Communication

Towards detecting pneumonia progression in COVID-19 patients by monitoring sleep disturbance using data streams of non-invasive sensor networks

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Abstract: COVID-19 caused pneumonia is a severe health risk that sometimes leads to fatal outcomes. Due to medical care systems' constraints, technology solutions should be applied to diagnose, monitor, and alert the disease progress for patients receiving care at home. Some sleep disturbances such as obstructive sleep apnea syndrome can increase the risk for COVID-19 patients. This paper proposes an approach to evaluate the patients' sleep quality, aiming to detect sleep disturbances caused by pneumonia and other COVID-19-related pathologies. We describe the non-invasive sensor network used for sleep monitoring and evaluate the feasibility of an approach for training a machine learning model for detecting possible COVID-19 related sleep disturbances. We also discuss a cloud-based approach for the implementation of the proposed system for processing the data streams. Based on the preliminary results, we conclude that sleep disturbances are detectable with affordable and non-invasive sensors.

Keywords: COVID-19; Sensors; Connected healthcare

1. Introduction

Coronavirus disease (COVID-19) is an acute infectious disease caused by Severe Acute Respiratory Syndrome (SARS-CoV) [1]. The authors in [2] reported the discovery of the SARS-CoV-2 to December 2019 in Wuhan, China. It is sometimes a deadly disease affecting mostly elderly patients and patients with specific comorbidities, the most frequent: hypertension, diabetes, severe asthma, respiratory, and cardiovascular disease [3,4].

Tang et al. in [5] report that hospitalized patients mostly have a case of pneumonia, being the leading causes of death failures in the respiratory and cardiac systems [6]. Clinical observations show that the COVID-19 disease can rapidly progress with a period from hospitalization to death for intensive care unit (ICU) patients and non-ICU patients of 15.9 days (standard deviation = 8.8 d) and 12.5 days (8.6 d, P = 0.044), respectively [6]. The disease can rapidly worsen, leading to respiratory failure and acute respiratory distress syndrome (ARDS) that requires intubation [7].

Due to the medical systems' capacity constraints in areas where the disease is widely spread, supportive care and patient' monitoring are limited. Early detection of pneumonia development in patients in self-isolation at home could enable medical staff evaluation and timely admission to hospital care.

Patients with medium and severe disease experience deterioration in their well being. Symptoms include cough, fever, dyspnea, musculoskeletal symptoms (joint pain, fatigue), and gastrointestinal symptoms [8]. Based on our earlier research [9–11], we propose a method for non-invasive monitoring of sleep disturbances, as developing pneumonia could affect the person's breathing and quality of sleep. To establish our assumption that at-home patient monitoring, specifically sleep monitoring, could detect worsening of the situation of COVID-19 patients or establish if they present a higher risk, in this paper, we review the literature for relations between COVID-19 and sleep, as well as the technology-aided patient monitoring.

In the next section, we provide a review of the literature on the relation between COVID-19 and its effect on sleep and technology-aided patient monitoring. In section 3, we describe our scenario for non-invasive sleep monitoring, and Section 3.2 proposes a cloud-based approach for sleep disturbance detection. The following section outlines the process for building a machine learning (ML) model to detect sleep disturbances that might indicate underlying COVID-19 issues. The results from the experiment are presented in 4. We discuss our findings and future work in section 5, and conclude the paper in 6.

2. Related work

To establish our assumption that at-home patient monitoring, specifically sleep monitoring, could detect worsening of the situation of COVID-19 patients or establish if they present a higher risk, in this section, we review the literature for relations between COVID-19 and sleep, as well as the technology-aided patient monitoring.

2.1. COVID-19 and sleep disturbances

COVID-19 associated ARDS imposes hypoxia [12], which is an indication of the development of more progressive pneumonia. Patients with hypoxia require urgent medical attention. Smartphone pulse oximetry has been used to detect hypoxia. While pulse oximetry is a direct way to detect hypoxia [13], it has the limitations that the patient must adequately use and know how to take measurements. It is also challenging to ensure that a person can keep the pulse oximeter attached to their finger during sleep. Due to lack of oxygen saturation, hypoxia causes sleep disturbance [14]. Sleep monitoring can thus detect potential hypoxia. While false positives from other causes affecting sleep are possible, a further pulse oximetry measurement by the patient or another caregiver can be used for confirmation.

Another aspect of how sleep monitoring could benefit from accessing risk factors for COVID-19 patients is by observing comorbidities' effects. McEvoy [15] shows that overnight oxygen deprivation caused by obstructive sleep apnea syndrome is a strong predictor of hypertension. Therefore by extension, obstructive sleep apnea syndrome (OSA) is an indicator of at least one risk factor for COVID-19 patients.

Yi-Fong Su et al. [16] have observed 34,100 patients, of which 2,757 patients had pneumonia during a mean follow-up period of 4.5 years. This study has shown that patients with obstructive sleep apnea syndrome experience a 1.20 fold increase in incident pneumonia. Thus, obstructive sleep apnea syndrome appears to confer a higher risk for future pneumonia. We have not found a similar study specifically for COVID-19 patients; however, Pazarli et al. [17] postulate that OSA may be a risk factor for mortality or deteriorate the clinical scenario in COVID-19 McSharry et al. [18] suspect OSA could potentially contribute to worsening hypoxemia and the cytokine storm that occurs in COVID-19 patients. Our approach for detecting obstructive sleep apnea syndrome symptoms could benefit in the diagnosis of this risk factor.

Patients with pneumonia, which are not on mechanical ventilation, are usually positioned so that the affected areas of lungs are on top [19]. In [9], we have shown that non-invasive sensors could be used to recognize motions in bed, including turning in bed from lying on the back to laying on the side. Detecting such movements could alert the caregiver to monitor the care receiver and, if needed, change their body position.

2.2. Technology-aided patient monitoring

Improvements in healthcare combined with an aging population with a greater need for health services provide a strain of hospitals and medical staff that not always scale with the needed capacity. This effect has been partially lesser by reducing inpatient hospital length of stay for some patients [20,21]. On the other hand, the tendency to reduce the length of stay in hospitals, also reducing exposure to hospital-acquired diseases, has created a need for at-home patient monitoring and care. Active monitoring of patients in home settings can improve adherence for patients receiving care at home [22].

Patient monitoring is a growing field of research, and various designs and systems have been proposed. A comprehensive review of remote patient monitoring was conducted in [23]. This study focuses on four categories, one of which is cardiovascular and respiratory-related diseases. The review shows that this technology is making an impact on society and the research community. The authors note that although researchers prefer to move towards contactless methods, there are still significant problems to be solved in contactless monitoring. These problems include adapting the system for different users and removing artifacts and noise from the contactless sensors. Vegesna et al. [24] have conducted a systematic review of remote patient monitoring using non-invasive technologies. This study shows that most systems use multiple components, and smartphones are often involved.

A collaborative healthcare system (COHESY) model is described in [25]. This model has a bio-network layer for collecting sensor data, a social layer, and a layer for interoperability with healthcare information systems. This system addresses data security issues such as authentication, privacy, data storage, transmission, and confidentiality.

A system for unobtrusive monitoring for sleep and respiration was proposed in [26]. According to the researchers, the system that uses a thin strip pressure sensor to measure the care receiver sleep efficiency and respiration rate has an accuracy similar to that of existing FDA approved sleep trackers. Two sensors were used in this study, the first one uses the piezoelectric effect, and the second is a force-sensing resistor. Once the analog signals are converted to digital, they are sent via Bluetooth to a smartphone and onward to an Internet server.

Another approach for obstructive sleep apnea syndrome monitoring and detection is through nocturnal pulse oximetry. This approach was studied in [27], where the authors showed an accuracy of the diagnosis of 96.7%. While the study was done in a hospital setting, the paper shows potential for home-based use of connected pulse-oximetry.

While pulse-oximetry provides a more accurate diagnosis for obstructive sleep apnea syndrome, there are many challenges with training care receivers to properly put on the device and consistently do that before sleep. Wearable devices can also fall off or cause discomfort to the patient. Given these downsides, and unobtrusive monitoring, using devices that require little or no human intervention can be a more consistent way to measure sleep patterns and sleep disturbances.

3. Methods

Our proposed solution consists of non-invasive sensors. We utilize two types of sensors, a piezoelectric sensor and PIR sensors. Other data sources, including patient input and digital medical records, are also introduced to the system. We present a cloud-based architecture to support the care receivers and care providers.

3.1. Sensor kit with non-invasive sensors for sleep monitoring

Noninvasive sensors can detect body or leg movements. According to [28], these movements are related to obstructive sleep apnea syndrome. Thus, we propose placing piezoelectric sensors under a mattress, as presented in figure 1. In this figure, a piezoelectric element is placed between two plates. The piezoelectric element generates a charge, which is amplified by a charge amplifier circuit transmitted via a wall connector to the central panel. The plates are used to amplify the movement of a person in the bed. This sensor's signal is then amplified using a circuit with the schematic shown in figure 10.

Figure 1. Piezoelectric based bed movement sensor under mattress

Other sensors are also used, such as a passive infrared (PIR) sensor module [9] placed above the bed, as shown in figure 2. These sensors are placed in a sensor case to provide the experiment's repeatability with a predetermined angle. It was used to detect events, including movements in the bed readable by under-mattress sensors.

Figure 2. Sensor module with PIR sensors

3.2. Cloud-based architecture

To support this study's goals, we propose a cloud-based solution that integrates data from various sources. The cloud infrastructure can also facilitate scalability with the resource demand and cost-optimization and simplify deployments to other locations. However, the module for data collection and basic processing should be implemented on edge [10].

The process for machine learning is presented in figure 3. The inputs to the system are sensor data, patient log, patient record, and medical questionnaire. The sensor data collection is elaborated in section 3.1. The patient log consists of self-reporting of measurable health parameters such as body temperature and pulse-oximetry. The patient record refers to the medical history of the patient, including any respiratory or sleep diseases. The questionnaire is filled by the patient, preferably using the web interface or smartphone app. The questions refer to health status that cannot directly be measured and are thus subjective. Typical questions would include qualifying the person's sleep and a symptom chart for common COVID-19 symptoms such as loss of smell and dry cough. The data is pre-processed on edge and then sent to the cloud. A medical professional can provide their diagnosis and input additional parameters. They could also request an examination by directly making an appointment with the patient or requesting manual measurements (pulse oximetry, blood pressure, temperature) using connected devices or manual input.

As the non-invasive sensors are not making direct measurements, their placement affects how the events are registered. This effect introduces challenges in generating ML models from multiple care receivers. However, when multiple sensors of the same type are used, the data difference and a temporal difference for the same sensor can be introduced as features in the model. The measured features should be invariant to amplitude or time-shifting, uniform amplification, additive noise, and time scaling transformations [29]. A reliable method for sleep disturbance recognition requires continuous monitoring of the application performance.

All input parameters create a feature set for the machine learning training that is performed in the cloud. The output of this process is the ML model that is then deployed to the healthcare gateway. For subsequent data received by the healthcare gateway, it can run the model and take actions when the output indicates worsening of the patient's well-being or pre-existing health risk is detected. The actions include alerting the medical providers or adding suspected events to the medical record.

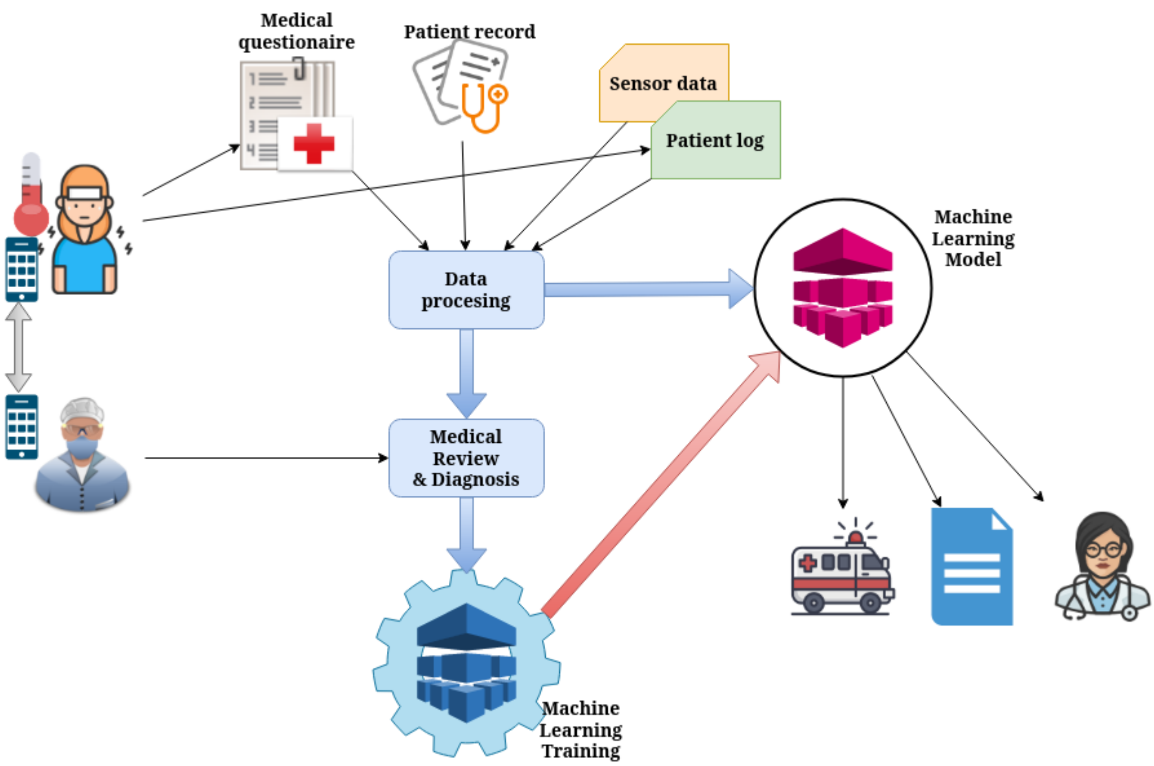

Figure 3. Machine learning features and model

Figure 4 presents the data flow model used to detect sleep disturbance using non-invasive sensors (PIR module and piezoelectric sensor), collecting the sensor readings from multiple care recipients.

The sensors can have direct wireless Internet connectivity and upload information directly to the cloud in a scenario where cost savings are the priority. However, utilizing the healthcare gateway, an edge device is preferable to offload initial data processing and enable faster scaling.

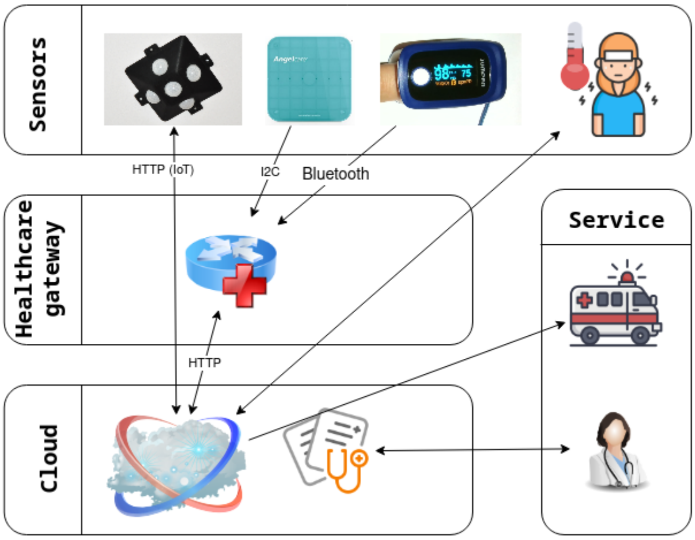

Figure 4. Communication framework

4. Results

The sampling rate was set to 33 Hz, providing a reading of 5 PIR sensors and 1 Piezo sensor every 30 milliseconds. The different experiments for the monitoring of sleep patterns were performed for over 8 hours. The PIR sensors are binary, and in the data set, they can have zero or one value. The piezoelectric sensor is analog input with voltage from zero to five volts represented as zero to 1000. For the analysis, we normalized this range between zero and one. The input range was less than the five volts due to signal noise and voltage drop from the amplifier circuit. The summary of the sensor data input is shown in Table 1. Here we notice that PIR1 and PIR5 that were facing away from the subject have a low activation rate compared to the other sensors.

Table 1. Summary of sensor readings

Sensor	Min	Mean	Max
Piezo	37	52.03	736
Piezo (normalized)	0	0.021503	1
PIR1	0	0.009828	1
PIR2	0	0.028537	1
PIR3	0	0.029203	1
PIR4	0	0.030796	1
PIR5	0	0.018591	1

Figure 5 shows the correlation between the different PIR sensors and the piezo sensor. It is quite interesting that all of them are significantly correlated.

Suppose we consider the built-in delay in the PIR sensors and the highly oscillating output of the piezoelectric sensor, reducing the correlation. In that case, the calculated correlation is very promising. Post-processing of the data can partially eliminate these factors. The delay of PIR sensors can be reduced by eliminating successive positive values in the time series. The piezoelectric signal oscillations can be ironed out using the sliding window method and then normalizing each event. Figure 6 shows the heat map where the piezoelectric data was averaged using a sliding window of 100 samples or 3.3 sec. We notice a very high correlation of up to 0.73 between the piezo sensor and

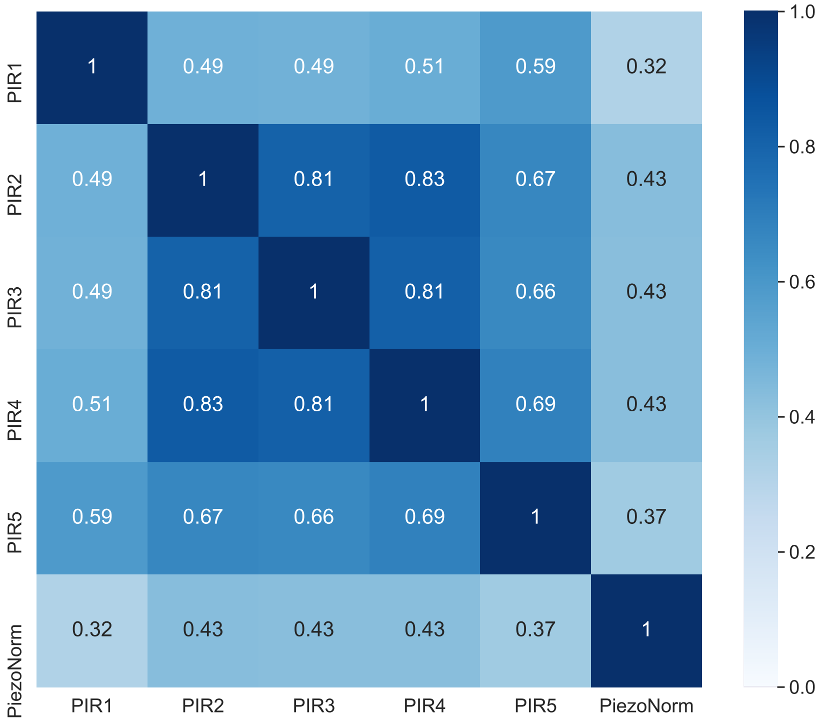

Figure 5. Correlation heatmap of the Piezo and PIR sensors

182 the second PIR sensor. Given that the maximal correlation among the PIR sensors is 0.83, this result
183 confirms that sensors can confidently detect movement in bed.

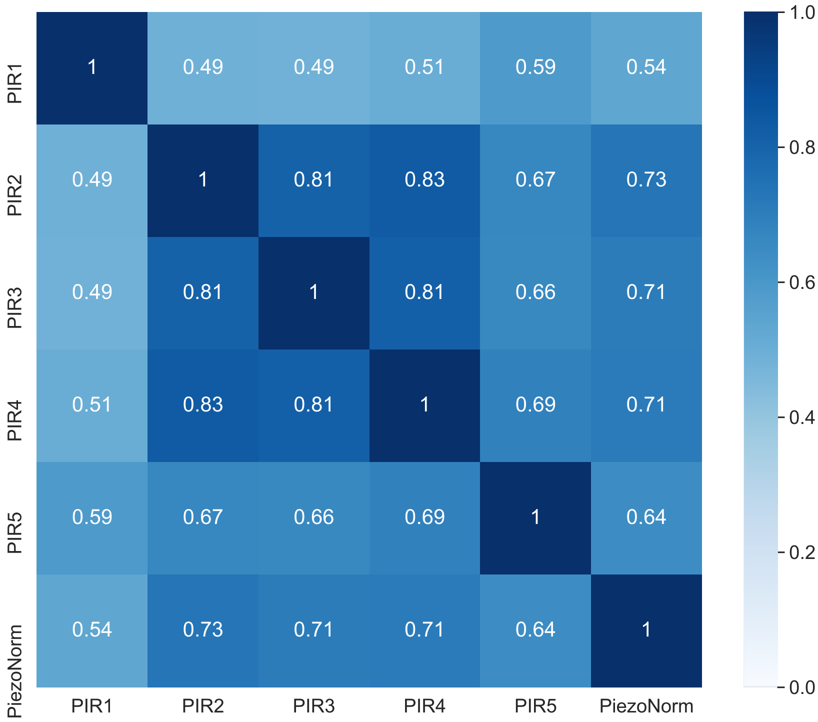

Figure 6. Correlation heatmap of the PIR sensors and Piezo with sliding window

184 To explore the data in greater detail, in Figure 7 we visualize the entire sleep interval. As we have
185 close to a million data points for each sensor, we average each 30-second interval. Since the sampled
186 data is mostly zero value, we normalize the data. Each line represents 30 seconds in the figure, and the

vertical length of the line represents the normalized average for that interval. It can be observed that most events detected by the piezoelectric sensor are detected by at least a few of the PIR sensors.

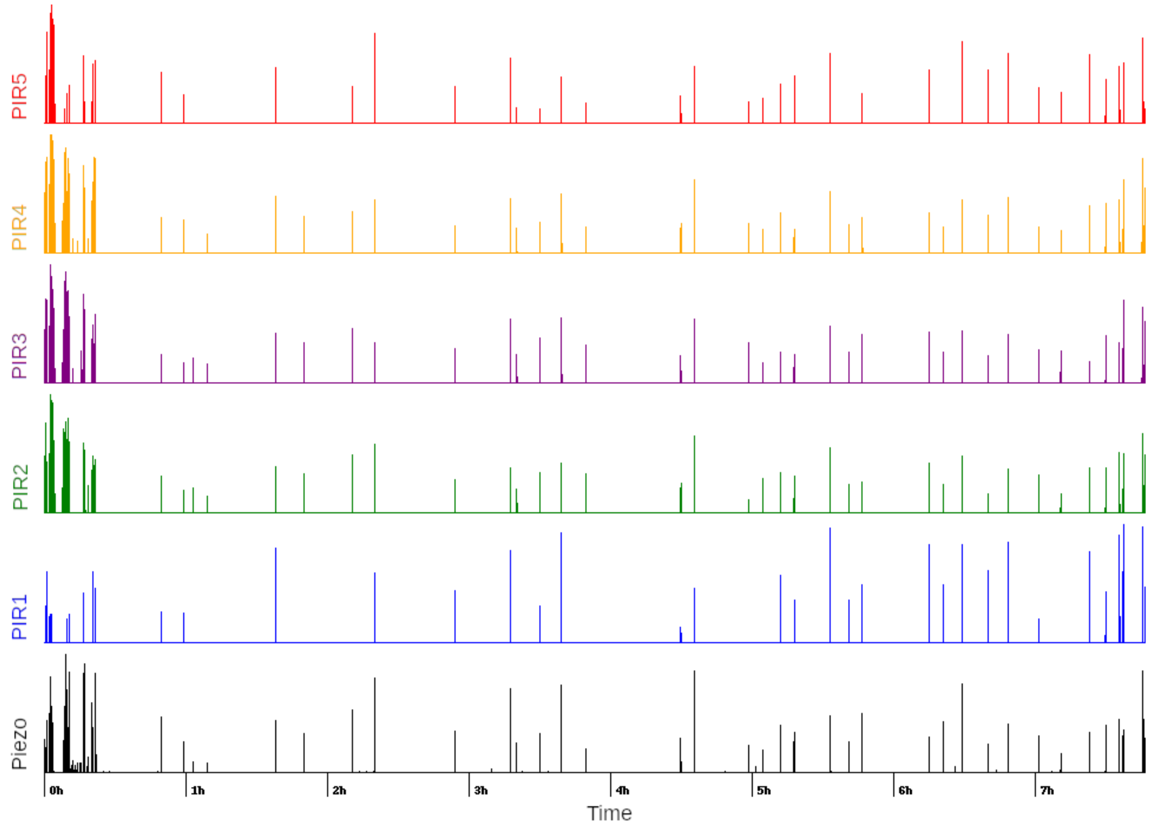

Figure 7. PIR and Piezo sensors activation (over 8 hours of sleep)

In figures 8 and 9, we present a heat-map of the sensors for the first and the last 40 minutes of the sleep interval. A rolling window was used to average the signal, especially from the piezoelectric sensor. We notice that PIR2, PIR3, and PIR4 are activated even for weaker signals from the piezo sensor. These sensors face the person at an angle with higher sensitivity. When this signal is stronger, which corresponds with more pronounced body movement, even the PIR1 and PIR5 sensors are activated.

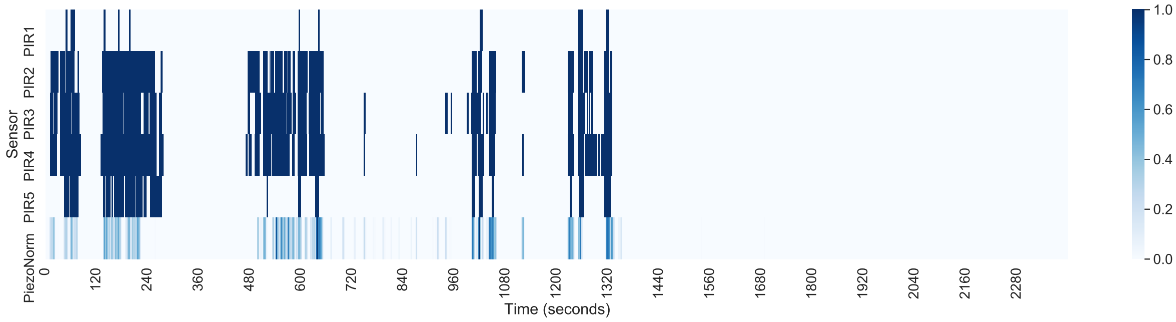

Figure 8. PIR and Piezo sensors activation (the first 40 minutes of the 8 hours of sleep)

We can conclude that noninvasive sensors are likely to register movements during sleep, as indicated by the high correlation. After labeling data using body sensors, the model would process and react only to noninvasive sensors.

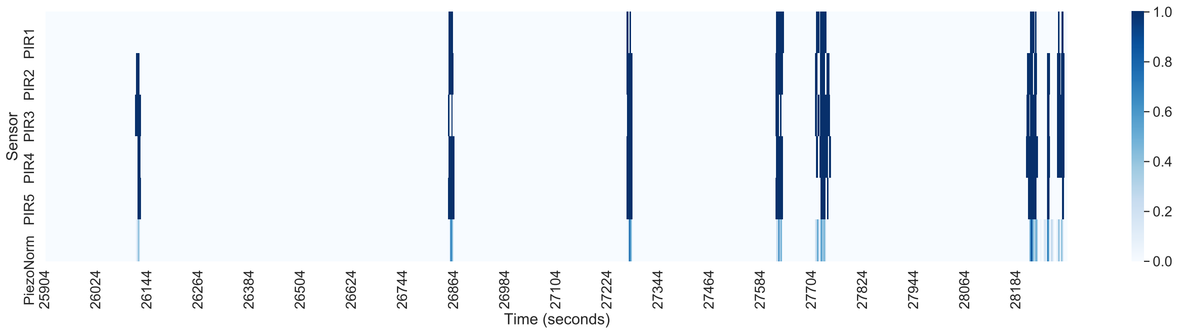

Figure 9. PIR and Piezo sensors activation (the last 40 minutes of the 8 hours of sleep)

5. Discussion

The proposed non-invasive sleep monitoring cannot directly be used for COVID-19 diagnosis and is not a replacement for professional hospital monitoring for critically ill patients. However, in situations where the patients are at home, our system can be easily placed in the bedroom to monitor if the patient situation has increased probability to worsen, affecting their sleep. Our approach can gather some of the data points needed to investigate further the effect of COVID-19 symptoms and how they affect sleep. However, clinical observation is also needed to precisely monitor the progress of the illness in patients and as a feedback loop to validate the hypothesis that COVID-19 symptoms affect sleep. A machine learning approach is a good fit for this type of analysis, given the amount of sensor data generated.

Our system can also be used as an indication of potential risk factors, such as obstructive sleep apnea syndrome. In the related work, we have presented research indicating the correlation between sleep disturbances and known effects in patients with COVID-19. A significant association between obstructive sleep apnea syndrome and COVID-19 death was found in [30]. This finding persisted when data were adjusted for demographics. The authors highlight the need for close monitoring of persons with infection that suffer from obstructive sleep apnea syndrome. The hypoxia associated with OSA will significantly affect patients with pneumonia and shortness of breath. The frequent periods of awakening during sleep result in sleep deprivation and poor sleep quality associated with suppression in immune response, which can facilitate susceptibility to SARS-CoV-2 infection [31]. OSA was associated with an increased risk of hospitalization and approximately doubled the risk of developing respiratory failure [32]. Given these risk factors and knowing that OSA is widely under-diagnosed [32], our approach can provide additional information for care providers to investigate and assess the patient's risk.

The strong correlation between the PIR sensors and the piezoelectric sensors with entirely different measuring methods confirms the validity of the sensor fusion approach in unobtrusive patient monitoring. In order to reduce signal noise, additional sensors of the same or different types can be added.

Another application that our non-invasive sleep monitoring approach could benefit is the long-term home care monitoring of patients who survived the acute respiratory distress syndrome (ARDS) and recovered after mechanical ventilation. Prior research has shown that sleep disturbance can increase in post-recovery ARDS patients compared to the general population [33,34]. Lee et al. [33] have followed a large group of patients who have survived critical illness associated with ARDS and have concluded that chronic sleep disorders, which originate during the acute illness, are present in some ARDS survivors several months after discharge from the hospital. Based on their study and research of literature, Doria et al. [34] have found that by median percentage, 67% of patients in early-stage and 39% in late-stage after discharge experience abnormal sleep.

An additional benefit of using our approach is to assist in the monitoring of patients with sleep disorders. Many sleep disorders centers were entirely closed during the Covid-19 pandemic either because they are situated in the hospital buildings or because the staff was re-tasked with COVID-19 care [35]. While therapy for obstructive sleep apnea syndrome using PAP devices is usually administered at home, sleep monitoring is done in these centers. Given the increased limitations and restrictions, the role of telemedicine for sleep disorders should be prioritized in the era of COVID-19 [36].

6. Conclusion

In this paper, we showed the links between COVID-19 symptoms and sleep disturbances. We presented a system consisting of multiple sensors of two types to monitor sleep quality and issues. Our experimental data showed a strong correlation between diverse types of sensors that detect movements during sleep. We discussed the relations found in the literature between movements in sleep and sleep quality and sleep disturbances. The monitoring of sleep and sleep disturbances, in turn, can indicate the existence of COVID-19 symptoms, including pneumonia and possible COVID-19 risk factors such as obstructive sleep apnea syndrome. Our approach can also be used as alternative home-based sleep monitoring when the patient cannot receive specialized monitoring in sleep centers due to the pandemic restrictions. In the future, we will collect data across multiple persons and various configurations of noninvasive sensors' placement.

7. Supplementary material

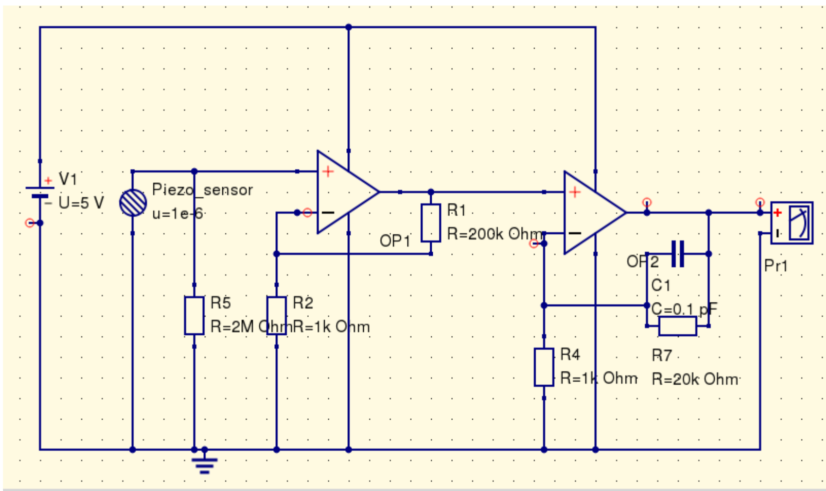

Figure 10. Amplifier circuit for piezoelectric sensor

Author Contributions: Conceptualization: A.D., V.T., and E.Z., methodology: A.D., V.T., F.F.R., N.M.G., and E.Z., software: A.D., P.L., and E.Z., validation: M.V.V, I.M.P, F.F.R., N.M.G., and V.T., formal analysis: A.D., M.V.V., and V.L., investigation: A.D., E.Z., P.L., M.V.V., I.M.P., writing—original draft preparation: A.D., E.Z., P.L., M.V.V., I.M.P., N.M.G., F.F.R., and V.L., writing—review and editing: A.D., E.Z., P.L., M.V.V., I.M.P., N.M.G., F.F.R., and V.L. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

COVID-19	Corona virus disease 2019
SARS-CoV-2	Severe acute respiratory syndrome - coronavirus 2
ARDS	Acute respiratory distress syndrome

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Sample Availability: Samples of the compounds ...... are available from the authors.