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Conception of a home-based sleep apnoea identification and monitoring system

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Abstract

Healthy sleep is one of the prerequisites for a good human body and brain condition, including general well-being. Unfortunately, there are several sleep disorders that can negatively affect this. One of the most common is sleep apnoea, in which breathing is impaired. Studies have shown that this disorder often remains undiagnosed. To avoid this, developing a system that can be widely used in a home environment to detect apnoea and monitor the changes once therapy has been initiated is essential. The conceptualisation of such a system is the main aim of this research. After a thorough analysis of the available literature and state of the art in this area of knowledge, a concept of the system was created, which includes the following main components: data acquisition (including two parts), storage of the data, apnoea detection algorithm, user and device management, data visualisation. The modules are interchangeable, and interfaces have been defined for data transfer, most of which operate using the MQTT protocol. System diagrams and detailed component descriptions, including signal requirements and visualisation mockups, have also been developed. The system's design includes the necessary concepts for the implementation and can be realised in a prototype in the next phase.

Keywords: sleep efficiency; sleep study; subjective sleep assessment

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1. Introduction

The enormous importance of sleep for human health, both physiological and mental, and for general well-being has been scientifically proven in numerous studies [1, 2]. It is, therefore, essential to maintain a healthy sleep, and it is crucial to identify sleep disorders in time and initiate the appropriate treatment to achieve this. The method of detecting sleep disorders depends on the type of disorder and should be chosen accordingly.

One of the most frequently occurring sleep disorders is sleep apnoea, which, according to [3], belongs to the "sleep-related breathing disorders" category. If we consider obstructive sleep apnoea (OSA), which together with central (CSA) and mixed apnoea forms its subcategories, it is currently estimated to affect approximately 936 million people worldwide between the ages of 30 and 69, using an Apnoea-Hypopnoea Index (AHI) criterion of five or more events per hour based on the American Association of Sleep Medicine (AASM) criteria [4]. Given this huge number and the fact that many people currently remain undiagnosed, it is clear that detecting sleep apnoea is of great significance.

Objective measurement in a sleep study is a standard procedure for diagnosing sleep apnoea [5]. Three main measurement types are used for this purpose, as described in [6]: Polysomnography (PSG), respiratory polygraphy and nocturnal oximetry. All three of these methods use sensors that are in direct contact with the patient's body. PSG provides the most accurate results, but it is a resource-intensive approach performed in the sleep laboratory and requires a trained technician to set up and monitor the study [7]. In PSG and sleep polygraphy, multiple sensors are attached to the human body to record the signals, which reduces comfort for the subject [8, 9]. Using a less resource-intensive method that could provide reliable results in detecting sleep apnoea by a less obtrusive recording of the required signals would be a significant step towards increasing the number of detected cases of apnoea that remain undiagnosed today [10].

The importance of the subject is also reflected in the research that has been carried out in this area. Different methods can be used for both signal recording and processing. In [11], for example, tracheal sounds are used to diagnose sleep apnoea to reduce the number of sensors required. In [12], ECG signals are analysed, although they have to be recorded with electrodes. A deep learning framework based on convolutional neural networks is used for processing, analysing the signal in 1-minute intervals and indicating the presence or absence of apnoea events for each of these intervals. Studies have also been conducted to assess the validation of apnoea diagnosis using questionnaires [13]. The combined use of the STOP-Bang with different cut-off scores and the excessive daytime sleepiness (ESS) questionnaires were found to provide a flexible balance between sensitivity and specificity. However, the results do not allow a recommendation to use questionnaires alone to diagnose sleep apnoea. There have also been experiments in the literature with the use of sensors that can be placed under the mattress with subsequent rule-based processing of the signals to detect sleep apnoea [14]. This method leads to a noticeable increase in user comfort but, at the same time, presents challenges due to a significantly reduced set of available signals. In [15], an accelerometer placed at the level of the diaphragm was used for signal acquisition. The system is supposed to detect apnoea events in real-time and to alert the user with a vibration on the arm.

Considering the relevance of sleep apnoea detection and based on the previous work [16] establishing the basics for such a system, the aim of the research presented in this article is to provide a concept for a home-based sleep apnoea detection and monitoring system to enable the subsequent elaboration of such a system.

2. Methods

Following the defined research objective, the research was carried out to select appropriate methods for subsequent implementation. In this section, a detailed description of the elements that are relevant to the evaluation procedure is given. The 'Methods' chapter has been divided into several subsections according to the aspects covered and to improve readability.

2.1. Literature research

Generally, a literature review is a process of collecting and analysing information from written sources such as books, articles and journals [17]. It is an essential part of research projects, including the design of a sleep apnoea detection system. Therefore, it was decided to use a literature review as the primary tool to provide a comprehensive overview of the current state of knowledge on the topic, thereby enabling comprehensive scientifically driven planning.

In the context of creating a concept for a sleep apnoea detection system, a literature review was chosen partly because it will help to identify the most relevant and up-to-date information about sleep apnoea, including its causes, symptoms and diagnosis. This information can then be used in the system's design to ensure that it correctly identifies sleep apnoea in patients.

In addition, the literature review can identify existing sleep apnoea detection systems and their strengths and limitations. This information can be used to develop new, more effective and innovative systems that build on existing systems' strengths and overcome their weaknesses.

Overall, the literature review is critical to the design of a sleep apnoea detection system as it helps to ensure that the system is based on the latest knowledge and research in the field.

Another essential tool for gathering information was to contact professionals working with sleep apnoea to obtain relevant information and to consider the existing knowledge in this field. This was done with the kind assistance of experts from the Charité – Berlin University of Medicine.

Overall, the analysis of the available literature on sleep apnoea detection systems and the incorporation of expert knowledge facilitated the development of a concept for a sleep apnoea detection and monitoring system.

2.2. Apnoea identification approaches

There are different possibilities for detecting sleep apnoea using artificial intelligence algorithms. First, deciding on the methodology to train the models and the subsequent classification of apnoea events is necessary. It is crucial to determine, first of all, whether to work with the complete time series of the patients (patient-based) or to divide the signal into windows of a specific duration (window-based). These two methodologies have advantages and disadvantages depending on which approach is chosen. In window-based, events can be detected within a window of a fixed duration as described in [18] and subsequently calculate the AHI through the number of windows detected as apnoea between the Total Recording Time (TRT). However, here we find one of the main disadvantages of using this approach. It is not possible to detect the precise duration of the apnoea event. An overestimation or underestimation of the number of apnoea events may occur since not all events are correctly counted because TRT is used instead of Total Sleep Time (TST) to calculate AHI.

On the other hand, in the so-called patient-based approach, where the entire signal is used, artificial intelligence models can calculate apnoea events on a second-by-second basis. This allows one to know the actual duration of the apnoea events [19]. However, it has the disadvantage that the AHI calculation is more complicated, as it would not be sufficient to count the number of windows predicted as apnoea events by the model as in window-based. Instead, it would be necessary to calculate how many apnoea events have been correctly classified, regardless of their duration. This entails further post-processing after the classification of the events by the models.

Another factor to consider is the type of classification to be developed during the training and evaluation of the models. That is, choosing to classify apnoea events (where apnoea and hypopnoea are included) and non-apnoea events. This is known as binary classification. On the other hand, there is the option of multi-class classification. In this case, it is intended to classify several events, such as apnoea, hypopnoea and non-apnoeic events. Different machine learning or deep learning models are chosen based on the selected methodology and the type of classification to be carried out. Currently, most of the models used are deep learning models, as numerous scientific papers in the literature show how deep learning models outperform machine learning models in detecting apnoea events [20]. In addition, using deep learning models largely avoids the feature engineering process, which is time-consuming and requires experts in the field of application. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are the most commonly used models. Some more complex models are modifications of the previous architectures, such as segmentation models like U-NETs that are made up of variations of CNNs [21].

Despite all of the above, when it comes to models for classification tasks intended to be used in a real clinical environment, other factors must be considered apart from the algorithm's performance. In particular, the explainability of the model. Model explainability plays an essential role in using artificial intelligence algorithms in a real clinical environment and should be considered in the development of models [22]. Therefore a balance should be sought between the pure performance of the models in apnoea event classification tasks, as well as providing a good explanation of the decision made by the models to classify an event as apnoea or non-apnoeic event. The goal is to avoid the so-called black-box problem.

3. Results

The following subsections provide the designed general structure of the system, use case visualisation and descriptions for each module of the system in detail. This will allow both a global view of the system and precise detail at the level of the individual components.

3.1. System overview

Based on an analysis of state of the art and current developments in the field of sleep apnoea detection, and taking into account the need for an accurate but at the same time comfortable measurement of the relevant data for the user, a concept of the system was developed. Figure 1 depicts the general structure of the proposed system with the main modules and directions of data transfer.

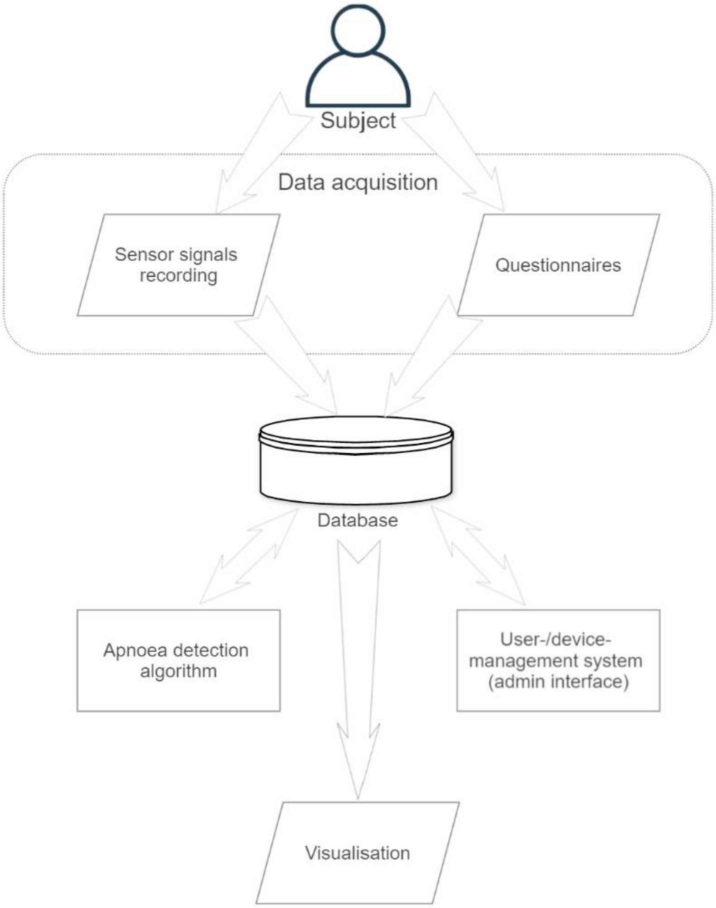

Fig. 1. General structure of system modules

It can be seen that the system consists of five main components, whereby “Data Acquisition” is divided into two sub-components – “Sensor Signal Recording” and “Questionnaires”, as the acquisition of data is performed by two methods. The other main modules – “Database”, “Apnoea Detection Algorithm”, “User/Device Management System”, and “Visualisation” - are described in detail in the following subsections.

One can also notice that the database is a central point for data storage and plays a vital role in communication to ensure the security and consistency of the data, being the only connection point to other modules. The design of the communication between the elements is described in more detail in the sub-section "System Communication".

3.2. Use cases

A UML use case diagram was created to provide an overview of the system's functionality [23]. This allows a graphical representation of use cases, including their relationships to the environment and other use cases. It describes at a high level of abstraction what functions and services a system provides to a user. Figure 2 shows such a diagram with two users, a patient/subject and a doctor.

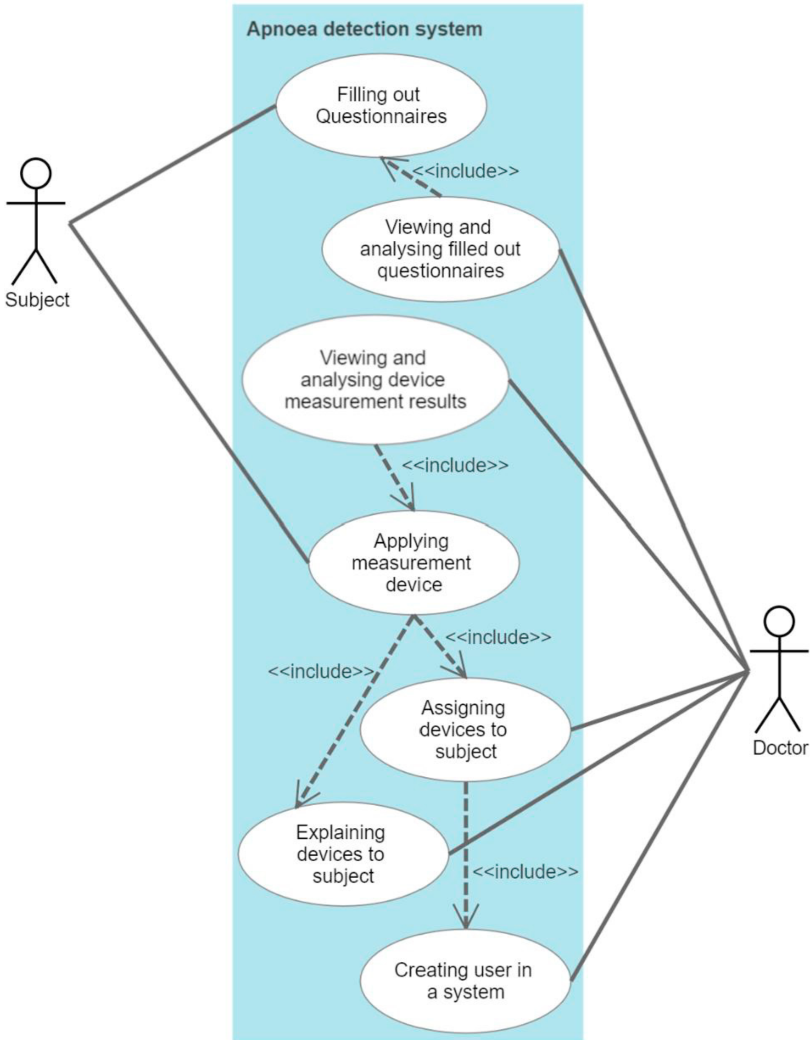

Fig. 2. Use Case diagram of the projected system

The system's main functions from the point of view of two user types are shown in Figure 2, including the relationships between them and the assignment to users. In general, it can be seen that the "Doctor" type of user has significantly more use cases, which is due to the fact that the system is primarily designed for the active use by "Doctor" (analysis and monitoring of the data) and "Subject/Patient" has a more passive role.

3.3. Data acquisition

Basically, the system should acquire two types of data:

- objective measurement using appropriate equipment
- the subjective measurement obtained by filling in the questionnaires.

We will consider each type separately, starting with objective measurement. After analysing current developments and considering the need for accurate and comfortable measurement for the user, it was decided to use electrical impedance pneumography (EIP) as described in [16]. This method has the advantages of being cost-effective, not complicated to use and providing accurate measurement results. The measurement result is a time series of amplitudes corresponding to the respiratory effort. In order to be integrated into the overall system, the system to be worn on the body should be equipped with a module for wireless transmission of the signal. In addition to the respiratory signal, heart rate and blood oxygen saturation should be measured to accurately detect sleep apnoea events, as the literature review has shown. For example, photoplethysmography (PPG) can be used for this purpose [24]. A PPG sensor should be placed on a finger, and then an additional module for wireless data transmission can be placed on the wrist and connected to the sensor with a short cable. To collect the recorded respiratory, pulse and SpO2 data and prepare them for transmission to the database, a central element is needed to receive the sensor signals wirelessly via the included transmission modules, process them, connect to the database and send the signals. PPG and EIP sensors, as well as the central unit, compose a device set representing a hardware part of the system for measurement. Figure 3 depicts one device set, including the communication modalities.

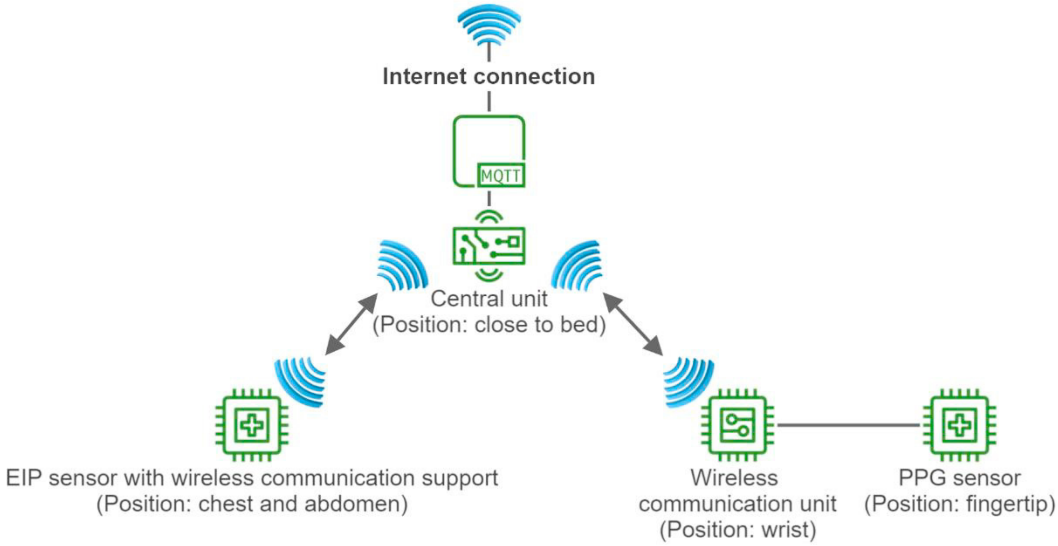

Fig. 3. Diagram of signal acquisition module with communication modalities

Filling in the questionnaires for the subjective measurement should be done online via a software platform available to the users through a user management system. The platform will include general questionnaires (gender, weight, height, etc.) as well as specific questionnaires relevant to sleep apnoea (anamnesis, STOP-BANG, Epworth Sleepiness Scale, etc.) to provide a comprehensive analysis. This module is coupled to the database to allow storage of the questionnaires for subsequent analysis and visualisation.

3.4. Database

To ensure centralised and secure data storage, the system should use a database shared by all the data to be stored. A list of the data to be stored is first drawn up to create the database structure.

After analysing the technical and medical requirements, the necessary signals, and the data to be visualised, the following list of data types to be stored was drawn up:

- Doctors list
- Patients list with general patient information
- Physiological signals (respiratory signal, heart rate, blood oxygen saturation)
- Questionnaires (with all questionnaires including the results of filling them out)
- Apnoea events (start and end points of all apnoea events)
- Device information

A separate table is created and then linked together for each of the above data types. The first step is to assign the patients from the patient list to the doctors, although there can be far too many relationships, as several doctors can monitor one patient, and one doctor can be responsible for several patients. Then all the other tables are assigned to the patients from the patient list with a one-to-many relationship, as several recordings for each patient are possible. Therefore several sets of every type of data can be assigned to each patient. To synchronise different data recordings between the tables, a unique ID of every recording is to be stored in every row of each table.

To facilitate data communication, the database should include an implementation of the back-end functionality with support for communication interfaces, as described later in the "System Communication" sub-section.

3.5. Apnoea detection algorithm

After analysing the requirements for the system and reviewing current developments, it was decided to pursue two parallel approaches to apnea event detection in the system concept. This would allow a comprehensive analysis of the signals and ensure accurate evaluation and calculation of the AHI and the length of the apneic events. The first approach selected is the development of a deep learning model fed with 60-second windows. The model will classify events according to whether they are apnoea events without distinguishing between apnoeas and hypopnoeas. One of the significant advantages of this approach is that the AHI calculation is simplified, as it can be calculated using the total number of windows classified as apnoeas by the algorithm divided by the TST. This approach also allows doctors to study events more accurately, as an apnoea event that usually lasts more than 10 seconds and less than 40 seconds should be included in the 60-second windows. However, herein lies one of the significant disadvantages of this approach. Events can be miscalculated as they can be split between two windows and not be included in 60-second windows. This approach is usually developed using a one-dimensional convolutional neural network model (1D-CNN).

The second approach avoids the drawback of being unable to calculate the total duration of the apnoea events. This second approach is known as segmentation and is usually applied through U-NETs. This type of model is fed by the whole physiological time series of the patients and allows the study of the prediction of the apnoea events second by second. It will enable better recognition of the duration of the events, although it implies a greater difficulty in calculating the AHI.

3.6. User-/device-management system

In order to facilitate flexible use of the system and to organise secure data access, the following user roles are envisaged:

- Doctor – being a role with full access to the data of all assigned patients for further analysis
- Patient – having a possibility of filling out the questionnaires and getting a visualisation of own data

In addition, multiple sets of devices are possible, as several patients can be examined at the same time, and different sets of devices can be used for several measurements on the same patient.

The system will have a module that integrates this functionality to allow the management of users and devices. It consists of a front end where users and device sets can be created and assigned to each other and a back end that processes the data, connects to the database, and stores it.

3.7. Visualisation

The system should provide visualisation of the stored in database data to allow precise inspection and analysis. The visualisation should be per patient and include the following data

- General information about the patient (weight, height, sex, etc.)
- Completed questionnaires, including their scoring according to the guidelines
- The measured signals (respiration, pulses, SpO2 signals) as time series for visual analysis
- Results of automatic detection of sleep apnoea events with periods labelled
- Calculated AHI per recording

It is essential to consider that the measurement results should be able to be visualised at different levels of detail - as a single measurement/night, but also over more extended periods of time to identify trends/changes, e.g. in AHI.

3.8. System communication

As can be seen from the previous subsections, the database plays a central role in the communication between the modules. This is to ensure the consistency and security of the data and to provide a clear structure to the system.

It follows that all modules must be able to communicate with the database. For this purpose, the interfaces that will enable communication must be implemented. Based on the analysis carried out, JavaScript Object Notation (JSON) was chosen as the data format [25]. This format allows for a simple yet comprehensive and clear data description. In addition, implementation is simplified by support for multiple programming languages. The JSON format is used to communicate between all modules to follow a standardised approach during implementation.

To select a protocol for communication, a state-of-the-art search was performed. Based on the results of this research, Message Queuing Telemetry Transport (MQTT) was chosen as the solution [26]. It provides robust and efficient data transmission that can be implemented securely and efficiently. The protocol requires a centralised organisation of data transfer suitable for the planned system - a server/broker can be implemented in the database module, and all other modules should be able to connect to it via clients to both send and receive data. For this purpose, individual "topics" should be created for all communication channels, which would receive data from modules, and then other modules would receive updates when the data changes by "subscribing" to these "topics".

The only exception to the use of MQTT and JSON is the communication between the objective measurement sub-component of the Data Acquisition module and the central element of that module. At this point, the objective measurement data is sent in raw format to the central element, which then converts it to a JSON file and sends the measurement data to the database via the MQTT protocol.

4. Conclusions and outlook

A detailed concept for the home-based sleep apnoea detection and monitoring system was developed on the basis of in-depth research into current developments to achieve a comfortable usage scenario. Besides a detailed description of the modules and the use cases, a specification of the communication processes between the individual components was prepared.

The developed concept design is the basis for subsequent implementation. Therefore, it was essential to develop a global system view as well as modules and communication models to ensure a comprehensive grounding for the implementation.

The next step will be a prototypical implementation based on the prepared concept, which will then be evaluated in a pilot test. After this step, it is possible to refine the concept and create a second prototype, which should already include adaptations derived from the test experience. Finally, after completing the above steps, a medical evaluation of the developed system should be carried out. This aims to provide a final assessment of the measurement quality, user-friendliness, security and stability of the system, which should lead to the elaboration of a market-ready solution in the future to put the knowledge and experience gained into practice.

Another possibility for future system enhancement is to combine it with other sleep analysis functions, such as sleep stage identification, as described in [27] or insomnia, as presented in [28]. This would allow the creation of a comprehensive sleep analysis system that could be used in a home environment.

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