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Edited by Marcin J. Kraśny, Dawn Walker, Inéz Frerichs, Andreas Demosthenous, Bill Lionheart, Andy Adler, Zhanqi Zhao, Rosalind Sadleir, Richard Bayford

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About the Event

It all started in Sheffield in the 1980s, with the first meeting held in 1986—exactly 40 years ago. Some of us were there at that very first gathering, helping to create it; some were only just born that year, others joined along the way. As stated by one of the founders of EIT, B. H. Brown, and D. C. Barber:

“The objectives of this workshop were to bring together workers in this relatively new area of research, with a view to sharing technical expertise and experience in order to enhance the quality and pace of the development.”

Today, we continue this tradition through the regular meetings of the EIT community.

This year marks the 40th anniversary meeting and the 26th International Conference on Biomedical Applications of Electrical Impedance Tomography.

We return to Sheffield, where it all began, a testament to the resilience and strength of EIT, this conference, and you, the researchers and delegates.

We hope you have an enjoyable and productive couple of days as our guest here in Sheffield.

EIT 2026 Organising Committee



First group photo of the EIT community, Sheffield 1986.

Organising Committee

Richard Bayford



Richard Bayford is Head of Biophysics at the Middlesex University Centre for Investigative Oncology and Head of the Biophysics/Engineering Group. He is Professor of Biophysics and Engineering at Middlesex University and an Honorary Visiting Professor in the Department of Electrical and Electronic Engineering at University College London. His research covers the development of biophysical models, novel algorithms, and instrumentation for imaging brain activity and neonatal lung function. He also works on multimodality imaging systems for nanoparticle-based imaging and therapy, deep brain stimulation, physiological modelling, medical signal processing, telemedical systems, and the development of novel silicon-based biosensors and lab-on-a-chip technologies for biomedical applications. He has more than 400 peer-reviewed publications.

Rosalind Sadleir



Dr Sadleir leads the Neuro-Electricity laboratory at Arizona State University. Her core activities are in computational modeling and neuroimaging relating to electrical properties of tissues, including direct measurement of current flow and conductivity in transcranial and deep brain stimulation. She is also actively involved in development and commercialization of electrical impedance tomography devices for applications including detection of intraperitoneal bleeding and intraventricular hemorrhage in newborns. Dr Sadleir's work is currently supported by NIH and private foundation funds.

Inéz Frerichs



Prof. Dr. Inéz Frerichs is the head of the EIT research group at the Department of Anaesthesiology and Intensive Care Medicine at the University Medical Centre Schleswig-Holstein, Campus Kiel, Germany. In her scientific career, she has been involved with different aspects of lung-oriented research (e.g., gas transport in the lungs, high-frequency oscillatory ventilation, respiratory mechanics, functional lung imaging, wearable lung monitoring). She has published 226 original articles (175 on EIT), 22 reviews and 23 book chapters. She was the coordinator and first author of the first Consensus statement on chest EIT.

Dawn C. Walker



Dr Dawn Walker completed a BSc in Physics (Hons.) at the University of Durham, UK in 1996 and a Ph.D. relating to modelling the electrical properties of epithelial tissues at the University of Sheffield, UK in 2001. She has subsequently developed further computational models focussing on capturing cellular interactions using an agent-based approach. Interests in cellular-based and multiscale modelling were extended through an RCUK fellowship, then lectureship based in the School of Computer Science in Sheffield. She is now a Senior Lecturer in the Complex Systems Modelling group in Computer Science and the Insigneo Institute in Sheffield, with research projects focussing on the development of cellular- and multi-scale models, with a particular focus on developing and optimising the Electrical Impedance Spectroscopy approach for early cancer diagnosis.

Andreas Demosthenous



Andreas Demosthenous is Professor of Analogue and Biomedical Electronics in the Department of Electronic and Electrical Engineering at University College London where he leads the Bioelectronics Group. His research interests include mixed-signal integrated circuits for biomedical, sensor, and signal processing applications. He has published over 400 papers, authored several book chapters, and holds multiple patents. He is a Fellow of the IEEE and IET, as well as a chartered engineer. He has served in numerous editorial and leadership roles across the IEEE Circuits and Systems Society.

William (Bill) Lionheart



Bill Lionheart is a Professor of Applied Applied Mathematics at the University of Manchester specialising in theory and practice of inverse problems and imaging. He works on a wide range of imaging methods including X-ray and neutron tomography, radar and low frequency electromagnetics, applied to medicine, engineering, security, materials, and land mine clearance. He has worked on EIT since 1985 pioneering FEM and regularization based reconstruction methods.

Andy Adler



Andy Adler is a Canada Research Professor in biomedical engineering in Systems and Computer Engineering at Carleton University in Ottawa, Canada. His research interests broadly in the area of biomedical measurement and robust data analysis, with a focus on EIT. Recently, his work aims to bring EIT to applications with animals, sports and stress.

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Zhanqi Zhao is a full-time Professor at the School of Biomedical Engineering, Guangzhou Medical University, and an Adjunct Professor in Critical Care at Peking Union Medical College Hospital. He began his EIT journey (focusing on clinical applications) in 2008. To date, he has published over 200 SCI journal papers and played a leading role in the vast majority of chest EIT clinical studies conducted in China. He was named a “World’s Top 2% Scientist” in 2025. As a consultant for several multinational companies, he has helped translate EIT technology from laboratory research into clinical routine, achieving successful translation from engineering innovation to clinical practice.

Marcin J. Kraśny

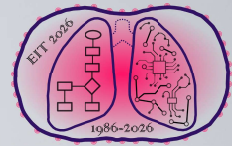


Marcin J. Kraśny holds an M.Sc. in Electronics Engineering and a Ph.D. in Materials Characterisation. Following postdoctoral research in medical devices, he specialised in the development of bioimpedance and electrical impedance spectroscopy (EIS) measurement systems. His expertise includes medical instrumentation, electronic hardware development, biosensors, signal acquisition, and impedance-based diagnostic technologies. He is an Adjunct in Medical Physics and Research Fellow at the University of Galway, Ireland, and a Research Scientist at Helmholtz-Zentrum Hereon, Germany.

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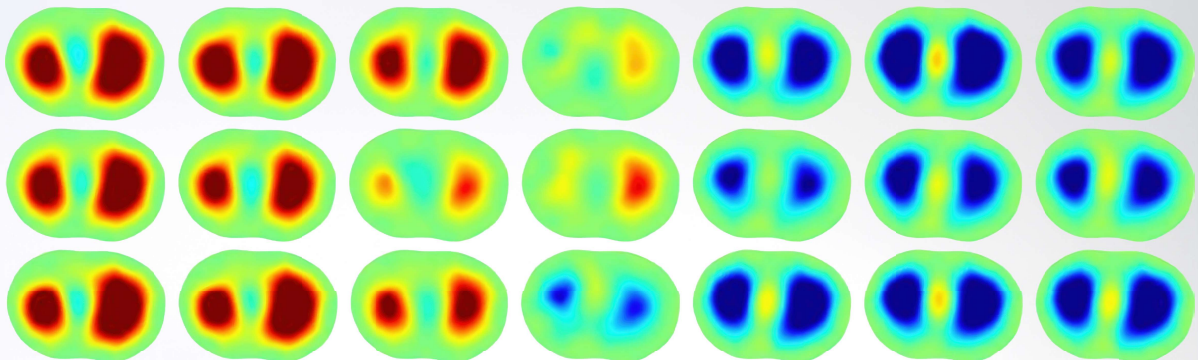


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Session 1: Lungs & Ventilation I

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Aerosol Deposition in Bronchiectasis: Regional Airway Obstruction is the Key

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Abstract: Aerosol deposition was tested in 52 patients with bronchiectasis with inhalation of ¹⁸F-NaF aerosol and PET/CT. It is confirmed that bronchiectatic regions received significantly less inhaled aerosol than non-bronchiectatic regions. Regional airflow obstruction is a key explanatory factor, as confirmed by EIT.

1 Introduction

Regional airway obstruction in bronchiectasis is thought to impair the delivery of inhaled drugs, yet direct in vivo evidence linking regional airflow limitation to aerosol deposition remains limited [1,2].

Recently, we demonstrated a close spatial correspondence between regions with limited airflow and decreased aerosol deposition in a patient with bronchiectasis and mild chronic obstructive pulmonary disease [3]. This study aimed to determine whether bronchiectatic (BE) regions receive less aerosol deposition than nonbronchiectatic (NE) regions within the same lungs, and to evaluate whether regional airflow obstruction derived from electrical impedance tomography (EIT) is a key determinant of this deposition deficit.

2 Materials & Methods

We conducted a prospective multimodal imaging study involving 52 patients with bronchiectasis. Participants underwent EIT during forced vital capacity (FVC) maneuvers to generate regional airflow metrics (FEV1/FVC and Time to 75% FVC), followed by ¹⁸F-NaF aerosol PET/CT to quantify regional deposition. Structural BE and NE regions were defined by CT. For the BE vs NE comparison, we quantified aerosol deposition using planar mean standardized uptake values (SUVmean) in regions of interests (ROI) on representative axial PET/CT slices. For EIT-PET/CT cross-modality analyses within the belt-centered sensitivity volume, deposition metrics were summarized within slab-based quadrant ROIs.

3 Results

An exemplary case is showed in Figure 1. In the left-lung dorsal regions, the aerosol deposition was low, and it corresponded to the airflow limitation.

Aerosol deposition was significantly higher in NE regions compared to BE regions (SUVmean: 1.13 ± 0.47 vs. 0.37 ± 0.12 , NE vs. BE; $P < 0.001$). It represented an approximate 67% reduction. NE regions also exhibited less severe EIT-derived airflow obstruction, characterized by higher regional FEV1/FVC (0.82 ± 0.14 vs. 0.50 ± 0.16 $P < 0.001$) and shorter T75 (0.52 ± 0.35 s vs. 1.76 ± 0.78 s; $P < 0.001$). Regional SUVmean correlated significantly with regional FEV1/FVC ($r = 0.47$, $P = 0.002$) and inversely with T75 ($r = -0.51$, $P = 0.001$) for BE regions. Similar associations were observed for NE regions (FEV1/FVC: $r = 0.42$, $P = 0.005$;

T75: $r = -0.49$, $P = 0.001$). We further used linear mixed-effects models with subject-level random intercepts to account for within-subject clustering of multiple ROIs. EIT-defined airflow obstruction accounted for the majority of the deposition deficit observed in BE regions (the BE coefficient was attenuated to -0.25 (95% CI, -0.43 to -0.07 ; $P = 0.007$), representing an approximate 56% reduction in effect size).

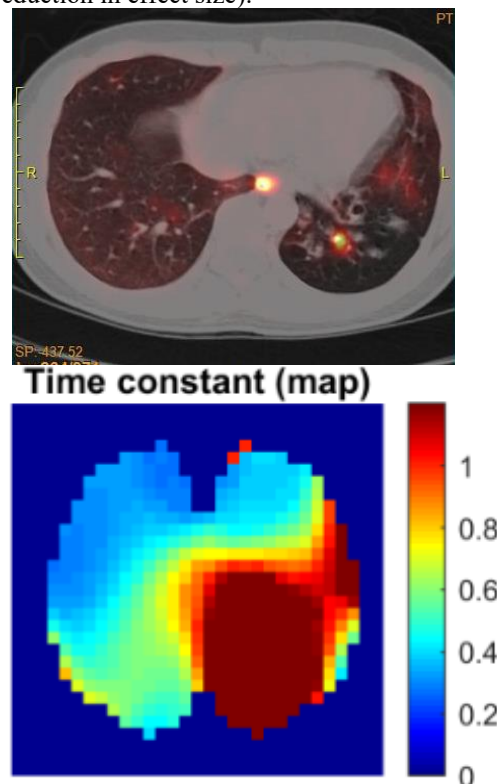


Fig. 1: Representative multimodal EIT and ¹⁸F-NaF aerosol PET/CT imaging in a patient with bronchiectasis. Top, axial fused PET/CT image. Bottom, flow limitation as assessed with regional expiratory time constant.

4 Conclusions

Structurally affected bronchiectasis regions receive significantly less inhaled aerosol. Regional airflow obstruction is a key explanatory factor and primary determinant of this impaired delivery. EIT may serve as a practical tool for regional functional assessment and for guiding personalized inhaled therapy in bronchiectasis.

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EIT-Derived Ventilatory Burden in Obstructive Sleep Apnoea

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Abstract: Obstructive sleep apnoea (OSA) severity is scored by apnoea–hypopnoea index (AHI) using PSG, but it ignores the depth and duration. We used EIT to compute ventilatory burden (VB) from respiratory volume, comparing it with VB calculated by nasal pressure airflow. EIT revealed higher VB in apnea-dominant patients.

1 Introduction

Obstructive sleep apnoea (OSA) is a highly prevalent sleep-related breathing disorder [1]. In current clinical practice, polysomnography (PSG) remains the gold standard for diagnosing OSA and grading its severity using the apnoea–hypopnoea index (AHI). AHI is a frequency-based metric (events per hour) and therefore does not capture the duration or depth of airflow reduction during apnoea and hypopnoea. To address this limitation, ventilatory burden (VB) has been proposed as a complementary severity measure and has shown promise for cardiovascular disease (CVD) risk stratification [2].

VB is typically computed from nasal pressure–derived airflow; however, during apnoea, the limited sensitivity of airflow signals often necessitates imputing zero-amplitude breaths, which may underestimate the true severity of airflow limitation [3]. EIT is a non-invasive functional imaging modality that enables continuous bedside monitoring of regional lung ventilation by measuring thoracic conductivity changes [4]. In this study, we continuously monitored respiration overnight using EIT and derived an EIT-based VB from the respiratory volume signal (RVS). We then quantitatively compared EIT-derived VB with VB estimated from conventional nasal pressure airflow. Our results show that EIT-based ventilation distributions differ significantly from those inferred from nasal airflow, particularly in apnoea-dominant patients. Moreover, EIT-derived VB is substantially higher than nasal airflow–derived VB in apnoea-dominant OSA, whereas the two VB estimates are comparable in hypopnoea-dominant OSA.

2 Materials & Methods

Ventilatory burden was first proposed by Parekh A *et al* [2] as a supplementary measure of OSA severity. To calculate the ventilatory burden using airflow, the onset and offset of each breath monitored by nasal cannula were annotated and the average amplitude of the airflow during the middle one-third of inspiration is then calculated breath by breath, and the amplitude was imputed as zero during the period of sleep apnoea [2]. Then, the breath by breath amplitude was then taken as the midflow amplitude normalized to the moving average of 10 prior breaths. Thereafter, a normalized histogram consisting of breath amplitudes ranging from 0 to a cap of 200% (bin width, 5) was defined as the overnight ventilatory distribution. From the ventilation distribution, the ‘classical’ VB is defined as the percentage of

overnight breaths with less than 50% amplitude [2]. For EIT-based VB estimation, the inspiratory respiratory volume signal (RVS) was obtained by summing pixel values across the EIT-derived ventilation images. The tidal volume (TV) was then computed as the difference in RVS between end-expiration and end-inspiration.

3 Results

In Fig. 1, we present the ventilation distribution and VB for an apnoea-dominant subject. Notably, the airflow-based VB (21.47%) is approximately threefold lower than the EIT-based VB (66.2%).

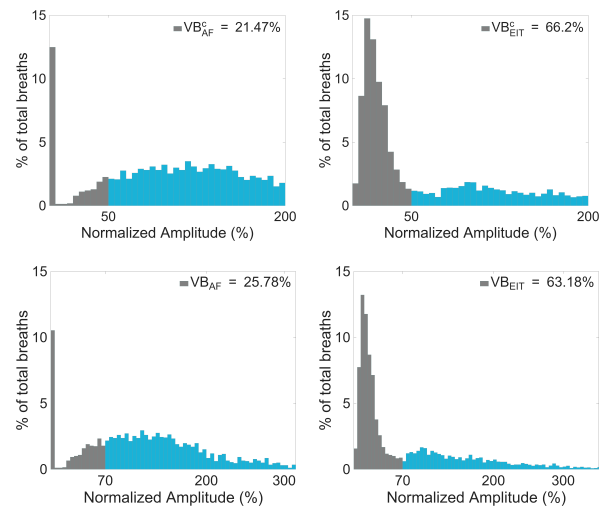


Fig. 1: The ventilation distribution and VB for one apnea dominant subject (AHI = 61.2/h, AI = 48.5/h, HI = 12.6/h).

4 Conclusions

Compared with VB calculated by airflow, the EIT-based VB reflects not only the depth of respiration but also the duration of apnea and hypopnea, thus it provides a more accurate estimation of the ventilation distribution especially for patients with a higher AI.

Acknowledgements

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Pulmonary perfusion assessment without breath-hold using pixel-wise linear regression in electrical impedance tomography

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Abstract: Ongoing ventilation challenges the monitoring of pulmonary perfusion with electrical impedance tomography (EIT) due to respiratory interference. We propose a linear regression approach to reduce ventilatory components and enable perfusion assessment. In ventilated pigs, temporal patterns consistent with apnea were observed.

1 Introduction

EIT enables bedside monitoring of pulmonary perfusion using saline bolus injection [1]. However, conventional approaches require breath-hold to separate ventilatory and hemodynamic effects, limiting applicability in spontaneously breathing or unstable patients.

Methods that allow perfusion assessment during ongoing ventilation are therefore of interest. We present a simple regression-based approach to suppress ventilatory interference

and enable perfusion imaging without apnea.

2 Materials & Methods

EIT data were acquired in 12 mechanically ventilated pigs subjected to saline bolus injection experiments using 10 mL of 7.5% hypertonic saline. The global impedance signal was used as a surrogate of lung volume.

A linear regression model was fitted pixel-wise to estimate the impedance variation due to ventilation [2]. Model parameters were identified from a pre-injection interval where impedance changes are dominated by ventilation.

The estimated ventilatory component was subtracted from each pixel signal, isolating the perfusion-related impedance changes during ongoing ventilation, as described in previous work [3]. The overall processing pipeline and validation steps are illustrated in Fig. 1.

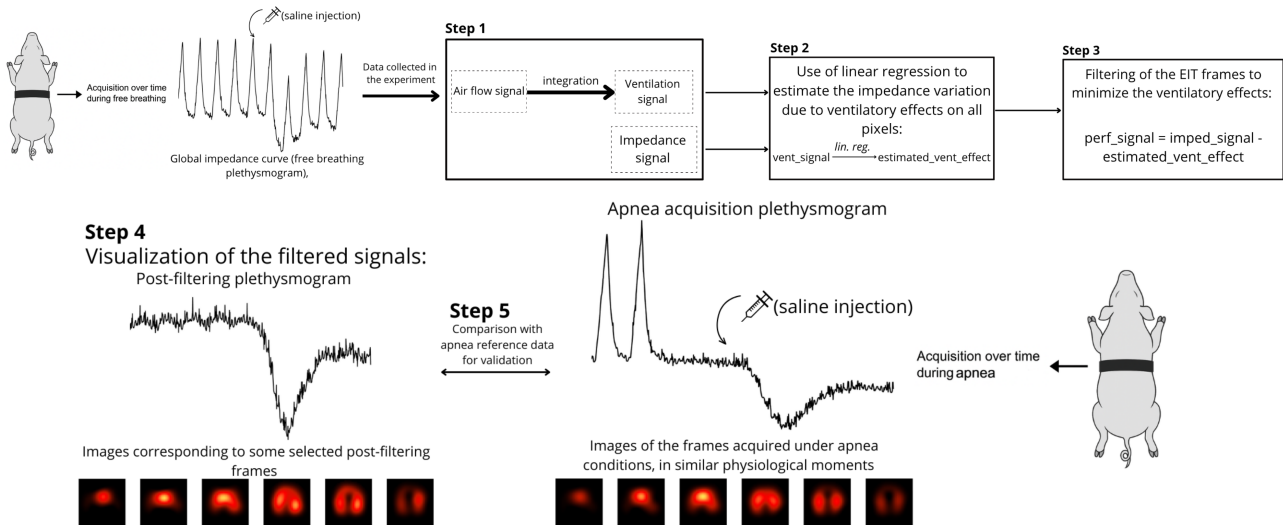


Fig. 1: Processing and evaluation pipeline: estimation and removal of ventilatory passage using pixel-wise linear regression (Steps 1–3), followed by visualization of contrast passage and comparison with apnea reference data (Steps 4–5).

3 Results

The proposed method enabled removal of ventilatory oscillations from global and pixel-wise impedance signals, revealing the saline bolus passage during ongoing ventilation.

Filtered signals enabled visualization of contrast passage during ongoing ventilation, with temporal patterns consistent with apnea reference data, as illustrated in the processing and validation pipeline in Fig. 1.

4 Conclusions

A pixel-wise linear regression approach enables pulmonary perfusion assessment with EIT without apnea. The method

effectively suppresses ventilatory interference while preserving relevant hemodynamic information, supporting its potential use for pulmonary perfusion monitoring.

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Correlation of EIT-Derived Regional Ventilation Parameters with Global Pulmonary Function in Post-Acute SARS-CoV-2 Patients

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Abstract: The study participants underwent various medical examinations, including lung function testing, to detect long-term sequelae of SARS-CoV-2 infection. Our study examined correlations between regional lung function measured by EIT and global lung function assessed by conventional methods.

1 Introduction

Following SARS-CoV-2 infection, persistent respiratory symptoms are common, yet global lung function tests often fail to detect regional ventilation defects. Electrical impedance tomography (EIT) is a bedside diagnostic tool for continuous evaluation of regional lung function suitable for use both in mechanically ventilated and spontaneously breathing subjects. The aim of our study was to assess the degree of agreement between regional lung function measurements obtained with EIT and global lung function parameters derived from conventional, clinically routinely used methods.

2 Materials & Methods

Study participants (n=160, n=81 female, n=79 male, age: 18-76 years, body height: 155-197 cm, body weight: 42-138 kg) were recruited from the population-representative COVIDOM study (German Registry for Clinical Studies No. DRKS00023742), investigating long-term effects of SARS-CoV-2 infections [1]. The study was approved by the Ethics Committee of the Medical Faculty of the Kiel University (Amendment to No. D537/20).

Global lung function parameters, determined by spirometry, plethysmography, lung diffusing capacity testing and oscillometry, were obtained from the existing COVIDOM dataset. EIT examinations were performed using the PulmoVista 500 device from Dräger (Lübeck, Germany) at a scan rate of 50 primary images per second in a sitting position. The breathing manoeuvres during the examination included regular quiet breathing, deep breathing, slow and forced vital capacity (FVC) manoeuvres. Approximately 300 raw EIT parameters [2] were extracted from the recorded datasets using the Parametric EIT Analysis Software (PEAS) software [3], describing both the spatial and temporal ventilation distributions and their heterogeneity. The EIT parameters

were calculated from individual image pixels and included regional volumes (e.g., tidal volumes or forced expiratory volumes in 1 second (FEV₁)), regional flows (e.g., forced expiratory flows between 25% and 75% of FVC (FEF₂₅₋₇₅)), regional intratidal expiration times (e.g., times needed to exhale 50 % of tidal volume or FVC (t_{E50})), and regional expiratory time constants (τ_E). Pearson correlation coefficients were calculated between EIT parameters and global lung function indices.

3 Results

Global pulmonary function testing revealed that 80 % of the examined study participants exhibited normal lung function based on the analysis of global FEV₁/FVC, FVC and total lung capacity (TLC) values according to the current German guidelines [4]. EIT data of sufficient quality for further analysis were obtained in all examined subjects. The correlation coefficients between EIT-derived regional parameters and global function tests were generally low ($|r| < 0.5$), indicating that EIT captures distinct regional physiological information not reflected in global averages derived from conventional examination methods. The collected data exhibited high inter-individual variability.

4 Conclusions

EIT provides complementary regional data that is not redundant with global pulmonary function tests. Given the low correlation and high variability, EIT is better suited for intra-individual monitoring (tracking changes over time) than for comparison against conventional normative values. These findings were observed in a population primarily lacking severe pulmonary limitations, which may have restricted the range of observable correlations.

Acknowledgements

The authors wish to thank Dr. Anne Hermes and Sarah Meier for their support in conducting the study.

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Temporal Ventilation Heterogeneity Detected by EIT during Quiet Breathing in COPD Patients

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Abstract: EIT-derived temporal ventilation heterogeneity during quiet breathing increases progressively across COPD severity stages (GOLD I-IV) and discriminates COPD patients from healthy controls without requiring forced respiratory manoeuvres.

1 Introduction

Chronic obstructive pulmonary disease (COPD) is one of the leading causes of death worldwide. It is a heterogeneous disease characterised by pulmonary abnormalities causing persistent respiratory symptoms and progressive airflow limitation across four severity stages. Pulmonary function testing is the standard method for diagnosis and staging but requires patients to cooperate and to be able to perform forced respiratory manoeuvres. We hypothesised that assessment of temporal ventilation heterogeneity during quiet breathing with EIT could be used to discriminate disease severity in COPD patients.

2 Materials & Methods

We report on data from 71 COPD patients (GOLD stages I-IV) [1] and 25 healthy non-smokers obtained from the ongoing prospective observational BREATHE study (University Medical Centre Schleswig-Holstein, Kiel, Germany). The study was approved by the local ethics committee and prospectively registered at German Clinical Trials Registry (DRKS, registration ID DRKS00035028). EIT data were recorded using PulmoVista 500 (Dräger, Lübeck, Germany) at 50 frames/s, with the electrode belt positioned at the 4th-5th intercostal space during spontaneous tidal breathing in a seated position. GOLD stages I-IV were defined based on forced expiratory spirometry. EIT images were reconstructed and analysed with the open-source Parametric EIT Analysis Software [2]. Each pixel's expiratory progression was tracked by

computing the time points at which 10%, 25%, 50%, 75%, and 90% of local tidal expiration had been reached (tE10-tE90). The coefficient of variation during expiration (tE_cv) was computed to quantify the degree of ventilation heterogeneity. Between-group differences in tE_cv were assessed by One-Way Analysis of Variance (ANOVA). The ability of EIT parameters to discriminate between COPD and healthy controls was assessed by computing the area under the receiver operating characteristics curve (AUC-ROC).

3 Results

All five tE_cv parameters differed significantly across groups and discriminated COPD from healthy controls (Table 1). tE10_cv showed the strongest (AUC 0.767) and tE90_cv the weakest discrimination (AUC 0.617). Furthermore, tE_cv values increased progressively with GOLD severity.

4 Conclusions

The current results suggest that EIT-derived temporal ventilation heterogeneity during quiet breathing increases across the four COPD stages and could be used to discriminate COPD patients from healthy controls. The strongest discrimination was observed for tE10_cv. These findings support EIT as a potential tool for assessing COPD severity and monitoring disease progression without the need for forced respiratory manoeuvres or patients' cooperation.

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Tab. 1: EIT parameters by diagnosis group.

EIT Parameters (quiet breathing)	Healthy (n=25)	GOLD 1 (n=12)	GOLD 2 (n=28)	GOLD 3 (n=18)	GOLD 4 (n=13)	AUC (COPD vs. Healthy)	P (ANOVA)
tE10_cv (%)	21.5 ± 5.4	27.2 ± 10.5	29.3 ± 14.5	32.7 ± 8.7	48.3 ± 17.4	0.767	<0.0001
tE25_cv (%)	17.7 ± 6.6	23.1 ± 7.5	23.8 ± 10.2	25.7 ± 6.9	37.7 ± 14.6	0.750	<0.0001
tE50_cv (%)	14.0 ± 4.3	18.7 ± 5.0	19.5 ± 8.8	20.7 ± 7.9	30.3 ± 12.3	0.756	<0.0001
tE75_cv (%)	11.8 ± 4.0	14.2 ± 4.1	15.5 ± 7.7	15.9 ± 5.9	23.0 ± 10.4	0.711	<0.001
tE90_cv (%)	11.1 ± 4.3	13.1 ± 3.9	12.8 ± 7.0	12.7 ± 3.7	18.3 ± 9.0	0.617	0.015

Abbreviations: EIT, electrical impedance tomography; tE10-tE90, time to reach 10%-90% of tidal expiratory volume; CV, coefficient of variation; GOLD, Global Initiative for Chronic Obstructive Lung Disease; AUC, area under the receiver operating characteristic curve; ANOVA, analysis of variance. Values are presented as mean ± SD unless otherwise noted. AUC refers to COPD (all GOLD stages) vs. Healthy.

Session 2: Regularisation, Optimisation and Machine Learning Methods

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Feature-Based Identification of Object Shape from Boundary Voltages in Electrical Impedance Tomography

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Abstract: We propose a feature-based approach for detecting the object shape from EIT measurements. A sensitivity analysis shows that the sensitivity distribution on the boundaries differs significantly with the object shape. A study of possible important features for shape detection shows that the behavior of the boundary voltages (BV) is sufficient for detecting the shape of the measured object. This can build the basis for automatically recognizing object shapes in image reconstruction.

1 Introduction

Electrical Impedance Tomography (EIT) reconstruction degrades when the assumed shape geometry does not match reality, e. g. in the non-invasive detection of foreign bodies in food products [1]. Existing approaches address this through improved forward models or joint conductivity-shape estimation, often relying on iterative solvers and prior assumptions [3, 4]. However, BV data are rarely analyzed from a feature-based perspective for lightweight geometry inference. This work extracts and evaluates features from BV measurements to identify low-dimensional descriptors that capture object shape.

2 Sensitivity Analysis and Feature Extraction

First, the BV data have been simulated for objects with a circular, rectangular, and triangular shape and including moving inclusions of 5-10% of the object area in 5 different positions. We considered thereby the case of adjacent current injection with a 16-electrodes configuration.

The distributions of the average sensitivities for different shapes is evaluated based on the Jacobian matrix, with spatial influence quantified via the Euclidean norm $\|\mathbf{J}\|$. From the BV signals, statistical features including minimum, maximum, range, mean, median, standard deviation (STD), and the average variation between consecutive BV measurements (AVG-V) are extracted. Based on a Fisher score analysis, we evaluated the feature sensitivity to the object shape and their robustness to measurement noise.

3 Results

The results (Fig. 1) show significant shape dependent variations. For the circular shape, sensitivity gradually decreases from the boundary towards the center, whereas in rectangular and triangular shapes a reduced sensitivity in the corners comparable to that in the central region. This difference in spatial distribution leads to more BV variations in rectangular and triangular shapes compared to the BV observed in circular shape.

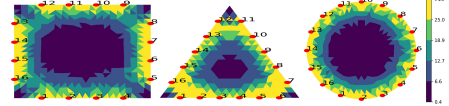


Fig. 1: Distribution of the average sensitivities for different shapes including moving inclusions of 5-10% of the surface area.

This has been reflected in the Fisher score analysis, where range and maximum achieve the highest separability ($F = 2286.95$, $F = 2207.69$), but exhibit unstable behavior under noise with no consistent trend. In contrast, the STD remains stable ($F = 126.09 \rightarrow 147.91$), while AVG-V shows less degradation ($F = 365.92 \rightarrow 285.30$) under increasing noise.

The Random Forest classifier (Fig. 2) achieves 100% classification accuracy, using STD and AVG-V features extracted from BV data that has multiple Gaussian noise levels up to 10%.

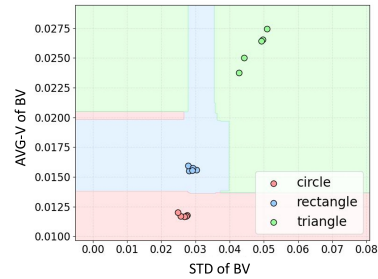


Fig. 2: Object shape classification using BV's STD and AVG-V.

4 Conclusions

BV measurements contain shape-dependent information that can be captured using simple statistical features, where STD and AVG-V enable robust shape discrimination under noise, enabling shape inference prior to reconstruction.

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Solving the Complete Electrode Model with Physics-Informed Neural Networks

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Abstract: We formulate the complete electrode model (CEM) within a physics-informed neural network (PINN) framework, where the electric potential is represented by a neural network optimized by minimizing the PDE residuals. Preliminary results show its promise, though further refinement is required.

1 Introduction

Compared with classic forward solvers such as the finite element method (FEM), neural forward solvers are mesh-free and seamlessly integrate into deep learning-based inversion frameworks. Previous work developed EIT forward solvers based on the *continuum model*[1][2]. However, the complete electrode model (CEM) proves more precise for practical EIT measurements. Here, we propose a neural CEM solver based on PINNs.

2 Methods

We formulate the CEM as PINN loss terms:

$$loss_{gov} = \frac{1}{N_{in}} \sum_{i=1}^{N_{in}} |\nabla \cdot [\sigma(\mathbf{r}_i^{in}) \nabla \phi(\mathbf{r}_i^{in})]|^2, \quad (1)$$

$$loss_{ex} = \frac{1}{L} \sum_{\ell=1}^L \left| \int_{\partial\Omega_{\ell}} j_n(\mathbf{r}) d\mathbf{r} - I_{\ell} \right|^2, \quad (2)$$

$$loss_{bc} = \frac{1}{N_b} \sum_{i=1}^{N_b} |j_n(\mathbf{r}_i^b)|^2, \quad (3)$$

$$loss_{robin} = \frac{1}{L} \sum_{\ell=1}^L \frac{1}{N_{\ell}^e} \sum_{i=1}^{N_{\ell}^e} |\phi(\mathbf{r}_i^e) + z_{\ell} j_n(\mathbf{r}_i^e) - V_{\ell}|^2, \quad (4)$$

where σ is electrical conductivity, ϕ is electric potential, $j_n = \sigma \partial \phi / \partial n$ is normal current density; $\mathbf{r}$ is spatial position (the superscripts ‘in’, ‘b’, and ‘e’ represent positions in the domain, on the boundary not covered by electrodes, and on the boundary covered by electrodes, respectively.); z_{ℓ} , I_{ℓ} , and V_{ℓ} are contact impedance, injected current, and electric potential of Electrode ℓ , respectively; N_{in} , N_b , and N_{ℓ}^e are numbers of collocation points in the domain, on the boundary not covered by electrodes, and on the boundary covered by Electrode ℓ (i.e., $\partial\Omega_{\ell}$), respectively; L is the number of electrodes.

The weighted sum of above losses is minimized on collocation points $\{\{\mathbf{r}_i^{in}\}, \{\mathbf{r}_i^b\}, \{\mathbf{r}_i^e\}\}$ randomly sampled from the domain. A 4-layer MLP (with *Tanh* activation except the last layer) represents the electric potential, mapping spatial positions to electric potentials. Its 4 layers contain 128, 128, 128, and 1 neurons, respectively. Network weights are Xavier-initialized and optimized via Adam ($\text{lr} = 1 \times 10^{-3}$).

3 Results

As shown in Fig. 1(a), a circular domain (diameter 0.14 m) with 16 evenly distributed electrodes (duty ratio 0.5) was created to test the method. The background conductivity and electrode contact impedances were set to 0.134 S/m and 1.5 Ωm^2 , respectively. A 1 mA current was injected. For comparison, an FEM solver using a triangular mesh and a PINN solver using randomly sampled collocation points [Fig. 1(a)] were both implemented. The PINN was trained for 400 epochs.

The electric potential distributions solved by FEM and PINN are shown in Fig. 1(c) and (d), respectively. While the profiles are similar, the PINN result exhibits a slightly larger magnitude than FEM. Fig. 1(b) presents the solved electrode potentials alongside their relative errors. Although errors for most electrodes remain below 5%, the maximum reaches 15%.

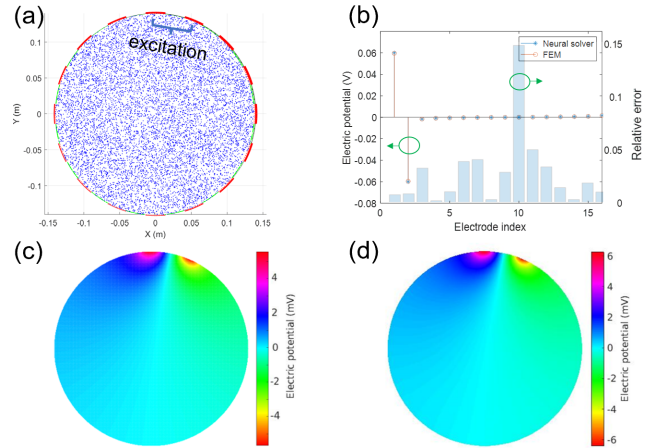


Fig. 1: (a) A circular domain with randomly sampled collocation points. (b) Solved electric potentials on electrodes. (c) and (d) Solved electric potential profiles of FEM and PINN, respectively.

4 Conclusions

We present the basic method and preliminary results of solving the CEM using PINNs. While the results are promising, noticeable discrepancies between FEM and PINN remain, indicating that further refinement of the PINN-based method is needed.

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Bedside EIT-AI for Pulmonary Embolism Assessment in Acute Hypoxaemic Respiratory Failure

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Abstract: We developed an end-to-end artificial intelligence-based electrical impedance tomography (EIT-AI) framework for bedside pulmonary embolism (PE) assessment in acute hypoxaemic respiratory failure (AHRF). In 200 consecutive patients undergoing saline-contrast EIT and reference-standard PE adjudication, the framework automated signal quality control, perfusion-defect segmentation, and PE probability estimation. In independent validation, an EIT-derived dead-space threshold of 30.37% yielded 90.9% sensitivity and 98.6% specificity. EIT-AI produced interpretable ventilation - perfusion mismatch maps, supporting radiation-free bedside PE assessment.

1 Introduction

Computed tomography pulmonary angiography is the reference standard for PE diagnosis, but transport and contrast exposure may be problematic in critically ill patients with AHRF. Saline-contrast EIT enables bedside assessment of regional perfusion and ventilation - perfusion (V/Q) matching, yet clinical implementation remains limited by operator dependence and subjective interpretation. We therefore developed an end-to-end EIT-AI framework to automate quality control, perfusion-defect analysis, and patient-level PE classification.

2 Materials & Methods

We analysed 200 consecutive AHRF patients who underwent saline-contrast EIT and reference-standard PE adjudication. EIT was acquired with a 16-electrode belt at the fourth intercostal space. During an end-expiratory pause (≥ 8 s), 10 mL of 10% NaCl was injected through a central venous catheter. Ventilation maps were derived from tidal impedance variation, and perfusion maps from the slope of regional impedance - time curves after saline injection. Ventilated and perfused regions were defined using a 20% threshold of the maximum signal, yielding ventilation-only, perfusion-only, and V/Q-matched regions. The EIT-AI pipeline included automated signal quality control, automated perfusion-defect segmentation, and patient-level PE probability estimation. Performance was assessed in an independent validation cohort of 48 patients (24 PE-positive and 24 PE-negative).

3 Results

Using the prespecified EIT-derived dead-space percentage for PE classification, a threshold of 30.37% achieved 90.9% sensitivity and 98.6% specificity. The framework generated bedside-interpretable maps highlighting regions of diminished perfusion with preserved ventilation, consistent with PE-related V/Q mismatch. A schematic overview of the study design, EIT-AI workflow, and main findings is shown in Fig. 1.

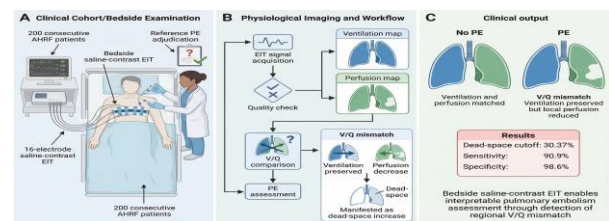


Fig. 1: Central illustration of bedside EIT-AI for pulmonary embolism assessment in acute hypoxaemic respiratory failure. The framework integrates saline-contrast EIT acquisition, automated quality control, ventilation/perfusion mapping, V/Q mismatch analysis, and patient-level PE classification.

4 Conclusions

In this AHRF cohort, saline-contrast EIT enabled accurate bedside PE assessment based on characteristic V/Q mismatch patterns. The proposed EIT-AI workflow may help standardise bedside implementation by automating key analytical steps and providing interpretable perfusion-defect outputs. Further prospective external validation is warranted.

Acknowledgements [optional]

The authors would like to express their gratitude to ...

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EIDORS v3.13

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Abstract: This paper announces the release of version 3.13 of the EIDORS software suite. We review its new features, and make available suitable EIT illustrations.

1 Introduction

We proudly announce the release of EIDORS version 3.13, for the 26th Int. Conf. on Biomedical Applications of EIT, in July 2026. The software is available at eidors.org and licensed under the GNU GPLv2 or GPLv3. Archived versions are available on Zenodo [1–7], and all versions available on sourceforge.net [8–10].

EIDORS provides free software algorithms for forward modelling and inverse solutions of Electrical Impedance and (to some extent) Diffusion-based Optical Tomography, in medical, industrial and geophysical settings. EIDORS also aims to share data and promote collaboration.

2 Features and Growth

Release 3.13 of EIDORS builds upon a strong foundation in reconstruction algorithms, adding and improving a number of aspects.

- improved / less fragile netgen interface
- refactored extruded mesh shapes
- support for acousto-electric tomography
- improved documentation
- graphics improvements and bug work-arounds
- support for new vendor file formats
- better octave support
- (As always) speed-ups and bug fixes

EIDORS-related citations continue to grow (table 1).

In conclusion, EIDORS version 3.13 (hopefully) continues to be useful.

Tab. 1: EIDORS Citations (Apr 2026, scholar.google.com).

Paper	Date	Citations
[14] A MATLAB package for the EIDORS project ...	2001	370
[12] Image reconstruction algorithms for ...	2002	211
[13] A Matlab toolkit for three-dimensional ...	2002	613
[9] EIDORS: Towards a community-based ...	2005	53
[10] Uses and abuses of EIDORS: An extensible ...	2006	1109
[8] Simple FEMs aren't as good as we thought ...	2008	26
[6] EIDORS version 3.9	2017	40
[4] EIDORS version 3.10	2019	9

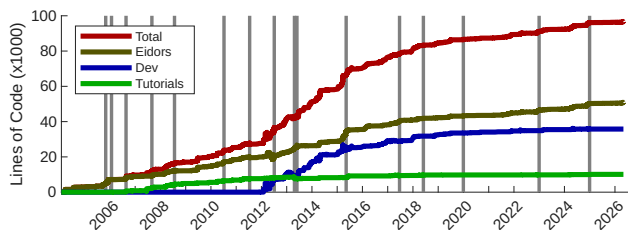


Fig. 1: Lines of Code (LoC) in Matlab files in the EIDORS code-base vs. time; Total (red), EIDORS (i.e. release branch, brown), Tutorials (green), development code (blue). Releases are indicated by gray bars (The 3.12 release is at the right).

3 EIT Illustrations

We make available software and illustrations of the basic concepts of EIT. Software is available in [eidors/examples/eit_intro](https://eidors.org/examples/eit_intro) and figures at [DOI:10.5281/zenodo.19702540](https://doi.org/10.5281/zenodo.19702540), under an creative commons license for use in papers and presentations (fig 2).

Illustrations of equipotential backprojection are often used to illustrate “how EIT works”, even though this is no longer used in any clinical or research EIT systems.

However, it is possible to illustrate linearized time-difference EIT image reconstruction in this way (Fig 2C). From a solution $\hat{\mathbf{x}}$ which minimizes: $\|\hat{\mathbf{x}} - \mathbf{J}\mathbf{y}\|$ for sensitivity matrix $\mathbf{J}$ and difference data $\mathbf{y}$, $\hat{\mathbf{x}} = (\mathbf{J}^T \mathbf{J}^T + \mathbf{R})^{-1} \mathbf{J}^T \mathbf{y} = (\text{Filter})(\text{Backprojection})\mathbf{y}$

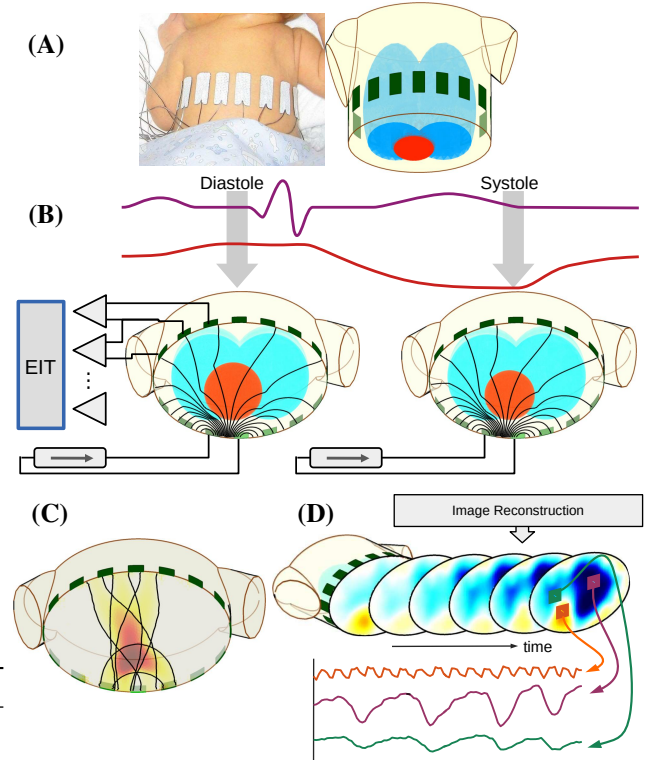


Fig. 2: EIT Illustrations (Images and data from [11]): (A) Subject and FEM; (B) adjacent-drive measurement and the equipotential lines associated with a change in heart blood volume; (C) EIT image from four most sensitive measurements of the heart region; (D) EIT images and waveforms of breathing and heart activity.

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We need good measures of pendelluft so EIT can guide care

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Abstract: EIT provides the only bedside way to examine pendelluft. However, EIT measures of pendelluft are inconsistent. We discuss the importance of standardized EIT measures and clarification of unsolved questions.

1 Introduction

Pendelluft is the movement of air between lung regions, occurring due to intra-tidal changes in local time constants (e.g. airway opening pressures), and pressure gradients resulting from inspiratory or expiratory effort. In effort-related pendelluft, often a decrease in ventral impedance is seen concurrent with an increase in dorsal impedance at the start of inspiration, suggesting air redistribution, likely due to a predominantly dorsal negative pleural pressure swing resulting from diaphragm contraction.

Pendelluft has been associated with worse outcomes, but causality and interlinked mechanisms are not understood. Potential mechanisms include increased “dead space” due to internal movement of air, high local lung stress contributing to both worse outcomes and pendelluft, and/or high effort as a common cause of e.g. fatigue and pendelluft.

Importantly, it is unclear whether pendelluft is a sign of potential lung injury, or independently causes or aggravates it. We must better understand these mechanisms before clinical studies and implementation of EIT during spontaneous breathing and assisted ventilation. Provided that EIT is the only practical technology to detect and monitor pendelluft, we should first agree on how to quantify pendelluft with EIT and which features to report.

2 EIT-based pendelluft measures

Several methods for quantification of respiratory effort-related pendelluft have been published. To note, EIT cannot directly measure air flows between regions, but flows can be inferred from changes in regional volumes.

Waveform based methods

- Difference between amplitude (total impedance change in a pixel) and tidal impedance variation (using global timing) as a fraction of the tidal impedance variation. [1]
- Difference between amplitude and tidal impedance

variation as a fraction of the amplitude. [2]

- Difference between amplitude and tidal impedance variation of four regions summed. [3]

Regional volume shift

- Difference in normalized impedance change between ventral and dorsal regions during inspiration. [4]

Reverse impedance change (RIC)

- Impedance change in the opposite direction (RIC) as a fraction of the amplitude plus RIC. [5]

Unfortunately, there is little consistency between these calculations. It is also not clear whether these capture (all) relevant features of pendelluft.

To explore how delay and waveform shape affect measures, we simulated the results in figure 1. This illustrates that measuring pendelluft based on delay may overestimate pendelluft, while only considering waveforms may underestimate pendelluft due to interference from the delay in ventral inflation.

Other potentially relevant features have, to our knowledge, not yet been studied, including inspiratory and expiratory pressure distribution throughout the thorax; regional airway opening and closing pressures, regional dynamic resistance and compliance, and regional inflammatory status.

3 Discussion

EIT is a potentially groundbreaking technology for the identification and management of pendelluft. However, currently proposed measures can over- or underestimate pendelluft. We recommend strong definitions, work to understand the limitations of proposed measures, and robust calculations.

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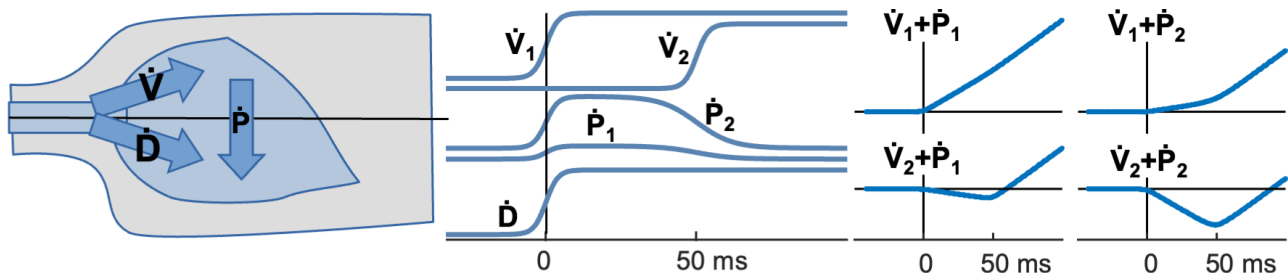


Figure 1: Illustration of pendelluft at the beginning of a breath, using two lung regions and three identifiable flows. (Left) Ventral ($\dot{V}$). Dorsal ($\dot{D}$) and Pendelluft ($\dot{P}$) flows in(to) the lungs. (Center) Prompt ($\dot{V}_1$) and delayed ($\dot{V}_2$) ventral flow and two levels of $\dot{P}$. (Right) ventral impedance over time. A delayed inflation does not mean (significant) pendelluft per se ($\dot{V}_1 + \dot{P}_2$ vs. $\dot{V}_2 + \dot{P}_1$). Differences in waveform amplitude do not relate directly to the amount of pendelluft ($\dot{V}_1 + \dot{P}_2$ vs. $\dot{V}_2 + \dot{P}_2$).

Session 3: Instrumentation & Hardware

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Open-Source Data Acquisition Hardware for Fast Neural EIT

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Abstract: Fast Neural EIT imaging typically requires a high-end, research-grade biopotential amplifier for data acquisition. To facilitate the dissemination of this technique, we developed a more affordable, open-source system, based on off-the-shelf components, that matches the performance of commercial solutions in nerve recordings.

1 Introduction

Fast Neural EIT (FN-EIT) images functional neural activity by detecting tiny impedance changes caused by ion channels opening in neural tissue [1]. Our lab previously developed the modular FN-EIT platform *ScouseTom* [2], which integrates a commercial, research-grade biopotential amplifier for high-resolution, high-speed data acquisition. While such amplifiers meet the stringent FN-EIT low-noise requirements, their high cost ($\approx \$25\text{--}40\text{k}$), proprietary software, and closed architectures may discourage adoption. Other *ScouseTom* sub-modules, such as the current sources, have already been replaced with custom solutions [3]. Here, we present an open-source, high-resolution, high-speed biopotential amplifier built from off-the-shelf components. Designed primarily for FN-EIT, it is broadly compatible with other biopotential recording applications (EEG, ECG, and EMG). To our knowledge, no existing open-source device combines all of these high-end features.

2 Materials & Methods

The device has specifications comparable to research-grade EEG systems: 24-bit resolution, 10 kHz bandwidth, 50 kHz sampling rate, 32 recording channels, eight auxiliary trigger channels, no custom ASICs, a battery-powered front end, and high-speed digital isolation. An FPGA board (Mimas A7 Mini, Numato Lab) provides digital control and USB data streaming to a PC. Data are acquired via a Python script and processed in MATLAB. A stacked PCB architecture allows short high-speed digital traces and separates the power, analog, and digital sections. An off-the-shelf 9-12 V power bank supplies the electrically isolated front end. After testing basic functionality of the device recording in saline solution, we performed a comparative in vivo test of the novel device by repeating our previously published FN-EIT nerve experiment [1] using both the original *ScouseTom* system and the novel device. EIT was performed on the main nerve trunk at 6 kHz, 150 μA using a 14-electrode cuff with a skip-4 protocol, while action potentials were evoked in the tibial branch of the same nerve by delivering electrical pulses through a bipolar electrode cuff. Coherent averaging was performed over 150 pulses for each EIT injection pair to reduce noise.

3 Results

The final device iteration had a compact size of $\approx 85 \times 85 \times 60$ mm, power bank excluded, and cost ≈ 270 USD (FPGA board excluded), two orders of magnitude lower than commercial high-end EEG recorders. Power consumption during recordings was 158 mA, enabling ≈ 57 hours of operation from a 9000 mAh 9-12 V power bank. In saline solution, noise levels in the full 0.1 Hz-10 kHz bandwidth

were 12.4 ± 0.3 μV and 10.5 ± 0.8 μV ($p=4.5\text{e-}10$, $N=29$ electrodes) for the custom and commercial devices, respectively. In nerve, baseline EIT voltages (BVs) collected by the custom and reference devices were highly correlated ($R>0.93$). Pre-stimulation noise levels were 0.36 ± 0.21 μV vs 0.83 ± 0.36 μV ($P<0.05$) for the novel and reference devices, respectively. Peak amplitude of evoked neural impedance changes (δV) detected by both devices was comparable in amplitude (2.0 ± 1.4 μV vs 3.2 ± 1.7 μV , $P<0.05$). Baseband neural evoked potentials (EPs) collected by the novel device had comparable peak amplitudes to the reference ones (121 ± 25 mV vs 130 ± 26 mV, $P<0.05$) and a visually similar shape.

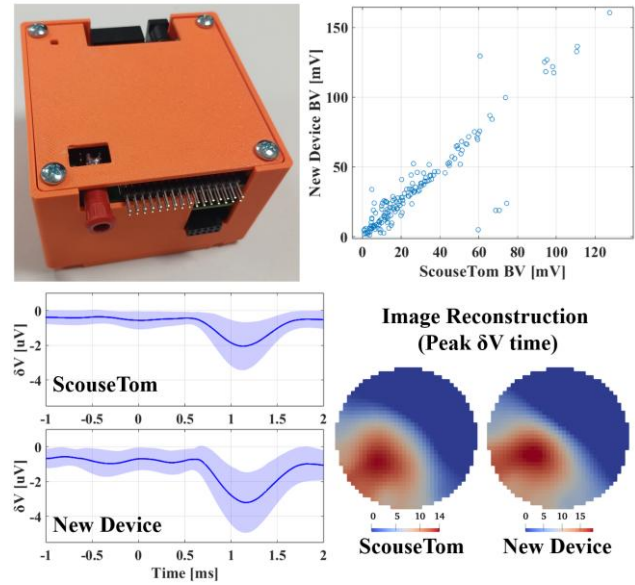


Fig. 1: Top left: The novel data acquisition device. Top right: BV correlation between the novel device and *ScouseTom*. Bottom left: Time course of impedance changes. Bottom-right: Image reconstruction.

4 Conclusions

Our device is a low-cost, compact, open-source solution for data acquisition in FN-EIT. Results from peripheral nerve recordings in the rat sciatic nerve are comparable to the reference instrument. Small but significant differences between devices in EP/ δV values may be hardware-related and be mitigated with calibration or be the result of nerve condition deterioration between recordings. In future iterations, we may expand the system to 64 channels, and incorporate analog auxiliary inputs.

Acknowledgements

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An FPGA-Based High-Speed Real-Time Frequency Division Multiplexed EIT System for Measuring Neural Impedance Changes

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Abstract: In this work, an FPGA-based high-speed EIT system for measuring neural impedance change (dZ) was developed, and the noise level in the measured signals was quantified in phantoms and in vivo. The system exhibits sufficiently low noise for measuring sub-microvolt dZ, indicating its suitability as a high-speed fnEIT system.

1 Introduction

Electrical impedance tomography (EIT) can be potentially used to image the impedance changes (dZ) associated with fast neuronal activity at a high spatiotemporal resolution (200 μm and 2 ms) [1]. To date, these images are reconstructed from temporally averaged neural activity recordings to improve the signal quality, limiting its clinical feasibility. A parallel EIT system using frequency-division multiplexing could enable real-time imaging of single neuronal events by simultaneously injecting current through multiple electrode pairs at different frequencies.

Impedance changes due to neuronal depolarisation are approximately 0.1-0.3% in fast neural EIT (fnEIT) recordings [2]. Characterising fast neural dZ with 2 ms temporal resolution requires a ± 500 Hz filter bandwidth; therefore, injected current frequencies must be separated by at least 1 kHz. Fast neural dZ decreases with frequency and has been characterised only up to 10 kHz [1].

The ScouseTom is an EIT system currently used for brain and nerve EIT in the UCL EIT lab. It allows users to control experimental parameters and data processing [3]; however, the bandwidth of its EEG recording system is limited by its antialiasing filter (7.5 kHz). Here, we developed and evaluated an fnEIT recording system for accurate and low noise dZ measurements at high frequencies (≥ 10 kHz).

2 Materials & Methods

2.1 System Design

The hardware comprises an eight-channel analogue front-end circuit, a 24-bit analogue-to-digital converter (ADC) evaluation module sampling at 512 kHz, an isolated level-shifting circuit, a Xilinx Artix-7 (Mimas A7) FPGA board for a high-speed data streaming, and a USB interface for data transfer to a host PC for further processing (Fig. 1).

2.2 System Characterisation

To assess system noise, experiments were performed on a resistor network approximating rat brain load, a resistor phantom that delivers a pulse wave resistance change, lasting 20 ms, of 0.15%, and a rat sciatic nerve in response to stimulation of individual tibial nerve.

For the first two test objects, a four-terminal configuration was used to measure resistances by injecting a 100 μA constant-amplitude current through a single electrode pair at 1-100 kHz, while voltages were recorded from other pairs.

In fnEIT of the peripheral nerve, the dZs were recorded, using a cuff array with a ring of 14 electrodes around the circumference of the nerve by applying an alternating current of 150 μA at 6 kHz to two electrodes and measuring voltages from other electrodes. The nerve was stimulated at 5 Hz; the data was then split into 200 ms epochs and averaged over 147 compound action potentials.

The noise was defined as the standard deviation compared to the background signal. It was estimated from the bandpass filtered (order= 1; BW= ± 500) and demodulated voltage signals and then compared to the ScouseTom system [3].

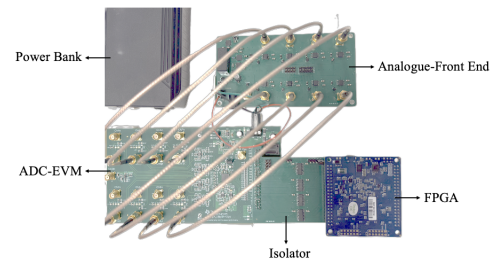


Fig. 1: FPGA-based high-speed fnEIT system hardware.

3 Results

Noise levels in the resistor network, resistor phantom, and in vivo (Fig. 2) were similar ($\approx 0.01\%$) for both systems.

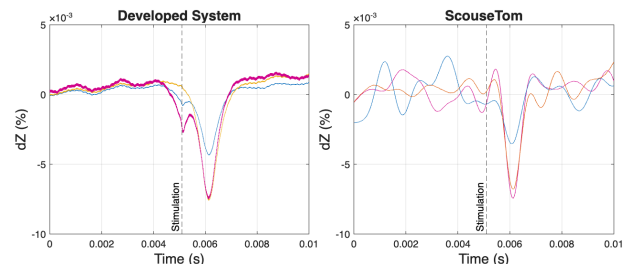


Fig. 2: In vivo averaged dZ traces across multiple channels: developed system (left) and ScouseTom (right), 6 kHz.

4 Conclusions

The developed system had comparable noise to the ScouseTom and demonstrated a reliable performance in measuring fast neural dZ at 6 kHz, with ongoing work investigating higher frequencies [4]. Although the system is currently limited to eight simultaneous channels, ongoing work aims to expand it to 64 channels, enabling a real-time frequency-multiplexed fnEIT for clinical neural diagnostic interfaces and close-loop neuromodulation.

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DMA-Optimised Acquisition Framework for Portable EIT Systems

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Abstract: This work-in-progress addresses conventional timing and throughput limitations through deterministic synchronisation and efficient data handling in microcontroller based EIT devices, enabling dynamic physiological monitoring while maintaining a lean hardware profile.

1 Introduction

The translation of Electrical Impedance Tomography (EIT) to portable and wearable applications is hindered by the trade-off between power efficiency and data throughput [1,2]. Conventional microcontroller based (MCU) architectures rely on CPU-intensive polling and low-bandwidth serial transmission, limiting frame rates for dynamic physiological monitoring.

This work proposes a high-performance framework designed to overcome these systemic bottlenecks by leveraging advanced hardware peripherals and a concurrency-optimised data pipeline.

2 Proposed Architecture

The framework transitions to a concurrency-optimised architecture leveraging the ESP32-S3 peripheral matrix. The system functional organisation is illustrated in Fig. 1.

2.1 Synchronous Signal Generation and Acquisition

To ensure phase coherence, the excitation signal is generated by a hardware peripheral sharing a common clock domain with the SPI-based 1 Msps ADC. This deterministic hardware synchronisation maintains a fixed phase relationship between excitation and acquisition, eliminating software-induced jitter and enabling reliable digital phase demodulation.

2.2 DMA-Driven Data Handling

Instead of CPU-intensive polling, Direct Memory Access (DMA) channels ADC samples directly into the Extended SRAM (PSRAM). This "RAM-centric" approach decouples acquisition from the main processor, allowing the CPU to dedicate its cycles to high-speed switching of the multiplexer network and managing precise settling intervals to minimise transient noise.

2.3 High-Throughput Storage and Streaming

To bypass wireless transmission bottlenecks, the framework implements a dual-stage buffering strategy. Data stored in RAM is periodically flushed to an onboard microSD card via the 4-bit SDMMC protocol. This provides a massive data sink supporting high frame rates (target >20 fps) without risk of buffer overflow. Post-acquisition, data can be streamed via Wi-Fi for cloud- or edge-based image reconstruction and analysis.

3 Preliminary evaluation

Initial benchmarks focus on throughput and timing determinism via analytical modelling.

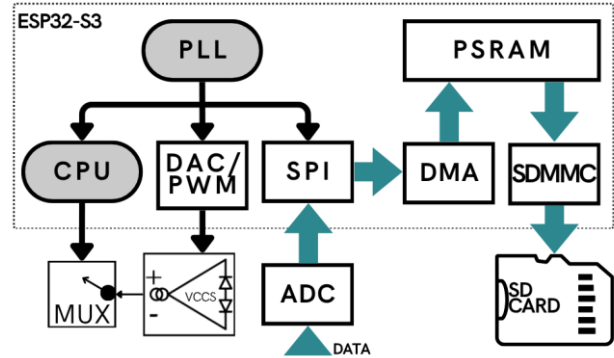


Fig. 1: Optimised EIT acquisition pipeline. The architecture highlights the synchronisation between signal generation and SPI sampling, bypassing CPU-intensive bottlenecks.

3.1 Acquisition Timing and Oversampling Strategy

At 50 kHz excitation, an 8-cycle oversampling window is implemented for SNR enhancement. Accounting for a conservative 10 μ s multiplexer settling time, each measurement takes 170 μ s. A 208-measurement frame is completed in 35.3 ms, yielding 28.3 fps, exceeding the 20-fps standard for capturing fast physiological transients.

3.2 Phase Synchronisation and Clock Determinism

Deriving excitation and acquisition clocks from a common PLL ensures deterministic phase alignment required for quadrature demodulation. Simulations confirm negligible phase-drift and sufficient SDMMC bandwidth for zero-loss logging during continuous monitoring.

4 Conclusions

This framework demonstrates that high-performance EIT can be achieved through intelligent component selection and ingenious peripheral management rather than increasing circuit complexity. By bypassing traditional MCU bottlenecks, the system reaches a temporal resolution that meets clinical standards for dynamic monitoring.

This development is a significant step towards the democratisation of medical technology, offering a high-speed, low-cost blueprint suitable for remote or resource-limited areas. Future work will focus on technical validation and signal integrity assessment, ensuring that precision remains accessible in a portable hardware profile.

Acknowledgements

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3D FE Simulations on Digital Twins to study Effects on Electrical Impedance Measurements on the Human Thorax

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Abstract: EIT measurements are influenced by electrode positions, body shape and composition. Simulations on digital twins of healthy subjects with EIT examinations in multiple planes were done based on MRI scans. Evaluation of simulated data showed similar effects as the measurements and can help to improve interpretation.

1 Introduction

Electrical Impedance Tomography can be used to study static and dynamic behaviour of the human lung. To date, clinical devices mostly use measurements in one single plane on the thorax. In order to investigate the whole lung as a real 3D object, an extension to more planes or real 3D configurations is necessary. To achieve this in normal conditions and in weightlessness, a multiple plane EIT device was developed and tested during parabolic flights [1]. While former measurements in one plane [2] yielded plausible results under normal conditions as well as in weightlessness, measurements in multiple planes showed surprising results. A clear gradient was particularly evident in sitting position in weightlessness, although an almost homogeneous air distribution in the lungs would be expected due to the lack of a gravity vector. Therefore, simulations have previously been carried out on a wide range of models based on CT scans of patients with healthy lungs [3]. These revealed large inter-individual variations. Consequently, we started creating subject-specific models.

2 Simulations on Digital Twins of Subjects

MRI data of the thorax was recorded on some of the test subjects who had been examined by EIT under changing gravity conditions during a parabolic flight. Using the MRI images, Synopsys Simpleware was used to segment the lungs, heart, large vessels, bones, fat, muscles and organs, the latter summarised as background. From this, volume meshes were generated and imported into COMSOL Multiphysics, where the various areas were parameterised with conductivity values from literature [4]. Electrode positions were generated in 4 levels with 16 electrodes each (3 of them the same plane as the original measurements) and configurations in adjacent drive patterns were used, analogous to the measurements. The process was executed by Matlab scripts. From the datasets, images of absolute resistivity were reconstructed and analysed to deliver the resistivities of left and right lungs in the same way as for real measurements [2].

3 Results

The evaluation of the synthetic data sets generally confirms the dependence of the tomographically determined lung resistivity on the plane position. This

means that the originally large differences between the measurement planes, which indicate a strong cranio-caudal dependency, are largely due to the influence of body shape and composition. After correction on the basis of the individual thorax models, this influence is considerably smaller. It remains to be investigated in more detail to what extent the low residual inhomogeneities are physiologically caused or whether an even more precise recording of the methodological influences is necessary.

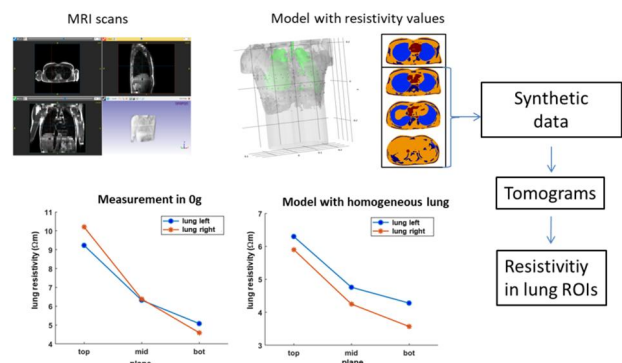


Fig. 1: Simulation and measurement results of a subject. From MRI scans of the thorax, a detailed model of the thorax (with extrusion to abdominal parts) with assigned conductivity is generated. Synthetic data sets are calculated and analysed tomographically. The reconstructed lung resistivity as a function of the plane position is compared with the result of the measurements.

4 Conclusions

Simulations on detailed digital twins of human subjects under investigation can give valuable information on the interpretation of EIT measurements in multiple plane or general 3D EIT in future.

Acknowledgements

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Automated Multi-Tissue FEM Generation for Electrical Impedance Tomography from CT Data

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Abstract: We present a fully automated pipeline for generating anatomically consistent multi-tissue Finite Element Models (FEMs) of the human thigh from computed tomography (CT) data. Evaluation showed high geometric consistency between CTs and FEMs, indicating reliable anatomical transfer and first EIT reconstructions were successful.

1 Introduction

In anatomically heterogeneous regions such as the human thigh, variations in tissue composition result in complex geometric structures and spatially varying electrical properties that must be adequately represented in numerical models used for EIT [1]. While radiographic imaging modalities provide sufficient contrast for multi-tissue modeling, the generation of anatomically realistic FEMs typically relies on manual or semi-automatic segmentation [2]. In this work, a fully automated pipeline is presented for generating anatomically consistent multi-tissue FEMs of the human thigh from CT data, enabling the direct creation of subject-specific forward models for EIT simulations.

2 Methods

The whole pipeline can be seen in Fig. 1. The dataset used to generate the pipeline consists of 94 unlabeled CT scans of the human thigh from multiple publicly available sources. Twenty-one scans are used for development and the remaining scans are used for evaluation.

2.1 Segmentation approach

The CT data is segmented using a hybrid approach. Muscle, fat tissue and the surrounding background are segmented using a classic intensity-based approach, as they can be distinguished by their corresponding Hounsfield units [3] and only a limited number of CT scans are available. Since the intensity values of bone marrow overlap with those of muscle and fat tissue, MedSAM [4], a deep learning foundation model for medical image segmentation, is applied to segment bone and bone marrow by incorporating automatically generated bounding boxes.

2.2 Finite Element Model Generation

Based on the multi-class segmentation masks, 3D surface representations of each tissue type are extracted using the

Marching Cubes algorithm [5]. Volumetric FEMs are generated for each tissue using the tetrahedral meshing algorithm PyGALMesh [6] and assembled into a unified multi-tissue model, where each tetrahedron is assigned a tissue-specific label. The resulting FEMs can be directly used for EIT simulations within the EIDORS frame work [7] without further manual post-processing.

3 Results

The pipeline generates anatomically consistent multi-tissue FEM models from CT scans (see illustrative example in Fig. 1). For quantitative evaluation, a subset of CT slices was manually segmented. These annotations are compared to both the automated segmentations and the corresponding virtual slices of the generated FEMs by computing Dice coefficients for each tissue type as well as the global voxel accuracy. The average Dice coefficients for the four tissue types range from 0.927 (muscle) to 0.789 (bone marrow) and the global voxel accuracy between manual segmentation and FEM-based representation is 0.943. Initial reconstruction results using the GREIT algorithm [8] further support the fidelity of the proposed pipeline.

4 Conclusions

We presented a fully automated pipeline for generating anatomically consistent multi-tissue FEMs of the human thigh from CT data. The results demonstrate that the proposed approach enables reliable anatomical modeling and produces FEMs suitable for EIT simulations without manual intervention. The pipeline is readily extendable to other anatomical regions and has the potential to facilitate large scale data generation and model-based studies in EIT research.

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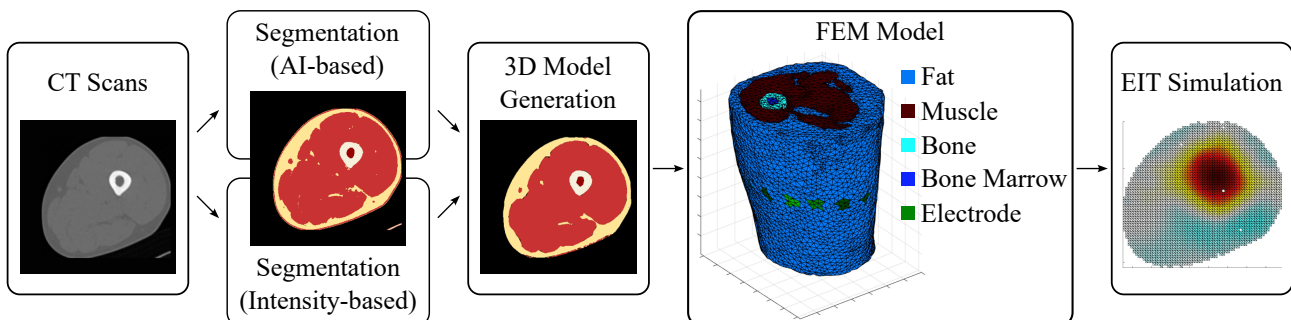


Fig. 1: Pipeline from CT scan to FEM model including segmentation and reconstruction.

Next-generation EIT: Will relaxation spectroscopy meet tomography?

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Abstract: Combining EIT with relaxation spectroscopy promises fast tissue characterization on cost-effective hardware. A simulation framework was set up, alongside evaluating the hardware requirements for a real implementation. Initial simulations using the "Distribution of Relaxation Times" (DRT) method performed as expected.

1 Introduction

Biological tissue exhibits not only resistive, but also capacitive behaviour. Capturing the frequency-dependent impedance response can be helpful for tissue classification. The traditional way of doing so is applying a set of different frequencies subsequently, or simultaneously in combination with a Fast Fourier Transformation (FFT), which both costs time and/or requires powerful hardware. An alternative approach is offered by relaxation spectroscopy, where a step function serves as excitation and the resulting relaxation curve is measured in time domain. This curve is then fit to a suitable model, which allows calculating the impedance for a wide range of frequencies. The goal of this project is to combine that principle with electrical impedance tomography (EIT). At first, it was to be examined through simulation, for which a framework was set up.

2 Materials & Methods

2.1 EIDORS modifications

The MATLAB toolkit *EIDORS* [1] is the de facto standard software of EIT research. For this project, *EIDORS* has the drawback of operating solely in the frequency domain, and not being designed for multi-frequency operation. These disadvantages were overcome by transforming the rectangular excitation function into frequency domain, then calling the *EIDORS* forward solver, and finally transforming the resulting voltage vector back into time domain. The frequency spectrum was covered by performing the simulation for each frequency independently. The FEM model was linked to the Gabriel-Gabriel database [2–4], which offers an extensive impedance dataset of numerous biological tissues across a wide range of frequencies.

A problem was the computational cost of running the simulation for each single frequency. This was addressed by using the forward solver only on the frequencies where the excitation function's FFT had a local maximum, and filling the gaps by cubic interpolation. To further enhance processing speed, modifications allowing to distribute the simulations across the available CPU cores were added.

2.2 Assessment of hardware requirements

The relaxation processes that can be measured with a certain hardware are limited by two factors:

1. The sampling rate
2. The length of the measurement window / the width of the excitation pulse

The first factor determines the smallest measurable time constant, the second one determines the largest one. Since

an infinite step function is impractical, and electrode polarisation is to be avoided, positive and negative rectangular pulses of a certain width are applied alternately. The Gabriel-Gabriel database showed that a measurement window of half a second already suffices to cover the slowest relaxation processes. For covering the fastest ones, a sampling rate of several MHz is required.

2.3 Material characterisation using DRT

The approach of fitting the relaxation curve to an impedance model, as mentioned in the introduction, has the disadvantage of many parameters, as well as being dependent on assumptions about the circuit form and initial guesses. The DRT method regards the impedance as an ohmic resistance in series with an infinitely dense series of RC circuits, which results in a continuous distribution of relaxation times. The eventual result is a spectrum of "relaxation strengths" $G(\tau)$, stating how much each relaxation time τ contributes to the overall signal. In practice, τ is within the limits τ_{min} and τ_{max} determined by the hardware, see [5] for details.

A discrete version of $G(\tau)$ can be numerically calculated from the measured relaxation curve using Tikhonov regularisation. After doing so for each EIT channel, scalar features emphasising different aspects (for example the ohmic resistance or the intensity of relaxation processes) can be extracted from $G(\tau)$, which are used as data frames for conventional EIT reconstruction algorithms.

3 Results

Initial simulations involving muscle, blood and fat were conducted. The properties of the respective tissue types (taken from the Gabriel-Gabriel database) could be recognised in the reconstructed EIT images.

4 Conclusions

In this work, combining time-domain impedance analysis with EIT was explored simulatively. A framework involving *EIDORS* extensions and the Gabriel-Gabriel database was implemented. The results of simulations using the DRT method for impedance reconstruction seem to confirm the principle.

Acknowledgements

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Session 4: Lungs & Ventilation II

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THOSIM: An EIT Lung–Thorax Simulation Platform

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Abstract: THOSIM (THoracic Open SIMulation) is a hybrid ex-vivo EIT phantom combining CT-derived 3D-printed porcine thoracic anatomy, an agar conductive medium, and a ventilated explanted porcine lung. Simultaneous 32-electrode EIT (EIT Pioneer Set, Swisstom) and spirometer recordings were obtained under two filling conditions (dry agar; agar + 0.9 % NaCl) and two electrode types (stainless-steel; custom flexible gold). EIT mean voltage correlated linearly with spirometer tidal volume under saline conditions; custom flexible electrodes achieved comparable SNR. THOSIM is a step towards a low-cost proof-of-concept for next-generation EIT algorithm validation.

1 Introduction

Reconstruction of regional conductivity changes in EIT requires validated forward models and test phantoms [1]. Existing phantom designs range from static or simply dynamic saline tanks to geometric approximations, sacrificing physiological realism. [2, 3]. THOSIM addresses this by embedding a ventilated, explanted porcine lung within an anatomically shaped agar phantom, enabling controlled breathing manoeuvres without live animal experiments.

2 Materials & Methods

Phantom construction. Porcine thoracic anatomy (vertebrae, ribs, sternum, lung cavity, heart) was segmented from CT data (Marc Bodenstein, University Medical Center Mainz, 2007), scaled to adult porcine equivalent, and FDM-printed. Structures were assembled inside a cylindrical plexiglas tank (30 cm diam., 50 cm height). A three-part, magnetically coupled negative lung shape was used to cast and then cleanly remove the agar cavity. Agar-agar (14 g/L+9 g/L NaCl) was poured at 41 °C and set overnight. A conserved explanted porcine lung (NASCO) was attached via a silicone-sealed tracheal connector.

Ventilation & acquisition. A Hamilton ventilator drove CMV+ breathing ($V_T = 450$ mL, 14 bpm, PEEP = 10 cmH₂O). A calibrated spirometer (100 Hz, $C = 4.95$ L/s/V) recorded flow and tidal volume. A Swisstom Pioneer Set (rev B; 200 kHz, 2 mA, 50 fps, 4-skip, 32 electrode) acquired EIT data. Mean voltage changes (ΔV) were extracted (Gaussian-smoothed [$\sigma = 2$], 2σ outlier-filtered) under four conditions combining dry/saline agar with stainless-steel or custom CT-compatible flexible gold electrodes (TPU substrate).

3 Results

Dry-agar conditions produced a paradoxical ΔV decrease during inspiration; saline filling restored the expected positive ΔV response. Time-aligned OLS regression (20 breaths, 0.05 L/s flow mask) between ΔV and tidal volume yielded high correlations for both dry ($R^2 = 0.94$, -143.6 ml/ μ V [steel]; $R^2 = 0.92$, -108.2 ml/ μ V [flex]) and saline ($R^2 = 0.88$, 85.7 ml/ μ V [steel]; $R^2 = 0.91$, 76.8 ml/ μ V [flex]) conditions. Both stainless-steel and flex electrodes produced usable SNR (Tab. 1). Phase lag was below 170 ms for both electrode types under saline, confirming adequate temporal fidelity.

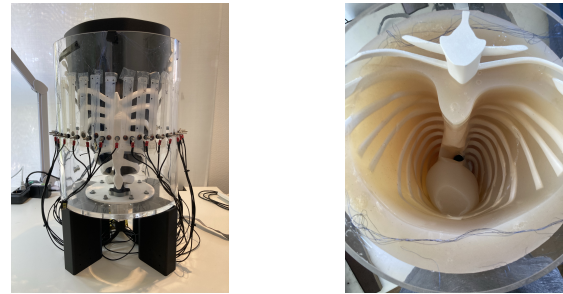


Fig. 1: Phantom setup. (left) Assembled tank with electrodes. (right) Agar cavity after lung inlay removal.

4 Conclusions

THOSIM is a viable proof-of-concept for a hybrid organic–synthetic EIT phantom. Saline filling proved mandatory for normal voltage responses. Custom flex electrodes provide a feasible CT-compatible alternative with comparable SNR to stainless-steel. A notable limitation of this ex-vivo model is the absence of cardiac perfusion, which constitutes a significant interference signal in clinical in-vivo scenarios. Future work will optimize dry coupling.

Acknowledgements

The author thanks the team of Faculty of Health Sciences for general support and Marc Bodenstein at University Medical Center Mainz for providing the porcine CT data.

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Tab. 1: Breath-amplitude SNR and phase lag ($V_T = 450$ mL). $\text{SNR}_{\text{breath}} = \text{breath amplitude} / \text{noise } \sigma$.

Cond.	Electrode	SNR (dB)	Lag (ms)
Dry agar	Steel	22.9	−314
Dry agar	Flex	24.4	−333
+ Saline	Steel	25.4	−163
+ Saline	Flex	26.5	−156

Differences in regional ventilation during induction of general anaesthesia between men and women: preliminary observations

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Abstract: Monitoring patients during induction of general anaesthesia revealed sex-specific differences in regional ventilation distribution. Female patients had a lower proportion of ventral ventilation throughout the whole induction process spanning from spontaneous breathing up to mechanical ventilation via endotracheal tube.

1 Introduction

Electrical impedance tomography (EIT) provides bedside, radiation-free imaging of regional lung ventilation and has become an established tool in the clinical context. Although EIT is widely used in clinical practice and research, only few studies have examined sex-specific differences in ventilation distribution. The available evidence is largely limited to studies in awake patients [1, 2], with only a single retrospective study investigating mechanically ventilated ICU patients [3]. Systematic analyses in this population remain scarce.

2 Materials & Methods

We present preliminary results of a retrospective analysis of data from two prospective observational studies registered in the German Clinical Trials Register (DRKS00012581 and DRKS00033074). Both studies were approved by the Ethics Committee of the University of Freiburg and written informed consent was obtained from all participants. A total of 49 patients undergoing general anaesthesia with endotracheal intubation were included (20 female, 29 male). Continuous EIT monitoring was performed throughout the anesthetic induction sequence using a PulmoVista 500 (Dräger Medical, Lübeck, Germany).

Ventilation distribution was assessed as the primary outcome using tidal variation [4] as surrogate parameter. Secondary outcome was homogeneity of ventilation distribution represented by the global inhomogeneity index [5]. Both parameters were calculated for the functional tidal images calculated for four phases of the induction process: spontaneous breathing (SB), preoxygenation (PO), mask ventilation (MV) and ventilation via endotracheal tube (ET). Groups were compared using unpaired t-tests for each phase. Results are presented as mean $\pm$ standard deviation. A p-value below 0.05 was considered statistically significant. The data presented are the first observations of an ongoing analysis comprising a more comprehensive multivariate approach.

3 Results

We found women to have markedly lower proportion of ventral ventilation for all four phases of the induction process compared with men (figure 1). During mechanical ventilation via facial mask as well as via endotracheal tube, air

was distributed significantly more homogenous in women compared with men (MV: 0.5 ± 0.08 versus 0.6 ± 0.11 , $p < 0.001$; ET: 0.49 ± 0.07 versus 0.56 ± 0.1 , $p = 0.002$). We found that men had a significantly higher body mass index (men: $24 \pm 2 \text{ kg} \cdot \text{m}^{-2}$, women: $22 \pm 2 \text{ kg} \cdot \text{m}^{-2}$, $p = 0.002$) and received significantly more tidal volume during mechanical ventilation via endotracheal tube (men: $582 \pm 50 \text{ ml}$, women: $464 \pm 36 \text{ ml}$, $p < 0.0001$). The latter effect persisted when normalizing the tidal volume to the body mass index (men: $24 \pm 3 \text{ ml} \cdot \text{kg}^{-1} \cdot \text{m}^2$, women: $21 \pm 2 \text{ ml} \cdot \text{kg}^{-1} \cdot \text{m}^2$, $p < 0.0001$).

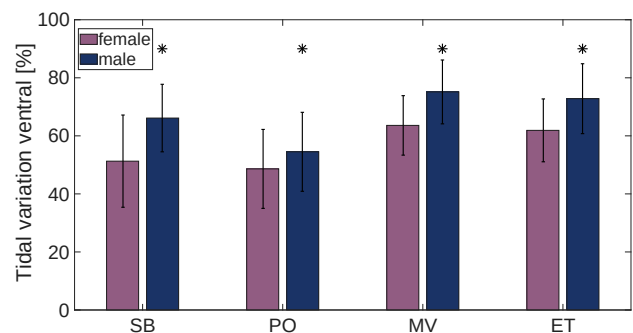


Fig. 1: Ventral tidal variation over the four considered phases of induction of anaesthesia. Women had lower shares of ventilation in the ventral parts of the lung than men during spontaneous breathing (SB), preoxygenation (PO), ventilation via facial mask (MV) as well as ventilation via endotracheal tube (ET).

4 Conclusions

Our preliminary analysis reveals a consistent sex-related pattern in the distribution of ventilation during anaesthesia induction. These differences coexist with higher BMI in men and larger absolute tidal volumes during ventilation via endotracheal tube. Importantly, normalizing tidal volume to BMI does not eliminate the sex disparity in volume.

Because the current data-set has not yet been subjected to comprehensive multivariate adjustment for potential confounders, the observed sex differences must be interpreted with caution. Confirmation as to whether these differences are caused by intrinsic sex-related anatomical or physiological factors will demand a fully adjusted statistical framework and, ideally, prospective validation in a larger, balanced cohort. The results presented here should therefore be regarded as exploratory and hypothesis-generating rather than definitive.

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Frequency-Domain EIT Features for Detecting Apnoea in Premature Neonates

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Abstract: Electrical impedance tomography (EIT) lung impedance signals from 15 premature neonates were analysed with fast Fourier transform and power spectral density before, during and after apnoea. Frequency features gave the best detection performance (AUC 0.981, sensitivity 85.96%, specificity 96.67%).

1 Introduction

Electrical impedance tomography (EIT) measures regional changes in thoracic impedance, enabling continuous, radiation-free bedside assessment of neonatal lung aeration and ventilation [1–3]. Apnoea of prematurity is frequent in preterm infants and is associated with oxygen desaturation, bradycardia and cardiorespiratory instability [4,5]. As apnoea alters the periodic structure of lung impedance waveforms, this study evaluated whether amplitude, dominant frequency, and power spectral density features can distinguish apnoea from non-apnoea periods.

2 Materials & Methods

Retrospective EIT lung impedance waveforms from 15 premature neonates (median gestational age 31 weeks) were segmented into pre-apnoea, apnoea and recovery windows. Signals were detrended and transformed using the fast Fourier transform (FFT); power spectral density (PSD) was calculated to quantify power across respiratory frequencies. Feature groups comprised time-domain amplitude descriptors, dominant-frequency/spectral descriptors and PSD-based power descriptors. Group differences were assessed using two-way ANOVA with Tukey's post hoc testing ($p < 0.05$). Classification performance was evaluated using ROC analysis and random forest models, where sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and area under the curve (AUC) were calculated and reported.

3 Results

Apnoea produced a clear spectral redistribution of EIT lung impedance signals. Frequency features were the strongest single-feature group (AUC 0.981), outperforming amplitude (AUC 0.813) and power (AUC 0.923). Combined-feature models, although yielding lower AUC, improved discrimination across complementary metrics; amplitude + power achieved the highest specificity (98.33%) and PPV (96.00%), while power + frequency achieved the highest sensitivity (89.47%). Full performance metrics are listed in Tab. 1.

4 Conclusions

Apnoea can be detected in the time domain through reduced breathing-signal amplitude, but this may not reliably distinguish true apnoeic events from shallow or irregular respiration. Frequency-domain analysis is more sensitive because it captures shifts in the distribution of signal energy and disruptions to the normal respiratory rhythm. Therefore, spectral features from neonatal EIT signals provide a robust, clinically relevant basis for automated apnoea detection in preterm infants. Larger multicentre studies are needed to validate this approach against clinical annotations and assess real-time bedside implementation.

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Tab. 1: Diagnostic performance of EIT-derived feature groups for apnoea detection.

Feature	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	AUC
Amplitude	54.39	88.33	68.89	80.30	0.813
Frequency	85.96	96.67	92.45	93.55	0.981
Power	78.95	88.33	76.27	89.83	0.923
Amplitude + Frequency	71.93	92.50	82.00	87.40	0.928
Amplitude + Power	84.21	98.33	96.00	92.91	0.980
Power + Frequency	89.47	97.50	94.44	95.12	0.979

Clinically unrecognised single-lung ventilation during infant intubation detected by EIT: a clinical case study

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Abstract: Electrical Impedance Tomography (EIT) was used to monitor ventilation distribution in a 7-month-old infant during general anaesthesia. Despite clinically confirmed intubation, EIT revealed right-dominant ventilation (92%), indicating single-lung ventilation. This remained clinically unrecognised. These findings support the role of EIT in perioperative airway monitoring.

1 Introduction

Endotracheal tube (ETT) malposition during infant anaesthesia may result in unintentional single-lung ventilation, that standard clinical assessment based on auscultation, oxygen saturation, and end-tidal CO₂ may not reliably detect [1,2]. Small airway dimensions and a short trachea, increase the risk of tube displacement in infants [3,4]. Electrical Impedance Tomography (EIT) provides non-invasive, real-time monitoring of regional ventilation distribution [5,6]. This case study illustrates the potential of EIT to detect clinically unrecognised ventilation abnormalities during infant intubation.

2 Materials & Methods

This case study is part of the larger prospective study on ventilation distribution during perioperative anaesthesia in infants. The ClinicalTrials.gov identifier for this trial is NCT03455413. Infants undergoing elective surgery were monitored during general anaesthesia using EIT (SenTec BB2, SenTec AG, Switzerland) with a 32-electrode textile belt positioned at the nipple level. Ventilation distribution was continuously recorded during induction, intraoperative care and up to 2 hours after extubation.

Treating clinicians were blinded to EIT data and performed standard clinical assessment, including auscultation, oxygen saturation, and end-tidal CO₂ monitoring. Peri-intubation events and clinical interventions were time-stamped to the EIT signal.

EIT data were analysed retrospectively to quantify regional ventilation distribution between right and left lung areas. Single-lung ventilation was defined as more than 90% of ventilation in a single-lung area. Ventilation asymmetry, absence of ventilatory patterns, and single-lung ventilation were identified and compared with clinical observations.

3 Results

A 7-month-old infant undergoing elective cleft palate repair was monitored during general anaesthesia. After intubation, the patient was connected to the ventilator, prior to which symmetrical breath sounds were noted on auscultation, together with other clinical parameters suggesting correct tube placement. However, retrospective EIT analysis demonstrated marked right-dominant ventilation (92%),

consistent with ETT malposition in the right bronchus. Clinical suspicion of ETT malposition arose later due to desaturation and elevated peak inspiratory pressures. A second auscultation again revealed symmetrical breath sounds, and the tube position was not adjusted. EIT analysis showed persistent right-sided ventilation. EIT would have identified single-lung ventilation immediately after intubation, which remained unrecognised clinically. The situation was resolved after the patient's head was tilted backwards during the preparations for the operating position, allowing the tube to move upwards and restore even ventilation.

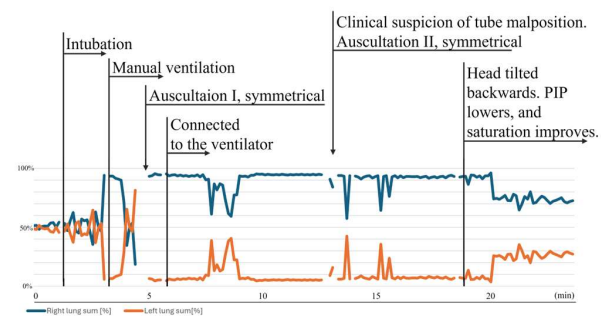


Fig. 1: EIT monitoring during intubation in a 7-month-old infant. Percentage of ventilation distribution of the right (blue) and left (orange) lung area. Despite symmetrical breath sounds on repeated auscultation, ventilation distribution remained 92% right-sided, consistent with ETT tube malposition. PIP = peak inspiratory pressure

4 Conclusions

EIT identified a clinically relevant abnormality in ventilation distribution that was not recognised by routine clinical assessment. The abnormality persisted despite repeated clinical evaluation and was accidentally resolved only after head reposition. Continuous monitoring of regional ventilation provides additional information on tube position and supports safer ventilatory care in infants.

Acknowledgements

We thank the infants and their families for participating in this study, and the paediatric anaesthesia staff at the Oulu University Hospital.

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Spatial Distribution of Ventilation Determined by EIT during Quiet Breathing and Ventilation Manoeuvres

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Abstract: Subjects with normal lung function were examined by EIT during quiet and deep breathing, as well as slow and forced full expiration to determine reference values of EIT parameters of spatial ventilation distribution. Minor differences in the right-to-left and ventrodorsal distribution were found between women and men.

1 Introduction

EIT is clinically used mainly in mechanically ventilated, critically ill patients to guide the ventilator therapy [1]. However, an increase in applications in spontaneously breathing patients with chronic lung diseases has recently been noted. The aim of our study was to define reference values for EIT parameters characterising the spatial distribution of ventilation at the level of the 4th–5th intercostal space in an upright body position, derived from examinations in subjects with normal lung function. An additional aim was to assess the effects of biological sex on these parameters.

2 Materials & Methods

After screening for exclusion criteria (z-scores for forced vital capacity (FVC) and the ratio between forced expiratory volume in 1 s (FEV₁) and FVC (FEV₁/FVC) $\leq$ -1.645), a total of 128 subjects with normal lung function (64 women, 64 men) were included in the study and examined by EIT. The subjects were recruited within the Kiel sub-cohort of the prospective, population-based cohort COVIDOM study (German Registry for Clinical Studies No. DRKS00023742) embedded in the German NAPKON platform. The study was approved by the Ethics Committee of the Medical Faculty of the Kiel University (No. D537/20). EIT measurements were performed using PulmoVista 500 (Dräger, Lübeck, Germany) in a sitting position. Quiet breathing (1 min), deep breathing (3 breaths), slow and forced full expiration were analysed. The main parameters, the ventrodorsal (CoV_{vd}) and the right-to-left centres of ventilation (CoV_{rl}), as well as the dorsal and

the right fractions (F) of ventilation were calculated using the Parametric EIT Analysis Software (PEAS) [2]. Statistical Analysis was performed with GraphPad Prism v.9.5.1 (GraphPad Software, San Diego, USA).

3 Results

The values of all analysed parameters are presented in Tab. 1. A highly significant effect of the type of ventilation was noted. Significant sex-dependent differences were also observed, with effect sizes ranging from small to moderate. During all four ventilation phases, women exhibited lower right F of ventilation than men, with similar findings in CoV_{rl}. During deep breathing, slow and forced full expiration, CoV_{vd} and dorsal F of ventilation were higher in women.

4 Conclusions

Analysis of spatial distribution of ventilation by EIT needs to take the type of ventilation (quiet breathing and various breathing manoeuvres) and the biological sex into account. The sex-dependent differences reflect the differences in chest anatomy and thoracoabdominal mechanics between women and men [3]. The former factor most likely affects the right-to-left and the latter the ventrodorsal ventilation distribution. The found reference values of EIT parameters can serve as initial guidelines for potential clinical use in upright patients outside of intensive care medicine. However, further studies are needed to increase the cohort and confirm the current values.

Acknowledgements

The authors wish to thank Dr. Anne Hermes and Sarah Meier for their support in conducting the study.

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Tab. 1: EIT parameters of spatial distribution of ventilation determined during quiet breathing and ventilation manoeuvres (mean $\pm$ SD). CoV_{vd}, ventrodorsal centre of ventilation; CoV_{rl}, right-to-left centre of ventilation; F, fraction; *, P<0.05, **, P<0.01, significantly different from women; P values in the last column show the significant effect of the analysed type of ventilation.

	Quiet breathing		Deep breathing		Slow full expiration		Forced full expiration		P value	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
CoV _{vd} (%)	49.7 $\pm$ 3.3	49.5 $\pm$ 4.4	48.3 $\pm$ 2.8	46.4 $\pm$ 3.4**	47.7 $\pm$ 2.8	46.1 $\pm$ 3.2**	47.6 $\pm$ 2.9	45.6 $\pm$ 3.9**	<0.0001	<0.0001
CoV _{rl} (%)	49.7 $\pm$ 3.7	47.9 $\pm$ 4.3*	50.2 $\pm$ 2.9	49.1 $\pm$ 3.1*	50.3 $\pm$ 3.1	49.3 $\pm$ 3.1	50.3 $\pm$ 3.1	49.3 $\pm$ 3.1	0.0240	0.0002
Dorsal F	0.486 $\pm$ 0.093	0.481 $\pm$ 0.122	0.445 $\pm$ 0.082	0.401 $\pm$ 0.102**	0.437 $\pm$ 0.084	0.400 $\pm$ 0.096*	0.436 $\pm$ 0.087	0.390 $\pm$ 0.111*	<0.0001	<0.0001
Right F	0.515 $\pm$ 0.064	0.556 $\pm$ 0.078**	0.499 $\pm$ 0.048	0.523 $\pm$ 0.054**	0.499 $\pm$ 0.047	0.519 $\pm$ 0.055*	0.498 $\pm$ 0.049	0.520 $\pm$ 0.057*	0.0001	<0.0001

Pressure and the lung: EIT's role to help diver breathing at depth

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Abstract: We developed a portable, water-proof EIT system for studying respiratory mechanics and lung gas distribution in water and during breath-hold diving up to 20 m. EIT data can be readily collected from divers. Our data suggest that posture results in lung gas re-distribution with gravity.

1 Introduction

Breath-hold divers are exposed to increasing pressure as they descend, which results in compression of gas filled spaces. The respiratory mechanics during breath-hold diving has long been of interest to respiratory physiologists since the relatively stiff chest of humans has suggested that negative intrapulmonary pressures should develop at depths as shallow as 20 m, resulting in an edema formation called lung squeeze. There are limited studies that have investigated the mechanism of lung squeeze, and EIT provides a new and novel opportunity to better understand how gas is distributed during diving.

To further investigate the possible use of EIT to study lung mechanics during breath-hold diving, our goal here was to determine the feasibility of wireless EIT data collection in two minute breath-hold dives up to 20 m.

2 Materials & Methods

We built a water-proof case (Fig. 1A) for a commercially available EIT system (VTM 100, Midas medical, Beijing, China) that was pressure tested to 50 m. To reduce loss of EIT signal in water and to assure thermal comfort, the diver wore a neoprene suit over the EIT belt. The cable connecting the EIT belt to the water/pressure-proof exited the neoprene suit by the neck to allow the diver to hold the EIT system.

This system was used to evaluate its ability to measure lung gas distribution during 2 minute breath-hold dives to 1, 5, 10 and 20 meters. Dives were performed in a 20 m deep freshwater pool in Madrid, Spain (YoBuceo), with human-research ethics clearance. The session was supervised by an experienced breath-hold diver that was certified by AIDA.

For breath-holds to 1 m, the diver submerged to the bottom of a ledge in a horizontal position. For dives to 5, 10 and 20 m, the diver descended head first and then turned to be head up when arriving at the target depth.

3 Results

The results from this pilot study clearly indicate that EIT is a useful tool to evaluate lung gas distribution during breath-hold diving. The results from the dives to different depths indicate that posture has a large effect on pulmonary gas distribution. During the breath-hold to 1 m, the gas volume decreased as the diver descended and then remained low, with a slight temporal increase (Fig. 1B). During dives to 5,

10 and 20 m, there was a similar decrease in pulmonary gas volume during descent, followed by a rapid increase upon reaching the target depth as the diver changed posture, i.e. head down to head up (Fig. 1C). This suggests that gas moves by gravity to the upper regions of the lung as posture changes.

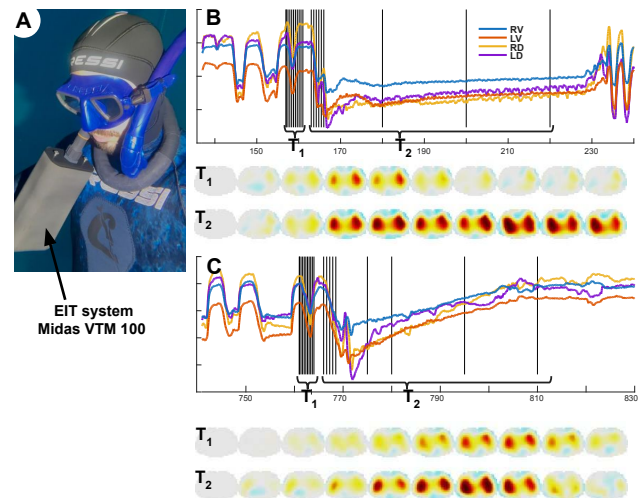


Fig. 1: EIT measurements from a diver (A) showing EIT signals in 4 ROIs from (B) a dive to 1 m depth and (C) a dive to 20 m depth. EIT images at times T1 (breathing at surface) and T2 (dive) correspond to vertical lines.

4 Discussion

The results from this pilot study clearly indicate that EIT is a useful tool to evaluate lung gas distribution during breath-hold diving. The results from the dives to different depths indicate that posture has a large effect on pulmonary gas distribution. During the breath-hold to 1 m, the gas volume decreased as the diver descended and then remained low, with a slight temporal increase (Fig. 1C). During dives to 5, 10 and 20 m, there was a similar decrease in pulmonary gas volume during descent, followed by a rapid increase upon reaching the target depth as the diver changed posture, i.e. head down to head up. This suggests that gas moves by gravity to the upper regions of the lung as posture changes.

EIT is possible in water and provides a unique opportunity to study pulmonary mechanics in breath-hold divers. This tool may help provide increased safety for the growing number of people engaged in the sport of breath-hold diving.

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Lung Imaging using Magnetic Induction Tomography: Results of the human study

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Abstract: This study investigates a new clinical imaging system based on magnetic induction tomography (MIT) for monitoring respiratory function. Bedside, real-time imaging of pulmonary function is important in many clinical settings. For instance, in intensive care units (ICUs), it is vital to monitor air delivery for patients undergoing mechanical ventilation due to respiratory failure. The results are based on healthy volunteers.

1 Introduction

Magnetic induction tomography (MIT) is an electromagnetic tomography technique that non-invasively produces cross-sectional and volumetric images of objects, showing contrasts in passive electromagnetic properties (PEP) such as conductivity, permittivity, and permeability. The MIT-based system includes an array of sensor coils on a belt designed for wearable imaging applications. MIT is a relatively new imaging modality aimed at reconstructing the body's interior conductivity distribution. In MIT, transmitter coils induce eddy currents within the body, and the resulting response field, generated by the conductivity perturbations are sensed by an array of receiver coils. While the inductive measurement of the respiratory system was proposed long ago [1] and some good in-vitro data was generated [2], there is no report of an MIT system for medical imaging application demonstrated in real life.

2 Results

This paper highlights several important points, from investigating the feasibility of a wearable, 16-channel MIT coil array for lung imaging in human volunteers. The MIT device can work between 400kHz and 9MHz. We can capture phase as well as amplitude data, where the total number of independent measurements is 120.

A person specific model was used by segmentation of a 3D CT scan, then by using COMSOL we produced sensitivity maps; Tikhonov regularisation was used for the image reconstruction.

Ethical approval was provided by the University of Bath to conduct a human study. In total 14 volunteers participated, both male and female, of differing height and weight, using a simple classification of chest size from Small, to Medium to Large.

Figure 1 shows an image of a breathing cycle. In Figure 2 we can see the total measurement (norm of 120 measured values) for breathing.

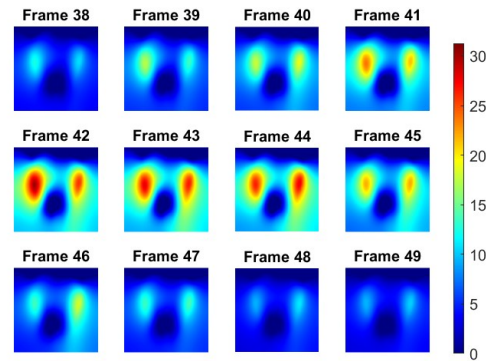


Figure1: Showing the breathing cycle

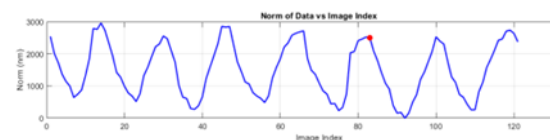


Figure1: The MIT signal over the cycle

3 Conclusions

MIT is a promising technique for real-time, non-ionizing pulmonary monitoring in ICUs. This article presents results from a new phantom study using a 16-sensor MIT array for real-time imaging of air volume in a simple lung phantom. The proposed MIT system is both low-cost and computationally cost-effective, making it an ideal candidate for bedside imaging.

Acknowledgements

The authors would like to acknowledge the anonymous volunteers for taking part in this study.

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EIT-based laparoscopic lung imaging: a phantom study

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Abstract: A laparoscopic EIT device was developed for in vivo lung nodule characterization. Experiments involving agar-based inclusions and bovine tissue samples quantify accuracy in terms of depth, size, and contrast, and validate real-time GUI-driven data acquisition and performance on biological tissues. An in vivo, human study is ongoing.

1 Introduction

Localizing a tumour or lesion and its margin are essential components of cancer resection procedures. Pre-operative work-ups including imaging and placement of hookwires or fiducial markers during biopsy procedures are important tools in guiding this localization [1]. Despite these approaches, it is often still challenging to intraoperatively identify the location and extent of a lesion. The inexpensive, safe, portable, and high tissue-contrast profile of EIT make it a promising technology for use in lung lesion localization and characterization. A stand-alone laparoscopic EIT device (Fig. 1A) was developed and evaluated in a series of agar and bovine phantom tests to characterize imaging accuracy. This study extends our prior work in evaluating a coupled stapler-EIT device [2].

2 Materials & Methods

A 6 cm long, 32-electrode (2x16) printed circuit board (PCB) was designed to serve as the EIT electrode array. The length was chosen based on simulation tests and surgeon feedback. The array is mounted to a custom 3D printed housing fixed within a stainless steel tube (10 mm diameter) for compatibility with laparoscopic procedures. All data was recorded using a 32-channel Sciospec EIT system.

2.1 Agar Inclusion Experiments

Experiments comprised 1512 recordings of agar inclusions of 10%, 20%, or 30% contrast and sizes of 0.5, 1.25, and 2.0 cm. Each inclusion was submerged in saline and translated to 24 different depths from the PCB face (1.25 to 30 mm in 1.25 mm steps) and offset in the long axis from the center to 3 cm off-center in 0.5 cm steps (Fig. 1B). Two Zaber linear stages controlled inclusion motion, and each inclusion was submerged for a maximum of ~5 minutes to limit time for ion diffusion, i.e. a loss of contrast. Optimized hyperparameters defining the coarse grid structure, sensitivity threshold, and Tikhonov factor were selected as those that yielded best performance to the deepest depths.

2.2 Bovine Tissue Experiments

A large sample of bovine tissue including a heterogeneous mixture of adipose and muscle was used to evaluate the device. A total of 26 areas were probed with a variety of muscle and adipose tissue distributions lying under the electrode array (see Fig. 1D). In addition to directly probing the tissue surface, some tests included a ~5mm thick layer of agar acting as a stand-off to evaluate the device's ability to image adipose-to-muscle contrast at depth.

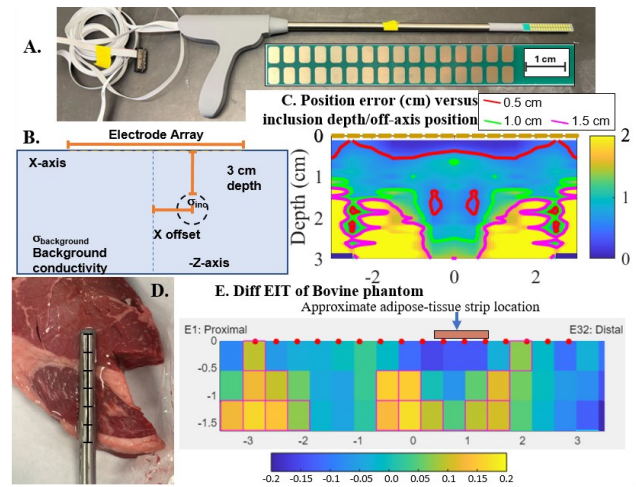


Fig. 1: A. Photo of the in vivo EIT device, B. diagram of the agar inclusion configuration (showing depth and long-axis offset). C. map of position error of agar inclusions (1.25 cm diameter / 20% contrast) using the optimal parameters. D. photo of a bovine tissue test and associated EIT difference image that qualitatively corresponds to the expected muscle-adipose tissue distribution.

3 Results

The agar inclusion experiments with optimized hyperparameters, yielded 0.9 AUCs down to a depth of 2.24 cm. A best-constant optimal threshold for inclusion detection was found to be a 40% maximum after both a series of relative and absolute threshold were searched. Overall, we found the position error was less than 1 cm in most cases (20-30% contrast & 1.25-2 cm inclusions) for inclusions up to a depth of 2.5 cm. The diameter error degrades much quicker, yielding errors less than 1 cm for depths to roughly 1 cm. A qualitative review of the bovine tissue conductivity images consistently agreed with the ground-truth adipose-muscle distribution for both surface and depth tests. Ringing artefacts observed in several images are likely due to the high adipose-to-muscle contrast and should be further studied.

4 Conclusions

Agar-inclusion and bovine tissue tests yielded optimal parameters and quantitative and qualitative performance metrics of this laparoscopic EIT device. Further quantitative assessment of bovine tissue experiments is ongoing in parallel with in vivo human deployment..

Acknowledgements

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3D EIT Improves Detection of Ventilation Inhomogeneity in Obstructive Lung Disease

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Abstract: Obstructive lung diseases are highly heterogeneous. Using measurements of equine asthma, we compared 2D and 3D EIT metrics against lung mechanics. 3D EIT showed greater sensitivity to treatment effects, indicating improved detection of ventilation heterogeneity.

1 Introduction

Traditional 2D EIT uses a single electrode plane, reconstructing a transverse slice, but obstructive lung diseases (OLD) exhibit heterogeneity along the craniocaudal axis, potentially missed by 2D imaging. 3D EIT, using multiple electrode planes, provides volumetric reconstructions, capturing a larger fragment of lung geometry.

We compare 2D and 3D EIT in assessing ventilation inhomogeneity in OLD, using an equine asthma model, and hypothesize that 3D EIT offers superior sensitivity.

2 Materials & Methods

Data were acquired from ten horses with severe equine asthma during exacerbation and remission phases, as described in [1, 2]. EIT images were reconstructed in 2D- and 3D (example Figure 1) and EIT metrics computed: Global Inhomogeneity (GI) [3], Regional Ventilation Delay (RVD) standard deviation [4], and Global Asynchrony Index (GAI) from Pixel Asynchrony Value (PAV) [5].

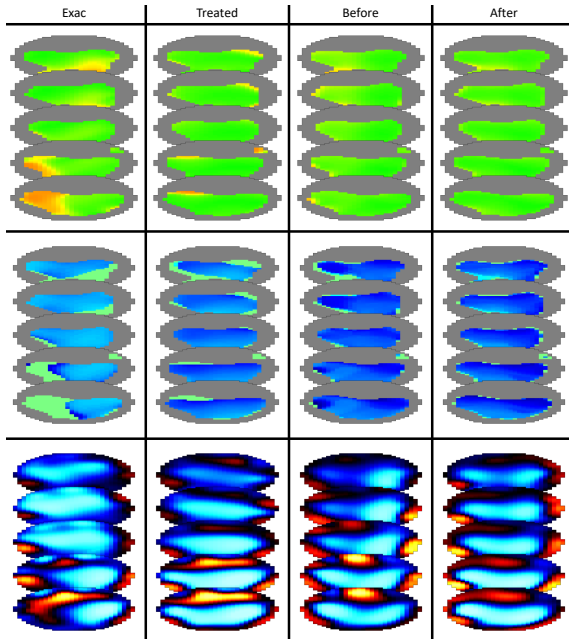


Fig. 1: 3D EIT functional maps of Pixel Asynchrony Value (PAV, top), Regional Ventilation Delay (RVD, middle), and Tidal Impedance Variation (TIV, bottom) from one horse with equine asthma under four conditions: exacerbation (Exac.), corticosteroid-treated remission (Treated), and pre-/post-salbutamol administration. Each panel contains five reconstructed coronal slices from the 3D EIT volume.

All metrics were calculated for 2D and 3D ROIs defined by 20% ventilation threshold. Paired t-tests compared metric changes against lung resistance R_L reductions.

3 Results

Paired comparisons (Exacerbated-Treated, $n=10$; Before-After salbutamol, $n=9$) showed R_L decreases ($p < 0.001$).

Tab. 1: Paired t-test p-values for 2D and 3D EIT metrics.

Metric	E-T (2D / 3D)	B-A (2D / 3D)
GAI	0.003 / 0.002	0.019 / 0.002
SD _{RVD}	0.627 / 0.042	0.614 / 0.058
GI	0.848 / 0.435	0.671 / 0.001

Paired t-test results for 2D and 3D EIT metrics (Table 1) show 3D metrics consistently have higher significance than 2D, especially for GAI and GI, while 2D SD-RVD failed to detect consistent changes. Figure 2 presents the paired 2D/3D comparisons for GAI, SD-RVD and GI.

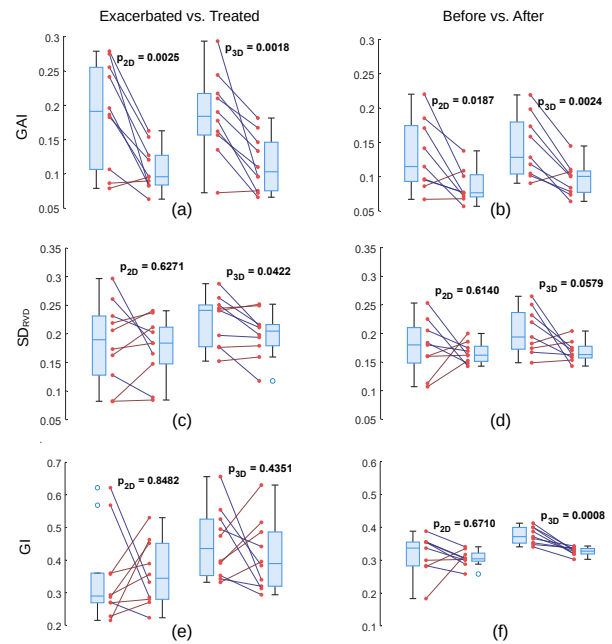


Fig. 2: Paired 2D/3D comparison of EIT metrics for the Exacerbated-Treated and Before-After salbutamol datasets.

4 Conclusions

3D EIT reconstruction better captures craniocaudal ventilation variations in obstructive lung disease and aligns more closely with lung mechanics represented by R_L .

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Impact of Ventilation and Perfusion Thresholds on Saline Contrast EIT-Derived V/Q Matching

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Abstract: We evaluated the impact of nine ventilation/perfusion (V/Q) threshold combinations on saline contrast EIT-derived metrics in 15 mechanically ventilated patients. Threshold selection substantially affected V/Q matching, dead space, and shunt estimates, with considerable inter-individual variability, highlighting the need for threshold standardisation.

1 Introduction

Saline contrast EIT enables bedside quantification of regional V/Q matching, dead space, and shunt in mechanically ventilated patients [1]. Ventilated and perfused pixels are defined by thresholds applied to the maximum pixel-level signal [2]. Studies used thresholds of 10–20% of maximum pixel value, with no consensus on optimal values or whether ventilation and perfusion thresholds must be equal. We aimed to explore the relative changes in EIT-derived V/Q parameters across different threshold combinations.

2 Materials & Methods

Analysis of 15 patients with acute respiratory failure from an ongoing study (NCT06438198) who underwent saline-bolus EIT assessment (PulmoVista, Dräger), with the bolus (10 ml 10% NaCl) applied during a respiratory pause at mean airway pressure. Data were processed in MATLAB R2015. Combinations of thresholds of 10%, 15%, and 20% of the respective maximum pixel-level signal (that is, tidal impedance variation for ventilation, and maximum slope for perfusion) were compared. V/Q matching, dead space, and shunt were computed [2]. For between-patient comparisons, each parameter was compared to its value obtained at the 10% ventilation and perfusion threshold (V10P10), hypothesizing the largest V/Q area. Differences

across threshold combinations were assessed using the linear mixed model with Wilcoxon signed-rank tests in R (4.2.3).

3 Results

Only perfused pixel counts decreased and only ventilated pixel counts increased with higher perfusion thresholds, whilst higher ventilation thresholds had the opposite effect (Fig. 1). Median deviations from the V10P10 reference are summarised in Fig. 2. For V/Q matching, increasing either threshold consistently reduced matching percentages, with the largest median reduction at V20P10 (−10.9%). The ventilation threshold exerted a greater influence than the perfusion threshold. For shunt, higher ventilation thresholds were associated with increased values (up to +15.2% at V20P10). Higher perfusion thresholds increased dead space estimates (up to +14.7% at V10P20). Opposing effects of the two thresholds on shunt and dead space were partially compensatory, yet both contributed to a reduction in V/Q matching. Substantial inter-individual variability was observed across all three parameters.

4 Conclusions

Threshold selection substantially affects the interpretation of V/Q matching, with ventilation thresholds predominantly driving shunt and perfusion thresholds driving dead space. Standardisation is essential for cross-study comparability. Key limitation is the absence of a reference standard validation, especially for perfusion; future work could incorporate CT-based lung contouring.

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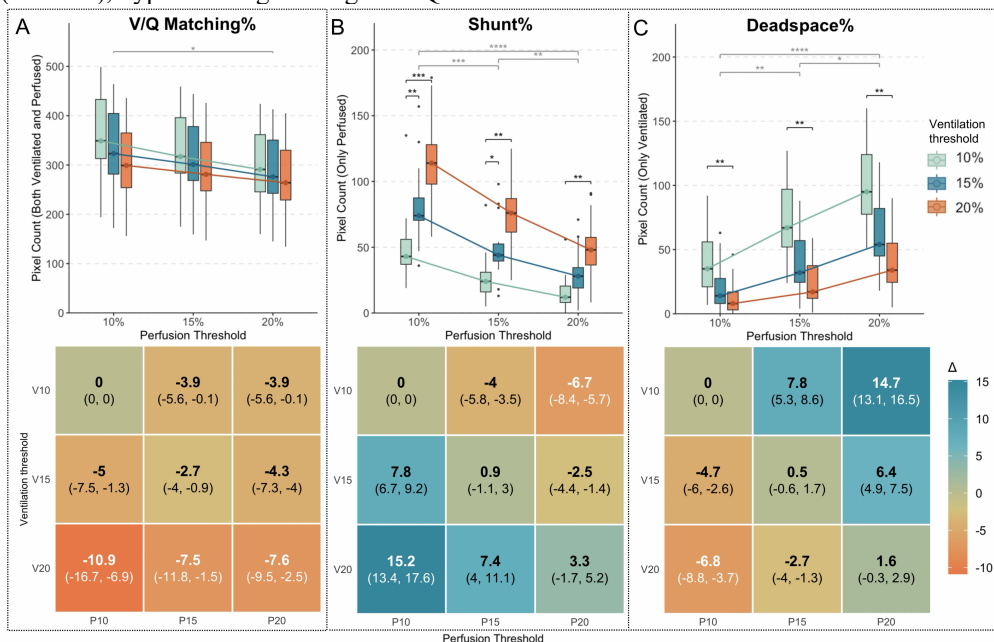


Fig. 1: Effect of ventilation and perfusion threshold combinations on regional lung classification. (A) Pixel counts and median percentage deviations from V10P10 for regions classified as both ventilated and perfused (V/Q matching). Pixel counts and median absolute deviations from V10P10 for regions classified as only perfused (shunt) (B) and only ventilated (dead space) (C). Upper panels show boxplots with median trendlines across perfusion thresholds (colour indicates ventilation threshold). Lower panels show heatmaps of median (IQR) deviations across 15 patients relative to V10P10. Significance brackets indicate: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$

Session 6: Image & Reconstruction

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Comparison of Probabilistic Generative Model Architectures for EIT Image Reconstruction

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Abstract: Probabilistic generative models are increasingly applied in the field of electrical impedance tomography (EIT) image reconstruction. This contribution highlights the challenges and limitations that should be considered when employing probabilistic models (PM) for EIT image reconstruction.

1 Introduction

EIT is a well-established procedure for reconstructing conductivity distributions. To create images from boundary voltage measurements, the underlying inverse ill-posed EIT problem is typically solved numerically. In recent years, machine learning (ML) reconstruction approaches have gained increasing popularity. Many ML approaches use PMs to generate the images. PMs are often highlighted for their higher image quality compared to numerical approaches. Thereby, the question remains: Is a high-quality image created by PMs a reliable reconstruction? In this work, we compare two PMs, the variational autoencoder (VAE) and the diffusion model (DM), in terms of their image reconstruction reliability without encountering EIT boundary measurements.

2 Methods

2.1 Probabilistic Generative Model

In [1], a VAE was used for the EIT image reconstruction task. The VAE is used to learn a probabilistic model of the solution space in order to improve the conditioning of the inverse problem. The VAE consists of an encoder that reduces the input dimensions of the conductivity distribution to a lower-dimensional latent space and a decoder that recreates the reconstructed conductivity distribution from the latent space. Another approach, presented by [2], utilized a three-stage convolutional U-network EIT DM for image reconstruction. The DM learns to denoise data by reversing a forward process modeled as a Markov chain that gradually adds noise. For the unsupervised training of the VAE and the DM, a dataset of conductivity distribution images must be provided.

2.2 Data Simulation

We created four datasets in Python by simulating images with 64×64 pixels, featuring circles, triangles, or squares. Three of the datasets (1, 2, 3) consisted of a single object with three different sizes, randomly distributed within the conductivity domain. The fourth dataset consisted of two of the three randomly chosen object geometries. It is possible that the two objects overlap in dataset 4.

2.3 Training of the models

A VAE and a DM were implemented with *tensorflow* (version 2.20). Each model was trained on each dataset. During training, the models were ensured to converge without overfitting. The VAE's latent space dimension was tested at 2 and 4, with the latter used for results. The full code and models are available on GitHub [3].

3 Result

In figure 1, the predicted images based on unknown test data samples are shown. Ground truth (GT) images are visualized in the left column. VAE(1) and DM(1) indicate the VAE and the DM trained on dataset 1. The first four rows are test samples generated from the compositions of datasets 1-4. Row 5 and the objects in row 6 are completely unknown test anomalies.

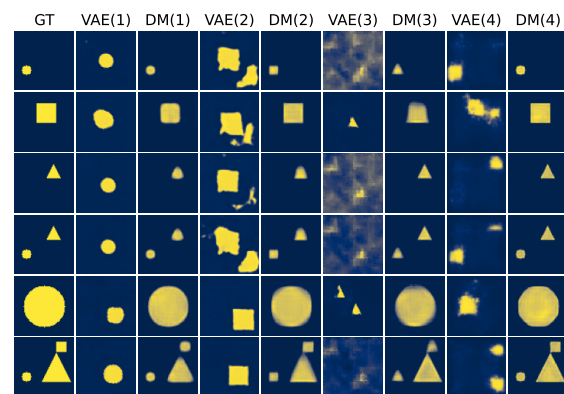


Figure 1: Prediction results of the VAE and the DM trained on the dataset inside the braces.

It is obvious that all VAE models enforce the object geometry and the number of objects in the predictions. The DM performs significantly better, especially in terms of the number of objects and their position. But even the better-performing DM forces the trained geometry shapes into the predicted geometries while maintaining good positional alignment; compare DM(3), row 1.

4 Conclusions

DMs and VAEs differ in structure and performance. VAEs learn a latent probability distribution, enabling fast sampling with a well-structured latent space. However, for our examples, they produce uncertain outputs. In contrast, DM that generated images by reversing a noise-adding process achieved good image quality. Especially when using a VAE, it is essential to ensure that the entire solution space of the application has been learned correctly. Otherwise, sharp images may be created that have no relation to reality.

5 Acknowledgements

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Single-Cell Conductivity and Permittivity Reconstruction by Complex-Electrical Impedance Tomography

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Abstract: This study proposes a complex Electrical Impedance Tomography (complex-EIT) method for single-cell imaging that enables simultaneous reconstruction of conductivity and permittivity distributions by considering a complex sensitivity matrix which includes $\mathbf{J}_{R,\sigma}$, $\mathbf{J}_{R,\epsilon}$, $\mathbf{J}_{X,\sigma}$ and $\mathbf{J}_{X,\epsilon}$ representing the partial derivatives of the resistance change $\Delta\mathbf{R}$ and the reactance $\Delta\mathbf{X}$ with respect to changes in conductivity $\Delta\sigma$ and permittivity $\Delta\epsilon$. The method successfully achieves simultaneous imaging of conductivity and permittivity at the single-cell level, demonstrating its potential for advanced non-invasive bioelectrical analysis.

1 Introduction

Single-cell visualization is essential for pathological research and structural modeling of cells and tissues. Conventional fluorescence imaging relies on probes to visualize intracellular structures but suffers from invasiveness, probe instability, and non-specific interference. Electrical impedance tomography (EIT) is a non-invasive technique that reconstructs conductivity distributions [1]; however, cellular components such as the cytoplasm and nucleus exhibit significant dielectric properties that cannot be captured by conductivity alone. In this study, we propose a complex Electrical Impedance Tomography (complex-EIT) approach for single-cell visualization. By simultaneously reconstructing conductivity and permittivity distributions, complex-EIT enables more comprehensive electrical characterization of single cells.

2 Complex-EIT

Complex-EIT is proposed to enable simultaneous reconstruction of conductivity and permittivity distributions by considering a complex sensitivity matrix which includes $\mathbf{J}_{R,\sigma}$, $\mathbf{J}_{R,\epsilon}$, $\mathbf{J}_{X,\sigma}$ and $\mathbf{J}_{X,\epsilon}$ representing the partial derivatives of the resistance change $\Delta\mathbf{R}$ and the reactance $\Delta\mathbf{X}$ with respect to changes in conductivity $\Delta\sigma$ and permittivity $\Delta\epsilon$ [2], as described as follows:

$$\begin{bmatrix} \Delta\mathbf{R} \\ \Delta\mathbf{X} \end{bmatrix} = \begin{bmatrix} \mathbf{J}_{R,\sigma} & \mathbf{J}_{R,\epsilon} \\ \mathbf{J}_{X,\sigma} & \mathbf{J}_{X,\epsilon} \end{bmatrix} \begin{bmatrix} \Delta\sigma \\ \Delta\epsilon \end{bmatrix} \quad (1)$$

$\Delta\sigma$ and $\Delta\epsilon$ are calculated according to Equation (2) by using the Tikhonov regularization method and the Gauss–Newton method.

$$\begin{bmatrix} \Delta\sigma \\ \Delta\epsilon \end{bmatrix} = \left(\begin{bmatrix} \mathbf{J}_{R,\sigma} & \mathbf{J}_{R,\epsilon} \\ \mathbf{J}_{X,\sigma} & \mathbf{J}_{X,\epsilon} \end{bmatrix}^T \begin{bmatrix} \mathbf{J}_{R,\sigma} & \mathbf{J}_{R,\epsilon} \\ \mathbf{J}_{X,\sigma} & \mathbf{J}_{X,\epsilon} \end{bmatrix} + \lambda \mathbf{I} \right)^{-1} \begin{bmatrix} \mathbf{J}_{R,\sigma} & \mathbf{J}_{R,\epsilon} \\ \mathbf{J}_{X,\sigma} & \mathbf{J}_{X,\epsilon} \end{bmatrix}^T \begin{bmatrix} \Delta\mathbf{R} \\ \Delta\mathbf{X} \end{bmatrix} \quad (2)$$

3 Experiments

The experimental setup included an impedance analyzer (IM3570, HIOKI, Japan), a PC for system control, a

multiplexer for electrode switching, a microscope, a pneumatic microinjector (IM-11-2, NARISHIGE, Japan), and a micro-EIT sensor. The micro-EIT sensor consisted of eight electrodes arranged in a circular configuration with a diameter of 40 μm . MRC-5 cells were measured with an applied current of 0.01 mA over a frequency range of 100 kHz to 5 MHz. Under microscopic observation, a single cell with culture medium was aspirated and placed onto the micro-EIT sensor, and microscopic imaging and complex-EIT measurements were performed simultaneously.

4 Results

Figure 1 shows representative complex-EIT results for a single cell, including the microscopic, conductivity, and permittivity images. The measurements were performed from 100 kHz to 5 MHz, and the reconstructed electrical properties showed frequency-dependent intracellular contrast. The contrast appeared mainly in a broad cytoplasmic region around 100 kHz, while it became more localized near the nuclear region around 1 MHz. Therefore, the conductivity image at 2 MHz and the permittivity image at 1 MHz are shown as representative examples. The reconstructed cell position agreed with the microscopic observation, confirming successful single-cell identification.

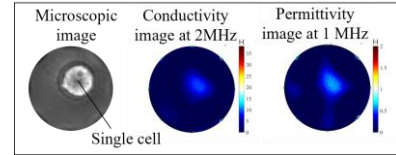


Fig.1 Single cell conductivity/permittivity distributions

5 Conclusions

In this study, we successfully demonstrated simultaneous imaging of conductivity and permittivity distributions at the single-cell level using complex-EIT. The ability to reconstruct both electrical properties concurrently provides enhanced electrical characterization of cellular structures and is expected to contribute significantly to advanced single-cell analysis and non-invasive bioelectrical imaging.

Acknowledgements

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Shape-Aware FC-UNet for Absolute EIT Reconstruction

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Abstract: UNet is widely used for electrical impedance tomography (EIT) reconstruction because it captures multi-scale spatial features from voltage measurements. However, conventional UNet models do not explicitly use geometric information of the measurement domain. We propose encoding the domain shape from electrode positions.

1 Introduction

The UNet [1] has become a popular choice in data-driven methods for EIT reconstruction. Due to its encoder-decoder design with skip connections it captures both local details and global context. Given an intermediate mapping of measured potential differences to a spatial grid representation, UNet models can learn a conductivity reconstruction that often surpass traditional absolute EIT (aEIT) methods in speed and image quality [2, 3]. However, the standard UNet architecture assumes that the initial spatial mapping already accounted for shape variation which is mostly not the case. This is limiting, since electrode placement and boundary geometry strongly affect current flow and measured voltages [4]. To address this, we augment the reconstruction network with a transformer-based shape encoder that learns latent geometric features directly from electrode positions.

2 Materials and Methods

Baseline Reconstruction Network We use FC-UNet [3] as a baseline. The FC-UNet first maps voltage measurements $\Delta \mathbf{u}$ to a spatial feature grid $\mathbf{G}_{\text{volt}} = \sigma(f_\phi(\Delta \mathbf{u}))$ via a fully connected layer with ReLU activation. Subsequently, the feature grid is processed by a UNet.

Shape-Aware Encoder To incorporate domain geometry, we introduce a transformer-based shape encoder that takes electrode coordinates $\mathbf{p}_i = (x_i, y_i, z_i) \in [-1, 1]^3$ as input. For each dimension, positional embeddings are generated using sinusoidal basis functions with multiple frequencies: $e(t) = [\sin(\pi 2^l t), \cos(\pi 2^l t)]$, $l = 0, \dots, L$.

The embeddings of all coordinate dimensions are concatenated to form an electrode token. A learnable *shape token* $\tilde{\mathbf{z}}_{\text{shape}}$ is prepended to the sequence to aggregate global geometric information. Shape and electrode tokens are processed by n_a self-attention layers. After self-attention, the shape token $\mathbf{z}_{\text{shape}}$ is extracted as a latent representation of domain shape and projected onto the same spatial grid as the voltage features using a fully connected layer $\mathbf{G}_{\text{shape}} = f_\theta(\mathbf{z}_{\text{shape}})$.

The measurement grid $\mathbf{G}_{\text{volt}}$ and the geometry grid are concatenated along the channel dimension. The concatenated representation is then processed by a UNet $\hat{\mathbf{x}} = \text{UNet}(\mathbf{G})$, where $\hat{\mathbf{x}}$ denotes the reconstructed conductivity image.

Data Generation Data were generated using FEM simulations with adjacent-drive patterns on human body meshes

derived from CT scans, providing varied anatomies and conductivity distributions.

3 Results

The Shape-FC-UNet achieves better reconstruction of both geometry and conductivity than the variant without a shape encoder. Figure 1 shows a representative example from the held-out test set. Notably, the FC-UNet without a shape encoder can still distinguish between different geometric measurement levels, suggesting that EIT measurements contain limited implicit shape information.

Table 1 reports structural similarity (SSIM), normalized cross-correlation (NCC) and the absolute reconstruction error for both methods, showing that shape information improves performance across all three metrics.

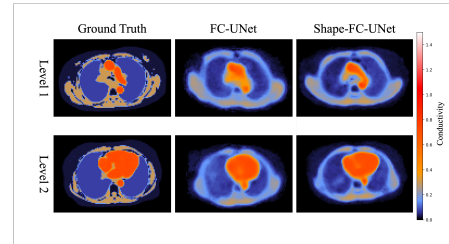


Fig. 1: Reconstruction results for two measurement levels for FC-UNet and Shape-FC-UNet.

Tab. 1: Quantitative reconstruction results on the test dataset.

Model	SSIM $\uparrow$	NCC $\uparrow$	MAE $\downarrow$
FC-UNet	0.597	0.728	0.075
Shape-FC-UNet	0.640	0.761	0.069

4 Conclusions

The incorporation of shape information can improve learning-based reconstruction methods in aEIT. Even sparse surface data, such as electrode coordinates, can enhance reconstruction accuracy and realism.

Acknowledgements

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Adjacent Decomposition Algebra for EIT Measurement Protocols

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Abstract: An algebra relating tetrapolar measurement protocols is described, allowing decomposition of any measurement pattern into a sum of adjacent patterns. Decomposition of skip-patterns reveals a ‘cofactor rule’ between the contact number and skip index, showing certain skip patterns contain fewer independent measurements than others.

1 Introduction

Electrical impedance tomography (EIT) measurement protocols are chosen for efficient data acquisition yet there is a potential misconception regarding the completeness of certain protocols. This paper presents a mathematical framework for quantifying the number of linearly independent measurements in a given set of tetrapolar injection patterns.

2 Methods

A tetrapolar resistance measurement pattern is defined as

$$R_{i,j;k,m} = V_{k,m}/I_{i,j}, \quad (1)$$

where $I_{i,j}$ is the current injected from contact i to j , and $V_{k,m}$ is the voltage measured at contact k relative to m , with C contacts $i \neq j \neq k \neq m \in \{1 \dots C\}$. One example of a measurement pattern is a so-called skip pattern consisting of current injection and voltage measurement pairs separated by a fixed number of contacts, called the skip number $s = j - i - 1 = m - k - 1$ (modulo C). A collection of D different tetrapolar measurements is here referred to as a protocol $\mathcal{P}$. For example, the skip- s protocol $\mathcal{P}_s$ would be the complete set of D_0 different measurement patterns having skip index s , where the number $D_0 = \frac{C(C-3)}{2}$ removes the usual reciprocity related redundancies.

The skip-0 or adjacent protocol $\mathcal{A} = \mathcal{P}_{s=0}$ forms a complete set of measurement patterns using adjacent current and voltage pairs, $\mathcal{A}_\alpha = i, (i+1); k, (k+1)$ spanning the D_0 -dimensional space of independent measurements with the pattern index $\alpha \in \{1, \dots, D_0\}$ [1].

An adjacent decomposition method is introduced to determine the number of linearly independent measurements in an arbitrary protocol $\mathcal{P}$ by decomposing each measurement into a linear combination of adjacent measurements in $\mathcal{A}$. As an example, for a fixed set of current contacts, the voltage measured between *non*-adjacent contacts (k, m) is the sum of the intervening adjacent voltage pairs: $R_{-, -; k, m} = R_{-, -; k, k+1} + R_{-, -; k+1, k+2} + \dots + R_{-, -; m-1, m}$. An analogous treatment decomposes non-adjacent current contacts, with the complete algebra considering whether the cyclically permuted voltage contacts are uninterrupted ($i < j < k < m$), or interrupted ($i < k < j < m$) by a current contact.

Thus, any measurement protocol $\mathcal{P}$ can be listed as linear combinations of adjacent measurements selected from $\mathcal{A}$. Let $\mathbf{R}^P$ denote the vector of D different resistance values measured according to the protocol of interest $\mathcal{P}$ and $\mathbf{R}^A$ denote the vector of D_0 resistance values measured according to the adjacent protocol $\mathcal{A}$. For any $\mathcal{P}$, we can construct a $D \times D_0$ decomposition matrix $\mathbf{M}(\mathcal{P})$ comprised

of elements $\{-1, 0, 1\}$, such that

$$\mathbf{R}^P = \mathbf{M}(\mathcal{P})\mathbf{R}^A. \quad (2)$$

It follows that the number of linearly independent measurements in $\mathcal{P}$ is equal to the rank of $\mathbf{M}(\mathcal{P})$:

$$D_1(\mathcal{P}) = \text{rank}[\mathbf{M}(\mathcal{P})]. \quad (3)$$

Since $D_1 \leq D_0$, a full rank $D_1 = D_0$ indicates that $\mathcal{P}$ spans the same measurement space as $\mathcal{A}$, while a lower rank indicates that $\mathcal{P}$ only spans a subspace. When $D_1 < D$, there are $D - D_1$ redundant measurements in the protocol.

3 Results & Conclusions

Skip patterns are often used to improve the signal-to-noise ratio in EIT experiments. By applying the adjacent decomposition method to skip protocols, the number of independent measurements in $\mathcal{P}_s$ found to be:

$$D_1(\mathcal{P}_s) = D_0 - (G-1)C + \frac{G(G-1)}{2}, \quad (4)$$

where $G = \text{gcd}(C, s+1)$.

This result reveals a cofactor rule that governs the number of independent measurements in skip protocols: $\mathcal{P}_s$ spans the full measurement space only if $G = 1$, meaning the contact number C and $s+1$ share no common cofactors. For example with $C = 16$ contacts whereby $D_0 = 104$, the skip numbers to avoid are: $s = 1, 3, 5, 7$ with $D_1 = 89, 62, 89, 20$, respectively. This finding has direct implications for measurement protocol selection, as it highlights the importance of selecting skip numbers that are coprime to the number of contacts to ensure complete coverage of the measurement space. Note this method is agnostic to the dimensionality of the system and is also *valid for any ordered list of contacts in 3D*.

This analysis also reveals an important scaling relationship for EIT simulations: whereas the total number of possible tetrapolar measurements scales as $\mathcal{O}(C^4)$ and the number of independent measurements as $\mathcal{O}(C^2)$, the adjacent decomposition introduced here reduces the number of current drive simulations required to exactly C , to simulate *all possible tetrapolar measurements*. This should significantly improve computational efficiency in forward models with large contact number C , such as 3D applications. Experimentally, it should also help to optimize measurement protocols, while providing a theoretical basis for previous empirical observations of poor skip protocol performances.

Acknowledgments

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Complete electrode model via Robin boundary conditions

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Abstract: General purpose FEM codes generally implement only local boundary conditions including Robin boundary conditions, while the Complete Electrode Model is a non-local condition. We demonstrate how to calculate the transconductance matrix applying Robin boundary conditions and integrating the total current on the electrode, then inverting this matrix to apply desired currents.

1 Introduction

Given a conductive body Ω with conductivity σ , we have a set of conductive electrodes $E_\ell \subset \partial\Omega$, $\ell = 1 \dots L$. The electric potential ϕ satisfies

$$\phi + \sigma z \frac{\partial \phi}{\partial n} = V_\ell, \text{ on } E_\ell, \quad (1)$$

and

$$\sigma \frac{\partial \phi}{\partial n} = 0, \text{ off electrode}, \quad (2)$$

where inside the body, z is the contact impedance between the body and the electrodes, and V_ℓ is the voltage applied to the E_ℓ . The total current on E_ℓ is

$$I_\ell = - \int_{E_\ell} \sigma \frac{\partial \phi}{\partial n} dA \quad (3)$$

If we specify the voltage on each electrode we consider the mixed Robin problem for

$$\nabla \cdot (\sigma \nabla \phi) = 0 \quad (4)$$

with boundary data (1) and (2). The resulting current is then given by (3). Conversely the Complete Electrode Model (CEM) [1] specifies the current from the non-local constraint condition (3) and (2) with (1) simply specifying V_ℓ as an unknown constant, to be determined after ϕ is solved for. Generally EIT systems apply specified current for patient safety reasons and the voltage is measured. Codes such as EIDORS designed specifically for EIT implement the CEM in a custom Finite Element Method (FEM) implementation. However there is some merit in using general purpose finite element codes. They are in general more widely validated, more consistently developed and maintained, and implement desirable features such as p refinement, infinite elements or perfectly matched layers. They typically do implement local boundary conditions such as Robin but not non-local constraint conditions. In this paper we demonstrate, in the special case of NGSolve, how to implement CEM by inverting a transconductance matrix.

2 Materials & Methods

We implement code using NGSolve (NetGen solve) Python interface to input electrode voltages, solve (4) on the mesh shown in figure 1 for the potential and current density along the boundary of the body.

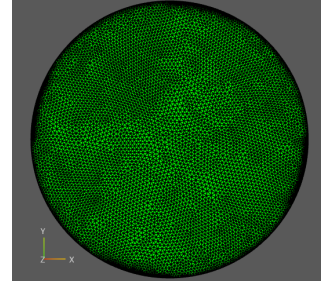


Fig. 1: Image showing the mesh created using Netgen's Python interface. For this mesh, the size of each segment is 0.1 m and there are 100 spline pieces used to approximate each of the $L = 4$ electrodes and the gaps between them.

We verify that the Robin boundary conditions hold by re-calculating the current density from the potential using equations 1 and 2. We show the comparison in figure 2.

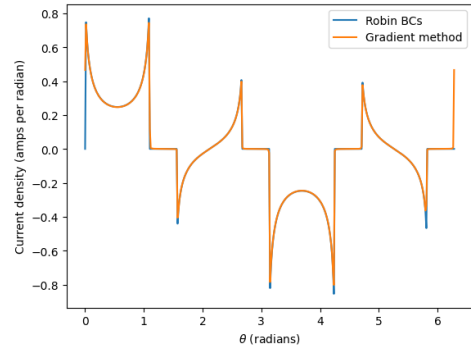


Fig. 2: Plot showing the current density as a function of angle, comparing the solution of the governing equation (orange) and the solution from the Robin boundary condition equations (equations 1 and 2; blue). This setup was for $L = 4$ electrodes with input voltages $V = [1, 0, -1, 0]$ V. In both cases, $z = 1 \Omega$ and $\sigma = 0.25 \text{ Sm}^{-1}$.

To apply specified currents our approach is first to apply a basis of voltage vectors. We choose the electrode-wise basis

$$\mathbf{V}_{ii} = 1, \mathbf{V}_{Li} = -1, \quad (5)$$

for $1 \leq j \leq L-1$ and $\mathbf{V}_{jk} = 0$. We then solve for the currents and assemble the transconductance matrix $\mathbf{T}$. Given a desired current vector $\mathbf{I}$ for example a biolar drive we calculate $\mathbf{V} = \mathbf{T}^{-1}\mathbf{I}$. This vector of voltages is then applied as Robin boundary condition using NGSolve.

3 Conclusions

This method works well for NGSolve and should apply also to COMSOL, FEniCS and other FEM codes in 2 and 3 dimensions. We will present results in the talk comparing with EIDORS and discuss issues of accuracy

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Reconstruction and Quantification using Quarter Electrode Arrays

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Abstract: An existing deep learning reconstruction method was used to determine if electrode arrays covering one quarter of the boundary could be used to reconstruct anomalies. We found anomalies could be imaged and quantified well using an eight electrode quarter array, with low and constant position error and amplitude responses.

1 Introduction

In many clinical settings, it is impractical to place electrodes circumferentially around the region of interest. In our target application of identifying abdominal bleeding in trauma cases, it is usually inadvisable to lift patients to place electrodes on the posterior abdomen, and there may be procedures or other injuries that would contraindicate covering the abdomen with EIT electrodes. Tikhonov or TSVD reconstructions using eight electrodes covering only half the abdomen (hemiarrrays, HAs) are severely affected by artifacts but still produce useful anomaly volumes [1]. Recently, deep-learning-based reconstructions produced excellent representations of both anomaly volume and anomaly location using hemiarrrays and phantom data [2]. In this study, we sought to determine whether reconstructions from data gathered with an eight-electrode array covering only a quarter of the abdomen (quarter-array, QA) could yield results comparable to those from a full-array reconstruction. **Fig. 1** illustrates HA and QAs.

2 Materials & Methods

2.1 Deep Learning Method

The deep learning method used here was based on that developed by Manning et al. [2], adapted as follows. Thirty-two-electrode training data representing 1-4 conductive or non-conductive anomalies within a 2D disc (24,000 samples) were created using EIDORS [3] and used to train a deep neural network mapping measurement vectors to conductivity images. Corresponding weights from this model were used as initial values for a quarter-array topology model.

2.2 Experimental Data

Data were collected from a 32-electrode phantom using a Sciospec 32-electrode EIT system and an adjacent acquisition pattern. Metal and plastic anomalies (2.5 cm in diameter) were placed in the tank as test objects. QA data were synthesized by superimposing full-array data, yielding measurement vectors of 40 measurements per data set.

3 Results

We found that the deep learning quarter-array could accurately reconstruct phantom data generated by metal and plastic anomalies. GREIT [4] figures of merit for single anomalies were recorded for both plastic and metal anomalies located at 0.8 of the tank radius and multiple angular locations. For either metal or plastic anomalies, the maximum position error was 0.1 over all angular locations.

Resolutions varied between 0.2 and 0.4, shape deformations varied between 0.1 and 0.2 and no apparent ringing was observed. Amplitude responses were consistently close to 1.

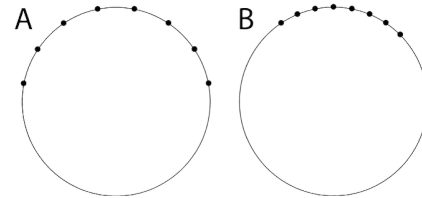


Fig. 1: Eight electrode arrays **A.** Hemiarray based on 16-electrode layout. **B** Quarter array based on a 32-electrode layout.

In **Fig. 2**, we illustrate results for a metal anomaly placed at different angular locations with respect to a central plastic anomaly. The metal anomaly was detected clearly when the plastic anomaly was directly between it and the array.

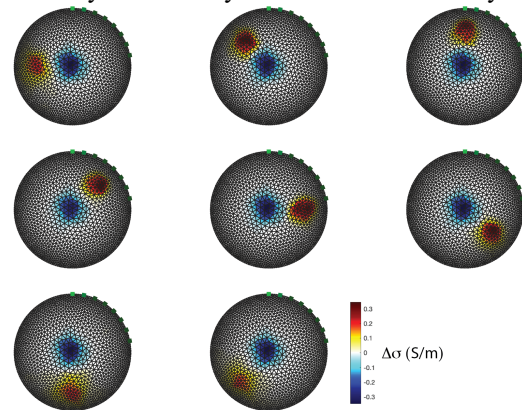


Fig. 2: Reconstructions of phantom data using QA deep learning model.

4 Conclusions

Despite the highly limited measurement geometry, anomalies were reconstructed and quantified accurately, with position error below 0.1 tank radii for all angles. These results suggest QA EIT may be feasible for trauma applications where circumferential electrode placement is impractical.

Further work in more realistic conditions is necessary to establish that QAs are feasible in trauma settings. However, the scenario shown in **Fig. 2** is salient to our application, as ultrasound, the main competitor to EIT in trauma applications, would likely not be able to detect bleeding directly behind an air pocket. This indicates that EIT may have an important advantage in bleeding diagnosis.

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Fast CGO-based 3D EIT Reconstruction from Partial Boundary Data

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Abstract: 3D CGO-based EIT reconstruction is explored for physically realistic partial boundary data with an eye on stroke monitoring. The method is direct (non-iterative), fast (2 sec.) and capable of static or dynamic imaging. Results show great promise as demonstrated on simulated and tank data and compared to classic TV and linearized methods.

1 Introduction

Fast, reliable 3D EIT reconstructions are highly desirable for medical applications ranging from thoracic to breast/brain imaging. CGO-based reconstruction methods rely on tailor-made nonlinear Fourier transforms to bypass the need for the repeated FEM-based solves, on highly dense meshes, required by classic optimization-based methods. Furthermore the CGO-based methods provide static (absolute) and dynamic (time-difference) reconstructions in approximately two seconds on a laptop, not fully optimized.

Over the past decade, CGO-based (D-bar) reconstruction has provided real-time, robust, and flexible 2D thoracic imaging. The progress for 3D analogs has been slower to develop, but recent advancements show great promise [2]. As many 3D applications are inherently partial boundary data scenarios, exploring extensions of the 3D CGO-based framework [1, 2] to limited boundary access scenarios is highly important [3].

2 Methods

The CGO-based method described here is based on transforming the original conductivity equation to a non-physical Schrödinger equation:

$$\nabla \cdot \sigma(x) \nabla u(x) = 0 \longrightarrow [-\Delta + q(x)]\tilde{u}(x) = 0.$$

Letting $\Gamma \subset \partial\Omega$ denote the subset of the full boundary $\partial\Omega$ that is accessible for data collection, we can compute an approximation to the Neumann-to-Dirichlet (current density-to-voltage) map $\mathcal{R}_\sigma^\Gamma$ corresponding to a conductivity of σ . This experimental data, along with a simulated $\mathcal{R}_1^\Gamma$ map for $\sigma = 1$, can be used to compute an approximation to the nonlinear Fourier data $\mathbf{t}_{\text{ND},\Gamma}^{\text{exp}}$. The point-wise conductivity σ can be recovered by applying the inverse Fourier transform to $\mathbf{t}_{\text{ND},\Gamma}^{\text{exp}}$ and solving a PDE to undo a change of variables sending us back to the conductivity equation.

The explicit steps of the $\mathbf{t}_{\text{ND}}^{\text{exp}}$ algorithm for partial boundary data are given by:

$$(\mathcal{R}_\sigma^\Gamma, \mathcal{R}_1^\Gamma) \xrightarrow{1} \mathbf{t}_{\text{ND}}^{\text{exp}}(\xi, \zeta) \xrightarrow{2} \mathbf{q}^{\text{exp}} \xrightarrow{3} \sigma^{\text{exp}}$$

Step 1: Compute the scattering data $\mathbf{t}_{\text{ND},\Gamma}^{\text{exp}}$ for each $\xi \in \mathbb{R}^3$, where $|\xi| \leq T_\xi$, and fixed $\zeta \in \mathcal{V}_\xi = \{\zeta \in \mathbb{C}^3 \mid \zeta \cdot \xi = 0, (\xi + \zeta) \cdot (\xi + \zeta) = 0, \xi \in \mathbb{R}^3\}$ via:

$$\mathbf{t}_{\text{ND},\Gamma}^{\text{exp}}(\xi, \zeta) = \int_\Gamma e^{-ix \cdot (\xi + \zeta)} (\xi + \zeta) \cdot \nu \left(\mathcal{R}_\sigma^\Gamma - \mathcal{R}_1^\Gamma \right) e^{ix \cdot \xi} (\zeta \cdot \nu) dS. \quad (1)$$

Step 2: Recover the approximate potential $\mathbf{q}^{\text{exp}}(x)$ for $x \in \Omega \subset \mathbb{R}^3$ using (2) with $\mathbf{t}_{\text{ND}}^{\text{exp}}$.

$$\mathbf{q}^{\text{exp}}(x) \approx \frac{1}{(2\pi)^3} \int_{\mathbb{R}^3} e^{ix \cdot \xi} \mathbf{t}_{\text{ND},\Gamma}^{\text{exp}}(\xi, \zeta) d\xi, \quad x \in \mathbb{R}^3. \quad (2)$$

Step 3: Recover the approximate conductivity σ^{exp} by solving (3) with $\mathbf{q}^{\text{exp}}$ and evaluating $\sigma^{\text{exp}}(x) = (\tilde{u}(x))^2$.

$$\begin{cases} (-\Delta + \mathbf{q}^{\text{exp}}(x))\tilde{u}(x) = 0 & x \in \Omega \subset \mathbb{R}^3 \\ \tilde{u}(x) = 1 & x \in \partial\Omega \end{cases} \quad (3)$$

Tolerance to noise in the data as well as imprecise knowledge of the true domain shape are explored. The CGO-based methods demonstrate a high robustness to this incorrect information.

3 Results

The algorithm was tested on simulated data corresponding to a multi-layer head model as well as experimental tank data with and without a skull. Reconstructions are compared to standard regularized TV (total variation) for absolute imaging, and standard linear difference imaging.

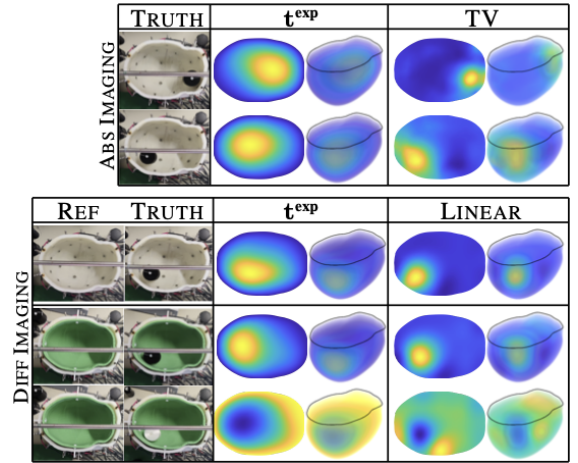


Fig. 1: Partial data reconstructions from tank data (open top) with and without a skull for absolute and difference imaging.

4 Conclusions

Our study showed that the $\mathbf{t}^{\text{exp}}$ method with partial boundary data was able to identify the targets even with incorrect domain modeling and high levels of noise [3]. While the TV and classic linear methods achieved sharper reconstructions with improved localization, the tradeoff comes with a high computational cost. The CGO-based method achieved reconstructions 90-360x faster for absolute imaging, and 15x faster for the difference imaging cases explored.

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DOI: 10.1109/TBME.2025.3633560

Session 7: Other (non-lung) Clinical Applications

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Area Clustering of Breast Cancer Tissues by Electrical Impedance Tomography Implemented with Gaussian Relaxation-time Distribution and Gaussian Mixture Models (EIT-GRTD-GMM)

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Abstract: Area of breast cancer tissues has been clustered by electrical impedance tomography (EIT) implemented with Gaussian Relaxation-time Distribution and Gaussian mixture models (EIT-GRTD-GMM) for breast cancer identification. Quantitative evaluation shows accurate estimation in diameter and area compared with corresponding CT-scan images.

1 Introduction

Breast cancer is the most commonly diagnosed cancer and the leading cause of cancer death among women [1]. Accurate clustering of breast cancer area is important for breast cancer identification. Reconstruction approach using Gaussian mixture model (GMM) can cluster different material in phantom experiment by utilizing conductivity spectra representing priori information [2]. Breast tissue characteristics analysed using Gaussian relaxation-time distribution (GRTD) shows breast cancer has unique characteristic compared to glandular and adipose tissue [3]. Therefore, integrating EIT with the GRTD and GMM provides a promising framework for tissue clustering in breast cancer detection.

2 EIT-GRTD-GMM

2.1 Frequency selection section

The frequency selection section selects optimum frequency range based on predicted relaxation time distribution function $\mathbf{y}^* \in \mathbb{R}^N$ by maximizing the probability expressed as function:

$$f^{\text{opt}} = \arg \max(p(\mathbf{y}^* | \mathbf{Z}^*) \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})) \quad (1)$$

where p is posterior distribution, $\mathbf{Z}^* \in \mathbb{R}^M$ is imaginary part of impedance, $\mathcal{N}(\cdot)$ denotes the Gaussian distribution.

2.2 Reconstruction section

The reconstruction section reconstructs conductivity distribution $\boldsymbol{\sigma}$ from the impedance distribution $\mathbf{Z} \in \mathbb{C}^{F \times M}$ iteratively by the Gauss-Newton algorithm with Tikhonov regularization to mitigate ill-posed-ness expressed as:

$$\boldsymbol{\sigma}^{r+1} = \boldsymbol{\sigma}^r + (\mathbf{J}^T \mathbf{J} + \gamma \mathbf{I})^{-1} \mathbf{J}^T \Delta \mathbf{Z} \quad (2)$$

where r is r -th iteration, λ is regularization factors and $\mathbf{I}$ is regularization factors [5].

2.3 Clustering section

The clustering section is formulated using a Bayesian Gaussian mixture model (GMM), where the joint distribution of the model is defined as

$p(\boldsymbol{\sigma}, \mathbf{s}, \boldsymbol{\mu}, \boldsymbol{\Lambda}, \boldsymbol{\pi}) = \{\prod_{n=1}^N p(\boldsymbol{\sigma}_n | \mathbf{s}_n, \boldsymbol{\mu}, \boldsymbol{\Lambda}) p(\mathbf{s}_n | \boldsymbol{\pi})\} \{\prod_{k=1}^K p(\boldsymbol{\mu}_k, \boldsymbol{\Lambda}_k)\} p(\boldsymbol{\pi}) \quad (3)$ where $\mathbf{s}_n \in \mathbb{R}^K$ represents cluster assignments, and $\boldsymbol{\pi} \in \mathbb{R}^K$ is mixture proportions. Based on the inferred approximate posterior distributions $p(\mathbf{s} | \boldsymbol{\sigma}, \boldsymbol{\theta}, \boldsymbol{\pi})$, the cluster assignments $\mathbf{s}$ are estimated.

3 Results

GRTD reveals dominant peak in relaxation-time distribution associated with breast cancer, glandular and adipose tissue. GMM clusters conductivity distribution based on these peaks to segment breast cancer region while excluding glandular and adipose tissues as background or noise.

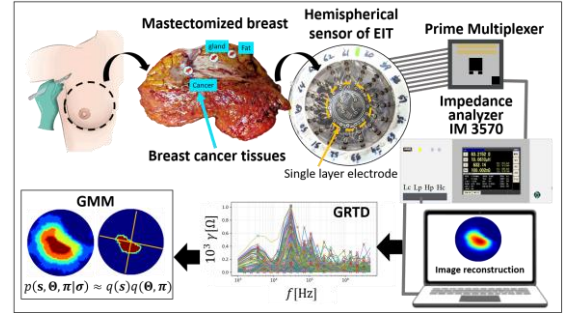


Fig. 1: Conceptual figure of EIT-GRTD-GMM.

4 Conclusions

EIT-GRTD-GMM was proposed and implemented in *ex-vivo* mastectomy experiments, showing accurate estimation of breast cancer regions through quantitative comparison of diameter D and area A with CT-scan images.

Acknowledgements

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Planar Frequency-Difference EIT (*pdfEIT*) for Investigation of Physiological Swelling in the Dorsum of the Foot

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Abstract: Planar frequency difference EIT (*pdfEIT*) has been proposed for investigation of physiological swelling in the dorsum of the foot. Planar sensor was attached to the dorsum of the foot to evaluate the spatial-mean conductivity ($\langle\sigma\rangle$) during prolonged standing. The $\langle\sigma\rangle$ over the time showed a consistent trend.

1 Introduction

Non-invasive investigation of physiological swelling in the lower limb is fundamental for comprehensive health assessment. Although frequency-difference EIT (*fdEIT*) offers thigh and calf monitoring through the use of circular sensors [1-2], current methodologies encounter challenges in monitoring the dorsum of the foot. This area is particularly crucial as an early and visible indicator of potentially severe diseases such as heart failure or renal disease [3]. Consequently, the integration of a planar sensor with *fdEIT* is essential to address the needs for monitoring at the dorsum region. In order to evaluate the performance of *pdfEIT*, bioimpedance analyser (BIA) is employed as a modality for non-invasive impedance monitoring of volume changes in the lower limbs.

2 Methods

The *pdfEIT* consists of a wearable planar sensor with 16 gel electrodes attached at the dorsum of the foot, a digital multiplexer (developed by Takei Lab.), an impedance analyser (IM3570, HIOKI, Japan), and a PC for image reconstruction, as shown in Fig. 1(a). The bioimpedance analyser (BIA) consists of a BIA system and electrodes (InBody S10, InBody Japan Inc.). The protocol consists of 20 minutes prolonged standing for each subject with *pdfEIT* and BIA measurement at 5-minute intervals, as shown in Fig. 1(b).

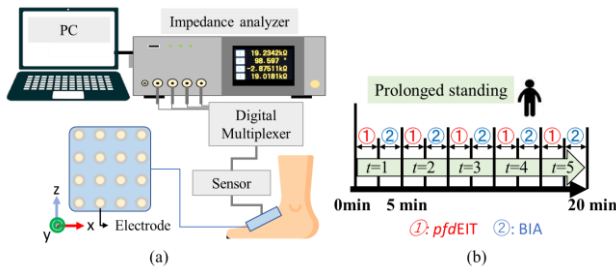


Fig. 1: (a) *pdfEIT* experimental setup and (b) protocol.

The Jacobian matrix element J_{mn} of the measured voltage pattern m at the mesh element n is achieved by [4]

$$J_{mn} = \frac{\partial v_m}{\partial \sigma_n} = \int_{\Omega} \nabla u(i^e) \cdot \nabla u(i^m) d\Omega \quad (1)$$

where $u(i^e)$ is the voltage measured by injecting current i into electrode e , $u(i^m)$ is the voltage measured by current i into pattern m , v_m is the measured voltage at the pattern m , σ_n is the conductivity at the mesh n , and Ω is the inner area

of electrical field in the sensor. The Gaussian-Newton method is utilized to reconstruct σ by [4]

$$\sigma = J^T \Delta Z - (J^T J + \mu I)^{-1} J^T \Delta Z \quad (2)$$

where μ is the hyperparameter. The impedance difference ΔZ_m is calculated as follows [5]

$$\Delta Z_m = \frac{Z_m^{f_2} - Z_m^{f_1}}{Z_m^{f_1}} \quad (3)$$

where $Z_m^{f_2}$ is measured impedance at high frequency f_2 and $Z_m^{f_1}$ is measured impedance at low frequency f_1 .

3 Results

Fig. 2 shows the experimental results of *pdfEIT* at the dorsum of the foot in response to prolonged standing provide a quantitative evidence. As the time increased, a change in $\langle\sigma\rangle$ was observed. This change is correlated with a change in the extracellular fluid within the subcutaneous adipose tissue due to prolonged standing [1]. An R^2 (R-squared) value of 0.69 in a linear regression analysis of $\langle\sigma\rangle$ change over time indicates a fairly strong relationship, and the general direction is well-captured. As reference, the ECW/TBW ratio from BIA demonstrates an increasing trend which suggest the occurrence of swelling [1].

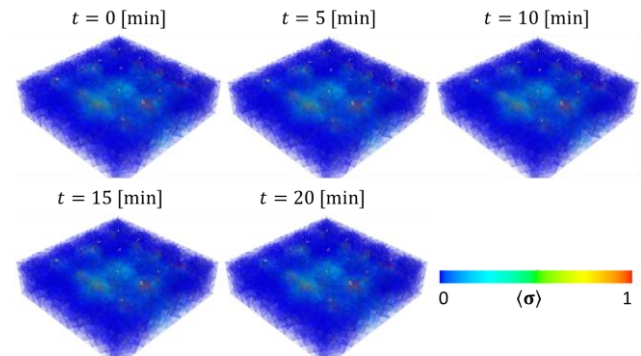


Fig. 2: *pdfEIT* experimental results of prolonged standing.

4 Conclusions

The *pdfEIT* successfully investigates the physiological swelling in the dorsum of the foot. This preliminary study improves the EIT monitoring of physiological swelling in the lower limb.

Acknowledgements

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Tissue-Engineered Oral Mucosal Models for Preclinical Evaluation of Electrical Impedance Spectroscopy in Oral Cancer

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Abstract: Early diagnosis of oral cancer is critical for improving outcomes and reducing mortality. In this proof-of-concept study, we developed *in vitro* models for preclinical evaluation of a novel handheld electrical impedance spectroscopy (EIS) device for detection of potentially malignant oral lesions.

1 Introduction

Globally, oral cancer is the 16th most common cancer with almost 400,000 new cases and 200,000 deaths in 2022^[1]. Early detection is critical for improving survival, yet oral cancer diagnosis remains challenging. Histopathological interpretation is time-consuming with high inter- and intra-observer variability, and scalpel biopsy is invasive, painful, and often performed on lesions that prove benign^[2]. Therefore there is a clinical need for rapid, quantitative and objective screening tools that reduce unnecessary biopsies and enable earlier treatment.

Electrical impedance spectroscopy (EIS) is a non-invasive technique that can characterise biological tissues by measuring their impedance to alternating current over a range of frequencies^[2]. Translation of EIS to oral cancer diagnostics is challenging due to regional variation in tissue properties across the oral cavity and the difficulty of distinguishing healthy, dysplastic, and malignant lesions from their overlapping electrical signatures. Here, we establish preclinical tissue-engineered models to evaluate whether our handheld oral EIS device can discriminate between disease states.

2 Materials & Methods

We engineered 3D *in vitro* models representing healthy, dysplastic, and malignant oral tissues. Normal oral fibroblasts were seeded within decellularised human dermis scaffolds to generate the lamina propria, while oral keratinocyte cell lines derived from healthy, dysplastic, and cancerous mucosa were seeded on top to form the epithelial layer. Models were cultured at an air-to-liquid interface for 10-14 days for epithelial maturation, and validated against native human tissue using immunohistochemistry. Models were probed using a handheld oral EIS device to measure electrical impedance across the engineered tissues, then subsequently fixed and processed for histological analysis enabling direct comparison of impedance measurements with tissue architecture.

These data were then integrated with finite-element mathematical modelling and machine learning approaches to investigate classification of healthy, dysplastic, and malignant tissue states.

2 Results

Histological analysis of tissue-engineered models (Fig. 1a-c) demonstrated features consistent with native pathology. Healthy models exhibited well-organised stratified epithelia, dysplastic models showed increased intercellular space with reduced epithelial cohesion, particularly within the basal compartment, and malignant models demonstrated marked architectural disorganisation with complete loss of epithelial stratification.

Mean impedance spectra (Fig. 1d) differed between healthy, dysplastic, and malignant models, indicating pathology-associated changes in tissue electrical properties, although partial overlap was observed between some individual measurements. Application of machine learning improved classification between different pathologies.

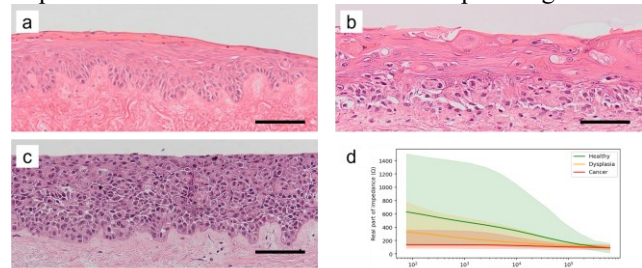


Fig 1: (a-c) Representative histology and (d) EIS readings of (a) healthy, (b) dysplasia and (c) cancerous tissue engineered models. Scale bar = 50 µm.

3 Conclusions

These findings support the use of tissue-engineered oral mucosa as a platform for developing and validating EIS-based diagnostic tools, highlighting the potential of EIS as a rapid, non-invasive method for early identification of potentially malignant oral tissues. Future work will focus on creating oral mucosa models for different regions of the oral cavity (e.g. gingiva, hard palate), prior to translating these findings into an *in vivo* setting.

Acknowledgements

The authors would like to thank Yorkshire Cancer Research (YCRSPF/2023/172) for funding this study.

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EIT for Sarcopenia evaluated on Phantoms and Human Subjects

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Abstract: Sarcopenia is a decline in muscle mass and quality associated with significant adverse health outcomes¹. This study investigated EIT as a method to potentially detect sarcopenia via 1) distinguishing healthy from diseased muscle phantoms, and 2) correlating EIT with ultrasound & CT metrics in a 10-subject pilot study.

1 Introduction

Sarcopenia, a decline in muscle mass and quality, is an often overlooked and undertreated disease. Accurate assessment can be achieved with advanced CT or MRI, but these are often expensive. Alternatively, EIT represents a promising low-cost tool for assessing sarcopenia given the strong impedance contrast between adipose and muscle tissue and the inexpensive, safe, and portable characteristics common to EIT. Ultrasound (US) is also a technology of interest for similar reasons. This work builds on our prior work in muscle-property imaging² and fast surrogate forward model (SFM) approaches³.

2 Materials & Methods

Two EIT strategies were considered: 1) an SFM approach, which uses a fast surrogate model to approximate the forward problem, followed by solving the absolute EIT problem (with the SFM), and 2) a constant best-fit conductivity approach, that uses thresholded impedances to tune where the conductivity will be most sensitive to muscle. **Phantom Experiments:** Experiments consisted of a 5cm thick agar block (muscle) submerged in a saline-filled tank (skin/fat layer). The block was placed either flat or angled (two angles used, Fig. 1C) relative to the electrode array and the array was moved away at 2mm increments using a linear stage going from 0 to 32 mm. For angled positioning, one end of the block started in contact with the electrode array, while the other end was at a fixed distance from the array (5.5mm and 12.7mm). Healthy and diseased muscle agars had $\sigma_{MH}=0.3S/m$ and $\sigma_{MD}=0.13S/m$, respectively, and the skin/fat layer (saline) was $0.02S/m$. A total of 102 samples were collected (2 blocks, 3 tests, 17 depths). Receiver operating characteristic (ROC) curve analysis was performed on reconstructed σ_{MS} using the SFM approach, differentiating healthy from diseased cases.

Human Pilot Study: In an Institutional Review Board approved study, EIT data was collected from a total of 10 subjects using a 12-cm long 32-electrode PCB (electrodes arranged in a 2x16 pattern, Fig. 1D) interfaced to a 32-channel Sciospec EIT system. Current was set to 1mA with 5 log-spaced frequencies spanning 10kHz to 100kHz. For each subject, data was collected from their left and right arm (brachioradialis) and leg (rectus femoris) muscles in a longitudinal direction (4 datasets/subject). US images were collected and segmented in terms of depth to muscle and

average muscle echo-intensity; standard-of-care CTs were segmented in terms of average Hounsfield units of the L3 muscle. Additional data included patient demographics, SARC-F score, (5x) sit-to-stand times, and grip strength. Correlations between constant-best conductivity and US echo-intensity or CT metric quantify the performance.

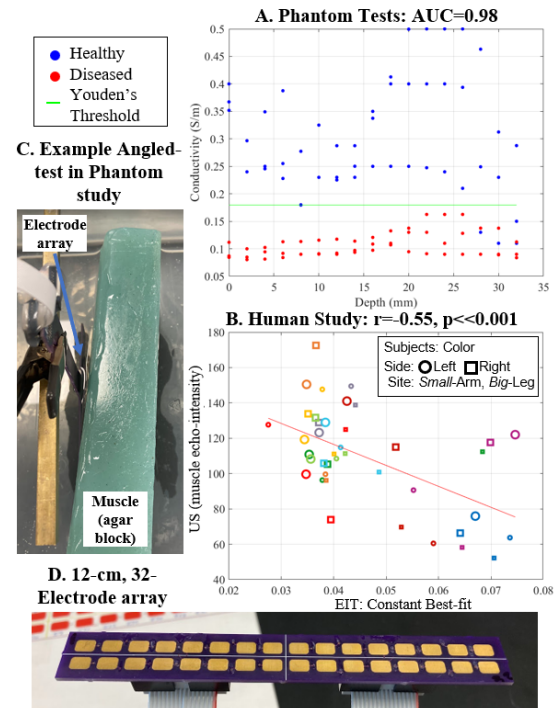


Fig. 1: A. Phantom and B. human study results, and Photos from the C. phantom experiment and D. human-subject array.

3 Results

The SFM performed well on phantom experiments, yielding an area-under-the ROC curve (AUC) of 0.98, while visually providing clear separation on almost all 102 samples (see Fig. 1A). Correlations of -0.55 and 0.63 ($p < 0.001$) for US and CT metrics, respectively, were found for the human study using the constant-best conductivity. Importantly, the moderate correlations are in directions expected assuming fatty-infiltration of muscle.

4 Conclusions

The overall approach appears promising. The constant best-fit approach seems to be a simple and promising way to quantify the EIT recordings.

Acknowledgements

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Clinical Analysis of Bioimpedance Breast Detector in Diagnosing the Malignancy and Benignity of Breast Tumors

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Abstract: All Electrical Impedance Mammography (EIM) parameters outperformed those of other imaging devices. Clinical trial of 262 patients undergoing breast surgery comparing Ultrasound, X-Mammography, and EIM examinations, and evaluating their sensitivity, specificity, false-positive rates, and false-negative rates.

1 Introduction

Incidence of breast cancer in women is 46.8 per 100,000 GLOBOCAN 2022. It is the most common cancer in women worldwide. Existing diagnostic methods exhibit deficiencies in both malignancy detection sensitivity and accuracy. EIM is effective for early and accurate diagnosis of breast cancer.

2 Materials and Methods

2.1 Trial Instruments

The EIM based breast imaging^[1] and its DAS configuration system^[2] have been used for this clinical trials compared to ultrasound and mammography.

2.2 Trial Design, Results and Evaluation

Using pathological diagnosis as the gold standard, statistical analysis was performed on the diagnostic results of EIM, ultrasound, X-ray mammography, and combined ultrasound-X-ray mammography to validate the efficacy of the EIM Device for breast cancer diagnosis.

Table 2: Evaluation of diagnostic results for EIM Device, ultrasound, mammography, and combined ultrasound and X-ray mammography (pathological diagnosis as the gold standard, with statistical analysis by surgical side, %)

Diagnostic Method	Sensitivity	Specificity	Positive predictive value	Negative predictive value	Missed detection rate	False positive rate	Precision
EIM	95.4	99.4	99.0	97.0	4.6	0.6	97.8
ultrasound	78.7	91.4	85.9	86.6	21.3	8.6	86.3
Mammography	56.5	97.0	92.4	77.0	43.5	3.1	80.7
ultrasound + mammography	85.2	90.1	85.2	90.1	14.8	9.9	88.2

Two centres: 1. Shanghai International Peace Maternal and Child Health Hospital (178 cases). 2. Taizhou Hospital, Zhejiang Province (84 cases). Age distribution: Mean 50, median 49 years old. The SS dataset included

261 cases (322 sides); PPS dataset comprised 213 cases (270 sides).

Table 1: Distribution of benign and malignant cases (Statistical unit: side)

Data set	Centre 1		Centre 2		Total of the two centres	
	benign	malignant	benign	Malignant	benign	Malignant
SS	139	92	53	38	192	130
PPS	118	81	44	27	162	108

3 Discussion and Conclusion

3.1 Discussion

1) EIM is effective at diagnosing benign and malignant breast tumours.

2) Ultrasound and X-ray mammography exhibit high specificity, but insufficient sensitivity. X-ray mammography missed 43.5% of malignant tumours.

3.2 Conclusion

1) The EIM device out-performs China's gold standard for breast tumour screening--ultrasound equipment significantly in all diagnostic indicators, and it surpasses the traditional gold standard, ie X-ray mammography equipment by a general investigation, and also demonstrates superior performance compared to the combined ultrasound and X-ray mammography diagnosis.

2) The EIM is based EIT's advantage, requires minimal time for each examination, and it is painless, non-invasive, and uses non-ionic radiation. In conclusion, the EIM device demonstrates exceptional clinical application value. Based on the reasons for case exclusion in this clinical trial, the future improvement opportunities for the EIM device are analysed as follows: 1) Enhance the power pre-processing and anti-interference capabilities of the EIM Examination Room to ensure the electromagnetic environment during installation meets the EMC specifications of the EIM device; 2) Optimize the ergonomic design of the device to ensure that the breasts of elderly patients are more fully immersed within the detection scanner area.

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Modelling of a label-free DNA Biosensor based on MIS

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Abstract: Electrical conductivity and permittivity of Deoxyribonucleic Acids (DNA) at multiple concentrations informed a three-dimensional electromagnetic simulation of DNA placed between transmitting and sensing coils. Magnetic Induction Spectroscopy (MIS) measurements (0.001-1 MHz) show sensitivity to the presence of DNA.

1 Introduction

Affordable and accessible Deoxyribonucleic Acids (DNA) detection remains a major challenge in global healthcare because most molecular diagnostic techniques rely on chemical labels, complex reagents, and expensive equipment [1]. The objective of this study was to investigate a fundamentally different approach based on Magnetic Induction Spectroscopy (MIS) to detect DNA concentrations in solution without labels, reagents, or physical contact.

2 Materials & Methods

Experimental complex impedance data [2] were used to estimate the bulk electrical conductivity and permittivity of Deoxyribonucleic Acids (DNA) at multiple concentrations, and these properties informed a three-dimensional electromagnetic simulation of DNA in a Polymerase Chain Reaction (PCR) tube placed between transmitting and sensing coils. An alternating magnetic field (0.001- 1 MHz) generated by the excitation coil induces a voltage on the sensing coil, and the presence of DNA produces measurable change in the induced potential. Simulations were carried out using COMSOL Multiphysics v5.0 (COMSOL Inc., Burlington, MA) [3].

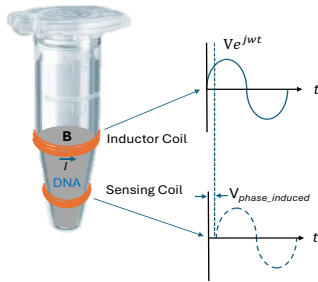


Fig. 1: 3D model of Deoxyribonucleic Acids (DNA) in a typical (200 uL) Polymerase chain Reaction (PCR) plastic tube container. DNA volume under analysis is 50 uL. An alternating magnetic flux density (B) is generated by an inductor coil through the injection of an alternating current ($Ie^{j\omega t}$).

The governing equation for the system was the frequency-domain formulation of Maxwell–Ampère’s law, expressed via the magnetic vector potential A :

$$(j\omega\sigma - \omega^2\epsilon_0\epsilon_r)A + \nabla \times (\mu_0^{-1}\mu_r^{-1}B) - \sigma v \times B = J_e \quad (1)$$

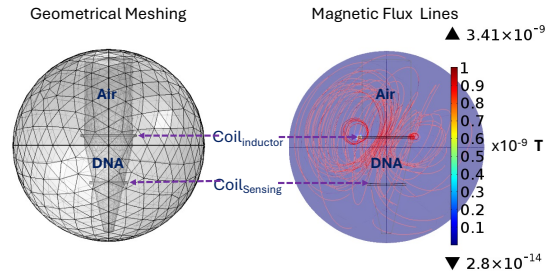


Fig. 2: Meshing of the geometrical model and simulation of magnetic flux lines as representation of magnetic field interaction.

3 Results

Multifrequency analysis revealed clear differences in the inductive phase shift as a function of DNA concentration, with maximum sensitivity near 1 MHz.

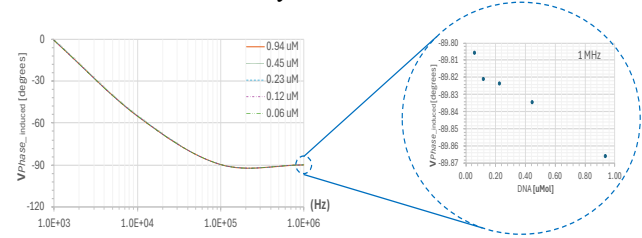


Fig. 3: Spectra of inductive phase shift estimated in the sensing coil at five DNA concentrations, a zoom view at 1 MHz.

4 Conclusions

Simulated results indicate a potential detection range of 0.06–1000 μMol , encompassing typical post-PCR concentrations. The findings demonstrate modelling-based feasibility for bulk DNA concentration detection.

Acknowledgements

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Synthetic- and *in vitro*- data enabled feature selection for EIS-based oral cancer diagnosis

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Abstract: Early diagnosis of oral cancer vs dysplasia remains a key factor in contributing to positive patient outcomes. We use a combination of synthetic and *in vitro* spectra from tissue engineered models of oral tissues, to train and finetune a classifier as a feature extractor for the classification of dysplasia and cancer. An AUROC of 0.883 was obtained when applied to *in vivo* data.

1 Introduction

According to WHO [1], in 2022 there were almost 400,000 new cases and 200,000 deaths related to oral cancer worldwide. Oral cancer diagnosis involves scalpel biopsy followed by histopathological assessment, which is a painful, invasive procedure, with long waiting times. Electrical impedance spectroscopy (EIS) is a non-invasive technique that allows real-time detection of pathological and cancerous tissue changes based on the influence of cellular level tissue structure on the opposition to the flow of alternating current. Discriminating between EIS spectra derived from dysplasia and cancerous oral tissues remains a significant challenge. In this pilot study, we explored AI-based methods for discriminating oral dysplasia from cancer, mitigating a scarcity of available *in vivo* EIS data by using models trained and finetuned on synthetic and *in vitro*-derived data to select the most effective features for application on *in vivo* data based diagnostic models.

2 Materials & Methods

2.1 Virtual Oral Tissues and synthetic EIS data

Finite element models, or “Virtual Oral Tissues” (VOTs) were developed based on morphological data retrieved from histology images of tissue engineered (TE) models of dysplastic and cancerous oral epithelium with cellular and tissue level morphological parameters varied across the observed range. The VOTs were used to simulate synthetic EIS data at 14 frequencies in the range [76 Hz-625 MHz], and the resulting spectra verified against EIS data collected from the TE constructs using a tetrapolar probe at the same frequencies to ensure VOT validity.

2.2 Classification pipeline

Machine learning and deep learning-based methods were trained on a synthetic dataset of 100 dysplastic and 100 cancerous EIS spectra. Specifically, four neural network architectures were investigated for feature extraction: multi-layer perceptron (MLP), convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM). These models were first trained on the synthetic data and fine-tuned on 191 *in vitro* measurements from 40 TE models. Three-fold cross validation was used to train and evaluate the model. This model was then used as a feature extractor in order to classify 57 *in vivo* readings from 35 patients [2].

3 Results

Synthetic and *in vitro*-derived EIS spectra revealed a promising agreement for all types of tissues. LSTM was identified as the best performing model, achieving a sensitivity of 93.8%, specificity of 96.0%, and AUROC (Area Under Receiver-Operator Characteristic Curve) of 0.987 for the *in vitro* data. However, simple fine-tuning of the trained model was not sufficient to classify an existing set of *in vivo* data [2]. This is due to factors including the more complex nature of *in vivo* tissue from different lesion sites and dysplasia grades, causing more variation in readings compared to the *in vitro*-derived data. Instead, the fine-tuned models were used as feature extractors by removing the classification head and using the resulting vector as input to a support vector machine (SVM) for *in vivo* classification. Once again, the LSTM proved the best model for feature extraction. This method achieved a 88.9% sensitivity, 90.8% specificity and 0.883 AUROC.

		Predicted Label	
		Dys	Cnr
True Label	Dys	107	4
	Cnr	6	74

a)

		Predicted Label	
		Dys	Cnr
True Label	Dys	36	4
	Cnr	2	15

b)

Fig 1: Confusion matrices showing predicted vs true labels for dysplasia and cancer spectra for a) *in vitro* data after fine tuning on synthetic spectra and b) *in vivo* data using the fine-tuned model as a feature extractor and SVM for classification.

4 Conclusions

This proof of concept study has demonstrated the utility of synthetic and *in vitro*-derived EIS data in determining the most effective features for differentiating between dysplastic and cancerous oral tissues. Future work will focus on refining the algorithm and retraining on additional *in vivo* data to further develop this novel idea..

Acknowledgements

The authors would like to thank Yorkshire Cancer research for funding this study (YCRSPF/2023/172).

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Magnetic Induction Spectroscopy as a tool for detecting cervical remodelling to predict preterm birth – findings of a pilot study

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Abstract: Preterm birth remains a leading cause of neonatal morbidity and mortality, with limited predictive accuracy from current screening tools. This study evaluated cervical magnetic induction spectroscopy (MIS) to detect cervical remodelling. MIS showed excellent prediction of preterm birth in symptomatic women and comparable performance to cervical length in high-risk asymptomatic women.

1 Introduction

Preterm birth (PTB) is a significant contributor to neonatal morbidity and mortality. Current screening strategies, such as transvaginal ultrasound cervical length (TVUSCL), have limited predictive accuracy. Cervical remodelling begins weeks before labour onset and can be detected through changes in tissue electrical conductivity.

Aims and objectives: We aimed to assess the feasibility of using cervical magnetic induction spectroscopy (MIS), a non-invasive, contactless technique that measures tissue electrical conductivity [1], to evaluate cervical remodelling and enhance the prediction of PTB.

2 Materials & Methods

Women with singleton pregnancies were recruited either at presentation with symptoms of PTB (n= 32) or asymptomatic (n=59) but at high risk of PTB based on a previous history of PTB. Cervical transresistance (CT) was measured at 15 frequencies (21–1013 kHz) using the MIS device between 20 and 28 weeks' gestation. Two bioimpedance experts independently assessed the quality of the derived spectral data, and spectra deemed poor quality

were excluded. The ability of CT to predict delivery <37 weeks was quantified and compared to TVUSCL using Receiver Operator Characteristic (ROC) curve analysis.

3 Results

In women presenting with symptoms of preterm labour, cervical transresistance measured at 20–22 weeks showed excellent predictive performance for PTB < 37 weeks (AUC 0.92, 95% CI 0.77–0.99), compared to TVUSCL (AUC 0.68, 95% CI 0.50–0.84). In asymptomatic high-risk women, MIS predictive performance was non-inferior to CL (AUC= 0.73, 95% CI 0.58–0.86 vs 0.71, 95% CI respectively) for predicting delivery < 37 weeks.

4 Conclusions

Similar to our previous findings from studies of Electrical Impedance spectroscopy, MIS is a promising non-invasive tool for predicting preterm birth in singleton pregnancies, especially in symptomatic women. Larger studies are necessary to confirm these findings and to assess their predictive usefulness for delivery within 1–2 weeks of assessment in women presenting with symptoms of threatened preterm labour.

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Tab. 1: Prediction of birth < 37 weeks Cervical trans-resistance and Cervical Length

		AUC (95% CI)	Sensitivity	Specificity	PPV	NPV	Positive likelihood ratio	Negative likelihood ratio
Symptomatic Group	MIS Trans-resistance	0.92 (0.77 – 0.99)	83.3 (35.9 – 99.6)	100 (86.8 – 100)	100.0	96.3 (81.3 – 99.4)	>21.7	0.17
	TVUS CL	0.68 (0.50 – 0.84)	80.0 (51.9 – 95.7)	43.9 (28.5 – 60.3)	34.3 (26.5 – 43.0)	85.7 (67.3 – 94.6)	1.43	0.46
	MIS + US CL	0.91 (0.76 to 0.98)	83.3 (35.9 – 99.6)	100 (86.8 – 100)	100.0	96.3 (81.3 – 99.4)	>21.7	0.17
Asymptomatic high-risk group at Visit 1	MIS Trans-resistance	0.73 (0.58–0.86)	83.3 (51.6 – 97.9)	59.4 (40.6 – 76.3)	43.5 (32.0 – 55.7)	90.5 (72.2 – 97.2)	2.05	0.28
	TVUS CL	0.71 (0.55 – 0.84)	19.1 (5.4 – 41.9)	93.2 (81.3 – 98.6)	57.1 (24.7 – 84.4)	70.7 (65.9 – 75.1)	2.79	0.87
	MIS + US CL	0.83 (0.68 – 0.92)	83.3 (51.6 – 97.9)	77.4 (58.9 – 90.4)	58.8 (41.5 – 74.2)	92.3 (77.0 – 97.7)	3.7	0.2
Asymptomatic high-risk group at Visit 2	MIS Trans-resistance	0.73 (0.57 – 0.853)	76.9 (46.2 – 95.0)	65.6 (46.8 – 81.4)	47.6 (34.1 – 61.5)	87.5 (71.5 – 95.1)	2.24	0.35
	TVUS CL	0.54 (0.38 – 0.69)	68.8 (41.3 – 89.0)	52.4 (36.4 – 68.0)	35.5 (25.8 – 46.5)	81.5 (66.8 – 90.6)	1.44	0.6
	MIS + US CL	0.72 (0.56 – 0.85)	76.9 (46.2 – 95.0)	70.0 (50.6 – 85.3)	52.6 (37.4 – 67.4)	87.5 (71.6 – 95.1)	2.56	0.33

Session 8: Experimental Methods and Validation

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Classification of Ambiguous German Sign Language Gestures Using Forearm Electrical Impedance Tomography

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Abstract: Adjacent-injection EIT is applied to classify five ambiguous DGS gesture pairs on the forearms of 10 healthy subjects. Separability is assessed via FDR. LDA, SVM, and kNN are evaluated under intra- and inter-subject validation. All pairs exceed 90% within-subject accuracy, while inter-subject performance decreases for M–N and U–V.

1 Introduction

Electrical Impedance Tomography (EIT) is a non-invasive and wearable sensing modality capable of capturing deep muscle activity through conductivity variations, offering advantages over surface- or vision-based modalities that are limited to superficial observations. Recent studies demonstrated the feasibility of EIT-based hand gesture classification using machine learning and deep learning methods. However, the potential of EIT for measuring deep muscle impedance changes and discriminating ambiguous DGS letters remains largely unexplored [1, 2].

2 Methodology

2.1 Data Acquisition and Preprocessing

EIT measurements are acquired from the right forearm of 10 healthy subjects using an 8-electrode system [3] under the adjacent injection pattern. Each subject performed ten DGS alphabet gestures (Fig. 1), with 10 repetitions per gesture. Five biomechanically and visually ambiguous pairs (A–S, M–N, U–V, G–H, O–C) are selected as the focus of the discriminability analysis. Signals are z-score normalised per subject over all 40 boundary voltages to remove inter-subject amplitude bias.

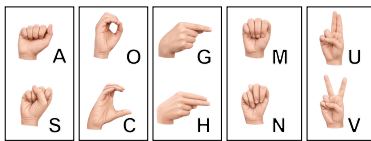


Fig. 1: Five ambiguous pairs of DGS alphabet

2.2 Discriminability Analysis

Fisher Discriminant Ratio (FDR) is selected as it provides a reliable measure of linear class separability even under small sample sizes [5]. Discriminability is further visualised via t-SNE [4], capturing non-linear cluster structure beyond linear projections. The results are shown in Tab. 1.

Tab. 1: FDR for ambiguous DGS gesture pairs.

Gesture pair	FDR (Mean $\pm$ SD)
O–C	3.24 $\pm$ 2.18
A–S	3.09 $\pm$ 2.15
G–H	1.33 $\pm$ 0.79
M–N	0.63 $\pm$ 0.33
U–V	0.43 $\pm$ 0.32

Tab. 1 indicates that OC and AS are the most separable gesture pairs, GH shows intermediate separability, whereas

MN and UV are the most ambiguous. This result is consistent with the t-SNE projections in Fig. 2.

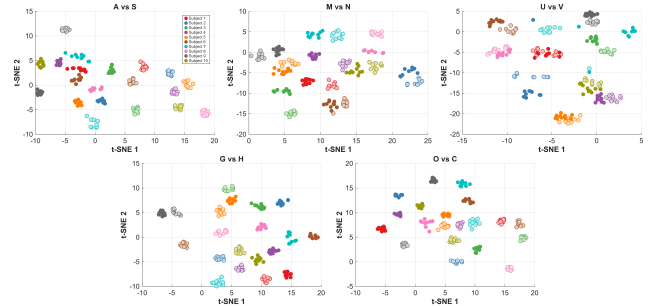


Fig. 2: Two-dimensional t-SNE projections per ambiguous pair (Light = first gesture, dark = second gesture).

2.3 Classification and Validation

Each ambiguous pair is classified using LDA, linear SVM, and kNN, evaluated under leave-one-repetition-out (intra-subject) and leave-one-subject-out (inter-subject) cross-validation. These classifiers are chosen for their effectiveness in gesture recognition with small datasets. The classification results are shown in Tab. 2.

Tab. 2: Classification accuracy (%) for ambiguous DGS gesture pairs under intra- and inter-subject validation.

Gesture pair	Intra-subject	Inter-subject
A–S	100	> 83
M–N	100	46–60
U–V	> 90	47.5–58
G–H	100	75–80
O–C	100	> 83

Intra-subject validation shows high classification accuracy in all gesture pairs. In contrast, inter-subject performance decreased for MN and UV, which indicates limited cross-subject generalisation due to anatomical and tissue-related variability. These findings support the potential of EIT-based forearm sensing for discriminating biomechanically ambiguous gestures.

3 Conclusion

EIT enables differentiation of ambiguous DGS gesture pairs under intra-subject conditions. However, reduced inter-subject performance for MN and UV highlights the challenge of subject variability and indicates that robust cross-subject generalisation requires further investigation.

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Magnetic Detection EIT with Optically Pumped Magnetometers (OPMs) in a Saline Phantom

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Abstract: We investigated the use of ⁸⁷Rb optically pumped magnetometers (OPMs) for magnetic detection EIT (MDEIT) at 1.5kHz. Experiments in a saline phantom demonstrated the sensitivity of the sensor to conductivity perturbations. This supports feasibility of neural imaging using OPM-based MDEIT.

1 Introduction

Fast neural EIT of the brain with epicortical electrodes has been demonstrated in preclinical models, producing images of neuronal activity in anaesthetised rats [1]. Clinical translation has so far been limited due to signal attenuation by the skull, requiring surgical placement of electrodes directly on the brain. Since the skull is effectively transparent to magnetic fields, MDEIT with OPMs offers a pathway to overcome the principal limitation of conventional EIT and enable non-invasive neural imaging. OPMs are quantum sensors that measure magnetic fields using laser-driven spin polarisation of alkali vapour atoms [2]. The original configuration implies zero-field regime, with intrinsic sensitivity centred at low frequencies. However, applying an external DC bias field shifts the atomic resonance, enabling detection in the radiofrequency domain. Previous work demonstrated maximal SNR of evoked neural impedance changes at ~1.5kHz [3].

2 Purpose

This work assessed whether ⁸⁷Rb OPM is sensitive to perturbations in a saline-filled phantom at EIT-relevant frequency by tuning sensor operational frequency to 1.5kHz using an external DC bias field.

3 Materials & Methods

A cylindrical tank (radius 4cm, height 5cm) filled with 0.9% saline was placed in a magnetically shielded chamber, with a QuSpin Gen-2 OPM [4] on the outer side of the tank between two injecting electrodes (Fig.1). The sensor was externally biased with 180nT DC field to a resonant frequency of 1.5kHz. A cylindrical sponge perturbation (radius 1.2cm, height 5cm, conductivity contrast 1.6%) was consecutively placed at eight different locations relative to the current injection path. With a constant 65μA current between two electrodes, the corresponding magnetic field changes introduced by perturbations were calculated as a percentage relative to the baseline field measured in the unperturbed tank. Additionally, finite element simulations were performed in EIDORS using custom MDEIT-specific MATLAB code [5] to model magnetic field changes associated with each of the eight perturbation positions.

4 Results

The pattern of magnetic field changes relative to the perturbation position agreed with the simulated magnetic

field changes ($r = 0.89$, $p = 0.003$). Maximum changes were observed for perturbations positioned directly in the current path (locations 1, 8): $\Delta B_1 = 1.47 \pm 0.11\%$, $\Delta B_8 = 1.35 \pm 0.13\%$, whereas perturbations furthest away from the current path produced the smallest response (locations 5, 6): $\Delta B_5 = 0.41 \pm 0.03\%$, $\Delta B_6 = 0.38 \pm 0.03\%$.

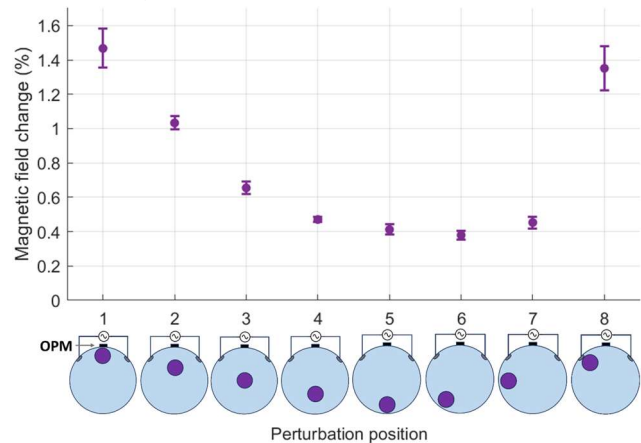


Fig. 1: OPM sensor responses to magnetic field changes induced by sponge perturbations placed at eight positions relative to the injecting electrodes ($I_{AC}=65\mu A$, $f=1.5kHz$).

5 Discussion

Operated at 1.5kHz, the sensor was able to detect magnetic field changes below 0.5% with the sponge perturbation placed furthest away from the current path (positions 5 and 6). The dependence on perturbation position indicates that the OPM is primarily sensitive to changes in current density distribution, with the strongest effects occurring where current pathways are most directly disrupted (positions 1 and 8). This spatial sensitivity, confirms that the system responds to conductivity-driven modulation of current flow and resulting magnetic fields, supporting its potential for impedance-based sensing applications.

6 Future work

Future work will implement a full 16-electrode injection protocol in a saline phantom followed by measurements in a realistic head phantom to enable imaging of perturbations at 1.5kHz. This will precede translation to animal and human studies.

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At last, an explicit SVD of the linearized EIT problem on the disk

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Abstract: After 40 years, we finally have explicit singular values and singular functions of the linearized EIT forward problem on the unit disk. For simplicity we treat the rotationally symmetric case and change variables from the conductivity to the Schrödinger equation.

1 Introduction

The singular value decomposition of the matrix of the derivative of the forward problem of EIT has played an important role in studying the ill-posedness and non-uniformity of resolution since the 1980s. Murai and Kagawa [5] used a numerical SVD for their resistor mesh/FEM model. The first two authors also calculated the SVD using a FEM model and in [1] used the singular values to show the relative unimportance of drive pair separation. See also [2] for numerical singular values for rotationally symmetric case.

2 Reduction to the truncated Hilbert transform

We specialise to the unit disk in two dimensions Ω . For simplicity we will treat the Schrödinger's equation version of the Calderón problem, via the well known Liouville transformation. Given $\nabla \cdot \gamma \nabla U = 0$ we change the variables to $u = \gamma^{1/2} U$ and $q = -\nabla^2 \gamma^{1/2} / \gamma^{1/2}$ in which case $\nabla^2 U + qU = 0$ and we study the map $F(q) = \Lambda_q$ where $\Lambda_q : U|_{\partial\Omega} \rightarrow \partial U / \partial r|_{\partial\Omega}$. For a perturbation $q + \eta$ the Fréchet derivative is given by $\langle f_2 DF_q \eta \rangle f_1 = \int_{\partial\Omega} \eta u_1 u_2$ where u_i has Dirichlet data f_i .

Now choosing $q = 0$ (i.e. $\gamma = 1$) and working in polar coordinates, we have solutions of Laplace's equation $r^{|k|} e^{ik\theta}$. Now looking at the special case where $\eta(r)$ and define $\mathcal{N} = DF_1^* DF_1$ as the normal operator, and a calculation using Fourier components of the boundary data, and summation of a series, gives

$$\mathcal{N}\eta(r') = \int_0^1 \frac{\eta(r)}{1 - (rr')^2} r dr$$

A change of variables to $x = (r^2 - 1)/(r^2 + 1)$, $y = (1 - r'^2)/(r'^2 + 1)$ reduces this to the finite Hilbert transform

$$\tilde{\mathcal{N}}\tilde{\eta}(y) = \int_{-1}^0 \frac{1}{x - y} \tilde{\eta}(x) dx$$

with $-1 < x < 0$ and $0 < y < 1$, specifically the case where the x and y intervals are adjacent treated by [3]. The main insight is to notice that $\tilde{\mathcal{N}}$ commutes with the differential operator

$$Ph = (x^2(1 - x^2)h')' + 2x^2h,$$

which has known orthogonal generalized eigenfunctions $\phi(x, \mu)$ in terms of hypergeometric functions [3]. As these

functions diagonalize P they also diagonalize $\tilde{\mathcal{N}}$ to the operator that multiplies by $\pi \operatorname{sech} \pi \mu$, these are a generalization of squared singular values.

The “conormal” operator $DF_1 DF_1^*$, in a Fourier basis, is the classical Hilbert matrix [4, Thm 3] with the same diagonalization $\pi \operatorname{sech} \pi \mu$.

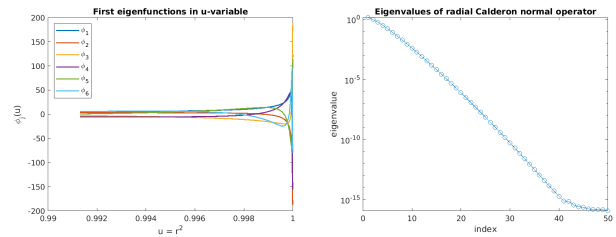


Fig. 1: L: The first few singular functions. They are concentrated near the boundary, and plotted on a truncated $u = r^2$ scale. R: First 50 eigenvalues on a logarithmic scale

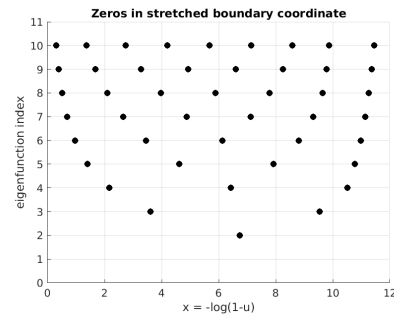


Fig. 2: Zeros of first few singular functions on a $-\log(1 - r^2)$ scale. Note approximately equally spaced.

3 Conclusions

The theory agrees with the exponential decay in singular values observed numerically. The extreme concentration of the singular functions at the boundary is perhaps a surprise. If the conductivity is assumed known in a small layer near the boundary the intervals in the Hilbert transform are disjoint, the operator compact, and the spectrum discrete. This is a hint that recovery of conductivity near the boundary (requiring small, close together electrodes) should be considered separately from the severely ill-posed problem of recovering conductivity in the interior.

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Frequency response of impedance changes during evoked activity in a rodent model

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Abstract: Frequency-division multiplexed electrical impedance tomography (FDM-EIT) requires a broad operational frequency range. This work evaluated its suitability for fast neural EIT, characterising impedance changes in the rat sciatic nerve during evoked activity up to 40 kHz, finding measurable changes up to this value.

1 Introduction

Fast neural EIT (fnEIT) has been demonstrated in rodent models using epicortical electrodes, successfully reconstructing fast neural activity with a resolution of 200 μm and 2 ms [1]. This is done using time-division multiplexing (TDM) and repeated averaging, leading to long data acquisition times and hindering real-time imaging. Frequency-division multiplexing (FDM) is a potential solution to this limitation, but it requires a large operational bandwidth to enable sufficient spacing between current injection frequencies [2].

Impedance changes occurring due to evoked physiological activity in the rat brain and nerve have, to date, only been characterised up to 10 kHz [3] and 15 kHz [4], respectively. Due to the filter parameters suitable for these impedance changes, injection frequencies must be spaced 1-2 kHz apart to enable FDM-fnEIT. Alongside the need for a minimum of ~ 32 electrodes for image reconstruction in the brain, this means a larger frequency range with measurable changes in impedance is essential.

The purpose of this study was to (1) extend the existing frequency characterisation up to ≥ 40 kHz and (2) determine the feasibility of implementing FDM-fnEIT to get closer to a real-time fnEIT system.

2 Materials & Methods

A female Sprague-Dawley rat (approx. 360 g) was anaesthetised with urethane. A custom cuff electrode array with 14 contacts was placed around the right sciatic nerve, and the posterior tibial nerve was electrically stimulated at 5 Hz to produce compound action potentials (CAPs). 150 μA_{pp} current was injected via one electrode pair, identified to produce the largest impedance changes (dZs), at frequencies ranging from 6 to 40 kHz, and subsequent voltages measured at eight other electrodes. A custom 8-channel DAQ system [5] was used in combination with the Scouse-Tom EIT system [2] to inject the current and record the impedance changes.

Data was band-pass filtered (3rd-order Butterworth filter, 2 kHz bandwidth around each carrier) and demodulated. Traces were then low-pass filtered (3rd-order Butterworth, 2 kHz cut-off) and split into epochs and averaged to ob-

tain, for each frequency, the maximum signal-to-noise ratio (SNR), and the peak impedance changes (dZs) in microvolts and in percentage with respect to the standing field.

3 Results

Impedance changes were measurable up to 40 kHz, with the largest dZs (0.012%, 14.64 μV , SNR = 40.34) observed at 6 kHz (Figure 1). The latency of the peak impedance changes (1.149 ± 0.018 ms) was consistent with the first peak of the CAPs.

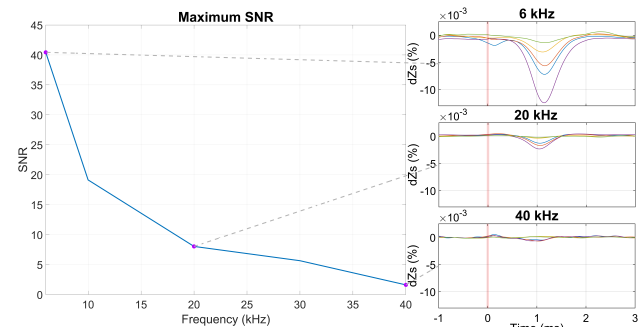


Fig. 1: Left: Peak value of the SNR recorded across frequencies. Right: Impedance traces measured at 6, 20 and 40 kHz, presented as the percentage change with respect to the background voltage. The red line represents the time at which the stimulus was applied.

4 Conclusions

Impedance changes in the nerve were observed within the range of frequencies from 6 to 40 kHz. This suggests that FDM-fnEIT is feasible for imaging activity in peripheral nerves, where a ring of 14 electrodes is sufficient. Current can be injected in parallel at all independent electrode pairs with a range of frequencies spanning ~ 28 kHz, with a bandwidth of 2 kHz allowing sub-millisecond temporal resolution and real-time data acquisition. Work is in progress to evaluate the frequency response in the brain to determine the feasibility of using FDM-fnEIT with ≥ 32 electrodes on the cortex.

Acknowledgements

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Session 9: Posters

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EIT with a wrapped-around electrode belt

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Abstract: Can we create EIT images when the electrode belt wraps around? Yes.

1 Introduction

EIT belts are sometimes not available in the right size. In that case, the belt is sometimes wrapped around the subject. This means that electrodes are in the wrong position for the original reconstruction algorithm, and that there is a vertical extent where the electrodes are overlapped.

We show that images can be reconstructed from such an electrode placement, by: 1) 3D Modelling of the body and electrode positions; 2) Reconstructing with a 3D algorithm; and 3) Taking a centre slice at the desired location

2 Methods: Data

As part of EIT data collection in brachycephalic beagles, EIT data were acquired with a Dräger Pulmovista 500. Since available belts were too small, the belt was wrapped around the thorax. Detailed photos of each animal were taken and a electrode positions noted so that an appropriate FEM (fig 1) could be modelled.

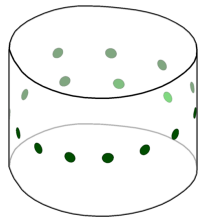


Fig. 1: FEM model with wrapped around electrodes

Brachycephalic dogs have shortened skull bones giving the face and nose a pushed-in appearance. These animals can have obstructive airways disease and often require surgical correction [2]. We conducted this study to define how different helmet CPAP levels alter cardiopulmonary mechanics in sedated dogs, providing physiologic evidence to inform more effective and safer clinical CPAP use.

3 Methods: Image Reconstruction

Using the custom FEM, an EIT forward model was created of the adjacent stimulation and measurement patterns. This model was used with 3D GREIT [1] to reconstruct images across multiple planes. Finally, the image in the centre plane (through the centre of the electrodes) was retained.

Data (available at DOI: 10.5281/zenodo.17829975) are shown in fig 3 during a transition of CPAP from 8–12 cmH₂O. We see an increase in EELI, a longer expiratory time, and a small ventral redistribution of ventilation.

To understand the effect, we compare images from regular and helical placement (fig 2). An offset in resolution and image amplitude is seen near the electrode overlap.

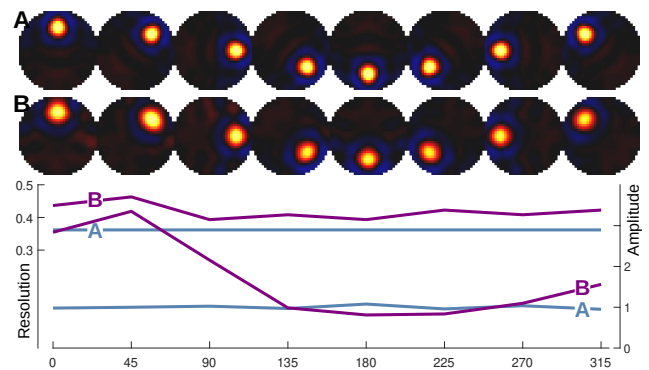


Fig. 2: Images from simulated data for (A) regular- and (B) helical-placement. Bottom right: amplitude, $\sum$ image normalized to $\sum A = 1$; left: image resolution, $\sqrt{\text{Area} > \frac{1}{2} \text{max}}$.

In summary, EIT images can be reconstructed if a too-large electrode belt has been wrapped; however, the resulting images have some distortions.

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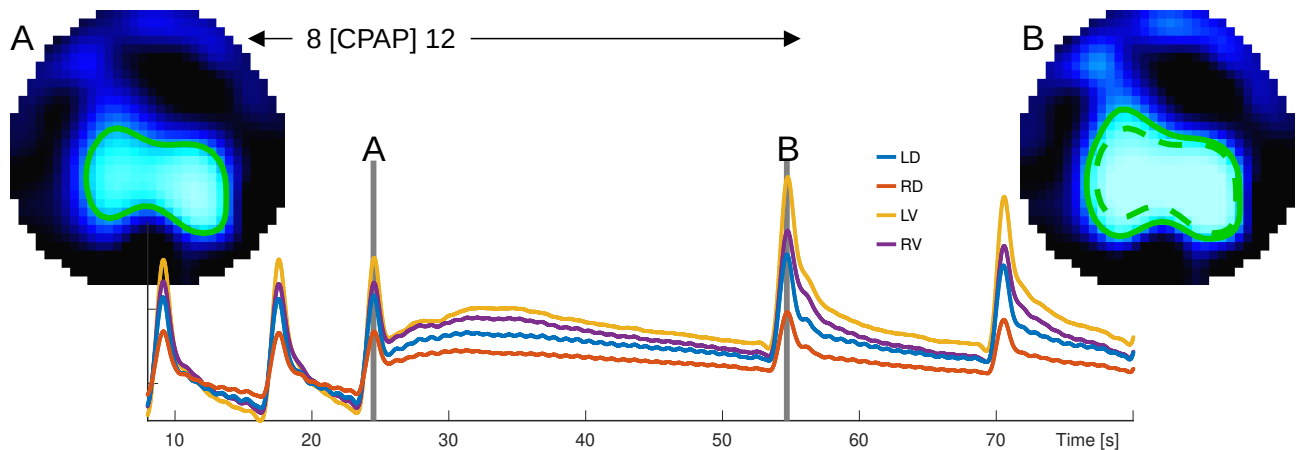


Fig. 3: EIT waveforms and images at indicated times of a beagle with CPAP transition from 8 to 12 cmH₂O

CVAE-g*EIT: A Conditional Variational Autoencoder for Complex-Valued Gastric EIT Reconstruction

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Abstract: CVAE-g*EIT has been proposed to reconstruct conductivity σ and relative permittivity ϵ of gastric tissue. CVAE-g*EIT processes complex impedance $\mathbf{Z}$ through an encoder-decoder conditioned on frequency f . Simulation results demonstrate that the frequency-dependent gastric tissue characteristics are accurately captured.

1 Introduction

Non-invasive monitoring of gastric processes is vital for assessing gastrointestinal health [1]. While gastric electrical impedance tomography (gEIT) provides gastric volume and function [2], standard methods struggle to resolve the complex-valued physical properties of biological tissues. Accurate characterisation requires simultaneous mapping of conductivity σ and relative permittivity ϵ [3], which fluctuate during gastric processes. However, traditional iterative algorithms are often limited by non-linearity and high computational costs when resolving complex impedance $\mathbf{Z}$ from resistance $\mathbf{R}$ and reactance $\mathbf{X}$. To overcome these challenges, a conditional variational autoencoder for complex-valued gEIT reconstruction (CVAE-g*EIT) has been proposed. By conditioning the generative process on frequency f , CVAE-g*EIT directly maps multi-frequency measurements to dual-channel physical property maps, enabling real-time gastric monitoring.

2 Methods

The CVAE-g*EIT employs a complex-valued encoder q_ϕ and decoder p_θ . The encoder maps complex impedance $\mathbf{Z} = [\mathbf{R}, \mathbf{X}]^T \in \mathbb{R}^{M \times 2}$ and frequency f to a latent distribution $\mathbf{z} \sim q_\phi(\mathbf{z}|\mathbf{Z}, f) = \mathcal{N}(\boldsymbol{\mu}, \text{diag}(\boldsymbol{\varsigma}^2))$. To enable backpropagation, $\mathbf{z}$ is sampled via the reparameterization trick $\mathbf{z} = \boldsymbol{\mu} + \boldsymbol{\varsigma} \odot \boldsymbol{\epsilon}$, where $\boldsymbol{\epsilon} \sim \mathcal{N}(0, \mathbf{I})$. The decoder $p_\theta(\boldsymbol{\gamma}|\mathbf{z}, f)$ reconstructs dual-channel physical maps $\boldsymbol{\gamma} = [\sigma, \epsilon]^T \in \mathbb{R}^{M \times 2}$. Optimization is performed by maximizing the evidence lower bound (ELBO)

$$\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\phi}; \mathbf{Z}, f) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{Z}, f)} [\log p_\theta(\boldsymbol{\gamma}|\mathbf{z}, f)] - D_{KL}(q_\phi(\mathbf{z}|\mathbf{Z}, f) || p(\mathbf{z}|f)) \quad (1)$$

Simulation data were generated by a computational gEIT setup with a 1 mA adjacent-current stimulation pattern. The model was trained over a continuous range (100 Hz to 10 kHz) and was evaluated at 10 discrete test frequencies to learn the spectral dependencies of gastric tissue.

3 Results

CVAE-g*EIT demonstrated high fidelity in reconstructing dual-channel physical maps from the simulated datasets. As shown in **Fig. 1**, the model accurately tracks frequency-dependent trends while maintaining the structural integrity of σ and ϵ . Quantitative results achieve Pearson correlations of 1.0 for σ and 0.998 for ϵ , alongside minimal normalized root mean squared error (NRMSE).

4 Conclusions

CVAE-g*EIT successfully achieves high-fidelity, dual-channel reconstruction of σ and ϵ from complex $\mathbf{Z}$ which includes $\mathbf{R}$ and $\mathbf{X}$, enabling robust, real-time non-invasive monitoring of frequency-dependent gastric tissue properties. Future studies will focus on experimental validation using dynamic physical phantoms to further establish clinical viability.

Acknowledgements

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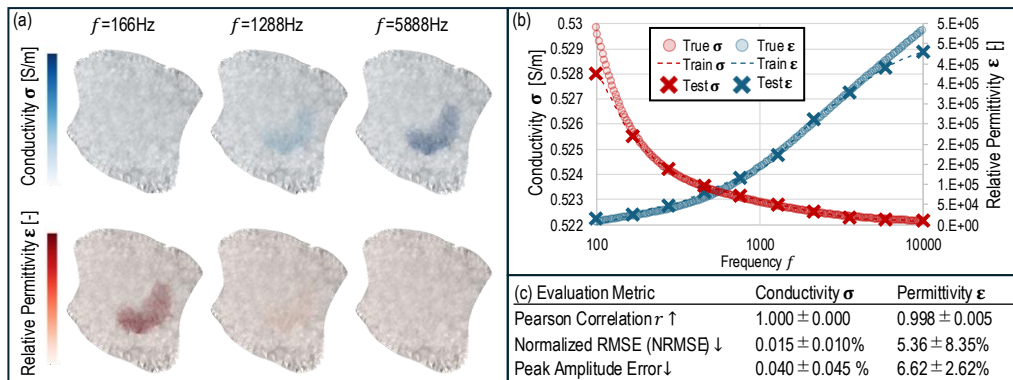


Fig. 1: CVAE-g*EIT reconstruction performance. (a) Dual-channel spatial maps of conductivity σ and permittivity ϵ over test frequencies. (b) Spectral tracking of true versus predicted values across the 100Hz to 10kHz range. (c) Quantitative summary of Pearson correlation, NRMSE, and Peak Amplitude Error for the test dataset.

Noise Separation for Electrical Impedance Tomography Using Weighted Nuclear Norm Robust Principal Component Analysis

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Abstract: This paper proposes a broadly applicable denoising method based on Weighted Nuclear Norm Robust Principal Component Analysis. Simulation results demonstrate that the proposed method possesses universal denoising capability against various types of noise, including Gaussian noise and salt-and-pepper noise.

1 Introduction

Due to the severely ill-posed nature of Electrical Impedance Tomography (EIT), even minimal noise in the voltage signals can cause severe distortion in the reconstructed image [1,2]. Robust Principal Component Analysis (RPCA) separates the data matrix into a low-rank component and a sparse component, which respectively represent the principal signal structure and the noise, thereby isolating the signal from the noise [3,4]. Yet conventional RPCA over-suppresses the dominant singular values that encode the essential signal features. To address this, this paper introduces the Weighted Nuclear Norm RPCA (WNN-RPCA), which assigns a weight coefficient inversely proportional to each singular value. Larger singular values carrying essential signal information are thereby preserved, whereas smaller noise-related ones are more heavily penalized, enabling a more accurate approximation of the true low-rank structure.

2 Principle of WNN-RPCA

2.1 Algorithm principle and formula derivation

A time window is first defined to extract a specified number of voltage vectors and assemble them into a joint data matrix. The joint matrix is then decomposed by WNN-RPCA into low-rank and sparse components. Only the low-rank matrix is retained and reconverted into voltage vectors for EIT imaging. The complete process is illustrated below:

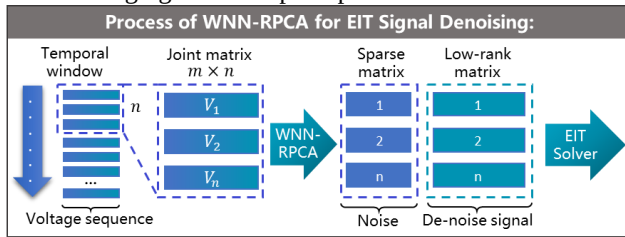


Fig. 1: Process of WNN-RPCA for ERT Signal Denoising

The objective function of WNN-RPCA is given by:

$$\arg \min_{A,E} \|A\|_{\omega,*} + \lambda \|E\|_1 \quad (s.t. M = A + E) \quad (1)$$

where $\|A\|_{\omega,*}$ denotes the weighted nuclear norm of matrix A , $\|E\|_1$ represents the L1-norm of matrix E . Regularization parameter $\lambda = 1/\sqrt{\max(m,n)}$, where m denotes the length of each voltage vector per frame, and n denotes the number of voltage vectors used to form the joint matrix.

The complete form of the weighted nuclear norm of matrix A is given below:

$$\|A\|_{\omega,*} = \sum_{i=1}^r \omega_i \sigma_i(A) \quad (2)$$

where $\|A\|_{\omega,*} = \sum_{i=1}^r \omega_i \sigma_i(A)$, $\sigma_i(A)$ denotes the i -th singular value of matrix A , $\omega_i = c/(\sigma_i(A) + \varepsilon)$.

The following iterative scheme is adopted to solve Eq. (1).

$$\begin{cases} A^{k+1} = \arg \min_A L(A, E^k, Y^k, \mu_k) \\ E^{k+1} = \arg \min_E L(A^{k+1}, E, Y^k, \mu_k) \\ Y^{k+1} = Y^k + \mu_k (M - A^{k+1} - E^{k+1}) \\ \mu_{k+1} = \min(Y, \mu_k, 10^{10}) \end{cases} \quad (3)$$

where $L(\cdot)$ is the augmented Lagrangian function, Y is the Lagrange multiplier matrix, μ is the penalty parameter.

2.2 Results

Gaussian noise and salt-and-pepper noise were added to the simulated data. Denoising and imaging were then performed using mean filtering, Gaussian filtering, wavelet filtering, RPCA, and the proposed WNN-RPCA method, with the results shown in the following figure:

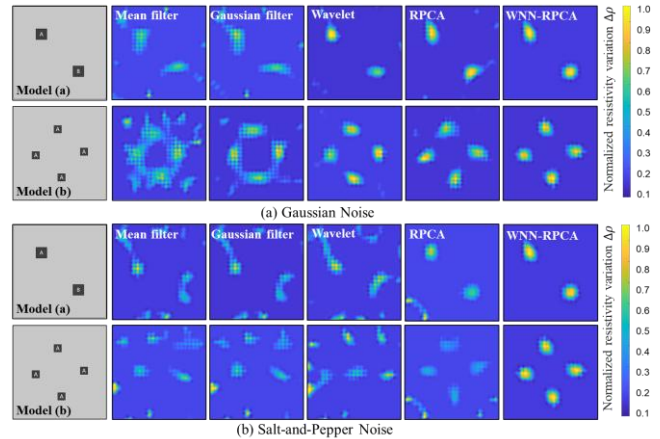


Fig. 2: Denoising Results for Gaussian and Salt-and-Pepper Noise Using Different Algorithms

3 Conclusions

- 1) Compared with conventional denoising methods, RPCA-based methods offer a distinct advantage when addressing Gaussian noise and salt-and-pepper noise.
- 2) By introducing a weighted nuclear norm that imposes different penalties on singular values of varying magnitudes, the denoising capability of RPCA can be further enhanced.

Acknowledgements

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EIT reconstruction in constrained micro-laryngoscopy applications

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Abstract: This study proposes an electrical impedance tomography reconstruction method to assist in the identification of squamous cell carcinoma margins using a micro-laryngoscopic probe. The approach relies on bioimpedance signals acquired from multiple positions on the tissue surface, which are integrated to enhance spatial information even under geometric and physical constraints. Simulation and experimental results demonstrate the potential of the method for providing accurate tumour margin detection.

1 Introduction

Accurate delineation of tumoral margins in the upper aerodigestive tract mucosa is essential for diagnosis and surgical planning, yet remains challenging due to limited anatomical access requiring endoscopic approaches [1]. Electrical impedance tomography (EIT) has shown potential for cancer detection [2] and tumoral margin delineation [3]; however, most of the existing frameworks do not account for the dimension constraints imposed by the endoscope's working channel. The objective of this work is to enable reliable EIT-based tumour reconstruction using miniaturized probes for micro-laryngoscopy exploiting probe motion across the tissue surface to enhance spatial information despite reduced probe size and electrode number.

2 Materials & Methods

Tissue volume was simulated using a homogeneous agar cuboid with a clinically relevant conductivity contrast [4] relative to a centrally located cylindrical inclusion. Experimentally, it was realized using two agar phantoms with different saline concentrations, assembled to mimic mucosal tissue with a tumoral mass. The higher conductivity central inclusion is visible within the phantom in Fig. 1b and is depicted in green for better visualization.

The micro-laryngoscopic probe was modelled based on the SmartProbe geometry [5], i.e., as a planar array of 4 electrodes placed on the upper surface of the test volume.

Two experiments were conducted: one in simulation and one using the agar phantom. In both cases, the proposed workflow begins with the acquisition of bioimpedance signals at 9 positions defined on a 3×3 grid on the tissue surface, which are then arranged into a unified measurement array to emulate a larger probe configuration. Measurements from a single position are subsequently replicated across all positions, thereby defining a homogeneous reference state used to perform a differential reconstruction. Finally, the conductivity distribution was reconstructed using a coarse-to-fine approach and the results were visualized on a superficial 2D slice extracted from the mesh.

2.1 Camera-based probe localization

During the experiments, probe positioning was performed using a robotic manipulator for controlled placement. Probe

positions were inferred using a marker-less YOLOv11-based keypoint detection approach, which is potentially applicable to the envisioned clinical scenario. This enabled the localization of the probe tip and computation of its distance from the reference origin in the centre of the gel phantom. Fig. 1a presents the experimental setup for data acquisition and probe localization, while Fig. 1b depicts the grid of acquisition poses on the agar phantom used for EIT reconstruction.

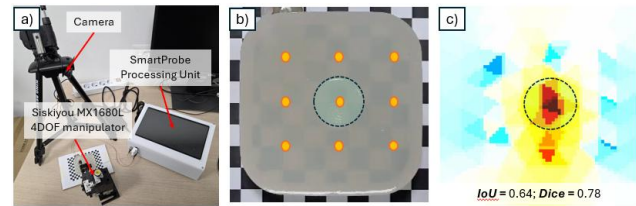


Fig. 1: Experiments with probe tracking and data acquisition. a) Complete experimental setup. b) Agar phantom used in the experiments (inclusion is highlighted in green, probe positions are annotated in yellow). c) Conductivity distribution map reconstructed from SmartProbe's measurements.

3 Results

In simulation, the reconstructed conductivity map exhibited a well-localized high-conductivity region, with good agreement in terms of position and shape compared to the ground truth. Consistent results were obtained on the agar phantom (Fig. 1c): the inclusion is successfully identified, and its spatial extent is reasonably well delineated despite the increased measurement variability and modelling inaccuracies typical of real data, as reflected by the performance metrics (IoU = 0.64, Dice similarity coefficient = 0.78).

4 Conclusions

The proposed reconstruction method shows potential for the identification of tumour margins under the geometric and physical constraints imposed by micro-laryngoscopic probes. By leveraging probe motion to enhance spatial information, the approach achieves consistent performance both in simulation and in experimental setups. The results demonstrate robust inclusion localization and delineation of its extent, supporting the feasibility of the method for application in clinical environments.

Acknowledgements

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Neural Network Post-Processing Resolves the Position-Size Trade-Off in 3D Breast EIT

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Abstract: Traditional EIT thresholding inherently trades tumour position accuracy for size accuracy. Applying a neural network to PCA-compressed NOSER reconstructions resolves this. Tested on a 3D breast model, simultaneous errors reached 3.4 mm and 1.3 mm, improving baseline size accuracy by 79%.

1 Introduction

Extracting tumour parameters from linearised EIT reconstructions requires thresholding the conductivity image to delineate a candidate region. A lower threshold captures more of the spatially diffuse anomaly and improves the centroid estimate, but overestimates tumour size. A higher threshold tightens the extracted region and improves size accuracy, but excludes peripheral elements that contribute to position accuracy. No single threshold optimises both metrics simultaneously [1].

This work evaluates whether a neural network can bypass this bottleneck entirely by learning a direct mapping from reconstruction features to tumour position, size, and conductivity contrast in a 3D breast EIT geometry. A full study is submitted to IEEE TBME [8].

2 Materials & Methods

A three-dimensional spherical-cap breast model (62.5 mm base radius, 40 mm height) was meshed using Netgen and imported into EIDORS [2]. The mesh comprises 19,403 tetrahedral elements with 16 electrodes arranged in three concentric rings, producing 208 boundary voltage measurements via an opposite-sensing protocol. Spherical tumour inclusions (10 to 30 mm diameter, 2x to 5x conductivity contrast) were placed within a 0.3 S/m background, generating 1,440 configurations augmented at three noise levels (80, 60, 40 dB SNR) to yield 5,760 samples, split 70/15/15 at the configuration level.

The proposed pipeline reconstructs each sample using NOSER [3] ($\lambda = 0.01$), compresses the reconstruction to 28 PCA components (95.2% variance, 700:1 reduction), and feeds these into a feedforward network ([256, 128, 64], ReLU, 20% dropout) that outputs five tumour parameters directly: three position coordinates, diameter, and contrast ratio. Six traditional baselines (three priors crossed with two threshold methods [4]) served as comparison.

3 Results

The structural trade-off is confirmed across all six traditional baselines. Tikhonov with Otsu thresholding achieves the best position of any method (2.9 mm) but inflates size error to 20.4 mm. The balanced baseline (Tikhonov, fixed 50%) reduces size error to 6.2 mm at the cost of 4.2 mm position. No traditional combination optimises both.

The neural network resolves this trade-off, achieving 3.4 mm position error, 1.3 mm size error, and 0.68 contrast error simultaneously. Fig. 1 presents the improvement over the balanced baseline: 79% in size ($p = 1.85 \times 10^{-122}$, $r = 0.801$), 69% in contrast, and 18% in position.

NOSER outperformed Tikhonov as the reconstruction prior for ML input despite producing weaker standalone images. NOSER reconstructions required 28 PCA components for 95% variance versus 19 for Tikhonov, indicating preserved spatial gradients that the network exploits [5], [6].

4 Conclusions

Neural network post-processing resolves the position-size trade-off inherent in linearised EIT reconstruction. The recommended pipeline feeds PCA-compressed NOSER reconstructions into a feedforward network, delivering accurate position, size, and contrast estimates simultaneously. NOSER's preservation of spatial information, rather than standalone image quality, determines its value as ML input.

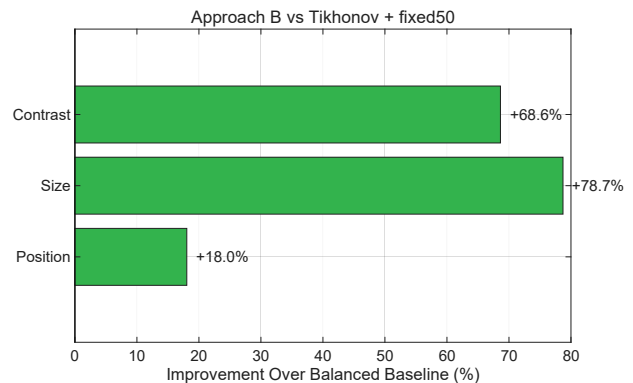


Fig. 1. Improvement of the neural network (Approach B) over the balanced traditional baseline (Tikhonov + fixed 50%) across all three tumour parameter metrics.

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On applying a collocational approach to inverse problems in electrical impedance tomography

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Abstract: We present a parametric PDE for EIT that accounts for internal conductivities and boundary shape. We then apply a collocational approach to construct a polynomial surrogate of the forward solution, enabling us to solve the inverse problem efficiently and reconstruct the aforementioned parameters.

1 Introduction

One of the applications in EIT is the detection of intra-abdominal hemorrhage in trauma patients. The traditional inverse problems aim to reconstruct the internal conductivities from voltage measurements on the boundary surface electrodes. However, this problem is ill-posed and highly sensitive to breathing and other motion, causing artifacts in reconstructed images. To solve these problems, we develop an extended parametric PDE for EIT and then implement a collocation approach to effectively build a parameter-to-observable map that is used in the inverse problem, following the work of [1]. Also, having an electrode hemiarray limits available data but is important to consider as it is applicable when the trauma patient has spinal injuries [2].

2 Methods and Preliminary Results

We extended the Complete Electrode Model (CEM) for electrical impedance tomography by explicitly incorporating parameters describing the conductivities and boundary shape. The geometry was represented as a smooth deformation of a reference domain, and conductivities were constrained to remain physically admissible via bounded, positivity-preserving mappings, following the work of [3]. This extended parametric PDE can now be numerically solved using the finite element solver of the MATLAB EIDORS package [4].

We then built a polynomial surrogate model for the parameter-to-observable map of the forward parametric PDE using a collocation approach. To numerically establish the dependency of the observables in terms of the parameters, we used a generalized polynomial chaos (gPC) approach to represent the observables as linear combinations of high dimensional tensorized Legendre orthogonal polynomials of the parameters. To reconstruct the gPC coefficients, we applied cubature rules based on Clenshaw-Curtis nodes, which served as our collocation nodes in the parameter domain. For each collocation node, the forward parametric PDE problem was solved deterministically using the MATLAB EIDORS package, and the corresponding electrode voltage measurements were evaluated. This is a key advantage of this collocation approach, as it only requires a finite number of deterministic simulations without reformulating the PDE making it a noninvasive method. However, the number of collocation points grow exponentially with the number of parameters. To address this curse of dimensionality, we used the Smolyak sparse grids [5].

Having that surrogate polynomial allowed us to efficiently solve the inverse problem using Tikhonov and other regularization techniques to simultaneously reconstruct the internal conductivities and the boundary shape. Below are preliminary results for solving the following regularized least-squares problem using a Levenberg-Marquardt method:

$$\min_{p \in [-0.5, 0.5]^N} \|V_{\text{surr}}(p) - V_{\text{meas}}\|_2^2 + \lambda_b \|p_b\|_2^2 + \lambda_\sigma \|L_\sigma p_\sigma\|_2^2 \quad (1)$$

where N is the number of parameters, $\lambda_b, \lambda_\sigma$ are regularization parameters, and L_σ is a Laplacian prior.

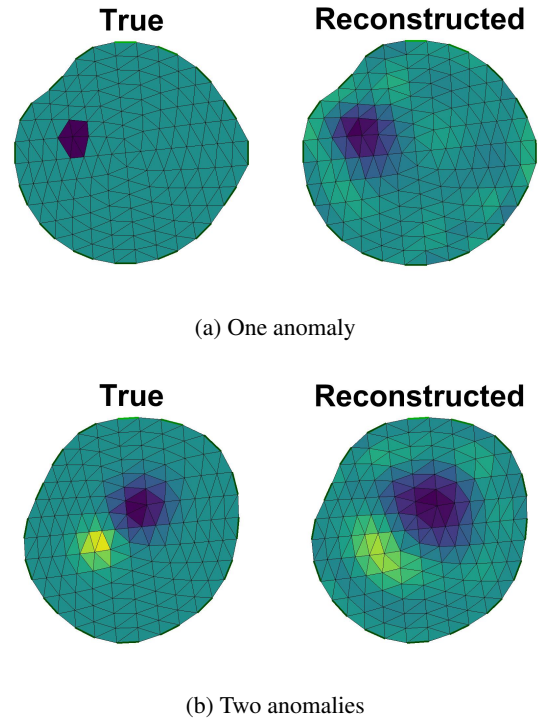


Fig. 1: Comparison of true internal conductivities and boundary geometry (left subfigures) with the corresponding reconstructions (right subfigures).

Acknowledgements

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EIT Channel Selection for Estimating Aortic Blood Pressure

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Abstract: Electrical impedance tomography is a powerful monitoring tool that can be used to estimate aortic pressure with a neural network. This paper explores the selection of subsets from the 1024 channels for more efficient network training. The results show an improved performance for appropriate selection strategies.

1 Introduction

The estimation of hemodynamic measures from electrical impedance tomography (EIT) in in-vivo data is a challenging task. The superimposed influence of ventilation, noise, and a missing high-quality model linking central aortic pressure (CAP) and EIT measurements aggravate the analysis. In a porcine animal study [1], it has been shown that convolutional neural networks (CNNs) can estimate CAP. A 32-electrode EIT system imposes $N = 1024$ measurement channels per frame. Since neural networks are critical to data quality, selecting a subset of EIT channels to feed into the network can most notably reduce the computational complexity and network size. Due to limited training resources, redundant and irrelevant features can negatively impact the network's training. Hence, channel selection can reduce overfitting and improve network performance [2]. The goal of this study is to investigate whether subset selection of EIT channels can reduce the network size while maintaining or even improving the accuracy of CAP estimates from in-vivo EIT data. In particular, systemic, structured, and data-driven strategies are considered.

2 Methods

2.1 Data Set

The utilized data originates from a porcine study on pulmonary hypertension [3] featuring EIT recordings and, simultaneously, aortic pressures from an invasive catheter. Previous work has presented a pipeline from raw data sets via preprocessing to a CNN estimating CAP curves using all 1024 EIT channels [1]. In this work, a base CNN structure featuring convolution, max-pooling, activation, fully-connected, and dropout layers is trained for each subset to estimate CAP curves. The input layer size varies with the C_j employed channels. The performance is compared on an unknown test set of a separate individual.

2.2 Structured Search

Cross-correlation based discriminant criterion (XCDC) is a channel selection algorithm that assesses the relevance of channels in discriminating the target data [4]. Developed for an EEG classification task, the algorithm was adapted for the regression problem to estimate the mean aortic pressure (MAP). The algorithm calculates a discriminant score D_i per channel, and the $C_{z,XCDC}$ best-scoring channels are then selected.

2.3 Systemic and Data-Driven Methods

Systemic methods are based on considering the recording geometry and dependencies. The strategies are *FirstHalf*, *NonReciprocal*, *NonInjectionMid*, *NonInjection*, *NonInjec-*

tionAdjacent, and *AortaIndex*. For the data-driven methods, the EIT data was analyzed by means of correlation, visual inspection, and Fourier transform. The strategies include *AutoCorr*, *CrossCorr*, *VisualIndex*, *FreqIndex*, *BolusIndex*, and *SinglePigBolus*. The appendix *Guard* means a less strict condition was used for the same technique and resulting in more used channels. Full code and further details can be seen in [5].

3 Results and Conclusions

The results of the systematic and data-driven approaches show that omitting specific channels can improve the network's estimation performance by removing irrelevant or redundant data. A total of 11 out of 16 variations outperform the full network. Fig. 1 shows a relevance score per channel calculated by comparing the results of all strategies to the full network and backtracking which channels were omitted when the results improved or worsened. The relevance is positive if the network performance worsens for omitting those channels and negative if the performance improves. The dark blue total score shows that a multitude of channels might be redundant or irrelevant, since omitting them improved performance.

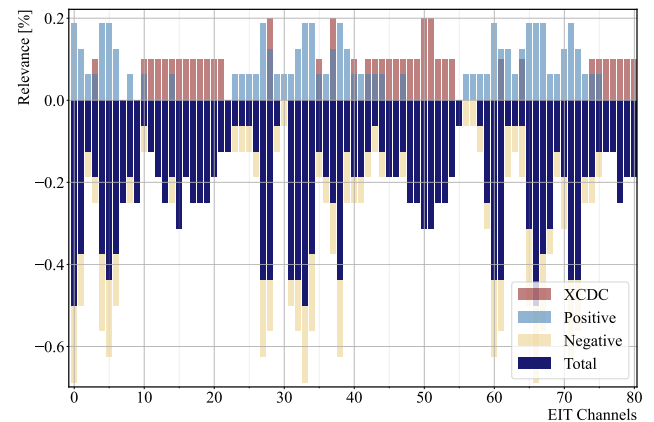


Fig. 1: Relevance of the first 80 EIT channels.

The structured search could not improve the network's performance in terms of mean absolute error (MAE), but the Pearson correlation coefficient improved for some subsets. The adaptation of XCDC for regression tasks can be enhanced in the future.

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A Software Toolbox for Electrode Placement Optimization in Layered Material EBI Sensing

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Abstract: Optimized electrode placement improves reconstruction of layered materials. This paper presents a toolbox that considers spatial coverage and sensitivity variation, enabling more accurate estimation of layer properties.

1 Introduction

Electrical bioimpedance (EBI) enables non-invasive tissue characterization. The spatial sensitivity and sensing depth of each current-sourcing electrode (CSE) and voltage-measuring electrode (VME) pair are highly dependent on electrode geometry [1]. In layered materials, measurements reflect mixed layer contributions, complicating estimation of electrical properties [2]. To address this, we propose a toolbox for optimizing electrode placement in layered-material EBI sensing.

2 Materials & Methods

In the case where current is injected at electrode A to ground, and voltage is measured between electrodes M and N , the apparent conductivity σ_a is given by Eq. 1, where h is the top-layer thickness, d the electrode distance, I the injected current, and $k = \frac{\sigma_1 - \sigma_2}{\sigma_1 + \sigma_2}$, with σ_1 and σ_2 denoting the conductivities of the top and bottom layers.

$$\frac{1}{\sigma_a} = \frac{1}{\sigma_1} + \frac{2}{\sigma_1} \frac{d_{AM} \cdot d_{AN}}{|d_{AM} - d_{AN}|} \sum_{n=1}^{\infty} \left(\frac{r^n}{\sqrt{d_{AM}^2 + (2nh)^2}} - \frac{r^n}{\sqrt{d_{AN}^2 + (2nh)^2}} \right) \quad (1)$$

The toolbox promotes diverse σ_a distributions, improving estimation of h , σ_1 , and σ_2 .

2.1 Optimization Method

The toolbox requires a set of parameters to create the electrode position design. These and the conditions where they are used, are given in Table 1.

Tab. 1: User-defined input parameters for the toolbox. B and O show the related boundary conditions and optimization objectives

Variable	Description	Unit	B	O
A	Defined search space area	mm	B_1	O_2
N_{el}	Number of electrodes	n	B_1	-
$\emptyset$	Electrode diameter	mm	B_2	-
σ_1, σ_2	σ of top and bottom layer	S/m	B_2	O_1
h	Thickness of top layer	mm	-	O_1
I	Current injection level	A	B_2	O_1
$V_{min,max}$	Sensor voltage range	V	B_2	-

B_1 ensures that the predefined number of electrodes is placed within the specified search space. B_2 defines the allowable electrode spacing range based on both geometric and sensor constraints. Electrode pairs with a distance greater than the range of d are excluded from mutual optimization, as distant electrodes have negligible influence on

the signal. The sensor measurement limits are converted from potential to distance, resulting in:

$$d \in \left[\max \left(2\emptyset, \frac{I}{\min(\sigma_1, \sigma_2) 2\pi V_{max}} \right), \frac{I}{\max(\sigma_1, \sigma_2) 2\pi V_{min}} \right]$$

A genetic algorithm is used to optimize electrode placement. Each candidate encodes electrode positions and valid CSE–VME pairs. Candidates are evaluated on three criteria: (O_1) uniformity of depth sensitivity, quantified via σ_a distribution; (O_2) spatial coverage of defined areas; and (O_3) the number of CSE–VME pairs which can be used in the σ_a calculation.

3 Results

An example use case is shown in Fig. 1, where the method is applied to a probe estimating muscle properties. The parameters σ_1 , σ_2 , and h model a two-layer system (skin/fat over muscle). The design is evaluated using simulation, and reconstruction of σ_1 , σ_2 and h follows the method in [3]. Fig. 1C shows the resulting σ_a distribution and reconstruction accuracy.

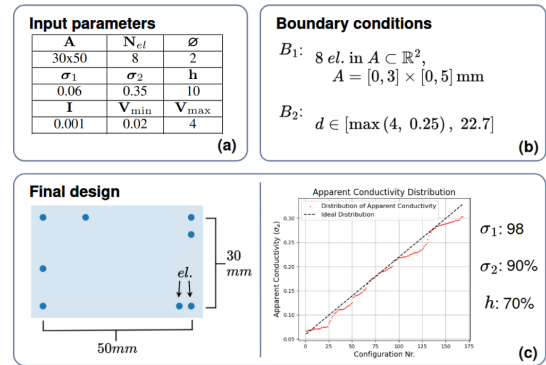


Fig. 1: Toolbox result using the muscle example. (a): Input parameters, (b): Boundary conditions, (c): Final Design and results.

4 Conclusions

The proposed toolbox enables optimized electrode placement for layered-material EBI sensing. Results show accurate estimation of layer conductivities with a limited number of electrodes, while thickness estimation remains more challenging. The method highlights the importance of measurement diversity and provides a practical tool for designing efficient EBI systems.

Acknowledgment

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Stable recovery of piecewise constant conductance on spider networks

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Abstract: In this work we get stable recovery of conductances on spider networks by combining structural assumptions with optimization techniques. This approach aligns with regularization strategies used in continuous EIT and provides a robust framework for discrete inverse problems.

1 Introduction

The inverse conductivity problem, originally introduced by Calderón [1], consists in determining the internal conductivity of a medium from boundary measurements of voltage and current. While the continuous formulation has been extensively studied, its discrete counterpart—posed on finite electrical networks—has received comparatively less attention.

In the discrete setting a finite connected graph endowed with edge conductances is considered. Given boundary measurements encoded in the Dirichlet-to-Neumann (DtN) map (or response matrix), the inverse problem consists in recovering the unknown conductance function on the edges.

Although uniqueness of recovery is known for certain classes of planar networks [2], the problem is severely ill-posed and large deviations in the recovered conductances are produced by small perturbations in the response matrix, especially for large networks [3].

This work focuses on *well-connected spider networks*, a subclass of critical circular planar graphs where uniqueness of reconstruction is guaranteed. We investigate whether imposing a piecewise constant conductance hypothesis [4] (that simulate different electrical behaviour of breast tissues for instance) restores numerical stability.

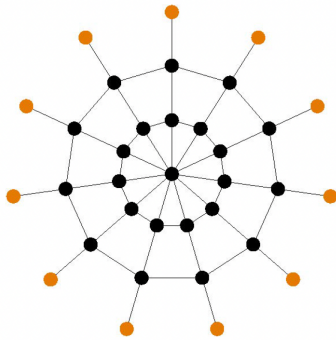


Fig. 1: Well connected spider network with 11 radii and 2 layers. The orange exterior nodes model electrodes in an EIT-like device.

2 Materials & Methods

Let $\Gamma = (V, c)$ be a finite well-connected spider graph with conductance function c . The combinatorial Laplacian is defined by

$$\mathcal{L}(v)(x) = \sum_{y \sim x} c(x, y)(v(x) - v(y)). \quad (1)$$

Given boundary voltages, the Dirichlet problem admits a unique solution, and the associated Dirichlet-to-Neumann

map DtN relates boundary voltages to currents. In matrix form, the response matrix is obtained via a Schur complement:

$$DtN = L(\delta(F); \delta(F)) - L(\delta(F); F) \cdot L(F; F)^{-1} \cdot L(\delta(F); F)^T. \quad (2)$$

The inverse problem consists in recovering c from N .

Although explicit recursive formulas [5] exist to recover conductances on spider networks, numerical experiments reveal strong instability. Not for small networks (e.g. 7 radii) but errors grow dramatically—even when the original conductance is constant and exact arithmetic is used with the number of radii in the structure (negative recovered conductances!, larger errors farther from boundaries)

As in the continuous setting, stability improves when the conductivity is known to be piecewise constant over a finite partition. Therefore we impose the piecewise constant hypothesis as a penalty term within an optimization framework.

Hence we formulate recovery as a constrained nonlinear optimization problem [6] where the variables are c_{jk} (edge conductances), c_i (subset conductances), and v_{ij} (interior voltages) and the objective function is

$$p = \|N - N'\|_F^2 + \mu \|c - c'\|^2, \quad (3)$$

where N' is the response matrix of the recovered network, $\mu \geq 0$ is the regularization parameter, and the second term penalizes deviation from piecewise constancy. This schema corresponds to a Tikhonov-type regularization, but with unknown piecewise constants rather than a fixed reference conductance.

3 Results

We have run [7] many numerical experiments that support our thesis. More than 1000 spider networks which number of radii varied from 7 to 47 and considering from 1 to 10 different types of tissues confirm that recovery error is extremely low, stable reconstruction is accomplished even for large networks and the ratio $\frac{\|c - c'\|}{\|N - N'\|_F}$ grows with the number of different tissues that are taken into account.

Furthermore, our numerical schema has proved to be robust to noise; response matrices were perturbed with random noise from 10^{-8} to 10^{-1} obtaining highly accurate recovery values when small perturbations and 'not so bad' results even for tremendous perturbation cases.

4 Conclusions

We have shown that our explicit recovery formula reformulated as a polynomial optimization problem stabilizes recovery. That this stability depends critically on the number of subsets in the partition. And that the proposed method is robust under up to severe noise alterations.

As a beautiful perspective, we expect to apply discrete approximations to medical imaging models such as EIT.

Surrogate for EIT Forward Modeling

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Abstract: The EIT forward problem can be solved by the finite element method (FEM). However, solving the underlying differential equations is computationally expensive and yields discrete solutions. We train a deep learning surrogate model to speed up inference of the potential inside a volume.

1 Introduction

EIT aims to predict the conductivity distribution inside a body from surface potential measurements. This can either be done by conventional method [1, 2], or by leveraging modern deep learning architectures [3, 4]. To validate the physical accuracy of the predicted conductivity distribution, $\gamma(x)$, one needs the electrical potential, $u(x)$, inside the body to calculate the residual of the conductivity equation.

$$\nabla(\gamma(x)\nabla u(x)) = 0 \quad \forall x \in \Omega \quad (1)$$

The electrical potential in the volume can either be obtained by simulation or by another deep learning model. Our aim is to build such a surrogate deep learning model that can accurately predict the electrical potential in the body. As this model is a continuous and differentiable mapping from conductivity distribution to electrical potential, we can leverage it in an iterative method to optimize the predicted conductivity distribution by enforcing adherence to the conductivity equation and to the measured boundary conditions. For example, the Gauss-Newton method can be used to iteratively improve the adherence of conductivity distribution to the measured electrical potentials.

2 Materials & Methods

For a proof of concept, we use FEM simulation data from cylindrical and cubic volume meshes with varying conductivity distributions. During training, the surrogate model receives a point cloud with corresponding conductivity values as input. A transformer-based encoder first encodes the local conductivity distribution around grid points. The encodings are then further processed by a secondary transformer to obtain latent representations on a grid. To predict the potential at a query position, we first interpolate the latent space at the query position. Subsequently, latent space representation and the query position are fed into an MLP to predict the electrical potential at the query position.

3 Results

Figure 1 shows the electrical potential from FEM simulation and from our model for a single conductivity distribution on a cylindrical volume mesh and the electrode potentials obtained by FEM and our model for two different

conductivity distribution.

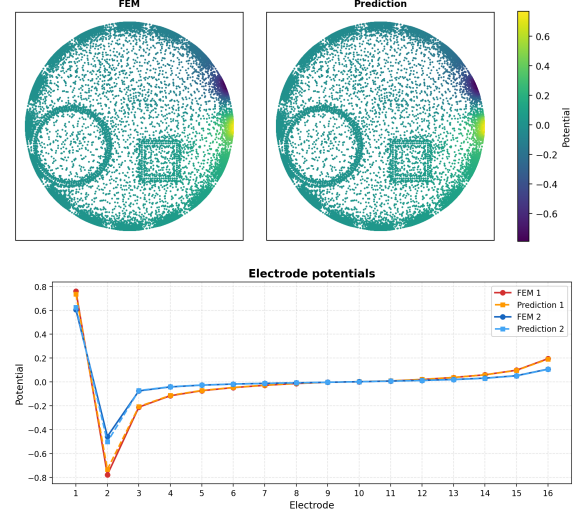


Fig. 1: Comparison of electrical potentials obtained from FEM simulations and from the surrogate model. The upper panel shows the electrical potential distributions on the cylindrical volume mesh for a single conductivity distribution, the lower panel shows the corresponding electrode potentials for two different conductivity distributions. The respective conductivity distributions were not part of the training set. The cylindrical domain has dimensions $R = 0.14$ m and $h = 0.07$ m. The background conductivity is set to 1 S m^{-1} and the objects have conductivities $\gamma_{\text{cylinder}} = 100 \text{ S m}^{-1}$ and $\gamma_{\text{cuboid}} = 63 \text{ S m}^{-1}$.

4 Conclusions

We have demonstrated that our surrogate forward model can predict the electrical potential for a given conductivity distribution. The model output is continuous in the output space and generates electrical potentials faster than FEM simulations. This is a first important step towards a learning-based and physics-grounded optimization of predicted conductivity distributions.

Acknowledgements

This work was funded by the German Aerospace Center (DLR) (50WK2274) and supported by NHR-Nord@Göttingen (project nix00012) with computational resources.

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PCB of Resistive Spider Networks for Conductance Recovery Validation

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Abstract: We propose PCBs of purely resistive network with a well-connected spider-like topology for experimenting with the recovery of conductances in DC. Bidirectional current sensors are used to acquire boundary measurements, while ADCs handle sampling and the I²C communication protocol streams data to an ESP32 microcontroller.

1 Introduction

Stable recovery of conductances in large-scale simulations was achieved in [1] by introducing the piecewise constant hypothesis, which assumes network conductivity remains constant across specific edge groups. This method overcomes instabilities previously observed in networks with more than 11 radii. We propose the implementation of various PCB configurations of spider-resistor networks $\Gamma = (G, \gamma)$, with $\ell \geq 0$ circles and $m = 4\ell + 3$ radii. The PCBs vary in the number of radii and piecewise constant subsets s . We use these PCBs to validate the recovery of piecewise conductances from the response matrix N , verifying the feasibility of this approach using physical hardware and high-precision instrumentation [2].

2 Methodology & Materials

The 2-layer PCBs were designed on KiCad and manufactured by JLCPCB. They consist of SMD resistors with tolerances of $\pm 0.1\%$ and ± 25 ppm, which are soldered, shielded, and distributed across the board to closely approximate a spider-like network. A multiplexer environment sets each boundary terminal on the PCB, denoted as x , to either a buffered potential u or GND, sequentially from x_1 to x_m . A total of $m \times m$ measurements are taken per frame. Bidirectional shunt current sensors are integrated at every boundary terminal. Readings from these sensors are sampled using a 16-bit ADC, which streams the data to an ESP32 microcontroller utilizing I²C serial communication protocol. These data are then processed to solve the inverse problem and estimate the edge conductances. We formulate this inverse problem as a polynomial optimization problem of the form

$$\min_{\gamma} \|N(\gamma) - N\|_{Fr}^2 + \mu \mathcal{R}(\gamma), \quad (1)$$

where $\mathcal{R}(\gamma)$ is a penalization term for piecewise constancy on s subsets and $\mu > 0$ is the regularization parameter.

2.1 Figures and tables

A PCB with $m = 15$ radii is shown in Fig. 1; it features 105 SMD resistors on the top side, while the current sensors, multiplexing circuitry, and ADCs are located on the bottom side. The recovery of conductances is performed using MATLAB, which executes the inverse problem algorithm. Tab. 1 presents the error in the conductance recovery for $\mu = 1$ and different number of subsets, s .

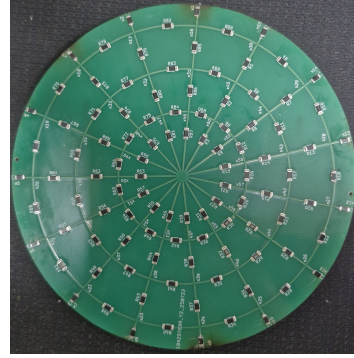


Fig. 1: PCB showing component distribution.

3 Results & Conclusions

In a particular example, we choose γ' to be constant on the spider network. The recovery of conductances using data from physical hardware appears feasible, as the algorithm behaves efficiently and remains stable across different numbers of subsets, estimating conductances with the errors shown in Tab. 1. The PCB implementation validates the feasibility of conductance recovery in hardware, providing a robust experimental platform for future extensions to complex admittances and EIT applications.

Acknowledgements

This work has been partially supported by the Spanish Research Council under project PID2021-122501NB-I00 and by AGAUR 2024 PROD 00092.

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Tab. 1: Error in conductance recovery with $\mu = 1$ and different s .

s	$\ \gamma - \gamma'\ $	$\max\{ \gamma - \gamma' \}$	$\ N(\gamma) - N\ _{Fr}$
1	$5.2514 \cdot 10^{-7}$	$6.0375 \cdot 10^{-8}$	$8.1854 \cdot 10^{-8}$
3	$7.1368 \cdot 10^{-7}$	$1.2737 \cdot 10^{-7}$	$9.2873 \cdot 10^{-8}$
5	$1.4072 \cdot 10^{-6}$	$2.4151 \cdot 10^{-7}$	$1.5150 \cdot 10^{-7}$
7	$6.9099 \cdot 10^{-6}$	$2.1389 \cdot 10^{-6}$	$3.9984 \cdot 10^{-7}$

Parameterized inversion of electrical impedance tomography with sparse and dense case sampling

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Abstract: When a conducting volume of interest can be represented with a parameterized model, the inverted parameterization can represent a more accurate reconstruction than a conductivity map achieved thru regularization. A simple algorithm establishes the parametric inversion for both sparsely and densely sampled datasets.

1 Introduction

When electrical impedance tomography is applied to a known system, such as the human body, a parameterized model can produce a more accurate reconstruction than a conductivity map. And if the number of free parameters is less than the total number of independent measurements, the sensitivity volume (SV) method [1] can be employed to identify a significantly reduced number of data measurements with the highest value for distinguishing these parameters. To achieve direct parametric inversion from this reduced set of measurements, a simple algorithm can establish the correspondence between training data and parameterized model cases.

Here [2] two training algorithms will be demonstrated: sparse sampling which interpolates the sampled parametric data, and dense sampling which parameterizes all possible

cases of interest. From the resulting training dataset, a simple nearest-neighbor query in data space yields a one-to-one correspondence with the model parameters for parametric reconstruction. Sparse sampling is demonstrated with an insulating cylinder in a saltwater tub whose diameter and angular position constitute a two-dimensional (2D) model space, and whose reduced high-value data space consists of 9 independent tetrapolar data measurements made with 15 available electrodes (Fig. 1). Dense sampling is demonstrated with a mechanical goldfish in a saltwater tub whose coordinates and orientation define a 3D model space, and whose reduced high-value data space consists of 16 tetrapolar data measurements made from 128 available electrodes (Fig. 2). The parametric method demonstrated here reduces the necessary number of data measurements by orders of magnitude compared to standard EIT to achieve higher accuracy within the parametric representation, and can, in principle, be expanded to complex 3D systems such as organs within the human body to achieve fast, high fidelity parametric reconstructions.

2 Materials & Methods

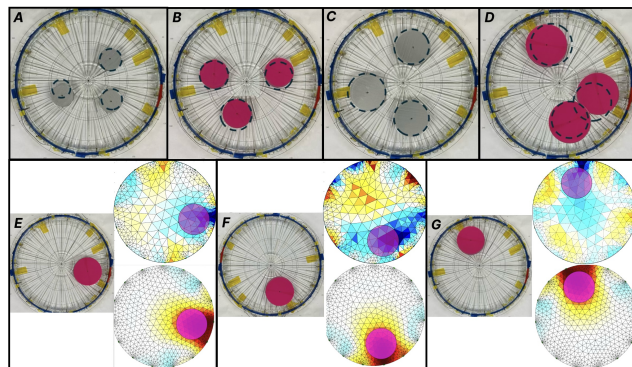


Fig. 1: Sparse parameterized sampling. Comparison of parameterized inversion from sparsely trained data with standard inversion methods. (A) A cylinder of diameter $d = 1.7''$ is placed in three different locations for three successive experiments shown as a photographic overlay for simplicity. Diameter d and position θ as predicted for each instance of cylinder placement is superposed (dashed circles). Same for (B) $d = 2.2''$, (C) $2.7''$, and (D) $3.2''$. (E), (F), (G) Left of each panel: Photograph of three placements of the $3.2''$ cylinder from panel D. Upper right of each panel: The parametric inversion (pink circle) is overlaid on an EIDORS mesh inversion using the same 9-measurement dataset. Bottom right of each panel: The parametric inversion (pink circle) is overlaid on an EIDORS mesh inversion using an order of magnitude more measurements (90). Parameterization shows more accurate representation with less data.

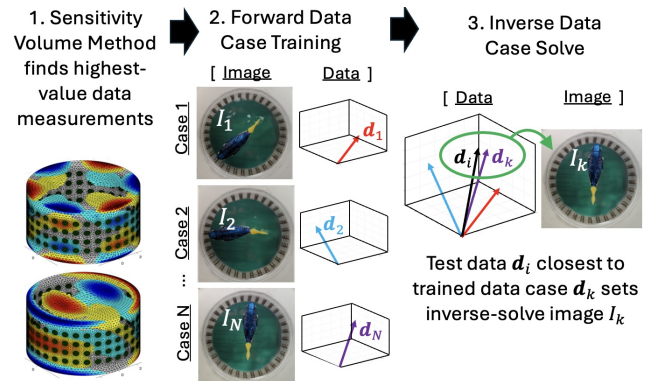


Fig. 2: Dense parameterized sampling. Step 1 shows mesh reconstruction of 3D volume and examples of two of polynomial basis functions used for identifying highest-value measurements with SV. Step 2 shows the data vectors d_k cataloged with N different image cases I_k using SV optimized measurements. In Step 3, the distance of the instantaneous data vector of interest is compared to the library of previously trained data vectors d_k via k -nearest neighbor algorithm to identify the nearest data case (where $k = 1$). The image associated with that case is then selected to represent the data inversion.

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Exploration of *In-Vitro* Tissue Impedance Spectrum and Discrimination Criteria for Breast Tumour Detection in *In-Vivo* Impedance Tomography

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Abstract: Breast Impedance Imaging using In-Vitro tissue impedance spectroscopy (EIS) demonstrated that pathological variations occurred due to postoperative ex-vivo tissue and body fat percentages, and the different ratios of lesion tissues and background tissues. This caused impedance differences between tissues that are important when distinguishing between benign and malignant lesions.

1 Introduction

Accurate biological impedance characteristics of single tissues and pathologies are needed to diagnose benign and malignant breast tumours amongst breast tissues using Electrical Impedance Mammography (EIM). The categories of breast tissues across the breast can be identified using multi frequency breast electrical impedance scans, based on the impedance frequency distribution map. This involves: 1) obtaining accurate electrical impedance characteristics of single breast tissues, 2) obtaining "in-vivo" electrical impedance multispectral scanning information of the different pathologies of breast lesions, 3) reconstructing the electrical impedance scanning information to obtain a visualized electrical impedance distribution map, 4) dividing the criteria for the diagnosis of benign and malignant tumours based on the electrical impedance frequency spectrum characteristics of single breast tissues, 5) mapping the distribution of breast tissues according to their electrical impedance characteristics 6) diagnosing the benign and malignant nature of a tumour based on the determining criteria "4)". This article explores the work of "1)" and "4)".

2 Materials and Methods

2.1 Trial Instruments and Trial Design

The Electrical Impedance Spectrum (EIS) *in-vitro* trial system [1] and the *in-vitro* test device (see Figure 1, left) and the electrical impedance mammography (EIM) system for the detection of breast tumors (see Figure 1, right).



Fig. 1: *In-Vitro* testing device (left), impedance mammography (EIM) system (right)

Two steps to obtaining accurate electrical impedance characteristics of the breast tissues: 1) Using EIS and EIM systems to measure the electrical impedance data of plant products and comparing the Cole-Cole parameters. 2) Using the EIS system to measure the electrical impedance data of fresh isolated human breast tissues, and performing calibration, purification, and simulation normalization to

obtain the electrical impedance frequency spectrum characteristics of each "approximately" single breast tissue.

2.2 Plant Related Items

The plant-based items include carrots, apples, melons, and cabbage. The impedance of each plant-based item is measured 20 times with 20 small pieces, so repeatable.

2.2.1 *In-Vitro* Test of Human Breast Tissue

The Shanghai Center's trial determined the electrical impedance data for 4 types of *In-vitro* post-operative breast tissues excised from subjects: tumour tissue, tumour edge tissue, glandular tissue, and adipose tissue. The EIS data of the two groups of benign and malignant tissues were calibrated (left in Figure 2) and "purified" to remove fat (right in Figure 2).

3 Result

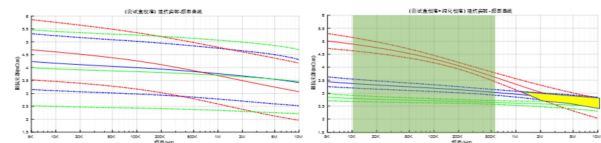


Fig. 2: Standard deviation of connective tissue (green), IDC (red) and fibroadenoma (blue) before (left figure) and after [2] (right figure) purification. Dotted lines above and below the solid lines are the +/- of standard deviation.

4 Discuss

The accuracy of the EIM system in diagnosing benign and malignant breast tumors theoretically depends on the following factors: 1) the accuracy of Cole-Cole parameters of single breast tissues - the electrical impedance data of breast tissues measured by EIS, and 2) how to eliminate and reduce interference from non-target tissues (fat and glands) in the reconstruction model of the EIM system. In the face of the above two factors, this article proposes the following further research directions: 1) continue to optimize EIS experiments, expand and optimize the EIS database, in order to further identify the detailed classification of benign and malignant breast lesions (such as IDC, fibroadenoma, cyst, etc.), 2) associate the interference of fat and glands with parameters such as race, age, BMI, etc. in the EIM reconstruction process, and further optimize the reconstruction model based on artificial intelligence deep learning optimization.

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Feasibility Study of Magnetic Induction Tomography for Thigh Muscle Activity Monitoring

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Abstract: The feasibility of using magnetic induction tomography (MIT) to detect thigh muscle activity was explored with a 16-coil sensor array. Repeated movements showed stable temporal responses, whilst different movements produced distinct spatial patterns. These findings indicate the potential of MIT for non-contact, non-invasive muscle monitoring.

1 Introduction

Muscle function assessment is important in rehabilitation, sports medicine and the monitoring of neuromuscular disorders [1]. The thigh muscles, particularly the quadriceps, play a key role in walking, knee extension and postural control. Magnetic Induction Tomography (MIT) is a non-contact, non-invasive imaging method. It generates an alternating magnetic field using an excitation coil and measures changes in the induced voltage via a receiving coil [2]. Because the electrical conductivity and dielectric properties of biological tissues influence the induced signal, MIT has the potential to detect responses caused by changes in tissue electrical properties, fluid distribution, or morphology during muscle activity.

This study investigates whether muscle activity can produce detectable and interpretable changes in MIT signal and reconstructed response maps.

2 Materials and Methods

2.1 MIT sensing system

A 16 coil MIT system was used to detect thigh muscle activity. In the MIT system, an alternating magnetic field is generated when an alternating current is passed through the excitation coil. This magnetic field interacts electromagnetically with the receiving coil, inducing a voltage in the receiving coil. This process can be simplified using the mutual inductance relationship as follows:

$$V = i\omega M \quad (1)$$

where V is the induced voltage in the receiving coil, i represents the current in the excitation coil, ω represents the angular frequency of the excitation signal, and M represents the mutual inductance between the coils. As the excitation current and frequency remain constant during the measurement process, V is linearly related to M . Since mutual inductance is influenced by the distance between the coils, their relative positions, orientation, and changes in the state of the region under test, MIT can reflect deformation or changes in the electrical properties of the target region through variations in the received voltage.

2.2 Experimental protocol

The MIT sensor array was secured to a predetermined position on the subject's thigh to minimise relative movement between the sensors and the skin during measurement. The

subject remained seated and kept the tested leg in a stable position. Each trial comprised three phases: an initial relaxation baseline, muscle activation, and post-movement relaxation and recovery. The experimental movements included knee extension, isometric resistance and sustained contraction; the same movements were repeated to assess the temporal consistency of the MIT signals.

3 Results

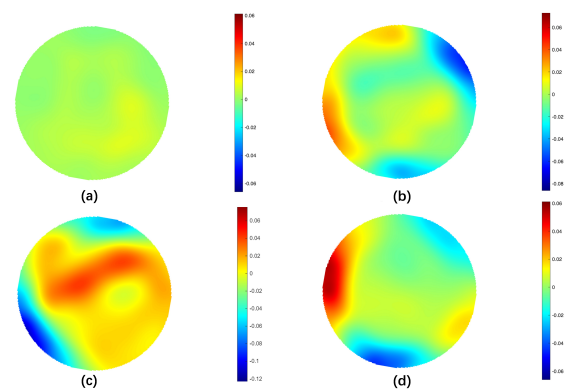


Fig. 1: Reconstructed MIT response maps of thigh muscle activity under different contraction conditions: (a) baseline, (b) knee extension, (c) isometric resistance, and (d) sustained contraction. The colour scale is kept consistent across the four maps, where warm colours show stronger reconstructed responses and cool colours show weaker reconstructed responses.

The experimental results indicate that MIT measurements reflect the temporal and spatial responses associated with thigh muscle activity, as shown in Fig.1. The same movement produced relatively consistent signal changes and reconstruction patterns across repeated trials, suggesting a degree of temporal reproducibility. Different movements exhibited distinct response distributions, indicating that the MIT signal possesses spatial discrimination capabilities. Furthermore, the signal remained briefly above baseline following the completion of some movements, suggesting that responses associated with muscle activity may persist for a short period after relaxation.

4 Conclusions

This study provides preliminary evidence for the feasibility of MIT for monitoring thigh muscle activity. Overall, MIT shows promise as a non-invasive method for muscle activity detection. Further studies are required to validate the correlation between the reconstructed results and actual muscle activation, incorporating anatomical localisation and additional experiments.

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Data-driven approach towards localising biomedical robot using EIT

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Abstract: A data-driven approach is proposed for localising a biomedical microrobot using EIT measurements by directly mapping boundary measurements to position, avoiding tomographic image reconstruction. The proposed method achieves comparable accuracy to image processing while reducing processing time, enabling efficient control.

1 Introduction

In biomedical robotics, accurate and real-time localisation of a millimetric robot within a conductive domain such as human body for surgery or culture environment for in vitro manipulation is essential for closed loop control. EIT is commonly used for this purpose by reconstructing conductivity images and identifying regions of variation corresponding to the robot [1] [2]. However, when only the position is required, image reconstruction introduces unnecessary processing time, resulting in delay preventing efficient control of the microrobot. This motivates a simpler data-driven approach that directly maps boundary measurements to position, for which linear regression is considered assuming an end-to-end relationship between the measurements v and the object's planar coordinates $p(x,y)$, expressed as: $p = vR$, where the matrix R allows direct localisation without image reconstruction and processing.

2 Methods

Using EIDORS library on Matlab, a 16-electrode 2D EIT model is considered, where the robot is represented as a circular conductive inclusion with radius 0.1, with domain radius being 1. To generate the training data, the inclusion is simulated at uniformly distributed locations p within the domain (221 points), and the corresponding voltage measurements v are obtained by solving the forward problem. A separate dataset (v_t, p_t) is generated from randomly distributed positions (100 points) for testing.

To model the relationship between the measurements and the robot's position, a linear regression model is employed, the learned mapping R is then used to estimate the positions of the test data: $\tilde{p}_t = v_t R$.

Adding Tikhonov regularization to the regression (Ridge regression) gives the following formulation of R :

$$R_\lambda = (v^T v + \lambda \mathbf{I})^{-1} v^T p \quad (1)$$

For comparison, localisation is also performed using image-based reconstruction. A Gauss-Newton solver with a NOSER prior is applied to reconstruct the conductivity change σ . A threshold ($Th = 0.9\max(\sigma)$) is used to extract the region corresponding to the robot, then the position is estimated as the center of mass of the selected elements.

3 Results and Discussion

The performance of the proposed and conventional methods are evaluated in terms of Euclidean distance error and execution time. Fig. 1 illustrates the true and estimated positions over multiple frames for noisy condition (60 dB SNR),

while Tab. 1 summarizes the mean localisation error for different methods across varying noise levels.

In the absence of noise, the regression based approach achieves accurate localisation without requiring regularization. However, when noise is introduced, it becomes highly sensitive, leading to significant degradation in performance. Tikhonov regularization is therefore introduced, with the regularization parameter λ selected empirically. Its optimal value is observed to vary with the noise level. With appropriate regularization, the regression method achieves accuracy comparable to the image reconstruction approach.

The reconstruction approach requires approximately 18 ms per frame to reconstruct the image and localise the robot, whereas the regression method takes 1.2 ms. These results are obtained on a standard CPU and could be further improved using hardware acceleration (e.g., FPGA). This difference is expected, as regression reduces to simple matrix multiplication, avoiding more complex computations involved in image reconstruction and processing.

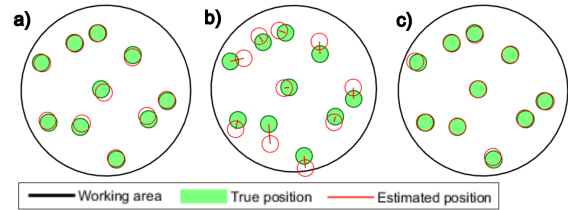


Fig. 1: Estimation on 10 different positions at SNR value of 60 dB using: a) reconstruction, b) linear regression, c) ridge regression.

Tab. 1: localisation distance error at different SNR levels.

SNR level	Reconstruction	Regression	Regularized reg.
∞	0.024	0.024	0.024
60 dB	0.022	0.136	0.030
40 dB	0.045	0.312	0.080

4 Conclusions

The results demonstrate that a simple regression between boundary measurements and robot's position can achieve comparable localisation accuracy at low-noise, while significantly reducing computational time, achieving fast and direct localisation using EIT measurements suitable for control. A key perspective is extending to real-time multi-robot localisation scenarios without image processing.

Acknowledgements

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Electrical Impedance Tomography for In-Situ Process Monitoring

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Abstract: This paper outlines methodological and technological advancements in Electrical Impedance Tomography (EIT) for the in-situ monitoring of dynamic multiphase processes, developed as part of the CRC1615 SMART Reactors project. Bridging electrical engineering, chemical engineering, and applied mathematics, we detail scalable hardware development, circuit-electrochemical co-simulations, and advanced data extraction techniques. Employing impedance spectroscopy and reconstruction-free analysis, we accurately map gas flow rates directly from raw voltages.

1 Introduction

In modern process engineering, the optimization of multiphase reactors requires a paradigm shift from empirical observation toward transparent, knowledge-driven control. EIT represents a powerful modality for the in-situ monitoring of these complex environments, capable of quantifying internal states such as gas-holdup and dynamic flow patterns. To realize this potential we employ an interdisciplinary approach that bridges application-specific hardware design with mathematical modelling and reconstruction frameworks. Rather than relying exclusively on traditional tomographic image reconstruction, our approach evaluates the feasibility of deriving critical chemical quantities directly from raw boundary voltage measurements. We interpret EIT as a distributed voltage sensor with optional tomographic output.

2 Materials & Methods

Data acquisition in highly dynamic multiphase flows demands a scalable and adaptable hardware strategy. Our development pipeline addresses this necessity through three tiers. First, we have developed a custom 32-electrode EIT system optimized for high-speed temporal resolution, tracking transient multiphase states and rapid chemical dissolutions. Second, to achieve the high spatial resolution required for volumetric analysis, we integrated a commercial 256-channel device from ScioSpec. Third, we are engineering novel hardware architectures utilizing multiple parallel current sources, designed to optimize current injection patterns for insight in fast-evolving media.

To achieve integration between hardware design and chemical process monitoring, we employ a continuously advanced co-simulation framework. By coupling hardware-level SPICE simulations with electrochemical models, we can predict electronic behavior and validate internal reactor states prior to physical deployment. Ultimately, this integrated paradigm establishes a foundation for the concurrent

co-development of customized hardware, high-fidelity electrochemical models, and advanced data processing.

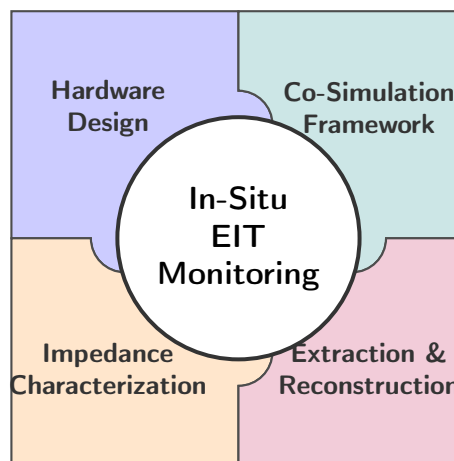


Fig. 1: Interdisciplinary Integration for in-situ monitoring: The four core methodological pillars act as interlocking components, demonstrating the concurrent co-development required to achieve autonomous monitoring in process engineering through EIT.

3 Results & Discussion

The derivation of critical process variables is achieved through two complementary mathematical pathways. The first pathway involves the generation of classical reconstructed spatial images by solving the highly ill-posed inverse problem, providing immediate visual mapping of the reactor's cross-sectional phase distributions. The second pathway utilizes direct, reconstruction-free analysis of raw voltage measurements to estimate key hydrodynamic metrics, such as volumetric gas flow rates. This bypasses traditional computational bottlenecks and mitigates image artifacts.

Furthermore, to disentangle overlapping physical effects we employ Electrochemical Impedance Spectroscopy (EIS). By sweeping across different frequency ranges, this spectroscopic approach provides the data needed to isolate specific reactor conditions. The continuous synergy of high-density hardware frameworks, co-simulations, and advanced mathematical solvers aims for a highly reliable distributed spatial sensor, establishing a robust foundation for autonomous, real-time chemical process engineering.

Acknowledgements

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Monitoring remission of equine asthma with EIT

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Abstract: There is great potential for EIT in the diagnosis of obstructive lung diseases. To support further research, we provide an interventional dataset of 3D EIT and lung-function measurements in equine asthma.

1 Introduction

Asthma diagnosis ideally involves the objective assessment of lung function. However, spirometry-based lung function testing is not sufficiently sensitive (e.g. can be normal during remission) and is often poorly tolerated. This study aimed to evaluate the 2-plane / 3D EIT as a non-invasive diagnostic tool in asthma, using horses with severe equine asthma (SEA), and characterize regional lung function changes during corticosteroid treatment. Horses with SEA underwent daily EIT and pulmonary function testing (PFT) for two days of exacerbation (hay exposure) and eight days of dexamethasone treatment. This study aims to advance research on EIT in obstructive lung disease by using 2-plane electrode belts and 3D reconstruction.

2 Methods: Animals

Ten horses with severe equine asthma belonging to the University of Montreal research herd were evaluated (with Animal Care Committee approval 23-Rech-2041). Four geldings and six mares were included: weight 565 ± 71.5 kg and age 14.3 ± 2.4 years. They were fed hay of variable quality twice a day, to induce asthma exacerbation. When clinical signs and pulmonary function confirmation of exacerbation were observed ($R_L > 1 \frac{\text{cmH}_2\text{O}}{\text{L/s}}$), treatment with oral dexamethasone (0.05 mg/kg PO once daily) was initiated and continued for 8 days to return horses to remission ($R_L > 1 \frac{\text{cmH}_2\text{O}}{\text{L/s}}$).

3 Methods: Measurements

A two-plane EIT belt was placed around the thorax of each horse after wetting of the hair with water, and/or application of non-conductive coupling gel (Fig 1). The cranial row of electrodes was placed immediately behind the olecranon at $\approx$ the 5th or 6th intercostal space. The caudal electrode belt was 25 cm from the cranial row. EIT data were recorded separately to PFT data (before in 7 measurements, after in 22 measurements, simultaneously in 11 measurements). EIT data were recorded using the Sentec BB-Vet EIT system at 50.9 frame/s, using a “skip 4” stimulation/measurement pattern with a “square” electrode placement, and reconstructed with 3D GREIT[1]. Data were recorded for a minimum of two minutes or 10 breaths.

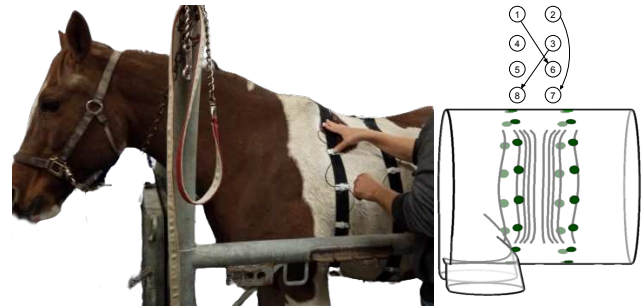


Fig. 1: Left: A horse with two-plane EIT electrode belts. Right: Electrode model sensitivity and stim/meas pattern.

Pulmonary function tests were performed: oesophageal pressure was measured using a thin-walled balloon catheter, while airflow was assessed with a pneumotachograph and differential pressure transducer connected to a respiratory mask. Pulmonary resistance (R_L) and elastance (E_L) were calculated using the lung single compartment model by dedicated software (FlexiWare 7.6). Measurements were performed on days 0, 1, 4, and 7 for nine horses, and on days 0, 1 and 3 for one horse that had a delay to exacerbation.

The dataset (doi.org/10.5281/zenodo.14779514) is available under a CC Attribution 4.0 Int licence.

4 Results and Discussion

EIT has great potential for diagnosis and titration of treatment for obstructive lung disease[2]. EIT research in humans has largely been restricted to observational studies, and the use of single electrode belts which do not measure the full 3D lung regions.

These data offer insight into this disease process. For example, Fig 2 shows increased T_{close} over the treatment phase. We hope that this freely available 3D EIT data set of asthma exacerbation and remission will facilitate improved understanding of EIT’s potential to provide useful diagnostic information in these diseases.

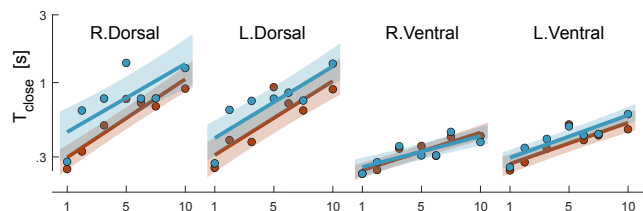


Fig. 2: Opening time (T_{close}) for a horse in eight regions (pink:cranial, blue:caudal), as a function of remission day.

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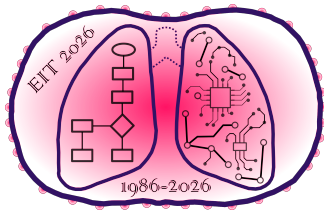
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Thank You!

See you next year!

