A Novel Method for Monitoring Data Quality in Electrical Impedance Tomography

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Abstract. Electrical impedance tomography (EIT) has the promise to help improve care for patients undergoing ventilation therapy by providing real-time bed-side information on the distribution of ventilation in their lungs. To realise this potential, it is important for an EIT system to provide a reliable and meaningful signal at all times, or alert clinicians when this is not possible. Because the reconstructed images in EIT are sensitive to system instabilities (including electrode connection problems) and artifacts caused by e.g. movement or sweat, there is a need for EIT systems to continuously monitor, recognize and, if possible, correct for such errors. Motivated by this requirement, our paper describes a novel approach to quantitatively measure EIT data quality suitable for online and offline applications. We used a publicly available data set of ventilation data from two pediatric patients with lung disease to evaluate the data quality on clinical data. Results suggest that the developed data quality could be a useful tool for real-time assessment of the quality of EIT data and, hence, to indicate the reliability of any derived physiological information.

1. Introduction

Electrical impedance tomography (EIT) has emerged as a promising technology for continuous monitoring of lung patients. In this application, measurement errors are inevitable due to dynamics of the human body (movement and sweat), electrode detachment and noise or drift in electronics [1] decreasing the clinical value of the acquired data. Although various approaches [2,3] have been proposed to date to detect EIT data errors, no systematic approach to quantifying EIT data quality has been offered. Particularly in an Intensive Care Unit (ICU), where it is vital that an EIT system provides a reliable and meaningful signal at all times, or alert clinicians when this is not possible, there is a strong need for a data quality measure. Motivated by this need, we define the requirements of a data quality metric for EIT, develop a metric that meets them, and an efficient way to calculate it.

2. Methodology

2.1. Overview

Our approach to measure and quantify data quality is based on the jackknife (leave-one-out) concept [4], which is an efficient cross-validation technique suitable for real-time applications. Briefly, we use an FEM model of the investigated domain to predict the value of an individual
voltage measurement from all the other measurements (the jackknife estimate). The comparison of the prediction with the actual measurement yields an estimate of the measurement error. The final data quality metric $q$ is a scalar quantity aggregated from all the individual measurement errors, following a suitable transformation.

2.2. Requirements
A useful data quality metric for EIT should satisfy the following requirements:

(i) $q$ should be bound between 0 and 1 ($0 \leq q \leq 1$), with 1 indicating perfect quality.

(ii) adding “good” data to the measurement vector should increase $q$.

(iii) conversely, adding more data of low quality should decrease $q$.

(iv) $q$ should be low if data is wrong (e.g. electrodes were placed incorrectly).

2.3. Formulation of data quality
We consider the case of dynamic (functional) EIT, where images of relative conductivity changes $m = (\sigma - \sigma_r) / \sigma_r$ are reconstructed from normalized voltage difference data $d = (v - v_r) / v_r$, where $v$ and $v_r$ are the subsequent and reference measurements, respectively, while, $\sigma$ and $\sigma_r$ represent the corresponding conductivity distributions inside the medium.

We define the error to signal ratio* * $\varepsilon \in \mathbb{R}^M$ as the estimated measurement error over signal

$$\varepsilon_i = \frac{d_i - \hat{d}_i}{S} = \frac{1}{S} \left( \theta_i^T \left( d - \hat{d}_i \right) \right),$$

for $i = 1 \ldots M$, where $d \in \mathbb{R}^M$ is the vector of measured data, and $\hat{d}_i$ is a jackknife estimate of $d$ based on all the data $d$ but its $i$-th element, $\theta_i$ is a vector $(M \times 1)$ of zeros with a single element $[\theta_i]_i = 1$ and $S$ represents the signal strength. Because the latter is not known a priori, we define $S$ as the mean of simulated normalized difference data generated by small (20% medium radius) spherical contrast (2:1 contrast-to-background conductivity ratio) at the center of the medium.

To obtain the jackknife estimates, we devise a reconstruction matrix $R_i$ based on the one-step Gauss-Newton schema, such that the $i$-th measurement channel is ignored. This is accomplished by defining a data noise covariance matrix as $\Sigma_n = (I + \mu \Theta_i)$, i.e. such that noise on channel $i$ is assumed to be much greater (by an additive factor $\mu \gg 0$) than on other measurements:

$$R_i = \Sigma_n J^T \left( J \Sigma_n J^T + \lambda^2 (I + \mu \Theta_i) \right)^{-1} \quad (2)$$

where $\Theta_i$ is a matrix $(M \times M)$ of zeros with $[\Theta_i]_{ii} = 1$.

Hence, we rewrite 1 as

$$\varepsilon_i = \frac{1}{S} \left( \theta_i^T \left( d - JR_i d \right) \right) = \frac{1}{S} \left( \theta_i^T \left( I - JR_i \right) d \right) \quad (3)$$

To speed up the calculations, we define a “quality” matrix $Q$ such that each row $i$ of $Q$ is given by $Q_i = \theta_i^T (I - JR_i)$. Thus

$$\varepsilon = \frac{1}{S} (Qd). \quad (4)$$

We then express the quality of an individual measurement $i$ as

$$q_i = \left( \frac{1}{2} \right)^{\left| \varepsilon_i \right|} = \begin{cases} 1 & \text{if } |\varepsilon_i| = 0 \\ \frac{1}{2} & \text{if } |\varepsilon_i| = 1 \\ 0 & \text{if } |\varepsilon_i| = \infty \end{cases} \quad (5)$$
where 1 indicates good quality, 0 — bad quality, and $\frac{1}{2}$ indicates that $|\varepsilon_i| = 1$. Finally, the proposed metric $q$ is the arithmetic mean of the individual $q_i$

$$q = \frac{1}{M} \sum_{i=1}^{M} q_i,$$

(6)

where $M$ is the length of the data vector $d$. Since $Q$ can be precalculated, as it does not depend on the data, the calculation of $q$ requires one matrix multiplication per data set (eq. 4), which is comparable to the computational requirement of linear image reconstruction.

2.4. Evaluation Data Set

The developed quality metric $q$ was evaluated using a publicly available data set from two mechanically ventilated patients with acute lung injury or acute respiratory distress syndrome (ALI/ARDS) undergoing a recruitment manoeuver to estimate the extent of regional lung overdistention and atelectasis [5]. The experimental protocol consisted of 1) a baseline ventilation stage, 2) a lung recruitment stage (increased airway pressure) under pressure-controlled (PC) mode, and 3) a PEEP (positive end-expiratory pressure) titration stage with airway pressure sequentially decreased to the lowest possible setting. The Goe-MT II EIT device (CareFusion, Hoechberg, Germany) was used for acquiring measurement data at a single frequency using 16 electrodes, and adjacent stimulation and measurement patterns.

3. Results

Fig. 1 shows $q$ values and EIT images reconstructed with three different algorithms, for the two patients (labeled 1 and 7) during each step of the experimental protocol described above, where R1-R4 stands for the lung recruitment (sequentially increased airway pressure) and T1-T4 for the PEEP titration (sequentially decreased airway pressure).

Patient 1 had consistent high $q$ values, which is reflected in the stable and largely artefact-free reconstructed images for all protocol steps with few image artifacts. These images reflect the expected shifts of ventilation distribution according to the protocol. In contrast, for patient 7 physiologically unrealistic images were obtained, particularly at stages R3 and T1 for the GREIT algorithm. This is reflected by the much lower data quality $q$ of during these two stages. Further analysis of the measurement data showed that the standard deviation of difference data at these stages has 3 times higher noise compared to other protocol steps (not presented).

4. Discussion

We propose a formulation of a data quality metric $q$ for EIT suitable for use in real-time applications. Our intention is to provide an indicator of the trustworthiness of EIT reconstructions that would inform their analysis and thus help preventing incorrect diagnosis. We set out with a list of requirements for a useful quality metric, which we discuss in turn below:

(i) $q$ is guaranteed to be bounded between 0 and 1, as desired, by the formulation of the individual $q_i$ in eq. 5. Preliminary results (not presented) suggest, however, that the threshold for $q$ below which measurements should be rejected is system dependent.

(ii) Because $q$ is the arithmetic mean of the quality $q_i$ of individual measurements, adding additional measurements with high $q_i$ will increase $q$.

(iii) Conversely, adding measurements with below-average $q_i$ will reduce the value of $q$.

(iv) Incorrect placement of electrodes or any other substantial difference between the domain and method of measurement and the model on which the Jackknife estimates are calculated will result in the latter being a poor match for the recorded data, causing $q$ to be low.
Our example of real clinical data illustrates the case for using a data quality metric. As shown in Fig. 1, images reconstructed from poor quality data may at times appear sufficiently plausible as to be analysed. An objective quality metric independent from the reconstruction algorithm and the appearance of the image could provide clinicians with an indication of the trustworthiness of the images being analysed, thus helping to avoid false diagnosis. Since the proposed quality metric is computationally efficient, it is well suitable for real-time and long-term monitoring of patients.

The proposed metric $q$ could also be useful to evaluate different EIT system performance, to monitor their long term stability, and as a test standard to measure hardware improvements.

5. References

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