JOURNAL OF MODERN SCIENCE
SPECIAL ISSUE
3/57/2024
www.jomswsge.com

DOI: doi.org/10.13166/jms/191424

GRZEGORZ BARTNIK
WSEI University in Lublin, Poland
ORCID iD: orcid.org/0000-0002-1898-535X

MAGDALENA GŁOWACKA
WSEI University in Lublin, Poland
ORCID iD: orcid.org/0000-0002-4117-2605

MICHAŁ GOŁĄBEK
Netrix S.A., Poland
ORCID iD: orcid.org/0000-0002-2696-505X

PAWEŁ TCHÓRZEWSKI
Netrix S.A., Poland
ORCID iD: orcid.org/0000-0001-8344-8828

TOMOGRAPHIC EXAMINATION OF THE HEAD MODEL THROUGH IMAGE RECONSTRUCTION FROM MEASUREMENT DATA

TOMOGRAFICZNE BADANIE MODELU GŁOWY POPRZEZ REKONSTRUKCJĘ OBRAZU Z DANYCH POMIAROWYCH

Abstract

This study aims to integrate ultrasound tomography with numerical algorithms to significantly enhance brain sensing capabilities for diagnosing critical brain abnormalities. Advanced ultrasound tomography, employing a high-frequency transducer array, captures intricate brain structures. The echoes processed by multi-channel receivers allow for three-dimensional imaging. Deep learning models, particularly convolutional neural networks, undergo rigorous training on extensive datasets. Hyperparameter tuning and regularization are key to model optimization. Algorithms handle large datasets, detecting subtle pathological changes in ultrasound images. The system demonstrates proficient image reconstruction and analysis. Implementing deep learning algorithms rectifies operator-dependent inconsistencies and imaging artifacts. The analysis shows significant improvements in diagnostic accuracy and processing time. The convergence of ultrasound tomography and deep learning faces challenges such as image quality variation, computational demands, and clinical integration. Despite these, the enhanced image clarity and the ability to conduct real-time analytics are promising. The study sets a new standard in neurological diagnostics, indicating the potential for sophisticated diagnostic tools to become accessible in diverse healthcare settings.

Streszczenie

Opisane badania miały na celu zintegrowanie tomografii ultradźwiękowej z algorytmami numerycznymi, dzięki czemu można zwiększyć możliwości tomografii mózgu w diagnostyce krytycznych nieprawidłowości z nim związanych. Zaawansowana tomografia ultradźwiękowa, wykorzystująca układ przetworników o wysokiej częstotliwości, rejestruje skomplikowane struktury mózgu. Echa przetwarzane przez wielokanałowe odbiorniki pozwalają na trójwymiarowe obrazowanie. Modele głębokiego uczenia, w szczególności konwolucyjne sieci neuronowe, są intensywnie trenowane na dużych zbiorach danych. Kluczowymi procesami w optymalizacji modelu są dostrajanie hiperparametrów i regularyzacją danych. Algorytmy przetwarzają duże zbiory danych, wykrywając subtelne zmiany chorobowe na obrazach mózgu uzyskanych dzięki ultrasonografii. System demonstruje sprawną rekonstrukcję i analizę obrazu. Zastosowanie algorytmów głębokiego uczenia umożliwia usunięcie części szumu związanego z pomiarami, a także potencjalnych artefaktów obrazowania. Analiza wykazała znaczną poprawę dokładności diagnostycznej i czasu przetwarzania. Konwergencja tomografii ultrasonograficznej i głębokiego uczenia napotyka wyzwania, takie jak zmienność jakości obrazu, wymagania obliczeniowe i integracja kliniczna.

Pomimo tego, zwiększona rozdzielczość i czytelność uzyskanych obrazów i możliwość przeprowadzania analiz w czasie rzeczywistym są obiecujące. Niniejsze badania wyznaczają nowy standard w diagnostyce neurologicznej, wskazując na potencjał zaawansowanych narzędzi diagnostycznych, które mogą stać się wkrótce dostępne w różnych placówkach opieki zdrowotnej.

Keywords: *Ultrasound Tomography, Non-invasive Imaging, Brain Sensing, Signal Processing, Medical Diagnostics*

Słowa kluczowe: *tomografia ultradźwiękowa, obrazowanie nieinwazyjne, badanie mózgu, przetwarzanie sygnałów, diagnostyka medyczna*

Introduction

Brain-sensing technologies are significant in medical diagnostics, fundamentally revolutionizing our understanding and treatment of neurological disorders (Qiu et al., 2021; von Ramm et al., 1978). This technological progression enables unprecedented levels of detail and clarity, offering more profound insights into the intricate workings of the human brain (Cuadra et al., 2005; Liu et al., 2022). Traditional imaging modalities like magnetic resonance imaging (MRI) and computed tomography (CT) scans, despite their widespread usage and reliability, come with a host of challenges that can hinder their effectiveness (Majumdar, 2018; Mikulka, 2015). High operational and maintenance costs make these technologies less accessible, particularly in low-resource settings, limiting their global reach and impact (Noda et al., 2023; Poudel et al., 2019). Moreover, the inability of these traditional methods to provide real-time imaging poses a critical barrier in scenarios where immediate intervention is crucial, such as during surgical procedures or in the emergency evaluation of traumatic brain injuries. Additionally, the extensive preparation and processing time required before definitive results can be obtained further underscores the need for more agile diagnostic tools. These significant limitations underscore the urgent need for more innovative solutions in the realm of medical imaging—solutions that are not only faster and more accessible but also cost-effective without sacrificing the accuracy and precision necessary for effective diagnosis (Koulountzios et al., 2021). The development of such technologies promises to democratize advanced healthcare, making it possible for a more comprehensive array of healthcare institutions to provide timely and accurate diagnoses, ultimately enhancing patient care and outcomes on a global scale (Zhao et al., 2019; Zhu et al., 2020).

In response to the pressing demands for more efficient and accessible diagnostic tools, cutting-edge techniques such as ultrasound tomography, when integrated with deep learning algorithms, have surfaced as up-and-coming alternatives (Kłosowski et al., 2020; Kłosowski & Rymarczyk, 2017). Ultrasound tomography, in particular, offers a non-invasive and safer imaging modality compared to its predecessors (Javaherian et al., 2020; Mazurek et al., 2020). This technique leverages sound waves to penetrate biological tissues, thereby producing detailed images of the human brain without the risks associated with ionizing radiation found in traditional methods like CT scans (Martiartu et al., 2020). Additionally, ultrasound equipment typically involves lower operational costs, which could significantly reduce the financial burden on healthcare systems and make advanced imaging capabilities more widespread, especially in under-resourced settings (Martiartu et al., 2020; Rymarczyk et al., 2019).

Despite these advantages, the intrinsic complexity of the brain's anatomy, with its densely packed neurons and intricate networks, poses a formidable challenge for extracting actionable insights from raw ultrasound images(Qiu et al., 2021; Rymarczyk et al., 2018). This is where deep learning algorithms come into play, bringing their robust analytical capabilities to bear on the problem. These algorithms excel in managing large datasets and identifying complex, often subtle patterns that are beyond the scope of human detection. By training on vast amounts of imaging data, these models learn to discern minor discrepancies and anomalies in ultrasound images that could indicate the presence of pathological changes.

Deep learning's ability to continuously learn and improve from additional data also means that these systems become more proficient over time, thereby enhancing their diagnostic accuracy (Kłosowski et al., 2020; Quang-Huy et al., 2015). This aspect is particularly critical in neurology, where early detection and precise characterization of disorders can significantly influence treatment outcomes. The integration of deep learning with ultrasound tomography not only aims to enhance the clarity and reliability of diagnostic images but also strives to provide real-time analytics, which is essential for rapid decision-making in acute medical scenarios (Kłosowski et al., 2023). Thus, this synergistic approach holds the potential to transform the landscape of neurological diagnostics, making it more dynamic, precise, and accessible than ever before.

The central goal of this research initiative is to seamlessly integrate ultrasound tomography with advanced deep learning techniques to enhance brain sensing capabilities significantly. This combination aims to use machine learning's advanced pattern recognition and analysis skills to make ultrasound images more precise and more detailed and make them more helpful in diagnosing and understanding brain diseases. Specifically, the integration of these two technologies is intended to drastically improve the diagnostic accuracy for a range of severe brain abnormalities, including tumors, hemorrhages, and other potentially life-threatening conditions. Such enhancements are crucial, as the early and accurate detection of these issues is often pivotal in determining the most effective treatment strategies and, by extension, improving patient outcomes. Furthermore, this research endeavors to streamline the entire imaging process. By incorporating deep learning algorithms into the interpretation of ultrasound data, there is potential to significantly reduce the time required to process and analyze the complex information captured in these images. This acceleration in data processing is expected to lead to quicker clinical decisions, enabling healthcare providers to offer timely and more effective interventions. This project's ambitious goal is to transform the field of neurological diagnostics fundamentally. By improving the efficiency, accessibility, and accuracy of brain imaging, this approach is poised to establish a new benchmark in the field, potentially making sophisticated diagnostic tools available to a broader range of healthcare settings globally. This could democratize access to high-quality healthcare, ensuring that advanced diagnostic capabilities are not confined to well-resourced tertiary care centers but are available across various clinical environments, enhancing the overall standard of care and patient management within the neurology field (Gao et al., 2019).

Background and Related Work

Ultrasound tomography represents a sophisticated evolution in medical imaging technology, distinguishing itself through its use of sound waves to generate detailed visual representations of internal body structures. This modality is based on the principle that sound waves transmitted into the body will reflect off tissues with varying densities at different rates and intensities. These reflected waves are captured and analyzed to produce images that can reveal valuable diagnostic information. The process begins with transmitting high-frequency ultrasound waves, typically 1–15 MHz, into the body using a transducer. As these waves traverse through different tissues, they encounter interfaces between tissues of different acoustic impedances. At each interface, a portion of the sound wave is reflected to the transducer, while the rest continues to propagate until it is either absorbed by the tissue or reflected further. The data collected from these echoes is then used to construct an image of the internal structure of the area being examined. Ultrasound tomography is advantageous in medical settings due to its non-invasive nature and the absence of ionizing radiation, making it a safer option than other imaging techniques like X-rays and CT scans. Moreover, the equipment is relatively portable and more cost-effective, facilitating the accessibility and the feasibility of conducting scans in various medical environments—from large hospitals to small clinics and even in field settings. In the realm of brain imaging, ultrasound tomography offers unique benefits. The brain, enclosed within the skull, presents a challenging subject for most imaging modalities due to the dense bone that can obscure or distort the imaging signals. Ultrasound tomography can be employed to navigate these challenges, mainly through techniques like transcranial Doppler sonography, which measures blood flow velocity through the brain's blood vessels. This is critical for assessing stenosis or emboli that could lead to strokes.

The development of deep learning models for image reconstruction and analysis in ultrasound tomography involves a meticulous process of selection, training, and optimization aimed at enhancing the capabilities of this advanced diagnostic tool. The journey begins with carefully selecting an appropriate deep-learning architecture, a decision that hinges on the specific requirements and challenges of medical imaging. Models such as convolutional neural networks (CNNs) have proven particularly effective due to their ability to process grid-like data and extract features from images, which is crucial for interpreting complex patterns in ultrasound scans. Training these models requires a substantial dataset of high-quality, annotated ultrasound images. These datasets teach the model how to accurately interpret the diverse textures and patterns associated with tissue types and pathological conditions. The training process involves feeding these images into the model, allowing it to learn incrementally and adjust its parameters to minimize the difference between its predictions and the actual data. This learning phase is both data – and computation-intensive, necessitating advanced GPUs and large-scale data processing architectures to manage and analyze vast amounts of data effectively. The optimization of deep learning models in medical imaging goes beyond simply improving accuracy; it also seeks to improve the model's efficiency and ability to generalize from training data to real-world scenarios. Techniques such as cross-validation and regularization are employed to fine-tune the model and prevent overfitting, where a model performs well on training data but poorly on unseen data. Additionally, hyperparameter tuning is conducted to find the optimal settings for parameters such as learning rate, number of layers, and number of neurons per layer, which are pivotal in shaping the model's learning capability and performance. Further refinement is achieved by applying transfer learning, in which a model developed for one task is repurposed for another related task. This is particularly beneficial in medical imaging, where pre-trained models on large image datasets can be fine-tuned with smaller medical images, significantly speeding up the learning process and improving model robustness. The culmination of this rigorous development process is a deep learning model adept at reconstructing high-fidelity images from ultrasound data and proficient in analyzing these images to deliver precise and actionable insights. Such models are integral to the push towards more accurate and timely diagnoses, supporting clinicians in providing superior healthcare. With advancements in artificial intelligence and machine learning, the potential for further enhancements in image reconstruction and analysis continues to grow, promising ever more sophisticated tools for medical diagnostics.

Deep learning models must be trained on various cases to generalize well across possible abnormalities. This necessitates a large and well-annotated dataset that covers a broad range of conditions, from standard to rare, each represented by high-quality ultrasound images. Gathering and curating such a dataset is time-consuming and requires extensive collaboration across multiple clinical sites. In addition to these technical and data-related challenges, computational constraints also play a critical role. Deep learning algorithms, particularly those involving complex architectures like convolutional neural networks, require substantial computational power and memory. This can be a limiting factor, especially in clinical settings where resources may be scarce or dedicated to other critical tasks. Optimizing algorithms to reduce their computational load without compromising performance is a key area of focus that requires ongoing innovation and testing. Lastly, integrating these sophisticated algorithms into clinical workflows poses its own set of challenges. Clinicians must trust the technology and find it adds value without disrupting existing protocols. Ensuring that the deep learning models can operate in real-time and are compatible with existing medical imaging systems is crucial for their adoption and effective use. Training clinical staff to use these new tools effectively and interpret their outputs correctly also requires careful planning and education. Despite these challenges, integrating ultrasound data with deep learning holds immense potential to transform medical imaging by enhancing diagnostic capabilities and enabling more precise and timely medical interventions. As researchers and engineers continue to tackle these challenges, the convergence of these technologies becomes increasingly viable, promising significant advancements in medical diagnostics.

Methodology

The ultrasound tomography system employed in this study represents a sophisticated integration of cutting-edge hardware and software tailored for optimal brain imaging. At the heart of the system lies an advanced ultrasound scanner equipped with a high-frequency transducer array capable of emitting and receiving sound waves in the 1–15 MHz range. This array is designed to provide satisfactory resolution and deep tissue penetration, essential for capturing the complex structures within the brain. The hardware setup includes a multi-channel receiver that processes the echoes received from the transducer array. Each channel can independently capture data, allowing for simultaneous recording from multiple angles and enhancing the system's ability to construct a comprehensive three-dimensional brain image. This capability is critical for accurately identifying and characterizing various brain pathologies. Complementing the hardware, the system's software is a robust platform developed to manage and analyze the vast data streams generated during scanning. It features advanced image reconstruction algorithms that transform raw ultrasound data into detailed visual representations. These algorithms employ sophisticated signal processing techniques to mitigate common ultrasound imaging challenges, such as speckle noise and acoustic shadowing, thus enhancing the clarity and usability of the images. Moreover, the software includes machine learning tools that refine image quality and assist in diagnostic processes. These tools are designed to learn from vast datasets of ultrasound images, improving their ability to discern subtle variations in tissue characteristics that may indicate the presence of disease. The entire setup is engineered to function seamlessly within a clinical setting. It includes an ergonomic design that allows easy maneuverability and adjustment, facilitating its use in various medical environments without requiring extensive setup changes. The system also incorporates real-time imaging capabilities, enabling clinicians to conduct dynamic assessments and make immediate decisions during diagnostic and therapeutic procedures. In practice, the ultrasound tomography system is used for brain imaging by strategically positioning the transducer array around the patient's head. Careful calibration ensures that sound waves penetrate the skull efficiently and that echoes are captured accurately, minimizing data quality loss. Once the scanning process is initiated, the system rapidly gathers ultrasound data, which is immediately processed by the onboard software to generate real-time images displayed to the clinician. This integration of high-performance hardware and sophisticated software makes the ultrasound tomography system an invaluable tool in neurological diagnostics, providing detailed insights into brain structure and function crucial for effective patient care.

In ultrasound tomography (transmission mode), a simple problem can be presented as a linear map.

$$\mathbf{x} = \mathbf{S}\,\mathbf{y} \tag{1}$$

where **S** is the sensitivity matrix, **x** is the vector of the measurement data. In contrast,the vector **y** is the material parameter or its difference calculated from the reference state. At the same time, the vector represents the solution to the inverse problem that is ought. It should be emphasized that the system of linear equations (1) is undetermined, and the matrix **S** is characterized by a high condition number. In practice, therefore, it is not possible to solve it directly, without adopting additional assumptions. Thus, the necessity of regularization naturally arises here.

The simplest method to reconstruct an image is the linear back projection method. This approach approximates the matrix for determining the inverse transformation using a column-normalized sensitivity matrix. It is not difficult to see that calculating a vector requires relatively little computational effort.

A more advanced procedure is decomposing the sensitivity matrix according to singular value decomposition. This method omits terms with which singular values are associated sufficiently close to zero, obtaining a stable solution to the inverse problem. The process described above is referred to in the literature as truncated singular value decomposition.

The opposite problem can be formulated in the form of an optimization problem. Let the function of the objective given be given by:

$$\mathrm{F}(\mathbf{y}) = \frac{1}{2}\{\,\|\,\mathbf{S}\,\mathbf{y} - \mathbf{x}\,\|^2 + \lambda^2\,\|\,\mathbf{R}\,\mathbf{y}\,\|^2\,\} \tag{2}$$

where λ is the regularization parameter (positive real number), while **R** denotes the regularization matrix. The regularization term limits the Euclidean norm of the **R y** vector. It can be shown that the derivative of function (2) takes the form:

$$\frac{\partial \mathrm{F}(\mathbf{y})}{\partial \mathrm{y}_\mathrm{n}} = [\,\mathbf{S}^\mathrm{T}(\,\mathbf{S}\,\mathbf{y} - \mathbf{x}\,)\,]_\mathrm{n} + \lambda^2\,[\,\mathbf{R}^\mathrm{T}\,\mathbf{R}\,\mathbf{y}\,]_\mathrm{n} \tag{3}$$

The use of the condition on the extremum leads to the following system of linear equations:

$$(\mathbf{S}^{\mathrm{T}}\,\mathbf{S} + \lambda^{2}\,\mathbf{L})\,\mathbf{y} = \mathbf{S}^{\mathrm{T}}\,\mathbf{x} \tag{4}$$

where $\mathbf{L} = \mathbf{R}^{\mathrm{T}}\,\mathbf{RL}$. Depending on the choice of matrix **L**, we get different methods of solving the inverse problem. In the simplest case, the **L** matrix is an identity matrix. Then we get a linear Gauss-Newton method with Tikhonov regularization. In another variant, the matrix remains diagonal, but the values on its main diagonal are determined according to the formula:

$$[\,\mathbf{L}\,]_{\mathrm{n,n}} = \left\{\,[\,\mathbf{S}^{\mathrm{T}}\,\mathbf{S}\,]_{\mathrm{n,n}}\,\right\}^{\mathrm{p}} \tag{5}$$

where p ∈ {[0, 1]. This choice leads to the one-step linear Gauss-Newton method with power regularization. In the particular case when we get a linear Gauss-Newton identifieswith Levenberg-Marquardt regularization. Regularization reduces (improves) the determinant of the principal matrix of the system of linear equations (4), which is particularly important in the context of performing numerical calculations.

This study uses a thorough process to create deep-learning image reconstruction and analysis models. This process includes carefully choosing the models, training them thoroughly, and ensuring they keep improving so that ultrasound tomography can be used for more diagnostic purposes. The foundational step in this process is to select the appropriate deep-learning architecture. Given ultrasound images' complexity and high dimensionality, convolutional neural networks (CNNs) are typically chosen for their proficiency in handling image data. CNNs are particularly adept at extracting hierarchical features from images, which is critical for identifying fine details in brain structures and distinguishing pathological changes. The training phase of these models is vital and demands a substantial dataset consisting of diverse, high-quality ultrasound images. These images must be accurately labeled, often by expert radiologists, to provide ground truth for supervised learning. During training, the model learns to correlate the input data (ultrasound images) with the expected output (diagnostic interpretations), adjusting its internal parameters to minimize errors. This phase is computationally intensive, relying on high-performance GPUs that can handle multiple iterations of data processing and model adjustments in reasonable time frames. The model is continuously optimized to improve its accuracy and efficiency. This involves tuning various hyperparameters, such as the learning rate, the number of layers, and the number of neurons in each layer, significantly influencing the model's performance. Techniques like cross-validation ensure the model performs well not just on the training data but also on unseen data, thereby preventing overfitting. Additionally, regularization strategies are implemented to simplify the model as much as possible without losing predictive power, thus making the model more generalizable and robust against the variance in new patient data. Moreover, transfer learning is often applied to enhance the model's capability to deal with real-world diagnostic scenarios. This involves taking a model that has been pre-trained on a large, generalized dataset and fine-tuning it on the more specialized dataset of ultrasound brain images. This approach leverages learned features from the broader dataset, which can significantly improve learning efficiency and predictive accuracy for identifying brain abnormalities. Once developed, these deep learning models undergo rigorous validation and testing with independent datasets to assess their diagnostic accuracy, reliability, and robustness. The ultimate goal is to integrate these models into the clinical workflow, where they can assist radiologists by providing enhanced image reconstruction and detailed analytical insights, thus facilitating more accurate and timely diagnosis. In addition to ensuring that the models can work in medical imaging environments with their different operational speeds and data integration needs, this integration also ensures that the models are powerful and helpful in improving medical diagnostics.

Results and Discussion

The Ultrasonic Tomography System (UST) depicted in Figure 1 is a sophisticated device designed to acquire and process comprehensive ultrasonic data. This system is good at giving raw full-waveform data and processed values of ultrasonic pulses' amplitude and time of flight (TOF). The acquisition parameters can be changed to fit the needs of different industrial processes. The design encapsulates an array of connectors on the left-hand side, which interface with the ultrasonic probes. These connectors are systematically arranged and numbered, facilitating a systematic approach to attaching the probes and ensuring an organized workflow. Each connector is linked to individual channels, permitting simultaneous data acquisition across multiple probes. The meticulous arrangement suggests a system capable of managing complex data sets, characteristic of extensive imaging or diagnostic procedures. A touch-screen display at the system's center provides a user interface for controlling the device and visualizing data. The display likely shows real-time graphs or images derived from the ultrasonic signals, allowing for immediate interpretation and adjustments. A touch screen indicates a user-friendly interaction model, enabling the operator to quickly change parameters, start or stop measurements, and navigate various functional menus. An array of LEDs serves as status indicators for the corresponding channels to the right of the touch-screen display. These indicators provide visual feedback on the operational status of each channel, such as active data acquisition or error notifications, offering a quick reference to monitor the system's performance during operation. The UST system is encased within a rugged, portable container, suggesting that it is designed for durability and mobility. This portability is essential for onsite diagnostics and data collection in various industrial settings. The case is outfitted with foam padding, ensuring the delicate electronic components are protected during transport. The UST device is a comprehensive, portable system designed for flexibility and precision in ultrasonic data acquisition and processing. Its construction indicates a tool that is both user-friendly and adaptable, suitable for an array of applications where detailed ultrasonic imaging and diagnostics are required. Integrating a sophisticated touch-screen display with multi-channel connectivity underscores the system's capability to deliver real-time, actionable insights crucial for industrial processes that depend on precision and efficiency.

Figure 1. *Ultrasound tomography device*

As shown in Figure 2, the system consists of eight four-channel measurement cards connected via an FD CAN bus to a measurement module. With a sampling rate of up to 4MBPS, each channel has its generator of alternating square waves with amplitudes of up to 144Vp-p and a maximum current capacity of 3A at any given time. Each channel has three eight-order filters, as shown in Figure 3, which display a measurement card with screening capabilities.

Figure 2. *The main module is mounted on cards with STM32H743ZI microcontroller*

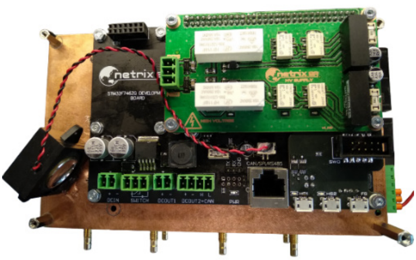


Figure 3. *Measurement card with shielding*

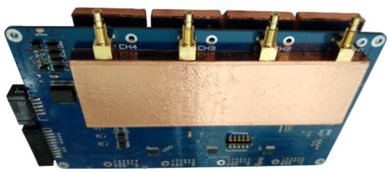
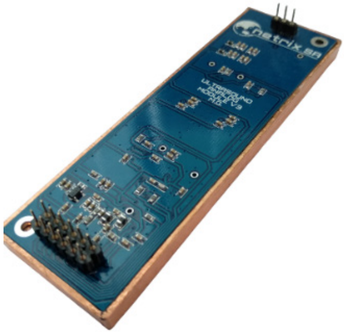


Figure 4 illustrates an analog module with an integrated amplifier, AD8331, with gain control via an external DAC converter, a signal conversion system for alternating acoustic signals to envelope ADL5511, and two differential amplifiers, THS4521.

Figure 4. *Analog module for ultrasonic card*



The distance of the module from the microcontroller and the fact that it is on the identical PCB as a high-voltage generator create a symmetrical differential output signal from the module that cuts down on noise interference. The UST system's ability to perform TOF and amplitude measurements is predicated on critical parameters that ensure the accuracy and integrity of data acquisition. The comparator threshold represents a pivotal threshold value that, when exceeded, prompts the TOF to be captured within the measurement matrix. The device autonomously identifies minimum and maximum signal values to convert percentage values to numerical ADC converter values. These settings, including the 'pull to the ground after extortion' and the window width in which the comparator cannot be triggered, are vital for ensuring the precision of measurements. To get accurate readings from the UST device, you must carefully choose the tomographic settings, thinking about the highest supply voltage, the resonant frequency, and the polarization. This rigorous approach is evident in the configuration settings used for the ultrasound tomography device measurements, demonstrating the system's capabilities and the complexity of operating parameters required to ensure accurate data collection and interpretation.

Figure 5 captures a sophisticated 2D head measurement setup featuring a head phantom encircled by a 2×16 array of 40kHz ultrasonic transducers. This intricate arrangement is connected to an ultrasound tomography system, which forms a comprehensive diagnostic station with a laptop displaying real-time data. The phantom, a replica of a human head, is central to the setup and is used for simulating the acoustic properties of human head tissues. It is positioned on a green base and will likely serve as a support structure and a reference for transducer positioning. The surrounding transducers, systematically placed and intricately wired to the tomography system, are poised to collect data by emitting and receiving ultrasound signals.

Figure 5. *2D head measurements 2×16 – 40kHz*

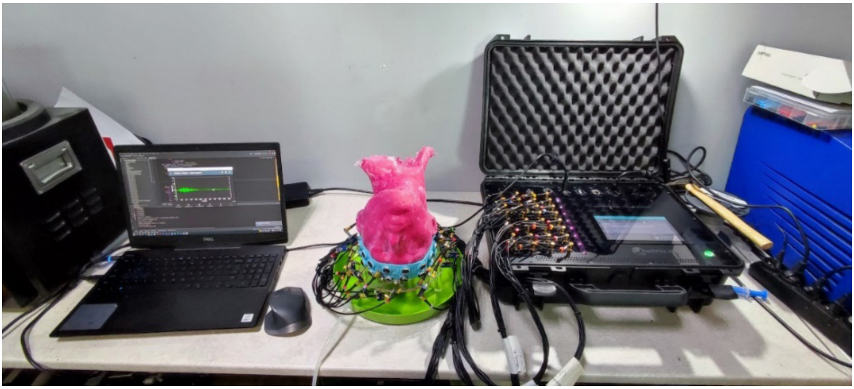
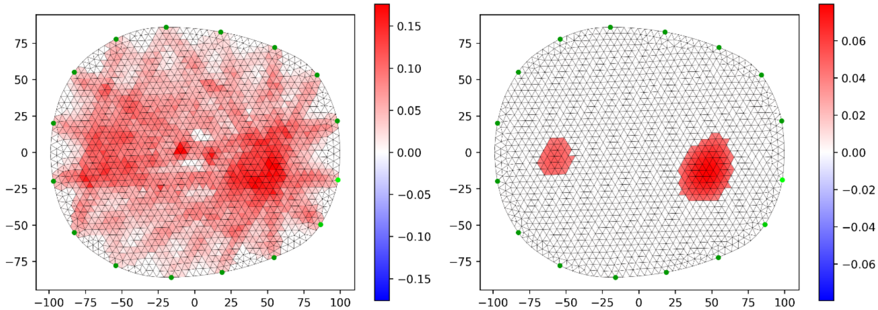


Figure 6 visually represents image reconstruction outcomes using the linear back projection method. Part (a) of the figure displays the initial reconstruction, which typically exhibits a certain degree of blurriness or noise, making identifying structures within the phantom less clear. Part (b) illustrates the enhanced clarity achieved after applying a Mexican hat filter, a post-processing step that helps to accentuate edges and reduce noise. This filter, named for its sombrero-like shape in two-dimensional space, effectively emphasizes the localized features within the image, thereby improving the contrast and detail resolution. The green dots on the periphery represent the locations of the transducers, offering a visual correlation between the data acquisition points and the resulting reconstructed images.

Figure 6. *Image reconstruction obtained using the linear back projection method: direct result (a) and after correction using the Mexican hat filter (b)*



(a) **(b)**

Together, these figures demonstrate the capabilities of the UST setup in capturing detailed acoustic data and the subsequent computational techniques used to refine the images. The contrast between the before and after images shows how important advanced filtering techniques are for getting clinically useful information from raw ultrasound data. This shows how important the hardware setup and the software algorithms are in modern diagnostic imaging.

Conclusions

Conclusions This investigation into the potential of ultrasound tomography, augmented by deep learning algorithms, for brain imaging has produced promising results. Through rigorous methodologies and advanced algorithmic implementations, the study has enhanced the resolution and diagnostic capabilities of ultrasound imaging and provided a pathway toward more accessible and real-time neurological assessments. The synergy between the high-frequency ultrasonic transducer array and the multi-channel data acquisition has enabled detailed brain structural imaging. Meanwhile, convolutional neural networks have been pivotal in interpreting complex imaging data, demonstrating substantial advancements in identifying critical brain pathologies with high accuracy. Despite encountering challenges such as image quality inconsistencies and computational resource demands, the study's outcomes have reinforced the feasibility of employing this integrated approach in a clinical setting. The system's adaptability to real-time processing needs and compatibility with current medical imaging workflows hold great promise for the future of non-invasive diagnostics. The research has conclusively shown that deep learning can significantly mitigate artifacts and operator-dependent variability in ultrasound data. This improves the quality of the diagnostic images and streamlines the process from data acquisition to clinical interpretation. Looking forward, the study underscores the need for continued enhancements in sensor technology, algorithmic refinement, and the expansion of training datasets to further the capabilities of ultrasound tomography in medical diagnostics. As this field advances, it is anticipated that such integrated systems will become integral components of healthcare, extending the reach of high-quality diagnostics to a broader patient base and setting new standards in patient care. This study lays the groundwork for the next generation of diagnostic tools expected to transform neurological diagnostics, making it more dynamic, precise, and accessible. The outcomes suggest a bright future where sophisticated diagnostic tools are not confined to high-resource settings but are available across diverse healthcare environments, democratizing access to advanced medical care.

References

Cuadra, M. B., Cammoun, L., Butz, T., Cuisenaire, O., Thiran, J. P. (2005). Comparison and validation of tissue modelization and statistical classification methods in T1-weighted MR brain images. *IEEE Transactions on Medical Imaging*, *24*(12). https://doi.org/10.1109/TMI.2005.857652

Gao, J., Zhang, H., Lu, P., Wang, Z. (2019). An Effective LSTM Recurrent Network to Detect Arrhythmia on Imbalanced ECG Dataset. *Journal of Healthcare Engineering*, *2019*, 10. https://doi.org/10.1155/2019/6320651

Javaherian, A., Lucka, F., Cox, B. T. (2020). Refraction-corrected ray-based inversion for three-dimensional ultrasound tomography of the breast. *Inverse Problems*, *36*(12), 125010. https://doi.org/10.1088/1361-6420/ABC0FC

Kłosowski, G., Rymarczyk, T. (2017). Using neural networks and deep learning algorithms in electrical impedance tomography. *Informatyka Automatyka Pomiary w Gospodarce i Ochronie Środowiska*, *7*(3), 99–102. https://doi.org/10.5604/01.3001.0010.5226

Kłosowski, G., Rymarczyk, T., Kania, K., Świć, A., Cieplak, T. (2020). Maintenance of industrial reactors supported by deep learning driven ultrasound tomography. *Eksploatacja i Niezawodnosc*, *22*(1), 138–147. https://doi.org/10.17531/ein.2020.1.16

Kłosowski, G., Rymarczyk, T., Soleimani, M. (2023). *Brain Sensing with Ultrasound Tomography and Deep Learning Algorithms*. 1–3. https://doi.org/10.1145/3570361.3615734

Koulountzios, P., Rymarczyk, T., Soleimani, M. (2021). A Triple-Modality Ultrasound Computed Tomography Based on Full-Waveform Data for Industrial Processes. *IEEE Sensors Journal*, *21*(18), 20896–20909. https://doi.org/10.1109/JSEN.2021.3100391

Liu, X., Zhang, T., Ye, J., Tian, X., Zhang, W., Yang, B., Dai, M., Xu, C., Fu, F. (2022). Fast Iterative Shrinkage-Thresholding Algorithm with Continuation for Brain Injury Monitoring Imaging Based on Electrical Impedance Tomography. *Sensors 2022, Vol. 22, Page 9934*, *22*(24), 9934. https://doi.org/10.3390/S22249934

Majumdar, A. (2018). An autoencoder based formulation for compressed sensing reconstruction. *Magnetic Resonance Imaging*, *52*, 62–68. https://doi.org/10.1016/J.MRI.2018.06.003

Martiartu, N. K., Boehm, C., Fichtner, A. (2020). 3-D Wave-Equation-Based Finite-Frequency Tomography for Ultrasound Computed Tomography. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, *67*(7), 1332–1343. https://doi.org/10.1109/TUFFC.2020.2972327

Mazurek, M., Rymarczyk, T., Kania, K., Kłosowski, G. (2020). Dedicated algorithm based on discrete cosine transform for the analysis of industrial processes using ultrasound tomography. *Adjunct Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers*, 82–85. https://doi.org/10.1145/3410530.3414381

Mikulka, J. (2015). GPU-Accelerated Reconstruction of T2 Maps in Magnetic Resonance Imaging. *Measurement Science Review*, *15*(4), 210–218. https://doi.org/10.1515/msr-2015-0029

Noda, T., Jinnai, Y., Tomii, N., Azuma, T. (2023). *Blind Signal Separation for Fast Ultrasound Computed Tomography*. https://arxiv.org/abs/2304.14424v1

Poudel, J., Lou, Y., Anastasio, M. A. (2019). A survey of computational frameworks for solving the acoustic inverse problem in three-dimensional photoacoustic computed tomography. *Physics in Medicine and Biology*, *64*(14), 14TR01. https://doi.org/10.1088/1361-6560/ab2017

Qiu, W., Bouakaz, A., Konofagou, E. E., Zheng, H. (2021). Ultrasound for the Brain: A Review of Physical and Engineering Principles, and Clinical Applications. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, *68*(1). https://doi.org/10.1109/TUFFC.2020.3019932

Quang-Huy, T., Duc-Tan, T., Tue, H. H., Linh-Trung, N. (2015). *Deterministic Compressive Sampling for High-Quality Image Reconstruction of Ultrasound Tomography*. https://arxiv.org/abs/1508.00647v1

Rymarczyk, T., Adamkiewicz, P., Polakowski, K., Sikora, J. (2018). Effective ultrasound and radio tomography imaging algorithm for two-dimensional problems. *Przegląd Elektrotechniczny*, *94*(6), 62–69. http://pe.org.pl/abstract_pl.php?nid=11120

Rymarczyk, T., Klosowski, G., Cieplak, T., Kozlowski, E., Kania, K. (2019). Application of a regressive neural network with autoencoder for monochromatic images in ultrasound tomography. *2019 Applications of Electromagnetics in Modern Engineering and Medicine, PTZE 2019*, 156–160. https://doi.org/10.23919/PTZE.2019.8781750

von Ramm, O. T., Smith, S. W., Kisslo, J. A. (1978). Ultrasound Tomography of the Adult Brain. *Ultrasound in Medicine*, 261–267. https://doi.org/10.1007/978-1-4613-4021-8_73

Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing*, *115*, 213–237. https://doi.org/10.1016/J.YMSSP.2018.05.050

Zhu, H., Cheng, C., Yin, H., Li, X., Zuo, P., Ding, J., Lin, F., Wang, J., Zhou, B., Li, Y., Hu, S., Xiong, Y., Wang, B., Wan, G., Yang, X., Yuan, Y. (2020). Automatic multilabel electrocardiogram diagnosis of heart rhythm or conduction abnormalities with deep learning: a cohort study. *The Lancet Digital Health*, *2*(7), e348–e357. https://doi.org/10.1016/s2589-7500(20)30107-2