistribution index was investigated by means of numerical simulations. We conducted a series of numerical simulations in terms of 26 different scales of dorsal lung atelectasis, then the simulation data were reconstructed with 20 different hyperparameters, at last the EIT reconstructions were used to investigate the behavior of the redistribution index. The result reveals that the function of the redistribution index to detect an outdated structural prior is relatively robust regardless of the optimal hyperparameter.

© Copyright 2023

This is an Open Access article distributed under the terms of the Creative Commons Attribution License CC-BY 4.0., which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

## I. Introduction

Electrical impedance tomography (EIT) is an imaging technique that can show the regional lung ventilation and aeration at the bedside. The raw EIT data are the voltage changes induced by the small current on electrodes attached around the chest. With the reconstruction algorithms, an EIT image is reconstructed using the raw data. Clinical research showed that EIT is helpful to adjust the optimal positive end-expiratory pressure (PEEP) setting for the acute respiratory distress syndrome (ARDS) patients, therefore reduces the ventilator related lung injury (VILI) in mechanical ventilation [1]. However, the EIT images are characterized by the low spatial resolution, the blurred anatomical alignment, and the reconstruction induced artefacts. These hinder the interpretation of the patient status in clinical settings.

With the introduction of the structural priors into EIT reconstruction process, the EIT images showed the improvement of the interpretability. Schullecke et al. and Chen et al. proposed an EIT algorithm with the structural prior derived from the CT images [2,3]. This structural prior is introduced by the basic function subset of discrete cosine transformation (DCT). The results showed the improvement of interpretability. However, the priors from morphological image have a possibility to lose validity if the patient status changes, such as the developing disease course. The outdated prior might induce a risk of the misleading results then compromising the diagnosis. Chen

et al. introduced the redistribution index (RI) to detect the outdated priors in the DCT approach [3]. It was clearly shown that the RI is a straightforward way to detect an outdated prior in the DCT approach. However, the calculation of the RI is based on the EIT images, which is not only influenced by the structural prior, but by the hyperparameter  $\lambda$  as well. In addition, the optimal  $\lambda$  should be determined for each data measurement. This can be challenging in clinical settings. It is crucial to study the influence of the  $\lambda$  in addition to the structural priors on the calculation of RI, so the behavior of the RI can be better understood, and outdated prior can be detected even when the optimal  $\lambda$  cannot be guaranteed.

## II. Material and methods

The reconstruction of conductivity variation  $\hat{\mathbf{x}}$  in EIT is an ill-posed inverse problem. Conductivity distribution changes  $\mathbf{x} = \sigma_2 - \sigma_1$  are not linearly related to the induced changes of the boundary voltages  $\mathbf{y} = \mathbf{v}_2 - \mathbf{v}_1$ . Under the assumption that the conductivity change  $\mathbf{x}$  is smooth and small in EIT, the reconstruction problem is described as:

$$\hat{\mathbf{x}} = (\mathbf{J}^T \mathbf{J} + \lambda^2 \mathbf{R}^T \mathbf{R})^{-1} \mathbf{J}^T \mathbf{y} = \mathbf{B} \mathbf{y} \quad (1)$$

where  $\mathbf{J}$  is the Jacobian matrix which maps the conductivity changes to the voltage variations.  $\mathbf{R}$  is a regularization, and  $\lambda$  is a hyperparameter to control the regularization. A DCT subset of cosine coefficients  $\mathbf{D}(p, q)$  can be used to modify the Jacobian matrix  $\mathbf{J}$ . The parameters  $p$  and  $q$  are the frequencies of the cosine function at the  $x$ -axis and  $y$ -axis.

The multiplication of  $\mathbf{D}(p, q)$  and a binary structural prior  $\mathbf{P}$  from morphological image yields a matrix  $\mathbf{C}(p, q) = \mathbf{P} \cdot \mathbf{D}(p, q)$ . The columns of the basic function subset  $\mathbf{S}$  are determined as  $\mathbf{S}_j = T(\mathbf{C}(p, q))$ , where  $T$  is a mapping function assigning each pixel of  $\mathbf{C}(p, q)$  to the FEM elements, which covers the corresponding pixel. The subset matrix  $\mathbf{S}$  is used to modify the Jacobian matrix as  $\mathbf{J}_{DCT} = \mathbf{J} \cdot \mathbf{S}$ , thus  $\mathbf{J}_{DCT}$  includes the information from the structural prior. Using (1) by substituting the modified  $\mathbf{J}_{DCT}$ , we can calculate the change of the DCT coefficients  $\tilde{\mathbf{X}}_{DCT}$ . The final EIT image  $\mathbf{H}$  is reconstructed using inverse DCT.

The simulations were carried out on MATLAB R2019a (Mathworks, Natick, MA, USA) with the EIDORS toolbox [4]. 26 different atelectasis scales ( $ATi$ ) from 0% ( $AT0$ ) to 50% ( $AT50$ ) of dorsal lung atelectasis were simulated. Redistribution index (RI) is introduced to detect the outdated structural prior  $\mathbf{P}$  embedded in the DCT approach [3]. RI indicates the error induced by the structural prior in the EIT images quantitatively. In this contribution, we introduced two types of structural priors into the EIT reconstruction:  $ATi$  prior which derives directly from each simulation setting  $ATi$ ; and  $AT50$  prior which represents 50% of the dorsal lung atelectasis. For each simulation setting  $ATi$ , the reconstruction was performed with  $AT50$  prior and the  $ATi$  prior. As the atelectasis scale is decreasing in the simulation settings, the  $AT50$  prior is expected to induce more errors into the EIT images, which is indicated by a larger value of RI. To investigate the influence of the  $\lambda$ , 20 different  $\lambda$ , i.e.,  $\lambda_1 = 1e-3, \lambda_2 = 2e-3, \dots, \lambda_{20} = 2e-1$ , were implemented into reconstruction.

### III. Results and discussion

The comparison of the mean square error between the simulation ground truth and reconstruction using each hyperparameter  $\lambda$  is depicted in Fig. 1. It shows that the mean square error stays rather stable when  $\lambda$  is no less than  $6e-2$ . When  $\lambda$  decreases below  $6e-2$ , the mean square error increases. When  $\lambda$  decreases to  $9e-3$ , the mean square error becomes rather stable again, but with a much larger error.

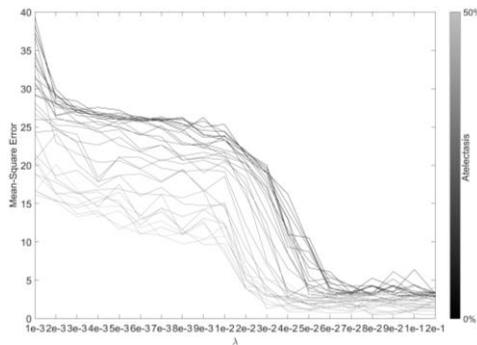


Figure 1: Mean square error between the ground truth and reconstruction from DCT approach using  $ATi$  prior. Different gray scale colors represent different simulation settings.

EIT reconstructions using the  $ATi$  prior and the  $AT50$  prior from two different simulation settings, i.e., 0% ( $AT0$ ) and 24% ( $AT24$ ) of the atelectasis, are shown as examples in Fig. 2. The  $AT50$  prior only reconstructs within the non-atelectasis area. When the atelectasis scales reduced, such as  $AT24$  and  $AT0$  shown in Fig. 2, the  $AT50$  prior will lose

validity and produce misleading results. Three  $\lambda$ , i.e.,  $\lambda_{15} = 6e-2, \lambda_{10} = 1e-3$ , and  $\lambda_3 = 3e-3$  are shown as examples in Fig. 2.  $\lambda_{10}$  and  $\lambda_3$  did not produce satisfying results as  $\lambda_{15}$ . The redistribution indices of the EIT images in Fig. 2 were calculated and depicted in Fig. 3. It is shown when the difference between the current patient status and the structural prior becomes larger, an increase will be expected in RI. This trend is observed in all the results with different  $\lambda$ . It is worth noting that the behavior of the RI is not very sensitive to the choice of  $\lambda$ . The robustness of the RI might make it possible to detect an outdated prior even when an optimal  $\lambda$  is not guaranteed.

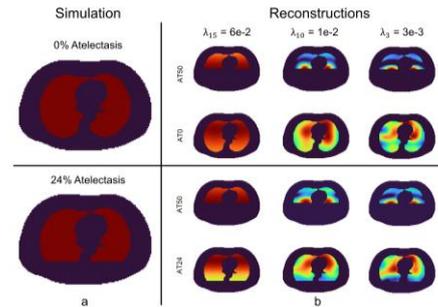


Figure 2: Simulation ground truth and reconstructions from DCT approach using  $AT50$  prior and  $ATi$  prior with three different  $\lambda$ .

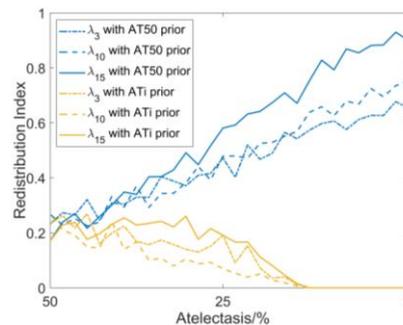


Figure 3: RI of EIT reconstructions using structural  $AT50$  prior and  $ATi$  prior with different  $\lambda$ .

### IV. Conclusions

The evaluation reveals the robustness of the RI to detect the outdated structural prior in the DCT approach. It is possible to extend its use to other EIT algorithms using priors.

#### AUTHOR'S STATEMENT

This research was partially supported by the German Federal Ministry of Education and Research (MOVE, Grant 13FH628IX6) and H2020 MSCA Rise (#872488 DCPM). Authors state no conflict of interest.

#### REFERENCES

- [1] I. Frerichs *et al.*, *Chest electrical impedance tomography examination, data analysis, terminology, clinical use and recommendations: consensus statement of the Translational EIT developmeNt stuDy group*, Thorax, vol. 72, no. 1, Jan. 2017.
- [2] B. Schullcke, B. Gong, S. Krueger-Ziolek, M. Soleimani, U. Mueller-Lisse, and K. Moeller, *Structural-functional lung imaging using a combined CT-EIT and a Discrete Cosine Transformation reconstruction method*, Sci. Rep., vol. 6, no. 1, p. 25951, May 2016.
- [3] R. Chen and K. Moeller, *Redistribution Index – Detection of an Outdated Prior Information in the Discrete Cosine Transformation-based EIT Algorithm*, in 2021 43rd Annual International Conference of the IEEE Engineering in Medicine Biology Society, pp. 3693–3696, Nov. 2021.
- [4] A. Adler and W. R. Lionheart, *Uses and abuses of EIDORS: An extensible software base for EIT*, Physiol. Meas., vol. 27, no. 5, p. S25, 2006.