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R-Mon: An mhealth Tool for Real-time Respiratory Monitoring During Pandemics and Self-Isolation

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***Abstract*—The current COVID-19 pandemic has emerged as a serious disease with life-threatening clinical manifestations and a high mortality rate. One of the major complications of this disease is the rapid and dangerous pulmonary deterioration that can lead to critical pneumonia conditions, resulting in death. The current healthcare system around the world faces the potential problem of lacking resources to assist a large number of patients at the same time; then, the non-critical patients are mostly referred to perform self-isolation/quarantine at home. With the advancement of IoT and Cloud technologies now it is possible to monitor patient's symptoms in real-time to detect and quickly report sudden and dangerous changes to the healthcare provider. In this paper, we propose the concept of R-Mon, an mhealth tool for diagnostic-assistance, and real-time communication with healthcare providers that can be used with COVID-19 patients in self-isolation and any other disease in pandemic situations. We propose the use of a pressure sensor under the bed that can monitor the respiratory rate and pulmonary function of the patients. We also propose a framework in which the detected information can be directly seen by the practitioner for the decision-making process. We envision that this kind of mhealth tool and framework can be implemented for better health response in future pandemics.**

***Keywords*—mhealth, pressure sensor, respiratory rate, real-time monitoring, IoT**

I. Introduction

Coronaviruses are a large family of viruses that can infect people and spread among humans in many forms such as with MERS-CoV, SARS-CoV, and now with the new virus SARS-CoV-2 (COVID-19) [1]. The clinical spectrum of COVID-19 infection appears to be wide, encompassing asymptomatic infection, mild upper respiratory tract illness, and severe viral pneumonia with respiratory failure and even death [2]. Pulmonary function testing [3] is a way to measure the effects of COVID-19. Patients whose pulmonary functions have not been compromised and do not require hospitalizations, an effective way to monitor is using telemedicine tools while in self-isolation [4]. Due to the high risk of diagnosed patients to develop severe respiratory distress, real-time monitoring of the respiration rates of these patients is desirable. Unfortunately, there is limited or no tool available for real-time monitoring. Even the Food and Drug Administration (FDA) has allowed the use of devices to monitor the patient's vital signs remotely [5]. Unfortunately, there are limited tools available for real-time at-home monitoring, and mostly of them requires the use of wearable devices (e.g. watch, cuff, belt, etc.) or invasive technologies (like cameras).

To avoid the inconvenience of using wearable and invasive devices to monitoring vital signs, some contact-free technologies have been proposed [6]–[9]. The advantages of contact-free sensing include continuous monitoring during the night as the patient does not need to be aware of the device itself, where wearable devices can be a disruption. Most of monitoring contact-free technologies are based on force sensors [10], load cells [11], multi-channel infrared sensor-arrays [12] , pressure sensors [13], vibration sensors [14], and ratio frequency [9]. Among these technologies, pressure sensors have gain popularity because they can be easily used under bed and chair and provide a signal that is strong enough for estimating the heart and respiration rate of the person. The pressure sensor also provides a limited space of sensing that can be useful when it is used under the bed and the person shares the bed. However, the use of only pressure sensors is not new and it cannot provide any extra feature for patients monitoring during pandemics. To address this, we propose a novel low cost mhealth framework that utilizes pressure sensors for easy real-time monitoring of patients along with a Cloud system to alert and report sudden changes and prediction of patient's condition to the healthcare provider. Fig. 1 shows the proposed design of the framework.

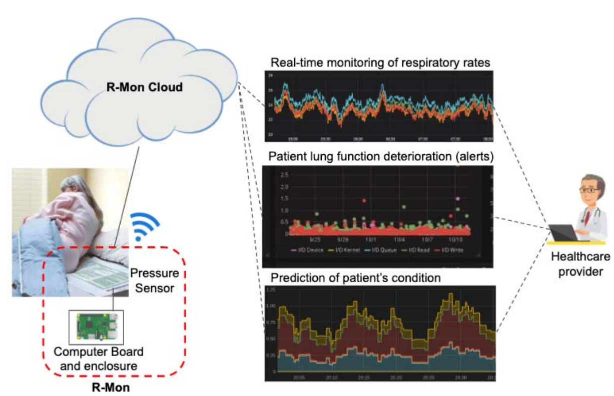

Fig. 1. R-Mon proposed framework

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TABLE I
WEARABLE AND CONTACTLESS DEVICES FOR MEASURING RESPIRATORY RATE AND ITS FEATURES.

Device	Respiratory Rates	Real-time Alerts	Home Monitoring	Patient Deterioration	Prediction of condition	Connection w hospital
Apple Watch [15]	x		x			
Jawbone [16]	x		x			
Phillips Alice [17]	x	x	x			x
WatchPAT [18]	x		x			x
Emfit [19]	x		x			
Beddit [20]	x		x			
ResMed [21]	x		x			
Early Sense [22]	x	x		x		x
Early Sense Live [23]	x		x			

The main contributions of this paper are:

- We present a framework concept that can monitoring respiratory rates in real-time and can be used for self-isolated patients during pandemics.
- We design a service framework that receives real-time patient information and analyze the data to infer the improvement or deterioration of the patient.
- We propose the design of a patient condition estimator that communicate the potential hospitalizations to the healthcare provider allowing them plan in advance the healthcare resources.

The rest of the paper is organized as follows: Section II presents the related work. We present the R-Mon architecture and its design in Section III. We introduce the challenges of implemented R-Mon in Section IV. The future work and conclusions are shown in Section V.

II. RELATED WORK

The respiration status can be monitored by breathing apparatuses [24], while the heart rate is typically measured by wearable devices [25]. However, those devices need body contact and are intrusive. Many people feel not comfortable to wear or forget to wear, especially when sleeping. There are multiple contact-based devices for measuring respiratory rate. For example, wearable devices like *Apple Watch* [15], *Jawbone 3* [16], *Basis Peak* [26], *Fitbit Surge* [27], and a number of other "smartwatch" devices that have been good in demonstrated their capabilities to measure heart rate; however, they lack of analysis of the person's sudden changes in respiration and deterioration of the pulmonary activity, and also they require user intervention for correct performance. Under-mattress devices like *Beddit* [20] and *Nokia Withings Sleep Tracking Pad* [28] measure sleep time, heart and respiration rates, sleep cycles; however, these measurements are not analyzed or sent to healthcare providers. EarlySense device [22] is the most near to real-time vital signs monitoring and has been developed to provide continuous monitoring of heart rate, respiration rate, and bed motion for patients in medical/surgical scenarios using a pressure sensor. EarlySense has two versions the hospital one [22] and a home one [23]. The hospital version is extremely expensive for home monitoring and the home version does not provide real-time communication of the patient condition analysis to the healthcare provider.

In the research field, multiple efforts have been made to provide cost-effective and contact-free devices for monitoring vital signs. For example *Clemente et al.* [14] proposed a contactless heart and respiration rate estimator using a vibration sensor under the bed; the study analyze the vibration signal of the person on a bed and determine its vital signs by applying double-envelope signal processing technique [14]. However, the application only works with one person on the bed. Additionally, multiple approaches have been done using WiFi contactless technology. More recently, some respiration monitoring systems based on commercial off-the-shelf transmitter-receiver were proposed. In [29], the ratio signal strength (RRS) measurements of a network of transceivers are utilized for extracting respiration, which was improved by [30] where RSS data from a single TX-RX pair can identify one's respiration. However, to mount all the devices in a place is very costly as multiple WiFi devices need to be adjusted to get a good result.

As summary, we provide on Table I only already tested commercial wearable and contactless technologies and their related to respiration rate and analysis of the patient. As it can be seen, there is a lack of a framework that also allows to identify the patient deterioration/improvement, the prediction of a dangerous condition, and the direct connection with the hospital/healthcare provider. Also, our proposed solution is cost-effective.

III. R-MON ARCHITECTURE

TABLE II
HARDWARE SPECIFICATION OF R-MON IOT SENSOR

R-Mon Hardware	Price Range
FSR01CE (pressure sensor)	\$9 - \$10
Raspberry Pi	\$40-\$50
Bundles of Wires	\$4 - \$5
Resistors a bundle	\$5-\$6
Power Supply (9V battery)	\$10-\$11
Pressure Feedback Display (Digital Multimeter)	\$22-\$23
TOTAL	\$90 - \$105

In this section, we present the proposed architecture of R-Mon framework. To provide a detailed explanation of the different used techniques and approaches, we divided the framework into three parts: respiration estimation, patient lung function, and prediction of patient condition. These are the three main functionalities that R-Mon will provide.

A. Respiration estimation

We propose to perform in-situ respiration estimations, which means that the analysis of the signals and the estimation of the respiratory rate will be done inside the IoT device. To do so, we need to provide a IoT device capable of collect and analyze data. We propose to use a flat pressure sensor under the bed connected to a Raspberry Pi which will collect the ballistocardiogram signals for analysis. The hardware specifications and price range are provided in Table II. The signal from the pressure sensor is read inside the Raspberry Pi using a buffer for data management. One option is to store the raw data inside the Raspberry Pi directly using a stream data database like InfluxDB [31] or use the buffer for inputting a sliding window of data. The sliding window can be established between 15s and 30s, which will provide almost real-time results.

Once the data is read by the computer board, signal processing algorithms are applied to extract the respiration rate. The proposed procedure is explained in Fig. 2.

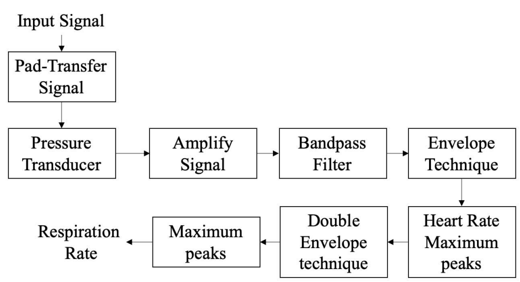

Fig. 2. Proposed methodology for respiration extraction

The signal is transferred and amplified to avoid losing information. Because the typical heart rate (HR) is between 40 bpm (beat per minute) and 150 bpm and the respiration rate (RR) is between 12 rpm (respiration per minute) and 25 rpm, which means the target HR/RR should include 0.2 Hz to 2.5 Hz, only a small frequency range is needed. Thus, we suggest to apply a bandpass filter with 0.1 Hz low-cut frequency and 8 Hz high-cut frequency to extract target vibration signals. To improve HR and RR estimation stability, we propose an envelope based HR estimation method. The envelope is a curve such that at each point it touches tangentially the signal. The parametric equations of the envelope are given implicitly as $U(x, u, C) = 0$ and $U'_C(x, u, C) = 0$. Once the envelope is obtained, the peaks can be used to estimate the HR. We then propose to use the HR peaks detected to generate the respiratory modulation signal by extrapolate them. Then we obtain the envelope of the signal and count the peaks to estimate the respiratory rate.

B. Patient Lung Function

Once the respiration rate is extracted, the data is sent via wireless connection to R-Mon Cloud. The travel of the data should be done using HTTPS protocol for security. The data is saved in the Cloud using InfluxDB [31]. InfluxDB is an open-source time series database developed by InfluxData [32]. It is written in GO and optimized for fast, high-availability storage and retrieval of time series data in fields such as operations monitoring, application metrics, Internet of Things sensor data, and real-time analytics.

Because results of the patient RR are stored in the Cloud, the healthcare provider can access patient's information in real-time. Furthermore, we have utilize Grafana visualization to allow the provider to set-up alarms when the RR passes certain up and down thresholds. When Grafana detects an "unusual" respiration value, it triggers an alarm in the dashboard which allow the healthcare provider to visualize the current status of the patient. Furthermore, the practitioner can visualize the past data by selecting the date range. Then, the framework allows to visualize both, current RR and historical information, which helps in the decision making process. Fig. 3 shows an example of visualization of the respiration rates over the time of three different patients using R-Mon. Note that the healthcare practitioner can visualize the respiration phase over the time.

Using continuous real-time and historical data of the person in bed, we can perform a prediction of the patient evolution to determine deterioration. We propose to follow a feature-based machine learning [31] technique and cross-validation methodologies [32] for patient evolution. The following steps are proposed: a) feature extraction: from the collected data, we aim to distinguish the main features of the signal that denote patient deterioration. These features are used to train the machine learning model; b) model selection: investigation of the best model for patient evolution is conducted during this process. Hyper-parameter will be studied to decide the best fit for the expected results c) training process: using labeled data from 20% of the time on bed, we propose to test the machine learning model to evaluate the matrix confusion of the results. This process leads in a better parameter selection for patient evolution estimation; d) testing process: The testing process is conducted with the other 80% of data for verifying accuracy respecting the testing process; e) evaluation: a cross-validation process is used to evaluate the performance of the patient evolution estimation.

The result of the patient deterioration or improvement will be presented to the healthcare provider in the same Grafana Window in order to help them to evaluate the patient in real-time.

C. Prediction of patient condition

Similarly to patient evolution, we propose to use the features of respiration rate and patient evolution to feed a Hidden Markov Model (HMM) [33] (that is a statistical Markov model in which the system being modeled is assumed to be a Markov process) for prediction of future hospitalization.

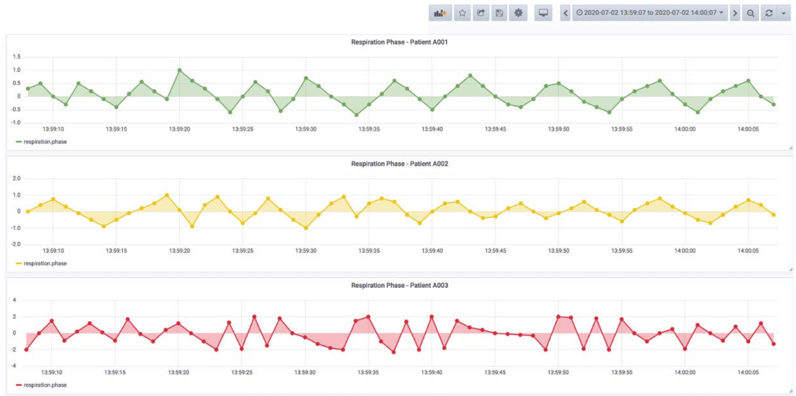

Fig. 3. Grafana example showing respiration rates

Hospitalization may occur when a rapid patient deterioration happens. We propose to treat the hospitalization problem as an evaluation problem for HMM. Given the Hidden Markov Model $\lambda = (A, B, \pi)$ and a sequence of observations O, find the probability of an observation $P(O|\lambda)$. A cross-validation process also is proposed to be conducted to verify the effectiveness of the model. The following steps are conducted: a) Feature selection: We need to extract the features that may better predict the future patient hospitalization; this process requires a deep study of the signal and segmentation of required sections. Typically the hospitalization occurs when there is exists frequently shortness of breath; then the quantities of shortness of breath and time periods need to be used to feed the model; b) Training procedure: The training procedure, based on the Expectation-Maximisation algorithm, set all the transition and the emission probabilities in order to maximise the probability of generating the sequences of the training set. The trained HMM is able to compute the probability of generating any new sequence; c) Testing: We also propose to apply the HMM process on test sequences to actually predict the hospitalization rates. d) Evaluation: a cross-validation process will be used to evaluate the performance of the patient hospitalization prediction.

The potential hospitalization are estimated daily, and shown to the healthcare provider. We hope that this proposed strategy can help the healthcare system to plan in advance the resources. For example, patients with potential deterioration can be redirected to hospitals with better capacity.

IV. Challenges

To implement a framework like R-Mon, multiple challenges need to be faced. Here we summarize the most important ones:

- *Data:* In order to provide accurate results regarding patient deterioration or improvement, the collected data must be enough for applying machine learning techniques. Even though the method can be applied with hours of data, it does not guarantee accurate results. Then, a trade-off need to be taken between the amount of data and the accuracy of the results.
- *User concerns about data security:* Using IoT devices that transmit data directly to healthcare providers may rise patient concerns regarding privacy of his/her data. This aspect is out of the scope of this paper, but it is real concern that need to be incorporate in the framework design. Even though the data is travel to the Cloud in a "secure" way using HTTPS protocols, methodologies about cyber attack mechanisms and data protection procedures need to be applied.
- *Validation against ground true:* A comprehensive validation against FDA approved devices should be performed before the use of R-Mon in healthcare systems. This comparison will help to improve the algorithms accuracy but at the same time requires exhaustive revision of the multiple available devices in the market and their acceptance in the medical community.

V. Future Work and Conclusions

Different aspects need to be addressed. Analysis of differences in various aspects including data submission, usability, and use pattern among different groups of users with COVID-19 or other diseases will be performed. Use of the special features of R-Mon can help practitioners in planning healthcare resources during pandemias, and controlling and monitoring patients in rural and unserved areas. We also plan to use the R-Mon infrastructure to promote longitudinal monitoring of other infesiouses diseases.

The validation of R-Mon against medical devices for respiration and lung function will lead to improvements of the algorithms inside R-Mon. We are going to follow a 'Continuous Process Improvement' (CPI) methodology [34]. In CPI In order to assess if improvement of a process or part of a process (task) is needed, one or more metrics reflecting the performance status of a particular task are polled periodically. The following steps are required: a) metric extraction: we are going to determine which metrics inside R-Mon algorithms needs to be improved after each round of comparison; b) error count: if the metric is falling after rounds of comparison, we need to estimate the error to understand the main features that affect that metric; c) modification process: after understanding the metrics error, a modification of the algorithm is conducted after carefully analysis of the improvement. d) controlling process: rounds of verification are made using the historical comparison data and new tests. After completion of this work, we expect to have (1) an accurate real-time R-Mon set of algorithms for estimating pulmonary function.

In this paper, we presented the idea of an mhealth tool for real-time respiratory monitoring during pandemics like COVID-19 when the patients are performing self-isolation at home. We proposed to use a cost-effective pressure sensor under the bed to extract in-situ respiratory rates and transfer the information to a Cloud for patient deterioration determination and prediction of future hospitalizations. The data and results are presented to the healthcare provider, who can monitor the patients and easily identify when some of those patients are presenting pulmonary deterioration.

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