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Design of a miniaturized wearable EIT system for imaging and hand gesture recognition

<https://doi.org/10.1515/cdbme-2023-1111>

Abstract: Hand gesture recognition using data from electrical impedance tomography (EIT) systems offers many promising applications, for example in the field of human-computer interaction. Due to its real-time capability and the use of harmless currents for humans, it can be used in medicine, robotics, or virtual environments. As already shown in similar works, for example by Zhang et al. finding a good compromise between accuracy, precision, framerate and the size of the system is a challenge [1], [2]. This work presents a truly wearable compact EIT system on a single $24.9 \text{ mm} \times 22.5 \text{ mm}$ circuit board consisting of standard components without application-specific integrated circuit. A neural network (NN) classifies two gestures. It is able to distinguish two different gestures with an accuracy of 78,33 % and a precision of 76,56 %. This work has a strong focus on the size of the system and provides a starting point for further research in compact wearable gesture recognition systems. It shows the challenge of the compromise between size and quality of the signals.

Keywords: Electrical Impedance Tomography, EIT, gesture, wearable, neural network, medical imaging, sensors

1 Introduction

EIT in medical technology is a non-invasive imaging technique, which uses currents in the microampere range and simultaneous voltage measurements to map the impedances to an area between surface electrodes.

Webster and Henderson introduced an EIT system for thoracic screening in 1978 and in 1982 Brown et. al performed the first in vivo EIT measurement and reconstructed an image of the forearm [3]. Since then, EIT has become well established in the field of health care [4], [5].

Compared to other systems, EIT is cheap, real-time capable and non-invasive, which makes it an interesting method for real time gesture recognition. An advantage over other gesture detection methods, such as camera systems, is the mobility of the system and the possibility to integrate it into a wearable wristband or smartwatch. This device can then be used for human-machine interaction for disabled people, for interaction with gesture-controlled robots or software or virtual- and augmented-reality applications.

In order to use such a device in everyday life, it must be handy and easy to operate. For this reason, this work develops a battery-powered EIT system whose main requirement is the size of a smartwatch. Wireless communication with a notebook computer and gesture classification using a NN are necessities. To demonstrate hand gesture recognition, we also specified the ability to distinguish two gestures as a requirement.

In most cases, an EIT system consists of surface electrodes, an impedance measurement system, and a reconstruction algorithm or, in our case, a gesture classification algorithm. This work focuses on the measurement system. There are different types of EIT measurement schemes, the two-pole measurement scheme and the four-pole measurement scheme. In the two-pole scheme, an alternating current is injected into one electrode and leaves the body at another electrode. The voltage measurement takes place between these electrodes. The measurement is repeated for a given pattern. In the four-pole scheme, an alternating current is applied to one electrode and leaves the body at another electrode, while the voltage measurement takes place between two different electrodes. This is also repeated for a given measurement pattern.

One advantage of the four-pole measurement scheme is that the contact impedances of the electrodes do not influence the measurement signal. A major disadvantage of the four-pole scheme is the additional hardware components required when optimizing the size. In the two-pole measurement scheme, only half of the multiplexers are needed. For this reason, we decided to implement the two-pole measurement scheme to minimize the space on the board.

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2 Related Work

There are few works combining EIT and hand gesture recognition. Four-pole measurement with eight to 32 electrodes has been performed [2], [6], [7]. This works required multiple printed circuit boards (PCB) or external hardware such as a Red Pitaya. The smallest PCB area of these systems is approximately 51 cm².

Two-pole measurements with 32 and with eight electrodes were also performed [1], [2], [8]. The smallest system of these two-pole measurement systems using 16 channels has a PCB area of 28.2 cm² [8]. None of the systems presented had the size of a smartwatch. Determination of accuracy is not evident in all cases, making comparison of results difficult. The results for gesture recognition vary between 76.7 % and 100 % within the cited papers [1], [2], [6], [7], [8].

3 Methods

In developing a small EIT system, each functional structure must be evaluated in terms of its size and loss of accuracy. Figure 1 shows the schematic overview of the wearable EIT system.

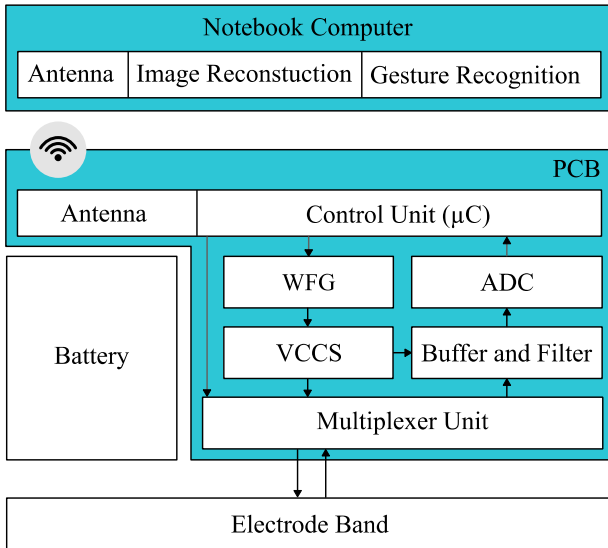


Figure 2: Schematic representation of the functional structures of the entire system. A Microcontroller (μC) controls the Waveform Generator (WFG), which generates a signal for the voltage controlled current source (VCCS)

3.1 Electrodes and Wristband

A wristband is developed, shown in Figure 3, consisting of 32 stainless steel (1.4404) electrodes. The cylindrical electrodes with a diameter of 4 mm and a height of 20 mm can be easily integrated into a flexible wristband. They are resistant to corrosion by perspiration.

3.2 Measurement Hardware

A signal generator based on the AD9837 generates a voltage with constant amplitude of up to 100 kHz. The measurement frequency can be varied. This signal is then the input to a voltage controlled current source. The current source is implemented as an improved Howland current source with buffer using small package rail-to-rail operational amplifiers of the type MAX44259 as shown in Figure 2.

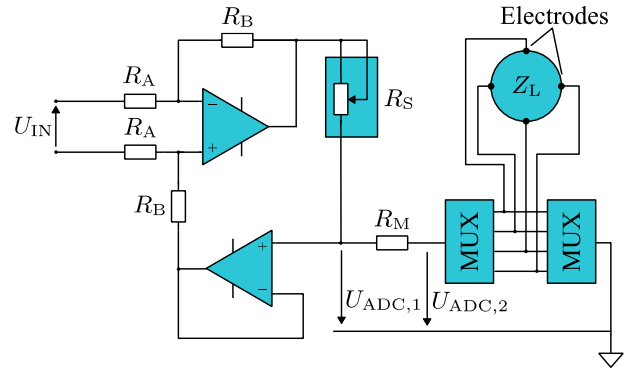


Figure 1: Basic circuit of the measurement system. The resistor R_S is implemented with a digital potentiometer to digitally adjust the current through the load impedance Z_L . R_M is used to measure the voltages to calculate the impedance. The MUX are selecting the electrode pairs.

A digital potentiometer is used to adjust the peak-to-peak value of the output current to achieve an optimal signal-to-noise ratio in combination with the load impedance. The potentiometer is shown in Figure 2. A current between 100 μA and 300 μA can be applied to obtain optimal voltages at the analog-to-digital converter (ADC).

The multiplexer unit consists of two two-way multiplexers with 16 to 2 channels (MAX14661). These multiplexers allow flexibility in electrode placement, leading to further designs with 3D imaging and more multiplexers in mind. The multiplexers connect one electrode to the current source and another electrode to ground, forming the two-pole measurement pair.

To determine phase and amplitude, a shunt resistor R_M is used to calculate the exact current through the body. Before the signals are filtered and sampled, a buffer prevents the signal from being affected by the measurement hardware. The

buffer is implemented using the same operational amplifier as in the improved Howland current source. An anti-aliasing low-pass filter removes noise. Then the signal is sampled with a dual-channel ADC. The AD4680 is used because it is capable to sample the signals simultaneously at ten times the signal frequency.

The entire system is controlled by an ESP32 with integrated antenna, as it is an easy-to-use IoT solution for wireless communication.

A battery supplies power to the system. The supply voltage is regulated to 3.3 V by a linear dropout regulator. The System is designed to only require one voltage level to minimize size.

3.3 Gesture Recognition

A fast Fourier transform is performed on the microcontroller to calculate the impedance at each electrode pair. After that, the results are sent to a notebook via Bluetooth. A user interface is being developed that provides a routine for acquiring large data sets of gestures that can then be used as training data for a neural network.

To verify the concept and justify the simplifications of the circuit, a dataset of 1200 gestures in total is recorded from the same individual. These gestures are split equally into open hand and fist. The entire series of measurements is recorded without interruption to ensure that the electrodes remain in the same position for each recorded gesture. The measurement frequency of 40 kHz and a peak-to-peak current of 100 μ A is used. The measurement duration is ten signal periods and starts ten signal periods after switching through the multiplexer. The NN is implemented in TensorFlow and has a basic structure of four dense layers and two dropout layers with twenty percent dropout after the first two layers. The impedance of each electrode pair is then the input data of the NN. The activation function is SIGMOID (Neurons: 992 to 64 to 32 to 8) except for the last layer where a RELU function (Neurons: 8 to 1) is used for classification. The NN is trained with 70 % of the data, while 20 % is used for validation. The last ten percent is used to test the trained NN independently of the training and validation data.

4 Results

The complete system is shown in Figure 3. The resulting system is a compact, battery-powered wearable that communicates wirelessly with a notebook computer.

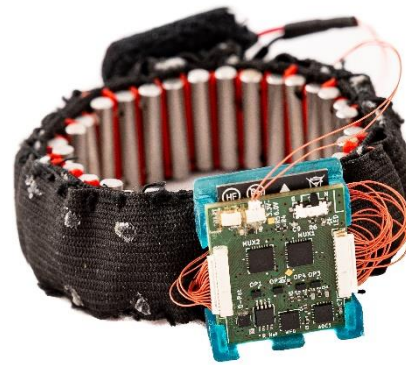


Figure 3: Wristband with electrodes and PCB containing entire the measurement hardware.

4.1 Hardware

Figure 4 shows a detailed view on the custom-made PCB with the size of 24.9 mm \times 22.45 mm. The whole measurement hardware is placed on a single PCB. Two small connectors are placed on both sides of the PCB connecting the 32 electrodes to the system.

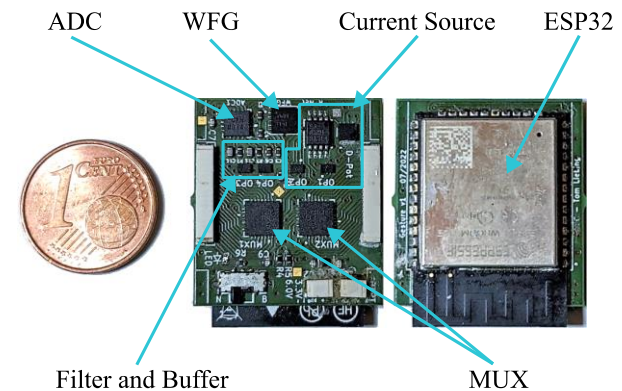


Figure 4: Left: a coin with 16 mm diameter reference Middle: top view on the PCB Right: back view with ESP32.

4.2 Gesture Recognition

The selected weights to perform the test data set on it had an accuracy of 94.4 % on predicting the training data and an accuracy of 81.32 % on predicting the validation data. The confusion matrix of the NN is shown in Table 1.

Table 1: Confusion matrix of the independent test dataset.

Prediction over Gesture	Fist	Open
Fist	46	17
Open	15	45

The corresponding accuracy in predicting the correct gesture of the independent test data is 78.33 %, and the precision is 76.56 %. To visualize the difference between the two gestures, a reconstruction of the mean values of all scans within a gesture is performed. The reconstructed images are shown in Figure 5. For the reconstruction of the images an absolute inverse Gauss-Newton solver of EIDORS is used [9].

The temporal resolution depends strongly on the number of samples in the measured sequence. It has been observed that the FFT is the step that takes the most time. Time can be saved with a different FFT implementation. It takes about ten seconds to perform a full measurement, including data transfer. In a second setup, the FFT was performed on a notebook computer. In this case, the entire measurement could be accelerated tenfold leading to a temporal resolution of around 1 second.

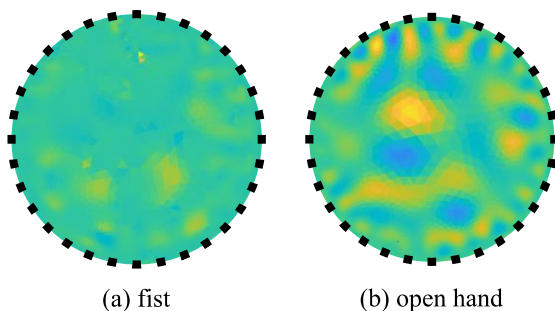


Figure 5: (a) shows the reconstructed image of the gesture fist and (b) shows reconstructed image of the gesture open hand. Both images are normalized to the maximum value of both images.

5 Discussion and Conclusion

An electrode wristband was first designed and built, which has good mechanical and electrical properties. The measurement setup was built and optimized to a minimal size of 24.9 mm × 22.5 mm and the PCB was integrated into the wristband. This PCB area size corresponds to about 11 % of the smallest four-pole systems and 20 % of the smallest two-pole systems. Even though the gesture recognition rates are lower than the recognition rates in previous publications, it was shown that the size of the measurement hardware can still be significantly reduced. Figure 5 shows that there are differences between the two gestures, even if they do not match the forearm anatomy.

Investigations of contact impedance have shown that there are major differences within the measurements. For this reason, we are aiming at four-pole measurement in the next

version. In combination with a smaller microcontroller, with a better ADC, we expect no significant increase in the size of the system, while at the same time significantly improving the gesture detection rates. In addition, the measurements will be more precise and the reconstructed images will be more accurate in terms of human anatomy. We also aim for a bipolar excitation current to minimize electrode polarization effects that could affect the measurement results.

Optimized FFT and digital signal processing will be key to achieving the goal of real-time temporal resolution with multiple gestures per second.

Author Statement

Research funding: The authors state no funding involved. Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: No ethical approval was necessary for this research.

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