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Abstract: Electrical Impedance Tomography (EIT) enables continuous, non-invasive monitoring of regional pulmonary ventilation; however, the influence of reconstruction parameters on clinically derived features remains poorly understood. In this study, thoracic EIT recordings from 31 subjects were reconstructed using the GREIT framework in pyEIT; five parameters were modulated at three perturbation levels ($\pm 10\%$, $\pm 25\%$, $\pm 50\%$). Nineteen ventilation features were extracted per configuration and their sensitivity was quantified via a normalised influence score. The sigmoid threshold ratio dominated all other parameters, while regularisation strength and background permittivity yielded identical effects, suggesting a shared computational pathway within the reconstruction matrix. These findings highlight the importance of standardising reconstruction settings and explicitly reporting reconstruction configurations in clinical and research applications of EIT-based ventilation monitoring.

Keywords: electrical impedance tomography, image reconstruction, ventilation monitoring, parameter sensitivity

1 Introduction

In patients receiving mechanical ventilation, inhomogeneities in lung tissue compliance and recruitability can simultaneously lead to regional overdistension of well-ventilated areas and cyclic alveolar recruitment of atelectatic regions. The resulting uneven distribution of shear stress and strain constitutes an important promoter of ventilator-induced lung injury (VILI), which may further impair lung function and even precipitate systemic inflammation [1]. Tailoring mechanical ventilation to the individual pathophysiology is therefore essential to mitigate VILI, especially in patients with acute respiratory distress syndrome (ARDS) [2, 3]. Over the past two decades, Electrical Impedance Tomography (EIT) has emerged as a compelling, non-invasive and radiation-free modality enabling real-time assessment of pulmonary ventilation at the bedside [4]. However, EIT image reconstruction entails solving a severely ill-posed inverse problem whose quality is governed by several algorithmic parameters—regularisation type, noise thresholding, and finite element mesh resolution [5, 6]. These choices directly influence spatial fidelity and noise robustness. For instance, the GREIT algorithm (Graz consensus Reconstruction Algorithm for EIT) offers uniform sensitivity across the imaging plane, yet may overestimate ventilated regions compared to Gauss–Newton approaches, thereby altering derived features such as the Centre of Ventilation (CoV) [7, 8].

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Despite increasing clinical adoption, the impact of reconstruction parameters on ventilation-derived features—such as the Global Inhomogeneity (GI) index, CoV, or regional ventilation delay—remains insufficiently characterised. Grychtol and Adler demonstrated that different parametrisations of the same algorithm lead to clinically significant differences in the resulting images [9], while Thürk et al. showed that only a narrow subset of GREIT configurations yielded consistent results across simulation and experimental data [10]. Bearing this in mind, the present study extends this line of investigation by systematically assessing how the reconstruction parameters of the open-source pyEIT implementation (v. 1.2.4) [11] affect ventilation monitoring features extracted from human thoracic recordings. The aim is to assess how reconstruction settings affect EIT-derived analytical outcomes, with a view to informing standardisation efforts in research and clinical applications of ventilation monitoring.

2 Materials and Methods

2.1 Background on GREIT Reconstruction

EIT is a non-invasive imaging modality that reconstructs cross-sectional maps of internal impedance distribution from voltage measurements collected at the body surface. In thoracic EIT, a set of electrodes, typically 16, is arranged around the chest. Small alternating currents are sequentially injected through pairs of electrodes, and the resulting boundary voltages are recorded by the remaining electrodes. The inverse problem of reconstructing the internal conductivity distribution from these surface measurements is inherently ill-posed, necessitating regularised reconstruction algorithms.

In this work, image reconstruction was performed using GREIT, a standardised linear reconstruction framework specifically designed and validated for lung ventilation imaging [12]. GREIT computes a reconstruction matrix R that maps the measured difference signal Δv , obtained between a reference frame and each subsequent frame, directly onto a discrete pixel image x on a predefined two-dimensional grid: $x = R \cdot \Delta v$. The reconstruction matrix is determined by training on a finite-element model (FEM) of the thorax. A set of training targets is simulated within the FEM, and R is optimised to reproduce point-spread function (PSF) characteristics across the imaging plane [12].

GREIT defines a set of performance metrics characterising an idealised EIT reconstruction. As defined by Adler et al. [12], the figures of merit, listed in order of priority, are: Amplitude Response (AR), Position Error, Resolution, Shape Deformation, Ringing, and Noise Amplification. These figures characterise the reconstruction matrix in a controlled simulation setting using idealised point targets within the FEM forward model. While these metrics provide a useful theoretical characterisation of the reconstruction operator, they do not directly quantify how parameter

choices affect the clinically relevant indices that are ultimately derived from EIT data in practice.

2.2 Data

Thoracic EIT recordings were acquired from 31 adult subjects using a Dräger PulmoVista 500 system (Dräger Medical, Lübeck, Germany) with 16 equidistant electrodes placed in a transverse plane at the level of the 4th–5th intercostal space. Subjects underwent volume-controlled mechanical ventilation. A maximal low-flow manoeuvre (MAX-LFM) was performed: four litres per minute were applied during inhalation, while exhalation was spontaneous. Only the inspiratory phase of each manoeuvre was retained for the present analysis. Data were sampled at 50 Hz. The clinical study from which the EIT data were derived was approved by the Leipzig University Ethics Committee (no. 196-11-ff-8042011).

2.3 Implementation and Perturbation Settings

This study analyses the sensitivity of functional EIT ventilation features to modulations of five parameters governing the GREIT reconstruction matrix R (Eq. 1):

$$R = W^T \cdot J^T \cdot (JJ^T + \lambda \Sigma_N^p)^{-1} \quad (1)$$

The Jacobian matrix J encodes the sensitivity of each electrode measurement to a unit of conductivity change in each FEM element. It is computed by linearising the forward model—that is, by approximating the non-linear relationship between conductivity distribution and boundary voltages as linear—around a chosen operating point, here the assumed background permittivity perm. This linearisation point determines which conductivity distribution is treated as the baseline, and since J depends on it, the choice of perm directly affects the spatial sensitivity pattern encoded in R . The noise covariance $\Sigma_N = \text{diag}(JJ^T)$ is a square matrix whose diagonal entries reflect how strongly each measurement is influenced by the overall conductivity distribution. Raising these diagonal entries element-wise to the power p produces an adaptive regularisation term: measurements associated with high sensitivity are penalised more strongly, low-sensitivity ones less so. Scaling this term by λ controls the overall regularisation strength. Inverting the sum $JJ^T + \Sigma_N^p$ solves for the conductivity update that best explains the measured voltage difference Δv . The weight matrix W maps the conductivity distribution defined on FEM element centres onto the fixed pixel grid on which the final image x is produced. This interpolation uses a sigmoid weighting function, assigning each pixel a smoothly varying contribution from nearby FEM elements. The pyEIT-specific parameter s controls how sharply the sigmoid transitions between contributing and non-contributing elements, while ratio determines the spatial radius within which elements are considered neighbours of a given pixel. Together, s and ratio govern the spatial resolution and blurring characteristics of the reconstructed image.

Each parameter was modulated independently from the pyEIT v.1.2.4 default baseline (p : 0.5, λ : 0.01, perm : 1, s : 20, ratio : 0.1) [11] at three perturbation levels ($\pm 10\%$, $\pm 25\%$, $\pm 50\%$), yielding 30 modulated configurations plus one baseline (31 total). These defaults represent the settings

most likely to be adopted in practice without prior domain-specific guidance. For each configuration, the full reconstruction pipeline was applied to real thoracic EIT recordings, producing a time-resolved series of impedance-change images from which functional ventilation features were derived. The sensitivity of each feature to parameter perturbation was quantified relative to the baseline configuration, with the aim of identifying which input parameters exert a meaningful influence on clinically relevant EIT-derived metrics and therefore require careful standardisation in practice.

2.4 Considered Features

For each subject, the inspiratory and expiratory phases were automatically delineated by identifying the time index of peak volume within the recorded trace. The resulting image stack (pixels $\times$ pixels $\times$ time) was sliced accordingly: frames from the onset of the MAX-LFM manoeuvre up to and including the peak constituted the inspiratory array, $Z_{\text{Inspiration}}(i, j)$, while the remaining frames were stored separately. Both stacks were subsequently low-pass filtered (5th-order Butterworth; 1 Hz cut-off) to attenuate high-frequency noise.

A functional region of interest (fROI) was derived from the filtered inspiratory stack as the temporal range image (pixel-wise maximum minus minimum). Pixels exceeding 20% of the maximum range value were retained, and morphological operations were applied to preserve only the largest connected component [13].

Regional Ventilation Delay (RVD) maps were then computed within the fROI. Each pixel time course was first normalised to its own minimum–maximum range, and the RVD value for each pixel was defined as the time at which the normalised signal reached 40% of its total excursion, expressed as a fraction of the manoeuvre duration [13] (Eq. 2):

$$\text{RVD}_{i,j} = \frac{t_{40\% i,j} - t_{\min}}{t_{\max} - t_{\min}} \quad (2)$$

Impedance change maps for the GI index and the CoV were obtained as the frame-wise difference between the last and first frames of the filtered inspiratory and expiratory stacks, respectively. The GI index was calculated over the fROI as the sum of absolute deviations from the median, normalized by the sum of absolute pixel values [14] (Eq. 3):

$$\text{GI} = \frac{\sum_{(i,j) \in \text{fROI}} |Z_{\text{Inspiration}}(i, j) - \text{Median}(Z_{\text{Inspiration}})|}{\sum_{(i,j) \in \text{fROI}} |Z_{\text{Inspiration}}(i, j)|} \quad (3)$$

The CoV coordinates were computed as the impedance-weighted centroid position within the fROI (centre-of-gravity method [15]), normalised to image dimensions and expressed as percentages (Eq. 4):

$$\text{CoV}_{k\%} = \frac{\sum_{(i,j) \in \text{fROI}} Z_{i,j} k}{\sum_{(i,j) \in \text{fROI}} Z_{i,j}} \cdot \frac{100}{D_k - 1}, \quad k \in \{i, j\} \quad (4)$$

where D_k denotes the image dimension along axis k (i.e., image width for i and image height for j).

A comprehensive feature set was extracted from the RVD maps, fROI geometry, and impedance change maps. This set comprised standard statistical descriptors (mean, standard deviation, median, percentiles, skewness, kurtosis), spatial autocorrelation metrics, gradient-based RVD features, morphological properties of the fROI (area, perimeter, eccentricity, solidity), and the coefficient of variation of RVD ($CV_{RVD} = SD_{RVD} / RVD$).

3 Results and discussion

The sensitivity of functional EIT ventilation features to modulations in five GREIT parameters (λ , p , perm , ratio , and s) was evaluated by varying each parameter relative to its nominal value. Across all 31 conditions and 19 EIT features, a total of 589 setting $\times$ feature combinations were analysed per record. The analysis included two components: a paired difference calculation quantifying the mean shift and sign agreement (ϕ_{sign}) relative to baseline, and a normalised influence score combining effect magnitude with cross-record consistency.

To enable comparison across features with different physical units, each feature's mean difference (Δ_{mean}) was normalised to the interval $[-1, 1]$ by dividing by the maximum absolute difference observed for that feature across all settings. An influence score was then defined (Eq. 5) as the product of the normalised effect size and sign agreement:

$$\text{Influence} = |\Delta_{\text{norm}}| \cdot \phi_{\text{sign}} \quad (5)$$

The influence score is a methodological index designed exclusively for ranking the relative impact of the five reconstruction parameters within this study; it is not intended as a clinically interpretable quantity. This metric is zero when the shift is negligible or records disagree on direction. It reaches its maximum of one when a feature shifts by the largest observed amount with perfect cross-record consistency. The scores are summed per parameter across all features at the maximum modulation level (+50%). Figure 2 shows the influence score of all parameters on each derived feature.

The ratio parameter dominated all other parameters by a wide margin (total influence 16.43), scoring more than four times higher than the next ranked parameter s (3.64). The strong sensitivity of roi_area to ratio is mechanistically attributable to this parameter's role in controlling the spatial radius of the sigmoid pixel-weighting function. Varying ratio expands or con-

Tab. 1: Analysis of 31 records where feature values demonstrated a uniform linear directionality within the same parameter setting. Direction of value change matching the 'label' row.

Parameter		Feature	Δ_{mean}	Δ_{std}	Label
λ	-0.25	roi_area	-12,74	25,34	↓
λ	-0.50	roi_area	-22,45	25,81	↓
p	-0.50	roi_area	15,39	12,03	↑
perm	-0.25	roi_area	-12,74	25,34	↓
perm	-0.50	roi_area	-22,45	25,81	↓
ratio	-0.10	sdrvd, variance_rvd	0,00	0,00	↑
ratio	-0.10	roi_area	-47,48	47,26	↓
ratio	-0.10	cv_rvd	0,01	0,02	↑
ratio	-0.25	roi_area	-93,32	53,06	↓
ratio	-0.25	cv_rvd	0,03	0,03	↑
ratio	+0.10	gradient_mean_rvd	-0,01	0,01	↓
ratio	+0.10	roi_area	24,94	15,10	↑
ratio	+0.25	sdrvd	-0,01	0,01	↓
ratio	+0.25	variance_rvd	0,00	0,00	↓
ratio	+0.25	roi_area	66,84	37,57	↑
ratio	+0.50	gradient_mean_rvd	-0,05	0,04	↓
ratio	+0.50	roi_area	139,40	68,15	↑
ratio	+0.50	cv_rvd	-0,03	0,04	↓
s	-0.25	roi_area	12,39	7,77	↑
s	-0.50	gradient_mean_rvd	-0,03	0,01	↓
s	-0.50	roi_area	45,45	27,25	↑
s	+0.25	roi_area	-11,48	25,92	↓
s	+0.50	roi_area	-15,29	26,06	↓

tracts the reconstructed active region, directly altering the number of pixels that exceed the 20% fROI threshold. This constitutes a reconstruction-driven segmentation effect rather than a physiological signal change, and underscores the particular importance of standardising ratio prior to any fROI-dependent feature extraction. The three remaining parameters showed comparatively lower and closely similar influence scores. Notably, λ and perm produced numerically identical results across all conditions. This equivalence is an implementation-specific consequence of Jacobian normalisation in pyEIT: under a homogeneous background, uniform scaling of perm rescales the FEM stiffness matrix but leaves the normalised Jacobian invariant, making perm perturbations mathematically indistinguishable from λ modulations. This behaviour may not generalise to frameworks employing inhomogeneous background models or alternative normalisation conventions.

For all five parameters, the magnitude of feature modulation scaled monotonically with the degree of parameter change across the three levels tested. Spearman's rank correlation between modulation magnitude and Δ_{mean} exceeded $|r| = 0.9$ for the large majority of feature $\times$ direction combinations, confirming strong correlation between magnitude of parameter change and magnitude of feature outcome. Figure 1 illustrates the response of ROI features to parameter modulation, as these were the most strongly affected.

These findings are consistent with previous observations on the sensitivity of EIT-derived indices to reconstruction choices. Zhao et al. [7] showed that features such as the GI index and CoV differ across algorithms; the present results indicate that substantial variability arises even *within* a single algorithm. Grychtol and Adler [9] reported that different parametrisations produce clinically significant image discrepancies, a conclusion that the dominance of the ratio parameter corroborates at the level of

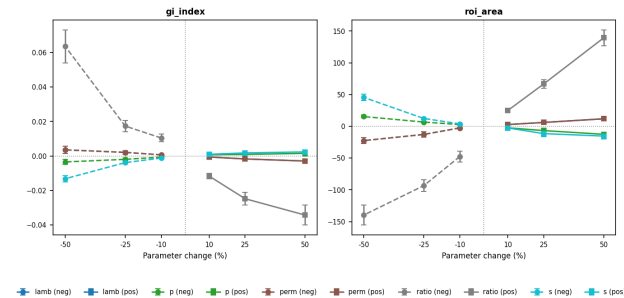


Fig. 1: Change of values for selected features in different parameter settings.

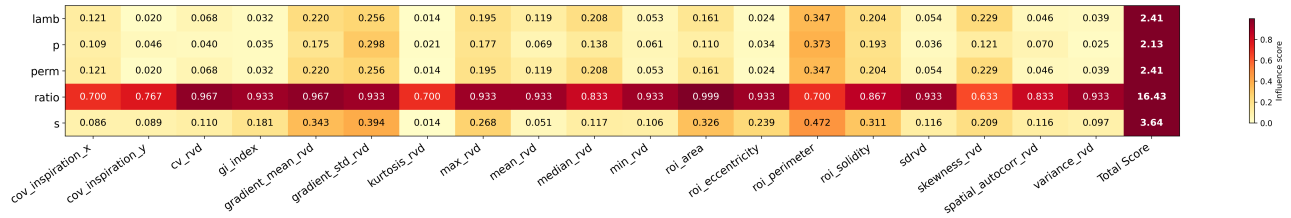


Fig. 2: Influence score of parameters on ventilation features compared to baseline. Values are normalized after calculation of the sum over all records. Total score is the summed influence score per parameter.

derived features. Thürk et al. [10], whose work is closest to the present study, found that only a narrow subset of GREIT configurations met all quality criteria in porcine data reconstructed with EIDORS; the present study extends their approach to 19 clinically oriented features extracted from human recordings via pyEIT.

This study is limited to a single reconstruction framework (GREIT via pyEIT) and a single acquisition device under volume-controlled ventilation. The generalisability of the observed parameter sensitivities to other algorithms, ventilation modes, or patient populations remains to be established. Moreover, in the absence of a ground-truth reference such as four-dimensional computed tomography, the analysis quantifies relative feature shifts rather than absolute reconstruction accuracy.

These results highlight the critical importance of standardising reconstruction settings, particularly the `ratio` parameter, prior to any fROI-dependent feature extraction, and suggest that reconstruction configurations should be explicitly reported in clinical and research applications of EIT-based ventilation monitoring.

Author Statement

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