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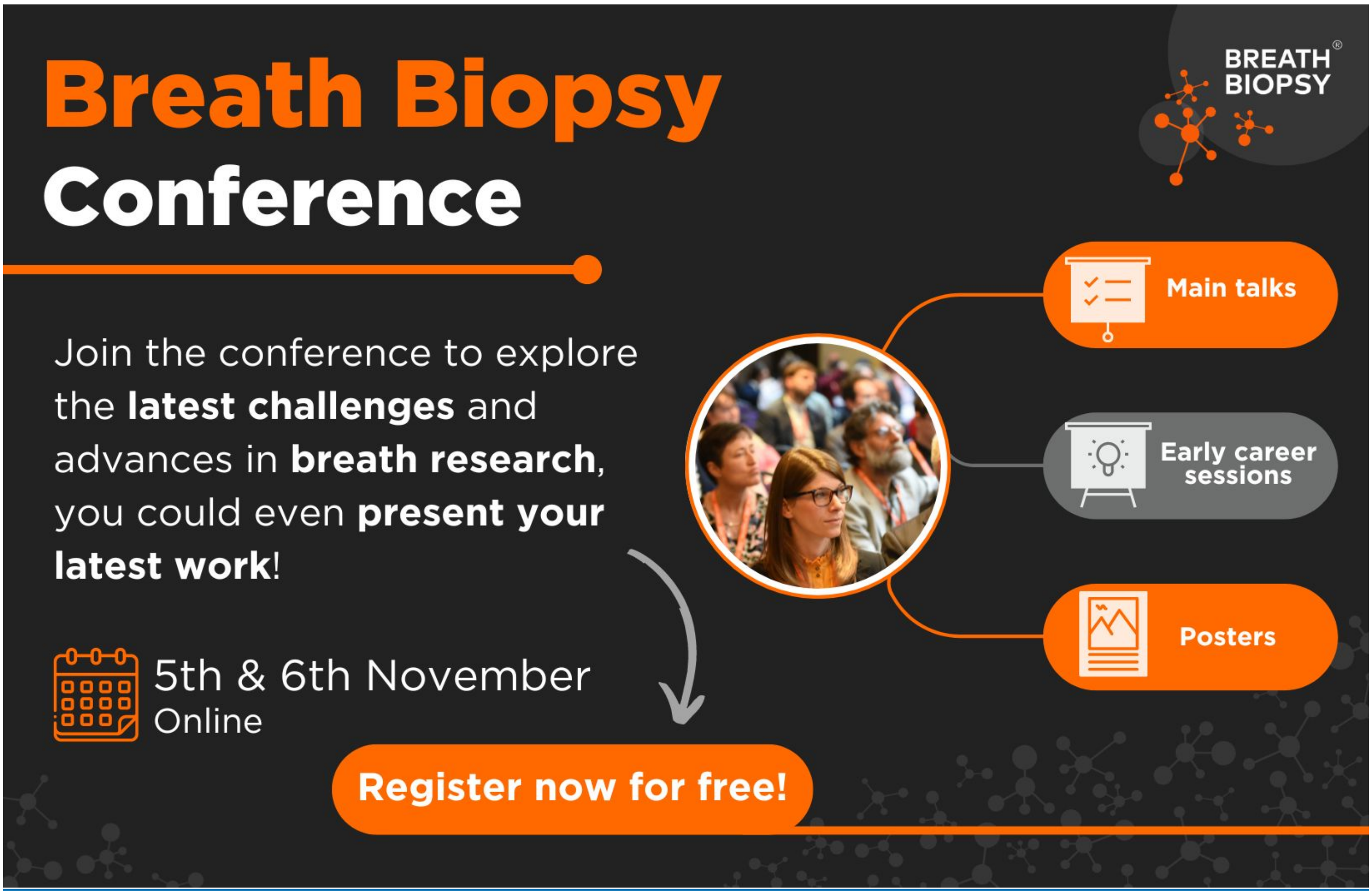

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EDITORIAL

Progress in electrical impedance tomography and bioimpedance

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Abstract

Scope. This focus collection aims at presenting recent advances in electrical impedance tomography (EIT), including algorithms, hardware, and clinical applications. *Editorial*. This focus collection of articles published by the journal *Physiological Measurement* introduces the Progress in EIT and Bioimpedance. It follows conferences in South Korea and Germany, that provided a platform for new research ideas.

One area that is emerging as an area of interest is data sharing due to the development of new and different electrical impedance tomography (EIT) systems, both as research tools and for clinical application in hospitals. This has led to several challenges as there is an array of different data formats and different protocols for data collection. More clinical studies are being undertaken with increasing number of subjects greater than 100. However, comparing the data from different studies becomes difficult due to varying data formats, electrodes belt positions and incompatible boundary conditions. Future adoption of EIT as a routine clinical tool requires a considerable increase in trial numbers and further efforts in standardisation of data and clinical calibration. There are several challenges that need to be addressed to tackle these problems.

Data sharing is the process of making the same data resources available to multiple applications, users, or organisations. Two key challenges are to standardise image formats of these data sets; and to use a common format for the raw boundary data used to reconstruct images. Data collection methods can vary from serial to parallel—along with the reconstruction methods, colours and tools used to visualise and extract clinical parameters. Making a comparison between images reconstructed in different ways is therefore difficult. Other barriers exist related to privacy and the risk of sharing personally identifiable information.

Other key issues relate to data protocols. Electrode array placements are not standardised or are ambiguously defined. This creates challenges in gathering uniform clinical data sets and makes parameter extraction complicated. Further, research systems rarely provide an integrated approach for data exchange with clinicians, and hospital systems used for clinical routine care are mainly focused on patient care while often providing reduced access for external researchers, thus limiting algorithm development. The anticipated use of artificial intelligence (AI) for the interpretation of EIT images will drive establishment of large data sets for training and validation of AI models, and with the goal of developing algorithms that will work safely and effectively across diverse patient populations and clinical settings. The advent of AI modelling thus makes it essential to standardise data protocols and images and is essential for the rigorous assessment of performance and reliability that is required by regulatory bodies.

Clearly stated and standardized protocols and data formats are therefore critically important for the clinical uptake of EIT, as is improved access to patient data while maintaining privacy. Despite the issues addressed above, there are common standards that could be used to share data and assess them. DICOM, for example, is a standard used for other image modalities that would offer a defined protocol for image sharing and analysis and has been a focus of discussion at recent conferences. However, one question remains '*what common feature do we need share data and how do we create a uniform clinical calibration method*?'

Next to this general issue that we are raising to stimulate discussion, in the following we briefly introduce the papers of this focus collection of EIT articles:

Currently, the most widespread clinical use of EIT is chest ventilation imaging. In fact, some recent reviews document how chest EIT may be applied to guide the ventilator therapy in mechanically ventilated patients (Heines *et al* 2023, Franchineau *et al* 2024, Frerichs *et al* 2024a), both in the intensive care unit (ICU) and operation theatre settings. The articles published in the recent collection 'Progress in EIT and Bioimpedance' that focused on chest imaging reflect this ongoing interest in ICU-related EIT applications (Wisse *et al* 2024a, 2024b), but they also discuss studies conducted within the fields of physiotherapy (Yang *et al* 2024a), veterinary medicine (Byrne *et al* 2024) as well as applications in spontaneously breathing subjects (Hülkenberg *et al* 2024, Frerichs *et al* 2024b).

The full potential of chest EIT monitoring in ICU patients will unfold only when the EIT findings are meaningfully combined with the existing patient monitoring data obtained by other medical devices used in the ICU. This has been described already in the seminal paper aiming to define the future developments and pathways for establishing chest EIT in routine patient care (Adler *et al* 2012). One of the basic clinical respiratory parameters is the respiratory rate. Different methods are applied to provide this vital parameter at the bedside, the most frequent ones being capnography and transthoracic bioimpedance measurement using the ECG electrodes. Here, Wisse and colleagues examined the accuracy of EIT in determining the respiratory rate in ICU patients during pressure-support ventilation and after endotracheal extubation (Wisse *et al* 2024a). In addition, the respiratory rate was also determined from EIT recordings obtained prospectively in healthy volunteers, breathing regularly at four different rates. The authors concluded that the respiratory rate derived from the chest EIT recordings exhibited an excellent accuracy. The lowest stability was noted in the successfully weaned patients after extubation. These results imply that chest EIT can be reliably used for clinical respiratory rate monitoring.

Wisse *et al* also addressed the topic of eliminating high-frequency cardiac artifact from lung images in this collection. In this paper, (Wisse *et al* 2024b), the group compared a number of automated filtering methods against digital low-pass filtering, including multiple digital notch filtering (MDN), empirical mode decomposition (EMD), and maximal overlap discrete wavelet transform (MODWT). While principal component analysis has also been used for this purpose, they determined that this was not an efficient computational approach. Wisse *et al* found that although low-pass filtering had advantages in terms of signal-to-noise ratio (SNR), there were larger relative and removal errors. The tested EMD, MDN and MODWT techniques all performed similarly in terms of removing high-frequency components. However, the MDN technique provided the best balance of SNR and error performance. Their results indicate that care should be taken in selecting an appropriate filtering method depending on the clinical and research objectives.

However, with respect to the cardiac-related EIT signal, there are ongoing debates on its usefulness. While some researchers consider the cardiac-related signal components to be artifacts (Wisse *et al* 2024b, 2024b), others find them useful information potentially related to lung perfusion which should be retained and may be analysed (Deibele *et al* 2008, Frerichs *et al* 2009, Pikkemaat *et al* 2014, Braun *et al* 2018). In fact, Hülkenberg *et al* demonstrated in a current study how to employ multi-dimensional ensemble EMD for source separation and lung perfusion mappings (Hülkenberg *et al* 2024). The separation was performed by analysing the dominant frequency spectra of the intrinsic mode functions extracted during the source separation process for all pixels. After separation and classification, the authors introduced perfusion maps.

Chest EIT has already been applied to describe and quantify retrospectively the effectiveness of chest physiotherapy (Eimer *et al* 2021) but its prospective use in developing individualized physiotherapy plans and guiding both the patient and the physiotherapist during pulmonary rehabilitation is rare (Li *et al* 2023). Yang and colleagues conducted a unique clinical study in patients suffering from chronic obstructive lung disease (COPD) in which EIT was utilized for training of pursed lips breathing. This specific type of breathing is used in pulmonary rehabilitation of patients with chronic airway obstruction since it is known to relieve subjective dyspnea as well as to improve pulmonary gas exchange and exercise tolerance. In the randomized study by Yang and colleagues, two groups of COPD patients were examined who received either conventional training of pursed lips breathing or training that utilized online chest EIT recordings for immediate feedback. Afterwards, the effectiveness of pursed lips breathing was assessed by EIT and a rating score. All analysed EIT parameters like the inspiratory depth, the expiration-to-inspiration time ratio, expiratory flow and its uniformity and end-expiratory volume stability revealed higher values in those patients who were trained using EIT compared with conventionally trained subjects. Based on these study results, the authors presumed that EIT might become a useful teaching tool for physiotherapists when COPD patients need to be trained how to perform pursed lips breathing.

Currently available commercial EIT devices offer the possibility to acquire EIT data in merely one chest plane. Thus, the way how the EIT electrode interface is placed on the chest defines which section of the lungs is examined by EIT. Clearly, this is a limitation because the chest anatomy and regional pulmonary function are dissimilar with respect to the craniocaudal chest dimension. Frerichs and colleagues performed a study on healthy volunteers with no history of lung disease in whom the EIT electrodes were placed consecutively at two transverse chest planes at the level of the 4th and the 6th intercostal space (Frerichs *et al* 2024b). The subjects were instructed to breathe quietly at first and then to perform a slow and a forced vital capacity manoeuvre. Four types of functional EIT images were calculated from the recordings. They represented the regional distribution of pixel values of tidal volume, slow vital capacity, forced expiratory volume in 1 s and forced vital capacity. The authors found that the spatial distribution of tidal volume and slow vital capacity differed significantly between the planes. The EIT parameters of dorsal fraction of ventilation and ventrodorsal centre of ventilation both identified more dorsal distribution of ventilation in the caudal chest plane. Such differences were not present during the forced ventilation. As a hypothesis, these results were attributed to different thoracoabdominal mechanics between the relaxed and forced types of ventilation.

Byrne and colleagues also examined the effects of chest plane on the spatial distribution of ventilation determined by EIT (Byrne *et al* 2024). The authors performed EIT measurements in standing sedated horses with simultaneous two-plane EIT data acquisition. The animals were studied during quiet breathing and rebreathing. The acquired EIT data were reconstructed into 3D EIT and ventilation distribution analysed in three lung slices. Interestingly, and similar to the upright human subjects (Frerichs *et al* 2024b), more dorsal location of the centre of ventilation was detected in the caudal than the middle and cranial planes. The animal data also revealed higher right-to-left ventilation distribution in the cranial plane than in the more caudal planes. Both the human (Frerichs *et al* 2024b) and the animal study (Byrne *et al* 2024) identified regionally dissimilar ventilation distribution between planes under physiological conditions. These data illustrate the importance of taking regional ventilation differences between chest planes into account which may be even more important in the presence of lung disease, in micro- or hypergravity and during artificial ventilation.

It is well known that EIT imaging would benefit from the knowledge of patient-specific anatomy allowing to produce subject-specific finite element method meshes for EIT reconstruction. In a recent paper, Murphy *et al* introduced a simple method how to generate individual 3D body scans using a specific app on an iPhone (Murphy *et al* 2024). When compared to a Polaris infrared tracker, the authors were able to obtain an accuracy of 5.2 ± 2.1 mm RMSE precision and 7.7 ± 2.9 mm RMSE accuracy on 9 healthy volunteers. The subject-specific meshes were reported to require a processing time of ca. 6.3 min, out of which about 3.4 min of user interaction were necessary.

Adjacent current administration and measurement patterns have conventionally been employed in EIT, although it is known that this may not produce optimal images (Isaacson 1986). In this collection, alternative methods of current administration are explored in three papers, involving applications to lung monitoring (Yang *et al* 2024b), stroke classification (Lee *et al* 2024); and by using sensitivity analysis (Onsager *et al* 2024).

Yang and colleagues investigated the performance of a wearable EIT belt for monitoring regional lung ventilation and perfusion in 12 healthy volunteers using four low-amplitude currents (as low as 125 μA) and either adjacent or opposite current injection (Yang *et al* 2024b). Performance was evaluated based on SNR, image quality assessed by lung separation, inverse artifact prevalence and boundary artifacts; and EIT-based clinical parameters including the centre of ventilation, global inhomogeneity index, and dorsal fraction of ventilation. They found that lung separation, and inverse and boundary artifacts were significantly worse for adjacent current injections at all current amplitudes. SNR was also superior for opposite current injections. These *in-vivo* observations are somewhat contradictory to other studies conducted in phantoms or models that found that adjacent current injection or other injection patterns may produce better results. However, for low-current studies in humans, Yang *et al* recommend using at least 500 μA for adjacent current patterns and 250 μA for opposite current patterns to ensure high SNR, image quality and clinical parameter determination.

In a modeling study, Lee and colleagues assessed the ability of different measurement strategies to identify hemorrhagic strokes (Lee *et al* 2024). An array of 32 electrodes was applied to the surface of multiple head models and the sensitivity of each electrode's reaction to placement of a blood-like of ischemic anomaly was assessed. The most sensitive electrodes (described as 'dominant contributors') were not necessarily those closest to lesions. Also, certain electrodes, often 'outer' or lower on the head, were consistently identified as dominant contributors across multiple head models, lesion locations and current patterns. The authors conclude that relying only on these outer electrodes for stroke classification does not produce the best performance, but also observe that an evenly spaced layout of electrodes such as a 10–20 array may provide good general coverage for stroke assessment.

Onsager and colleagues introduced the so called 'sensitivity volume' as a key metric for evaluating EIT measurement protocols to improve noise tolerance and speed (Onsager *et al* 2024). Their method involved mapping each EIT measurement to a vector in model space, where the collective measurements defined a sensitivity volume. The measurement protocol with the maximal sensitivity volume was identified as having the greatest sensitivity and mutual orthogonality. A generalized distinguishability criterion was used to quantify noise tolerance improvements. The authors report that this approach reduced the choice of measurement number to the same dimension as the model space therefore improving inversion speeds by reducing the need for regularization. Relative improvements caused by adding more electrodes were also determined. They found that the improvements in sensitivity allowed for noise tolerance up to several orders of magnitude greater than standard methods. Thus, the sensitivity volume approach provides a means to determine optimal injection patterns and improve EIT performance in practical applications.

The development of new technologies, including artificial intelligence and advanced sensors, is ushering in a new era for EIT research. These progresses are pivotal for addressing the inherent challenges of EIT, notably its ill-posedness and nonlinear inverse problems. (Hyun *et al* 2023) researched removing motion noise in EIT signals using machine learning, and (Liu *et al* 2023) applied novel deep images prior (DIP) for EIT image reconstruction using regularization induced by convolutional neural networks.

Ameen and colleagues have introduced a novel approach with their Truncated Spatial-Spectral Convolutional Neural Network (TSSConvNet) (Ameen *et al* 2024). By integrating spatial, spectral, and truncated spectral paths, the TSSConvNet overcomes the limitations inherent in traditional EIT issues that rely solely on local information. In parallel, Herzberg and colleagues have adopted the graph U-Net to handle irregular meshes and introduce a new level of flexibility and efficiency (Herzberg *et al* 2023). This approach significantly reduces computational costs and enhances the accuracy of early iterate reconstructions, demonstrating the potential for high-dimensional applications and the ability to generalize from 2D to 3D domains. These studies highlight the impact of integrating novel computational approaches and neural network architectures in advancing EIT technology, paving the way for more accurate, efficient, and versatile imaging solutions in medical and scientific research.

Mason and colleagues proposed the magnetic detection EIT for imaging neural activity using optically pumped magnetometers (Mason *et al* 2023). This new sensor addresses the technical difficulties posed by the highly resistive skull, showcasing the feasibility of 3D neural imaging with superior accuracy compared to traditional EIT methods. This research provides a robust framework to open an era in neural imaging by developing a comprehensive computational pipeline and comparing various reconstruction algorithms. Moreover, Oliveira and colleagues present another application in bioimpedance by exploring the use of bioelectrical muscle localized phase angle as an indicator of muscle power and strength in young women (Oliveira *et al* 2023). Such interdisciplinary applications highlight the broadening scope of bioimpedance beyond conventional areas of monitoring respiration and haemodynamics, extending into new domains such as muscle strength quantification and neural activity imaging.

These pioneering attempts to integrate new technologies into EIT research could open new frontiers in medical imaging and physiological monitoring, heralding a future where EIT plays a crucial role in diverse scientific and clinical settings.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

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