

Redistribution Index – Detection of an Outdated Prior Information in the Discrete Cosine Transformation-based EIT Algorithm

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Abstract—The morphological prior information incorporated with the discrete cosine transformation (DCT) based electrical impedance tomography (EIT) algorithm can improve the interpretability of the EIT results in clinical settings. However, an outdated prior information can yield a misleading result compromising the accuracy of the clinical decisions. Detection of the outdated prior information is critical in the DCT-based EIT algorithm. In this contribution, a redistribution index calculated from the DCT approach result was proposed to quantify the possible error induced by the morphological prior information. Two simulations in terms of different atelectasis and collapse scales were conducted to evaluate the plausibility of the redistribution index. Thus, an experiential threshold for redistribution index was adopted as an indicator to the outdated prior in DCT-based EIT approach. A retrospective research was conducted with the seven-day patient monitor data as a proof-of-concept to verify plausibility and comparability of the redistribution index. From the evaluation, the redistribution index qualifies the function as an indicator for the outdated prior in the DCT-based EIT approach.

Clinical relevance— This establishes an indicator to advice an update to the morphological prior information embedded in EIT approach, which lower the risk misleading interpretation of EIT results in mechanical ventilation monitoring.

I. INTRODUCTION

Electrical Impedance Tomography (EIT) is used to visualize the regional lung ventilation and aeration distribution from current induced voltage changes through the electrodes attached on the surface of the chest[1]. This technology has been shown practical in reducing ventilator induced lung injury (VILI) and instructing clinicians to set appropriate positive end-expiratory pressure (PEEP) levels for mechanically ventilated patients in the intensive care unit (ICU)[2], [3]. However, low spatial resolution, blurred anatomical alignment, and reconstruction induced artefacts hinder the interpretation of the status of patients in clinical settings. Introducing structural information into EIT images will eventually be helpful for clinicians in forming a more direct comprehensive insight[4].

Prior information can vary, but is usually based on previous empirical studies of the tissue conductivities or the anatomical constraints or both. Assigning certain properties, e.g. conductivities, to a predefined area might be the most common approach to embed prior information in the EIT reconstruction process. e.g., Glidewell et al. use the shape of the lungs to group FEM elements and to assign different

values[5]. Another principle to include the prior information is introduced as a subset of basic functions constraint method. The subset of the basic functions is of abundant selections. Vauhkonen et al. chose a series of representative ensemble of expectable conductivity distributions based on the physiological information within the body[6].

Generally, these existed researches yield a universal prior template for all the possible examined subjects. As for a more personalized and more patient-specific prior, Schullcke et al. proposed a novel EIT algorithm with the prior as a subset of basic functions using the patient related morphological images, e.g., CT images taken when the patients are admitted to the hospital[7]. The generation of the constraining subsets uses the discrete cosine transformation (DCT) of the related morphological images.

Even though this algorithm has shown an attractive personalized result, it comes with the same problem as all prior information always induces: results are just as good as the validity of the prior assumptions. The DCT-based methodology might not be always valid considering the fact that the status of the patient is changing over time. The outdated prior information might induce a risk in terms of misleading interpretation of the results.

The objective of this contribution is to introduce an effective approach to detect the outdated prior information applied to the DCT-based EIT algorithm. A redistribution index was proposed to quantify the difference between the constrained and the unconstrained DCT results. Simulations in terms of different scales of atelectasis and collapse were conducted for evaluation purpose. Redistribution indexes were calculated using the constrained and the unconstrained DCT results of every simulated scales. Thus, a threshold value of the redistribution index was initially yield to determine the outdated prior information. At last, this criterion was tested with a retrospective long-term patient monitoring dataset.

II. METHODS

A. DCT-based EIT reconstruction

The classical approach for reconstruction of conductivity distribution $\hat{\mathbf{x}}$ in difference EIT is presented in 1 where vector $\mathbf{x} = \sigma - \sigma^{baseline}$ is the change in internal conductivity distribution σ and $\mathbf{y} = \mathbf{v} - \mathbf{v}^{baseline}$ is a vector containing the differences of measured voltage \mathbf{v} .

$$\hat{\mathbf{x}} = \underset{\mathbf{x}}{\operatorname{argmin}} \left\{ \|\mathbf{F}(\mathbf{x}) - \mathbf{y}\|_2^2 + \lambda^2 \|\mathbf{R}\mathbf{x}\|_j^2 \right\} \quad (1)$$

if only small conductivity changes are observed, the forward model $\mathbf{F}(\mathbf{x})$ can be linearized around a reference

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conductivity $\sigma^{baseline}$ such that $F(\mathbf{x}) \approx \mathbf{J}\mathbf{x}$, where $J_{i,j} = \left. \frac{\partial y_i}{\partial x_j} \right|_{\sigma_{ref}}$ forms a Jacobian matrix \mathbf{J} . An element $J_{i,j}$ maps small voltage changes at the position i of \mathbf{y} to a conductivity change of the element j within the discretized domain in a FEM model. The \mathbf{R} is a regularization which have several options. In this contribution a Laplace prior \mathbf{R}_{LP} was used. Equation 1 can be solved in a closed form with linearization:

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

where the matrix \mathbf{B} functions as a reconstruction matrix which calculates the impedance distribution variation from the measured boundary voltages. One common method to include prior information as grouped different tissue properties in the setting of $\sigma^{baseline}$ on which \mathbf{J} is depending[5].

The other method to include the constraining prior information is to introduce a series of basic functions $s_1(p, q), s_2(p, q), \dots, s_M(p, q)$ to modify the Jacobian matrix \mathbf{J} . The reconstructed conductivity change $\hat{\mathbf{x}}$ in 2 is written:

$$\hat{\mathbf{x}} = (\mathbf{J} \mathbf{S}^T \mathbf{J} \mathbf{S} + \lambda^2 \mathbf{R})^{-1} \mathbf{J} \mathbf{S}^T \mathbf{y} = \mathbf{B} \mathbf{y} \quad (3)$$

where $\mathbf{S} \in \mathbb{R}^{N \times M}$ represents the matrix of constraining basic functions, N is the number of the elements in the FEM. In this contribution, the basic function subset \mathbf{S} is obtained by element-wise mapping of FEM-elements to basis vectors of a Discrete Cosine Transform (DCT) of the personalized morphological image \mathbf{A} .

$$V_{p,q} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{m,n} \cdot D(p, q)_{m,n} \quad (4)$$

where the cosine function combinations implemented in the basic function subset are formed as $D(p, q)_{m,n} = \alpha_p \alpha_q \cos \frac{(2m+1)p\pi}{2M} \cdot \cos \frac{(2n+1)q\pi}{2N}$. p and q are the frequencies of the cosine function at the x -axis and y -axis respectively. In this contribution p and q are chosen as 15 frequencies at either axis as $p, q \in (0, 1, \dots, 14)$.

The multiplication of $D(p, q)_{m,n}$ and an anatomical binary lung image $P_{m,n}$ yields matrix $C(p, q)_{m,n} = P_{m,n} \cdot D(p, q)_{m,n}$. The columns of the basic function subset is determined as $s_i = \mathbf{T}(C(p, q))$, where \mathbf{T} is a mapping function assigning each pixel of $C(p, q)$ to the FEM elements which covers the corresponding pixel.

B. Simulation data

The simulations were carried out with MATLAB R2019a (Mathworks, Natick, MA, USA) using the EIDORS toolbox[8]. In the simulation, initially the FEM-elements belong to lung area were assigned to a conductivity of $\sigma_{lung}^{initial} = 0.5$, the remaining elements were set to $\sigma_{non-lung}^{initial} = 1$. With this initial configuration, $\mathbf{v}_{initial}$ was generated.

The first simulation involved different scales of dorsal lung area atelectasis from 0% to 50%. Ventilated lung tissue was set assigned to a conductivity of $\sigma_{lung}^{ventilated} = 0.25$, while the collapsed area was set to remain $\sigma_{lung}^{atelectasis} = 0.5$. This configuration yielded the $\mathbf{v}_{atelectasis}$ for reconstruction. The

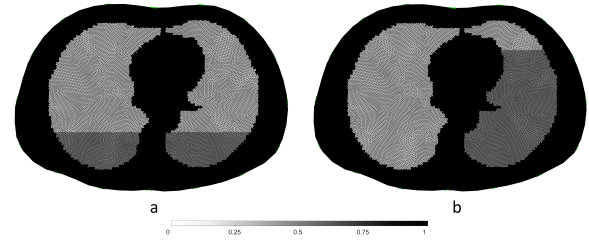


Fig. 1. The FEM models used for simulation. (a): Atelectasis model; (b): Collapse model.

second simulation used the same values for conductivity configuration, but involved different scales of left lung collapse from 0% to 100%. This simulation yielded the $\mathbf{v}_{collapse}$ for reconstruction. One example from each simulation was depicted in Fig. 1.

In the reconstruction part, 25% of the Gaussian noise was added to the $\mathbf{v}_{atelectasis}$ and $\mathbf{v}_{collapse}$. To prevent the 'inverse-crime', different meshes are used for simulation and image reconstruction. During reconstruction, three different prior information, namely lung contour (non-constrained prior), accurate prior, 100% left lung collapse prior or 50% dorsal atelectasis prior (fixed constrained prior), were employed into the DCT approach. These two scopes of simulations were used to evaluate a criterion to detect an outdated fixed constrained prior information.

C. Redistribution index

A DCT-based basic function subset generated from a morphological image can include more constraints on reconstruction in addition to the lung shape. For example, the area shown as atelectasis in the CT witnessed little change in EIT results. This constrain in subset \mathbf{S} is specified by the corresponding Hounsfield scale in the CT image which derives the $\mathbf{T}(C^c(p, q))$. If only a lung shape without details is specified, the $\mathbf{T}(C^{nc}(p, q))$ will allow the reconstruction in the whole lung area. The redistribution index is proposed to quantify the amount of the 'leaking' reconstruction from a constrained area to a non-constrained area using the same measurement data, or more theoretically, the redistribution of the pixel value histogram. The redistribution index is explained as:

$$RI = \frac{\sum_{xy \in \text{cons}} (\hat{\mathbf{x}}_{xy}^{nc} - \hat{\mathbf{x}}_{xy}^c)}{\sum_{xy \in \hat{\mathbf{x}}_{xy}^c} \hat{\mathbf{x}}_{xy}^c} \quad (5)$$

$xy \in \text{cons}$ expresses the constrained area in the morphological constrained area, $\hat{\mathbf{x}}^c$ is the DCT approach result using the constrained area prior, and $\hat{\mathbf{x}}^{nc}$ is the DCT approach result without the constrained area prior. Equation 5 will yield a value between 0 and 1. The flowchart to calculate the redistribution index is depicted in Fig. 2.

D. Patient data

The retrospective patient data was recorded with Pulmo-Vista500 (Draeger Medical, Luebeck, Germany). The study

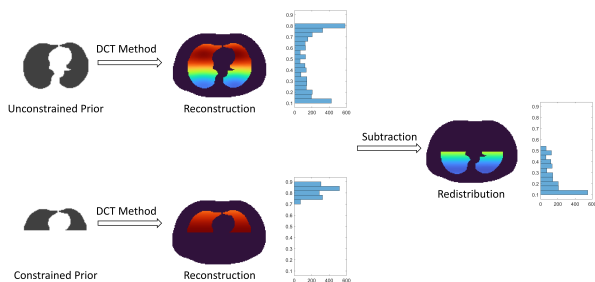


Fig. 2. The redistribution index calculation flowchart. The examples were derived from a simulation of 25% atelectasis. The example constrained prior is set as 50% atelectasis.

was approved by the Human Investigation Review Board University of Szeged (approval number 67/2020-SZTE). The trial was registered on ClinicalTrials.gov under NCT04360837. Written informed consent was obtained from the patients or their legal representatives, the methods were carried out in accordance with the approved guidelines and regulations. The patient was deep sedated, intubated and ventilated with a positive end-expiration PEEP step maneuver performed. The study period was seven days. The corresponding CT dataset at the first day of the ICU admission showed the dorsal part of the left lung as atelectasis.

DCT approach was implemented on the patient data, but with different prior, to obtain the EIT results. The constrained prior includes the atelectasis area and other anatomical information from the patient CT taken on day 1 before the EIT measurement. The non-constrained prior only specify the lung contour from the same CT. Thus, the redistribution index was calculated from EIT results at every PEEP step on day 1, day 3 and day 7.

III. RESULTS

A. Simulations

Simulation reconstruction examples, namely 50% left lung collapse and 25% dorsal atelectasis, were displayed in Fig. 3a. The redistribution indexes were calculated and depicted in Fig. 3b. The DCT approach results, which used the prior of 100% collapse or 50% atelectasis, only allowed the reconstruction within the pre-defined area. Thus, these results cannot imply the real simulation status. From the depicted redistribution indexes of either simulation, redistribution index increased as the atelectasis scale or collapse scale decreased. In other words, when the difference between the real status and the fixed constrained prior information became more notable, an increase will be expected in the redistribution index. When this prior-reality difference becomes unbearable, or more specifically, will lead to a misleading result, the redistribution index will reach a threshold. At this time, for EIT evaluation process there exists no consensus on the best criterion to claim an EIT result mislead a realistic status. We note that the control of the prior-reality difference within 30% will yield a rather tolerate result. Thus, at this difference point the redistribution index is around 0.4, which was used as a

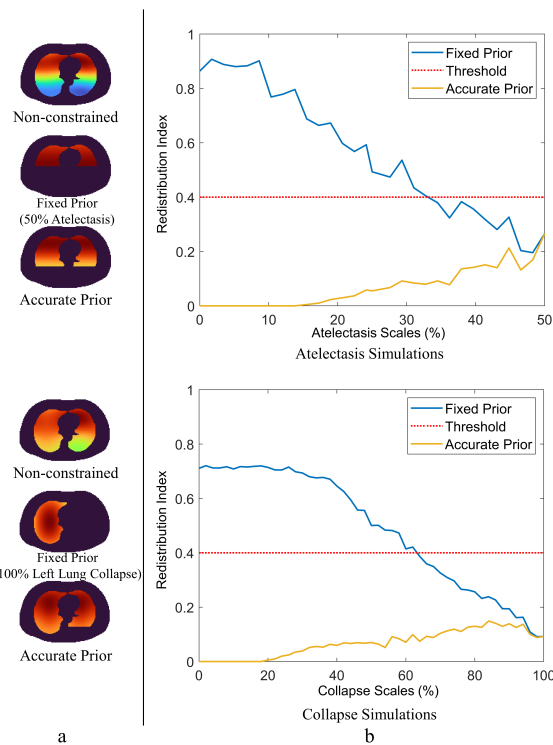


Fig. 3. The example DCT approach results and corresponding redistribution index from the two-scope simulations. (a) The example DCT results with different priors employed. Upper: Examples from the simulation of 25% of atelectasis; Lower: Examples from 25% of the left lung collapse. (b) Redistribution indexes calculated from the two-scope simulations.

temporary threshold.

B. Patient data

The example images of conductivity distribution change relating to the PEEP trial at PEEP 22 cmH₂O of the subject on day 1 and day 7 were depicted in Fig. 4a. The image of the conductivity distribution change between different PEEP scales is used to determine the potential recruitment and the possible overdistention. In both DCT approach reconstruction, we can find a trend of decreasing potential recruitment (the red and yellow area shown in Fig. 4a) from day 1 and day 7, though with different priors. In addition, a possible overdistention can be observed on day 1 (the dark blue area shown on day 1 in Fig. 4a). The redistribution indexes of each PEEP step on day 1, day 3 and day 7 were plotted in Fig. 4b. In general, the redistribution index is larger when the PEEP level is higher. However, on day 1, when the PEEP rose from 22 to 25 cmH₂O the redistribution index dropped from 0.39 to 0.32. On day 3 and day 7, the largest redistribution index is smaller than the largest of day 1. On day 7, the distribution indexes stayed rather stable in all PEEP levels.

IV. DISCUSSION

In this contribution, we proposed the redistribution index with the aim to detect an outdated morphological prior

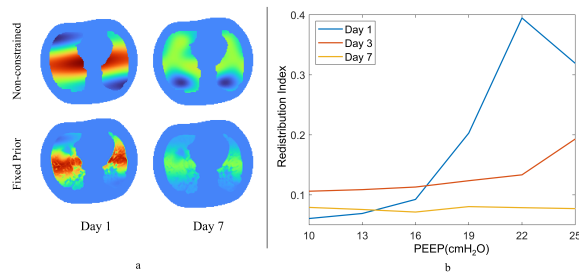


Fig. 4. Exemplified conductivity distribution difference images and corresponding redistribution indexes. (a) The difference image of ventilation distribution at PEEP 22 cmH₂O of the patient on day 1 and day 7. Upper row: result from non-constrained prior; Lower row: result from fixed prior; (b) Redistribution indexes calculated at different PEEP steps on day 1, day 3 and day 7.

information used in the novel DCT-based EIT algorithm. A redistribution index threshold was hypothesized by two scopes of simulations on collapse lung area and atelectasis respectively. It was demonstrated that there is a straight forward way to quantify the effect of an outdated constrained prior on the result of the DCT approach. In Fig. 3b, an increasing trend of redistribution index was obvious when the difference between the fixed constrained prior and real status became more notable. When the redistribution index reached 0.4, we can hypothesize the fixed constrained prior to be outdated. It is recommended that the integrated priors in the DCT-based EIT algorithm should be checked and updated at this point, e.g. by available patient measurements or by predicting potential changes based on pathophysiology or both.

It is worth noting that the accurate prior employed DCT approach results are expected to be accurate, but the redistribution was still observed. This can be explained that the non-constrained prior DCT approach allows the reconstruction in the entire lung area, and the spatial resolution of EIT result is low. In addition, the redistribution indexes for the accurate prior results remained much lower than the threshold. For the retrospective patient data, with the higher PEEP, the larger redistribution index can be expected. The higher PEEP could ‘recruit’ closed alveoli, which might improve atelectasis regions to open and to ventilate in a relatively normal fashion[9]. As the fixed prior was derived from a CT before the PEEP trial, it can be different from the patient status under a higher PEEP. The decrease of the redistribution index on day 1 at PEEP 25 cmH₂O might be explained by the possible overdistention or ventilator induced lung injury (VILI) due the high PEEP. The generally smaller redistribution indexes on day 3 and day 7 compared with day 1, and the rather stable trend on day 7, can both be explained by the deteriorating patient condition and less recruitment in a PEEP trial. It is worth noting that for the PEEP steps 10 and 13 cmH₂O on day 3 and day 7, the redistribution index is larger than that of day 1. This might suggest the physiopathological status of the patient has changed.

One of the limitations of this research is that threshold

is hypothesized with a standard of a rather tolerate DCT approach result by only two-scope simulations. It should be evaluated with further researches. In simulations, the conductivity distributions were based only on a simple physiological assumption. While in clinical settings, the patients are expected to suffer from several symptoms. It should be more accurate to yield a threshold from clinical data. Another limitation is on the patient data evaluation. Unfortunately, we did not obtain the CT images from the patient following the days of the hospital admission. So we cannot compare the DCT approach results from an updated prior to the current results.

Nevertheless, through both simulations and patient data analysis, the redistribution index can suggest the potential changing of the patient status. Thus, it could be used as an indicator for the outdated prior in the DCT-based EIT approach. Updating the prior information in the DCT approach can facilitate the accurate interpretation of the EIT results.

V. CONCLUSIONS

The redistribution index was proposed and the related preliminary evaluation were done in terms of simulations and retrospective patient dataset. The evaluation result suggested the potential of the redistribution index to detect an outdated prior information in a DCT-based EIT algorithm. Considering the calculation method of the redistribution index, it should be able to extend this definition to other EIT algorithms using the prior information.

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