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Design of a sleep apnoea detection system for a home environment

Maksym Gaiduk*[a], Lucas Weber*[a], Ángel Serrano Alarcón*[b], Ralf Seepold[a,c], Natividad Martínez Madrid[b,c], Simone Orcioni[d], Massimo Conti[d]

[a]*HTWG Konstanz, Alfred-Wachtel-Str. 8, 78462 Konstanz, Germany*
[b]*Reutlingen University, Alteburgstr. 150, 72762 Reutlingen, Germany*
[c]*I.M. Sechenov First Moscow State Medical University, 2-4, Bolshaya Pirogovskaya st., 119435 Moscow, Russian Federation*
[d]*Università Politecnica delle Marche, via Brecce Bianche, 60131 Ancona, Italy*

Abstract

Normal breathing during sleep is essential for people's health and well-being. Therefore, it is crucial to diagnose apnoea events at an early stage and apply appropriate therapy. Detection of sleep apnoea is a central goal of the system design described in this article. To develop a correctly functioning system, it is first necessary to define the requirements outlined in this manuscript clearly. Furthermore, the selection of appropriate technology for the measurement of respiration is of great importance. Therefore, after performing initial literature research, we have analysed in detail three different methods and made a selection of a proper one according to determined requirements. After considering all the advantages and disadvantages of the three approaches, we decided to use the impedance measurement-based one. As a next step, an initial conceptual design of the algorithm for detecting apnoea events was created. As a result, we developed an activity diagram on which the main system components and data flows are visually represented.

Keywords: Sleep apnoea; impedance measurement; system design.

* Corresponding authors. These authors contributed equally. Tel.: +49-7531-206-703.
E-mail address: [maksym.gaiduk, lucas.weber]@htwg-konstanz.de, angel.serrano_alarcon@reutlingen-university.de

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1. Introduction

Obstructive sleep apnoea (OSA) is one of the most common sleep disorders, with an estimated 936 million people aged 30-69 years (men and women) affected worldwide using an AHI criterion of five or more events per hour and the American Association of Sleep Medicine (AASM) criteria [1]. Central sleep apnoea (CSA) has a lower prevalence of 0.9% but can also lead to health complications [2]. Objective findings from a sleep study are necessary for the diagnosis of sleep apnoea [3]. According to [4], there are three main types of sleep studies used for this purpose: polysomnography (PSG), respiratory polygraphy, and nocturnal oximetry. All these three approaches are obtrusive, i.e., direct contact of the sensors used with the subject's body. Besides, PSG, which provides the most specific results, is a resource-intensive approach requiring a sleep laboratory and a trained technician to set up and monitor the study [5]. In PSG and sleep polygraphy, a significant number of sensors attached to the body are used [6]. Using a less resource-intensive method, which could provide reliable results for sleep apnoea detection by non-intrusively recording the necessary signals, would be an essential step towards increasing the number of diagnosed apnoea cases underdiagnosed today [7, 8].

Recent research has confirmed that the identification of sleep apnoea events can be performed in a non-intrusive manner. For example, this can be done by analysing the respiratory signal from sensors under the mattress/bed sheet [9, 10, 11] or using algorithms to process the acoustic signal [12, 13]. Other approaches, e.g., oximetry- or electrocardiogram-based, can be applied, as presented in [14]. The best-achieved accuracy for research devices using a non-obtrusive approach reported in [14] is 86%. According to [14], the respiratory analysis provides the most accurate results in detecting sleep apnoea.

Electrocardiograms may be analysed for the detection of OSA as described in [15]. The achieved accuracy of apnoea events recognition may reach up to 98% on a minute-by-minute basis. Another three ECG-derived respiration methods for sleep apnoea detection are presented and compared in [16]. The achieved classification accuracy for detecting one-minute epochs with sleep apnoea events was 81%, 79%, and 84%.

Detecting sleep apnoea syndrome without applying objective measurement but only using screening questionnaires and the Epworth sleepiness scale was evaluated [17]. The results have indicated that whereas a sensitivity of these approaches may be significant (up to 86%), specificity is typically low (21%-51%).

As it can be seen, the research on sleep apnoea detection topic is a relevant one. However, most available solutions introduce significant inconvenience into a typical night flow due to the need to use many sensors to be attached to the human body. The main objective of this work is to propose a design to detect apnoea in the home environment. The system should be easy and convenient to use and have as little impact as possible on the typical sleep routine.

2. Methods

2.1. System structure

One of the essential points for the system design is determining its components. To achieve this, it is first necessary to define the system needs clearly. After conducting the literature review and several discussions with sleep physicians, the following list of requirements was compiled:

- The system should record and visualize the respiration flow, with visual recognition of the differences in amplitude over the time of inhalation and exhalation.
- The system shall recognize apnoea and hypopnoea events with the start and end times. The total number of events shall be calculated for each recording.
- As users of the system, medical doctors should label the detected apnoea events on the respiratory graph. It is also essential to provide a possibility to correct the detected events (e.g., wrongly detected, not detected, duration is wrong).
- A desirable requirement would be to detect the person's position and the recognition of sleep/wake states.

The next step is to determine the data flows within the system. Since it is known from the requirements that the respiratory signal can first be recorded, then processed, and finally visualized, it can be concluded that there can be

several data transfers that should be precisely defined. Furthermore, it is essential to ensure that all data transfers are secure from external access because sensitive medical data is involved. For this purpose, the first step is to anonymize the data and to transmit it exclusively via a secure communication protocol. Authentication of the senders and recipients of data packets could also contribute to the security of communication.

The results of the initial system design and the planned data flows are presented below in the section "Results".

2.2. Selection of the measurement approach

As outlined in the "Introduction" section, several sensor types can be used to measure the respiratory signal. After a pre-selection based on literature research, three were analysed in detail to find an optimal solution for the designed system.

2.2.1. Radar-based approach

Radar is a remote sensing technique based on electrical wave propagation and reflection on different surfaces and has been employed for various distant measurements throughout different fields of science. Its application for measuring vital bio signs has been initially demonstrated in the late 20th century [18, 19]. Since then, radar has been deployed in various use cases to measure vital signs such as breathing and heart rate [19]. Most recently, with the development of MIMO-Radars (Multiple Input Multiple Output radars) that can provide a two-dimensional radar measurement, the applications have become more adaptable to complex situations with persons not directly in front of the sensor or with multiple persons in the frame [19, 20]. In the scope of apnoea detection, the breathing- and heartrate-signal are two vital signals of interest that can be measured using a radar sensor [21]. The radar sensor measures the distance and velocity of surfaces that have significant impedance differences compared to air by measuring runtime and frequency shift of an electrical field sent out in several impulses and reflected by the surface. In breathing and heart-rate detection, this surface is the thorax of a person (see Figure 1).

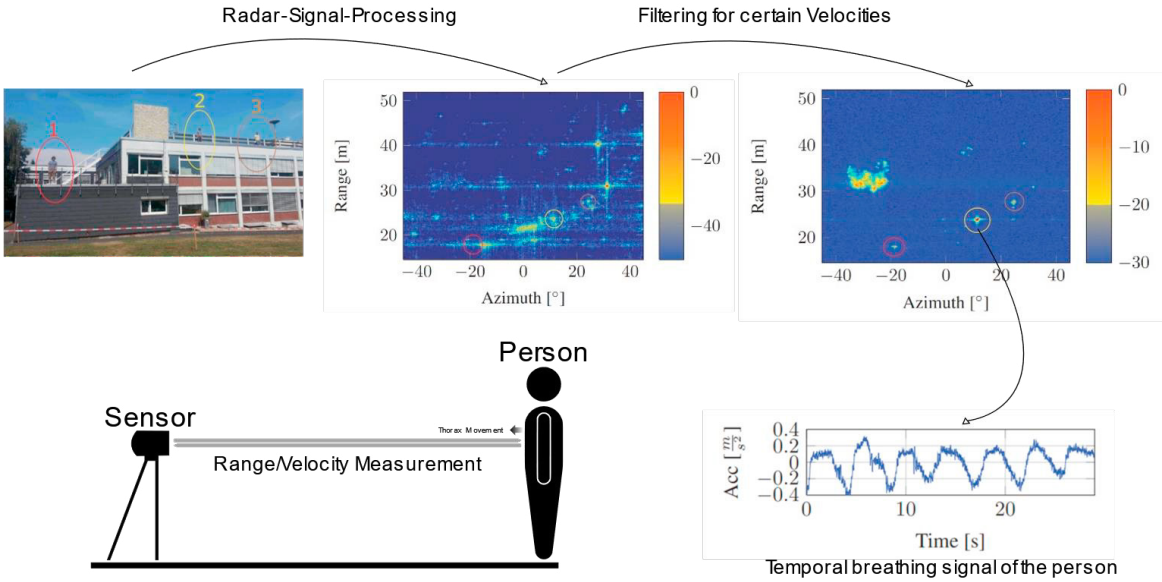

Fig. 1. Visualization of the radar measurement for breathing and example of measurement from [20]. Velocity is coded in colors.

Measurement of this information over time can then be used to extract periodic movements of the object (i.e., breathing). The MIMO-Radar essentially uses multiple radar sensors that are significantly offset. The runtime difference for multiple antennas is used to compute a two-dimensional distance map that can be filtered to extract the position and signals of persons (as in Figure 1).

In our application case, this sensor has several advantages and disadvantages. The main advantage is the capability of measuring the remote. With the proper calibration, the measurement can be done through several layers of clothing

and bedsheets, which is a unique advantage for remote sensors. This makes the sensor unobtrusive. In addition to that, the sensor is capable of measuring multiple persons at once. The main disadvantages are careful calibration and the shift of amplitude due to the orientation of the sensor with respect to the person. Unfortunately, the sensor can only measure the vectorial part of the movement or speed parallel to the measuring direction. The part orthogonal to the direction of measurement is therefore not measurable. As a result, the absolute value of the measurement is distorted when the person moves and is no longer directly comparable with previous values. In the extreme case of an orthogonal movement of the chest to the sensor, no more breathing is measured.

2.2.2. Pressure sensors

While lying on the bed, movement or breathing produces some pressure on the surface below the chest. The changes in a pressure level can be measured by sensors placed under the body. Not only pressure but as well the differences in the acceleration of the sensor caused directly by movement can be measured [22]. The recorded signal contains, in general, a movement of a person and part of the environment. The movement of a person includes the following main components: movement caused by skeletal muscle [23], breathing movement [24], heartbeat movement [25]. Several types of sensors may be used to record these signals: accelerometer [26], force-sensitive resistors [27], load cells [28], piezoelectric [29]. A good review of systems for monitoring vital signals using sensors placed in a bed is presented in [30].

Respiration monitoring is of interest for further detection of sleep apnoea events, and it could be performed with the sensors placed under a mattress / under a bedsheet. This kind of measurement may also be applied to detect sleep/wake states [31]. In general, the structure of the proposed system may be visualized as presented in Figure 2.

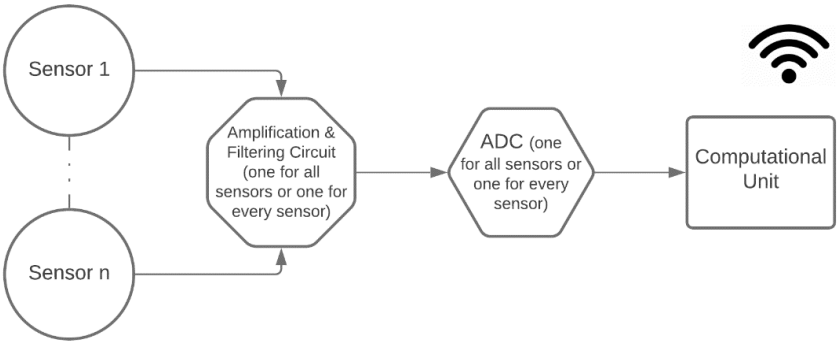

Fig. 2. System structure with several "in-bed" sensors.

There are several advantages of using this art of measurement:

- The proposed solution may partially substitute the respiratory inductive plethysmography (RIP sum) signal known from traditional polygraphy/PSG.
- Respiration and movement signals are measured contactless.
- Potentially Sleep/Wake states may be detected by analysing the movement part of the signal.

However, some difficulties should be overcome in case of implementation:

- Respiratory flow cannot be measured with this kind of system.
- As a measured signal includes a movement component (which has a higher amplitude than a respiratory signal), respiration cannot be measured perfectly and will have some inaccuracy.
- The position of a human body may affect the amplitude of measured signal flow, and consequently, the quality of recognition may decrease. Furthermore, this circumstance may cause false-positive detections of sleep apnoea.

In order to ensure a sufficient level of accuracy and convenience, various points should be considered:

- Sensors may be placed under a bed topper. Ideally, sensors are integrated in some kind of sheet for easy installation.

- A system must be expandable, as the number of sensors may be first specified after performed tests and can differ for diverse installations. At least eight sensors will be required.
- The output signal must have a clear breathing waveform for the further processing and detection of apnoea events. For that, hardware filtering and amplifying the signal are essential.
- Synchronization of signals from different sensors is crucial for correct system functioning.

2.2.3. Impedance measurement

Pulmonary ventilation or breathing is considered to be one of the main physiological signals when it comes to detecting sleep disorders. In particular, breathing is significantly essential in the pathophysiology and clinical monitoring of OSA [32]. Consequently, respiration measurement is commonly included by the AASM guidelines for the development of portable devices to detect sleep disorders [14,33].

Nowadays, there are several methods for monitoring the patient's breathing or respiration; for example, methods based on respiratory sounds or respiratory airflow through facemasks or cannulas are often used. However, such methods are unpleasant and intrusive for patients [34]. For this reason, a large variety of different approaches have been developed to be as non-invasive as possible for a Home Sleep Apnoea Test (HSAT) [35]. Along with intrusiveness, portability and accuracy must also be considered whether portable devices can be used to detect and monitor sleep apnoea events. Methods based on volume changes and body motion fit these requirements and have become widely used in pneumology [36]. One such method can be implemented using electromagnetic sensors to measure pulmonary function parameters such as the tidal volume or the respiratory rate [37]. Specifically, this method is represented by a set of techniques that are divided into electrical impedance pneumography (EIP) or also known as transthoracic impedance pneumography (TIP), respiratory inductive plethysmography (RIP), and thoracic impedance tomography (TIT) or also known as electrical impedance tomography (EIT).

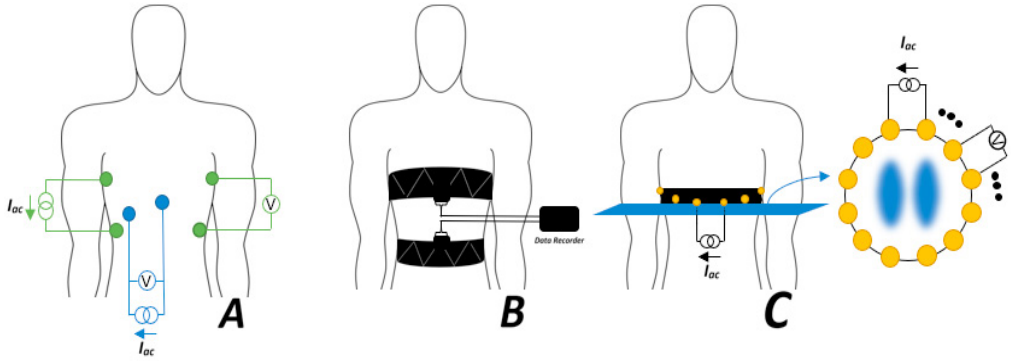

Fig. 3. Different configurations to measure pulmonary function parameters by using electromagnetic sensors. (A) EIP (B) RIP (C) TIT.

These three techniques present differences in terms of configuration (see Figure 3) and operation. EIP measures the electrical impedance variation caused by the respiration cycle between two electrodes (bipolar configuration) or four electrodes (tetrapolar configuration) arranged on the chest, depending on whether the electrodes are used to sense voltage and conduct current at the same time or not. RIP uses two copper wires; one transducer is placed around the rib cage around the abdomen and the other on the chest. Throughout the respiration cycle, volumetric changes appear, and that causes the two wires to self-induce. On the contrary, EIT is an imaging tool and ionizing radiation-free monitoring system that uses a belt with electrodes placed around the chest to measure changes in the electrical impedance to obtain images of the pulmonary ventilation. Its functioning consists of applying a small alternate electrical current through two of the electrodes on the belt, measuring the resulting voltage on the remaining ones. [32, 36, 37]

This set of techniques share some similarities. However, as explained above, there are differences regarding their application, use, and results. Table 1 contains some relevant characteristics of the impedance techniques and includes some advantages and disadvantages regarding their use in HSAT. Although EIP is susceptible to errors due to changes in motion, it seems to meet all the requirements for use in outpatient settings. EIP is cost-effective, non-invasive, easy

to use without the need for clinicians, simple set-up, no need for extensive computational resources, and the possibility of using different configurations to assess different lung regions.

Table 1. Main characteristics of techniques by using electromagnetic sensors.

Types of Impedance	Physiological Measurement	Configuration	Advantages	Disadvantages
EIP or TIP	Respiration Rate Tidal Volume Others	Bipolar or tetrapolar (electrodes placed on the chest)	Cost-effective Easy-to-use Regional lung assessment	Prone to errors due to changes in motion and posture
RIP	Respiration Rate Tidal Volume Others	Two copper wires around the upper body	Easy-to-use	Tissue motion artifacts
TIT or EIT	Respiration Rate Tidal Volume Image of lung ventilation	Thoracic belt with electrodes	High image resolution	Complex image reconstruction Large number of electrodes

2.3. Apnoea detection method

Automatic sleep apnoea detection for various classes using different computational algorithms is a recent and essential topic in the scientific field of biomedical informatics. In a recent review by Mendonca et al. [14] and from Padovano et al. [38] one can see an uprising of published articles from 2003 to 2017. Their review presents various methods with a variety of different input signals to detect multiple classes of apnoea. From the review, it becomes clear that most papers in this period use handcrafted features and classical machine learning algorithms like random forests, support vector machines, and furthermore. Since 2017 the researchers tend to use more convolutional neural networks to use raw signals [39, 40, 41]. Those networks range up to very deep with millions of trainable parameters that require millions of examples to be trained and archive high scores. Although it is unpublished work, Nassi et al. [41] have a comparative overview about the best performing algorithms until 2020, where most of them employ some neural network. Almost all algorithms published in the referenced literature make their apnoea prediction in discrete timesteps by either calculating numerical features over a fixed number of samples or feeding the networks with discrete amounts of samples (fixed signal slices). This results in a fixed window classification. Cutting the signal into overlapping windows and doing multiple classifications allows them (in extreme cases) to do sample-wise classification. This kind of continuous event detection creates vast amounts of overhead computation time.

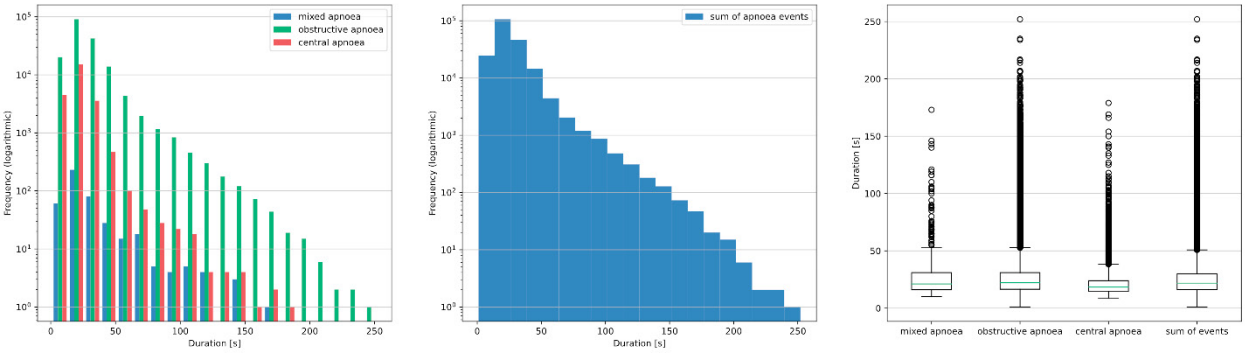

Fig. 4. Evaluation of the annotated apnoea events in the SHHS database. The left and center graphs show the frequency of events over their duration in seconds. Please note that the frequency axis for both is logarithmic. The right graph shows the boxplot and, therefore, median duration and quartiles for the annotated events.

Unfortunately, our analysis of the SHHS database [42, 43] shows that apnoea events are of different lengths, providing additional information to the physician (See Figure 4). In order to keep the computational effort low, we propose to use fully convolutional neural networks. Those networks originate from the field of computer vision and

image segmentation and are not fixed to a particular signal length as they output the same or slightly downsampled versions of the input but with class probabilities [44, 45]. We plan to employ these networks to do a continuous assessment of apnoea events. In the supplementary material of [40], the convolutional neural networks do not perform significantly worse than the networks with additional recurrent parts. Therefore, we propose to use fully convolutional neural networks like U-Net [45] to keep the computational effort low for continuous classification of apnoea events.

3. Results

3.1. System structure

After analysing all system requirements and considering all the relevant points for the system implementation, a system design was developed. The activity diagram of the designed system is presented in Figure 5. As it can be seen, the complete system can be split into three different parts or modules: hardware, support portal, and machine learning (ML) server. The system's functioning as a whole can be understood by following the data flow through these modules.

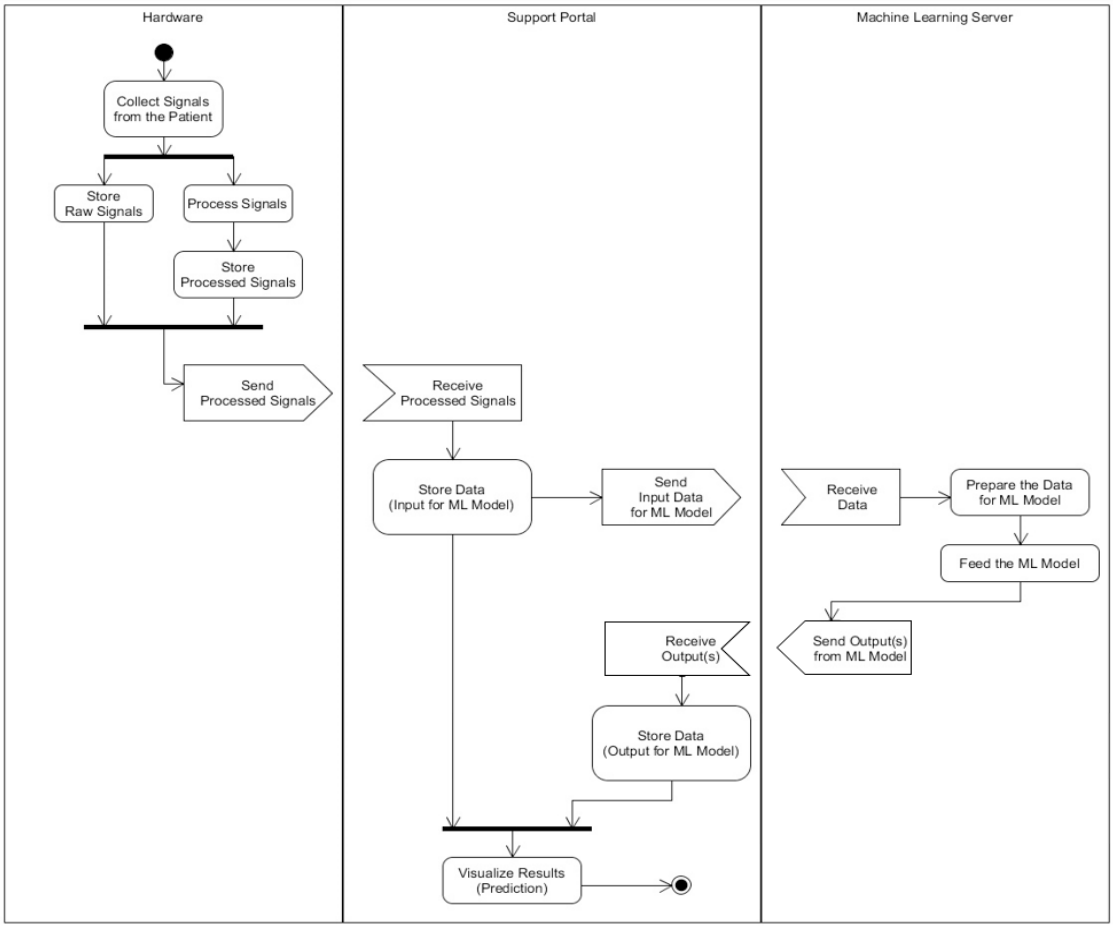

Fig. 5. Activity diagram of the system as a whole.

Firstly, the process starts on the hardware module with the collection of the physiological signals from the patient. These signals are the most critical type of data used in the entire system and are stored in a raw format and a processed format (after filtering and amplifying the initial signal) on the hardware module. Secondly, once the signals are processed and stored on the hardware part, the data is transmitted to the support portal. Then, the signals are stored in a database. After storing the data on the support portal, the data transmission to the ML server occurs. Thirdly, on the

ML server, further data preparation is performed to put them in a format adequate for the following analysis by the ML algorithm. By doing so, the risk of any inconvenience during the signal analysing period caused by possible data incompatibility is being reduced.

Moreover, data preparation has the aim of enhancing the quality of further prediction of sleep apnoea events. After performing the ML server operation of sleep apnoea detection, the ML model generates an output that includes the identified segments with the apnoea events. This output is transmitted back to the support portal, where it is being stored. The prediction can then be retrieved by the user, in this case, the doctor, to visualize the results of the sleep apnoea detection process. The final result is the calculated apnoea-hypopnoea index, which indicates the severity of sleep apnoea by the patient if it was detected. Moreover, the doctor gets a visualization of additional information extracted from the collected data, such as the respiratory signal.

3.2. Measurement approach

As explained in section 2.2.3, EIP measures variations in transthoracic electrical impedance. This fact is possible due to the impedance generated on the chest. This impedance comprises two components, a relatively constant impedance of 500 Ω (known as baseline impedance) and a varying impedance (known as respiratory impedance) [36, 46, 47]. Two principal factors that occur during breathing cause such variations. Firstly, there is a volume increase in the volume of gas during inhalation, which is relative to the volume of fluid in the lungs, which causes a decrease in conductivity. Secondly, there is an increment in conductance paths due to expansion during inhalation (see Figure 6) [46]. Taking these two factors into account, an increase in electrical impedance takes place throughout the respiratory cycle.

To record the electrical impedance signal, it is necessary to inject a high-frequency AC signal into the human body. This signal acts as a carrier modulated by the amplitude of the low-frequency signal originating as a result of respiration. Subsequently, this modulated signal must be demodulated to extract the low-frequency respiratory signal [47].

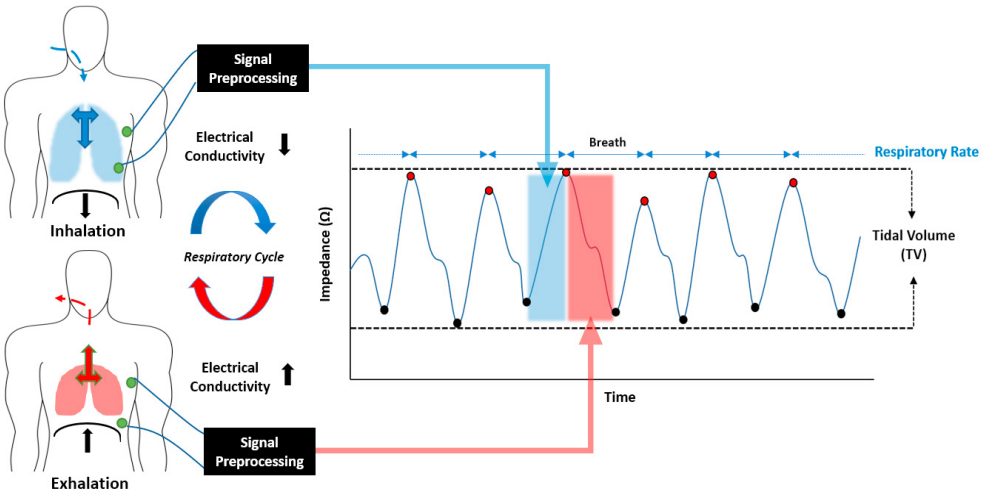

Fig. 6. Representation of the breathing signal by applying EIP.

As demonstrated in previous studies [48], impedance signal preprocessing is essential to achieve motion artifact detection and removal, cardiac content suppression, and calibration for respiratory parameter estimation once the signal has been captured. After signal preprocessing, output like the one shown in Figure 6 should be accomplished. It allows analysis of respiration for sleep apnoea detection.

4. Conclusion and outlook

The conducted thorough analysis of the hardware and software solutions and the system's structure enabled creating a detailed design of a 'sleep apnoea event detection system'. In addition to the configuration of the components and

their requirements, a data exchange model was developed. A set of requirements to be developed was compiled, which enabled a comparative analysis of the alternative solutions.

However, despite the scientific approach, the analysis performed has some limitations. First, only three methods for recording breathing were investigated in detail; other approaches were excluded only based on a preliminary literature review. Therefore, it cannot be completely ruled out that other suitable techniques would enable respiratory monitoring and, consequently, accurate detection of sleep apnoea according to the requirements created. Another limitation is that only a few practical tests of the system components have been carried out so far, which means that potential problems in practical use cannot be excluded entirely.

The next planned step is to conduct initial individual tests with the selected components with subsequent evaluation. After that is done, the development of the prototype for system integration testing is planned. Finally, after completing the preliminary stages, a medical evaluation of the developed system will be conducted to verify its accuracy and usability and security, and stability and provide a market-ready solution.

Acknowledgments

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