Data Analysis Methods for Health Monitoring Sensors: A survey

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***Abstract*—Innovations in health monitoring systems are fundamental for the continuous improvement of remote healthcare. With the current presence of SARS-CoV-2, better known as COVID-19, in people's daily lives, solutions for monitoring heart and especially respiration and pulmonary functions are more needed than ever. In this paper, we survey the current approaches that utilize the advantages of sensor technologies to sense, analyze, and estimate health data related to respiration, heart, and sleep monitoring. We focus on illustrating the signal processing and machine learning techniques used on each approach to facilitate researchers' understanding of how data is processed nowadays. We have classified the reviewed papers into two main categories: contact and contactless sensors. In each category, we discuss the different types of used sensors, the data analysis technique, and the accuracy of those techniques.**

***Index Terms*—Signal processing (SP), machine learning (ML), remote monitoring, internet of things (IoT), respiration and pulmonary function.**

I. Introduction

Health monitoring systems are widely used for patients who need isolated care, unconscious patients who cannot get medical attention for themselves, and also for neonatal patients who need special attention. The recent coronavirus pandemic has enabled more applications for remotely respiration, heart, and sleep monitoring on large scale. As it is well-known, monitoring systems rely on sensor technologies. Currently, there are multiple research studies for remote monitoring using different types of sensors. In this paper, we analyze the current state-of-the-art sensor technologies used for health monitoring. This survey is also important to help researchers to know the remaining challenges of the different sensing techniques used. We have categorized the sensors based on contact and contactless technologies; all these technologies are related to monitoring respiratory rates, heart rates, and sleep patterns. Additionally, we categorized the approaches' techniques and used algorithms based on signal processing (SP), and machine learning (ML). In this study, we are going to review the different sensor and data analysis techniques currently used to monitoring these challenged features.

II. Techniques Review

We surveyed 38 papers related with remote monitoring of respiration, heart, and sleep that were published between 2004 and 2021. We classified the type of sensors contact and contactless technologies. Among these types of sensors, we classified three type of applications such as respiratory analysis, respiratory & heart analysis, and sleep pattern estimation. We additionally highlighted the use of pressure and vibration sensors because those are non-invasive technologies currently in trend. We also analyzed the data analysis techniques used on each approach and found papers that relies purely on SP techniques, mostly of them are based on time and frequency analysis. On the other side, there is a current tendency on using ML algorithms for estimating respiration, heart and sleep patterns. We found techniques that range from logistic & linear regression (LR) to Deep Learning (DL), Neural Network (NN), Artificial Intelligence (AI), Random Forest Regression (RFR), Gradient Boosting Regression (GBR), Adaptive Boosting Regression (ABR), Random Forest Classifier, and Decision Trees.

Fig. 1 presents the different types of sensors (contact and contactless) used on each studied approach; the different types of applications (respiratory only, respiratory & heart, and sleep monitoring) of the different approaches is also shown in the figure. Note that we also specify three types of sensors inside the "contact" sensors: wearable (wear by the user on his/her body), pressure (pressure sensor that are in contact with the human body), and vibration (vibration sensors that are also in contact with the human body).

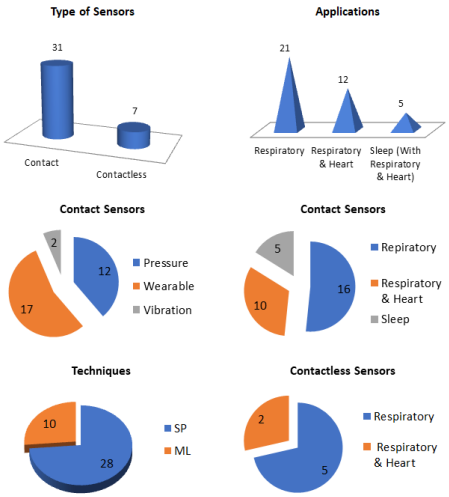

Fig. 1. Sensor types, applications and techniques of each one of the surveyed papers.

III. Contact Sensors

The vast majority of the surveyed papers are based on contact sensors. We define contact sensors as sensors that either have to be worn by the person (wearable) or touch the person in some way (like non-invasive pressure and vibration sensors.) We also surveyed with type of data analysis techniques were used on each approach. In the following sections, we elaborated the type of techniques used and the advantages and disadvantages of each approach. Fig. 2 shows the specific signal processing and machine learning techniques found on the approaches based on contact sensors.

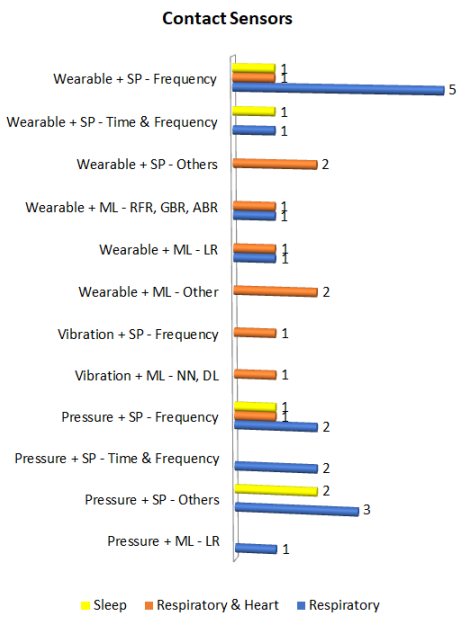

Fig. 2. Types of data analysis techniques used on surveyed contact sensor approaches

A. Signal Processing Techniques

1) Wearable Sensors: Frequency and time domain analysis, filtering processing, and statistical analysis are the common denominator in the applications that use wearable devices for respiratory monitoring.

In a survey conducted by Lanata et al. [1], it is shown that time-domain analysis is used to demonstrate the hypothesis that the spirometer sensors are not affected by movement artifacts, and therefore can be considered as gold standard for respiratory monitoring. On the other side, the frequency-domain analysis is done to estimate the Fast Fourier Transform (FFT) of the output signals to analyze their frequency components. The four different methodologies to monitor respiration activity include inductive plethysmography, impedance plethysmography, piezoresistive pneumography, and piezoelectric pneumography. Those have been implemented into wearable and comfortable systems using spirometers as sensors. Fig. 3 shows an example of a wearable spirometer for respiration estimation.

In 2018, Dan et al. [2] presented a wearable respiratory monitoring sensor measuring measurement of human respiration using frequency analysis of the data. The authors obtained the angular velocity of an accelerometer to extract the respiratory waveform, calculate the respiratory rate, and retrieve accurate respiratory phase information. The consistency between the respiratory angular velocity and the respiratory frequency obtained from the reference signal was represented by a Bland-Altman. The mixed processing results of the three frequencies (normal, high, and low) indicate that there is a high-frequency data point outside of the confident interval. In general, for these three frequencies breaths, the respiratory rate obtained by the breathing angular velocity can fulfill the desired requirements, and the respiratory rate can be determined using the angular velocity acquisition device. Fig. 4 illustrates the synchronous acquisition system to extract respiratory data proposed in [2].

Fig. 3. Biopac system used as spirometer[1]

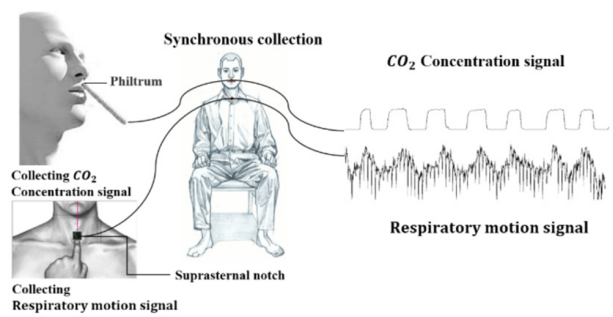

Fig. 4. Synchronous acquisition system to extract respiratory data[2]

Few types of sensors also have been developed related to body movements. For example, Tao et al. [3] use a graphene-paper sensor for detecting human motions and may in the future led into respiration estimation. The graphene pressure sensor is placed in the soles and palm of the hand, and the motion signals can be tested. It is also applied to the throat of the tester to detect the vibration signal of vocal cords when the tester is speaking. This pressure sensor is also effective for detection of violent pressure changes that shows excellent performance in the range of 0 to 20 kPa (Kilo Pascal). The fabrication process is demonstrated cutting the tissue paper into squares and leave them to soak in the GO solution. Then with thermal reduction method, the samples are transformed into reduced GO (rGO) paper. After electrode connection and encapsulation, the graphene pressure sensors show excellent flexibility. If combined with a machine learning algorithm and other technologies, it will be possible for graphene pressure

sensors to achieve gait recognition, motion monitoring, and other functions. [3]

2) Vibration Based Sensor: Vibration sensors are a non-invasive technology that provide information of around environments. The following paper use vibration sensors to touch a person and extract the information of his/her vital signs without the need of wear the device all the time. Nguyen et al. [4] presented in 2019 an approach to monitoring respiration and heart using vibration sensors and frequency domain analysis. Using Fast Fourier Transformation (FFT), the frequency characteristics of the sensor outputs with and without respiration can be obtained integrated the cantilever with an air cavity, which, in turn, was connected to a tube which is able to measure the vibrations. Therefore, the structure proposed in this study is suitable for development of wearable devices for monitoring pulse wave, blood pressure, and respiration rate which is suitable and stable for continuous health monitoring in various applications. Fig. 5 illustrates the schematic diagram of the method in [4].

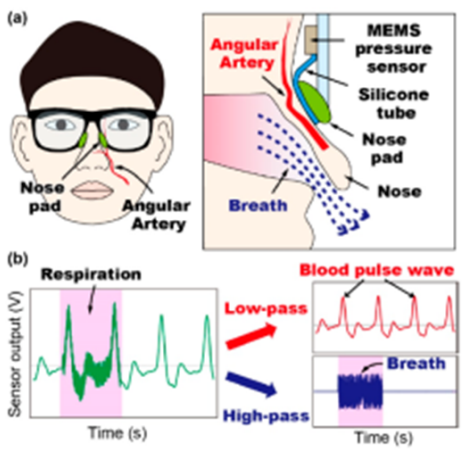

Fig. 5. (a) Conceptual schematic diagram Nguyen et al. method to simultaneously measure blood pulse wave and respiration rate using a single sensor device attached to the nose pad of eyeglasses (b) Sensing principle: The pulse wave and respiration rate are measured using the low-pass filtered and high-pass filtered signals of the output of the proposed sensor, respectively. Figure from [4].

3) Pressure Sensors: Pressure sensors have been also used for measuring respiration and heart rate when entering in contact with the person's body. Chen et al. [5] developed an approach that utilizes frequency domain analysis for measuring heart and respiration. They developed a system based on a flexible enhanced Hollow Micro Structured-Self-Powered pressure sensor (HM-SPS) placed on the bed. It can be placed directly underneath the chest of a participant with a bedsheet in between to simultaneously monitor the heartbeat and respiration waves. The hardware modules, consisting of a signal filtering unit, an amplifying unit, a converter, and a Bluetooth transmission unit. The units are integrated into a minimized circuit board. The software modules include signal sampling, processing, and displaying units where the real-time respiration waves, respiration rate, and heart rate were systematically obtained and transmitted to a mobile phone. The feasibility for smart non contact real-time heartbeat and respiration monitoring, a set of hardware and software modules was utilized. Fig. 6 shows the fabrication and placement of the sensor proposed in [5].

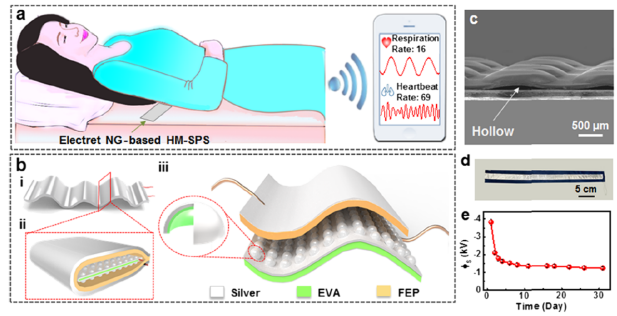

Fig. 6. Fabrication of the HM-SPS for heartbeat and respiration monitoring presented in [5] (a) Schematic design of the health monitoring system (b) Schematic structure of the HM-SPS strip. (i) overall view, (ii) oblique section view, and (iii) expanded view. The inset in (iii) is a zoom-in HM, which is cut by a quarter (c) SEM image of the EVA film with HMs. (d) Digital image of the HM-SPS strip. (e) Surface potential (Os) decay of the FEP electret film

In 2017, Nizami et al. [6] presented a system called SimNewB. SimNewB consists of a pressure-sensitive mat (PSM) that acquires data from neonatal patients to estimate the respiration rate. The results in this research indicate that the frequency domain approach is superior to the time domain approach. In the same type of application, neonatal respiratory monitoring, Bekele et al. [7] presented in 2018 an approach to monitoring patients in the neonatal intensive care unit (NICU). They used a pressure sensor a three methods for respiratory rate estimation: Dyadic Wavelet Transforms (DWT), time domain peak searching without DWT, and a frequency based method. In this research study as the actual patient was consistently moving (e.g. stretching, yawning, adjusting) large error was produced in the frequency-based method and in the time-varying RR observation. This can also be noted that the mean absolute error is being calculated by comparing the output from the RR estimation method with the gold standard RR, as determined from the patient monitor data. Fig. 7 shows the SimNewB system proposed in [7]

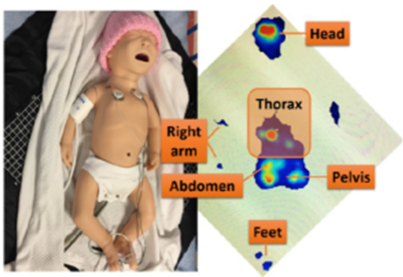

Fig. 7. SimNewB lying supine on XSensor PSM over a crib mattress, with the pressure image shown on the right [7]

In 2020, Valero et al. [8] presented an approach called R-Mon. R-Mon is an architecture framework consisting on a pressure sensor, a raspbarry Pi, and a digitizer. R-Mon

captures the pressure signal of a person on the bed and estimates the respiration using autocorrelation functions and envelope and peak estimation. The approach is based mostly on time-domain analysis. The system also provides real-time visualization of the respiratory data and is envisioned to be used to help practitioners in planning healthcare resources during pandemics, and controlling and monitoring patients in rural and unserved areas. [8]

4) Sleep Monitoring Sensors: Sleep is one of the most important factors in the neural development of preterm infants, suggesting that its continuous monitoring could provide an indicator of such development over time.

In 2016, Rotariu et al. [9] presented a wearable prototype sensor with an user-friendly Graphical User Interface (GUI) to estimate the respiratory frequency and apnea episodes of patients. The device architecture includes a) piezoelectric thoracic belt attached on the chest with Pneumotrace II respiration transducer b) a custom developed module for signal conditioning containing low noise operational amplifiers; c) data acquisition module - Arduino Leonardo board based on ATMega32 microcontroller with A/D convertors d) Tablet PC running Windows 10 OS (Allview Impera). The interface has been developed using LabWindows/CVI to display the temporal waveform of respiratory frequency and to activate the alerts in the interface when a sleep apnea episode is detected for the selected patient. The monitoring device is suitable for continuous long-time monitoring of respiration and detection of apnea episodes. The approach could be an alternative to medical supervision in healthcare institutions, with a detection degree of accuracy similar to the commercially available devices. Fig. 8 illustrate the framework presented in [9].

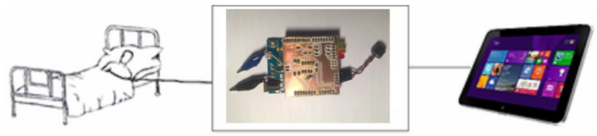

Fig. 8. Continuous respiratory monitoring device with Arduino Leonardo microcontroller board – overall architecture [9]

Because movement counting is important in sleep monitoring to determine the restlessness of the body, in 2018, Soleimani et al [10] present a pressure sensor mat (PSM) to detect movements in a bed. The authors use a method called Maximum Distance Occupancy to detected the movements. Despite the beneficial aspects of the maximum distance occupancy detection method, it is very costly and time-consuming, because complexity is greatly increased to build the detection system of this algorithm. The processing time for occupancy detection was found to be high on the computer system with an Intel Core i7 2.93 GHz CPU, 8 GB RAM, and Windows 7 Professional SP1 64-bit, so maximum distance occupancy detection may not be practical in real-time processing.

In the same area, Alaziz et al. [11] present an approach to detect movements for sleep analysis using a pressure sensor prototype. The approach uses a simple threshold-based algorithm for in-bed body movement detection using low-end load cell sensors. The system is called MotionScale, and its components include load cell sensors, a differential amplifier, a power control circuit, and a wireless communication unit (A-to-D convertor). The software components involve interpolation, normalization, filtration, feature extraction, and detection and classification can lead packet loss interference. The ability to accurately monitor a person's body movement during sleep can enable an array of applications, ranging from sleep monitoring to abnormal body movements detection. A number of bed-mounted sensing systems have been proposed for this purpose, including pressure sensors, temperature sensors, ultrasound sensors, load cell sensors, and custom-made sensors. Fig. 9 shows an overview of the MotionScale.

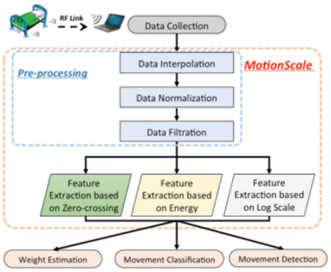

Fig. 9. Overview of MotionScale System[11]

B. Machine Learning Techniques

Even though the majority of the approaches for respiration, heart, and sleep monitoring in contact sensors are based on pure signal processing techniques, there is an increasing number of approaches that use machine learning techniques to produce the same estimation.

Park et al. [12] presented the use of vibration sensors for heart and respiration estimation using deep learning and neural networks algorithms. The approach is called HeartQuake which is a low-cost, accurate, non-intrusive, geophone-based sensing system for extracting accurate electrocardiogram (ECG) patterns using heartbeat vibrations that penetrate through a bed mattress. The filtered vibration signal to eliminate noise introduced in the signal collection process is used as an input to a bi-directional long short-term memory (Bi-LSTM) based deep learning model to generate corresponding ECG signals.

Inan et al. [13] presented an approach for estimating the cardiac function using a graph mining algorithm. The approach is based on a noninvasive wearable device capable of recording electrical and mechanical aspects of cardiac function and graph mining techniques analyzing the cardiac response to submaximal exercise to identify compensated and decompensated heart failure (HF) states and to track the clinical course of the patients. The graph analytic technique works based on multiple extracted features from the seismocardiogram (SCG) signal. This algorithm can also potentially be implemented in a real-time monitoring system to evaluate the status of patients with

HF because its time complexity is low. Fig. 10 illustrates the approach presented in [13].

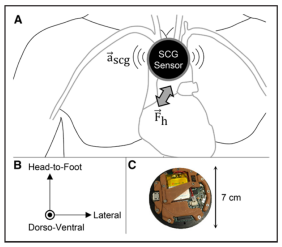

Fig. 10. SCG and ECG sensing patch [13]. A) The SCG signal represents the vibrations of the chest wall in response to the movement of the heart and blood with each heartbeat. SCG is measured using a miniature, 3-axis accelerometer, typically positioned on the midsternum. B) The SCG signal consists of vibrations in 3 axes. C) A custom, small, wearable patch for measuring SCG and ECG signals was designed. The patch is placed on the chest using 3 gel adhesive electrodes and stores data locally on a micro secure digital card.

Huang et al. [14] presented a wearable sensor for respiration and heart monitoring using Random Forest Regression(RFR), Gradient Boosting Regression(GBR), and Adaptive Boosting Regression(ABR) algorithms. A pressure-sensing array with differ4ent elements was utilized for continuous blood pulse-wave monitoring. Each element comprises polydimethylsiloxane (PDMS), which is a conductive polymer film and an inter-digital electrode pair on a flexible substrate. In order to remove noise and artifacts from the raw pulse-wave signals, a Hilbert–Huang transform (HHT) method was employed to process the data. The measured pulse wave signals corresponded to the simultaneously measured systolic blood pressure (SBP) and diastolic blood pressure (DBP) of the patient.

Chen et al. [15] presented a wearable sensor for respiratory monitoring using a random forest classifier and decision trees implemented in Python. The wireless wearable sensor is composed of an "emitter" to radiate ultrasound and a "receiver" to receive the distance-elapsed attenuated ultrasound. It also has two sensors to monitor the chest and abdominal respiration within quiet breathing. Characterized by its ability to reduce overfitting problems and rank the importance of variables in classification naturally, the random forest classifier has been widely used in machine-learning applications. Even though the generic classifier displayed low accuracy in predicting the posture of the subjects, this study showed consistent accuracy in monitoring the respiratory behavior of the subjects for managing respiratory diseases.

Raj et al. [16] presented a 3-axis accelerometer for monitoring respiration using a Linear Regression algorithm. A gateway device was also used for cloud connectivity which is typically a smart phone/tablet using Bluetooth. One of the major problem faced in the clinical environment was device misplacement, primarily because of the small form factor. Accuracy is limited in range, movement of the subject and presence of objects or people nearby. Fig. 11 shows the hardware block diagram and PCB design presented in [16].

Table I and table II shows a summary of the diverse contact techniques for remote monitoring of respiration, heart and sleep.

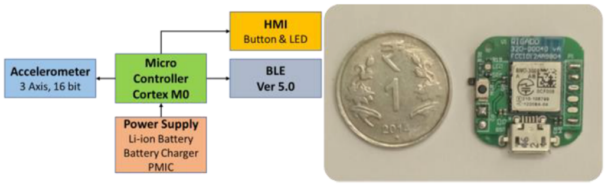

Fig. 11. Hardware block diagram and PCB design[16]

IV. Contactless Sensors

We also surveyed papers that utilize contactless or non-contact sensor technologies. Fig. 12 shows the graphical presentation of the different surveyed sensors.

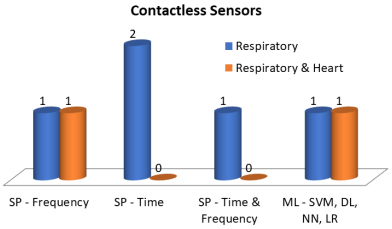

Fig. 12. Different type, application, technique used in Contactless Sensors.

Shahid et al. [17] presented respiratory monitoring sensors in 2020 that uses machine learning techniques for the diagnosis, screening, tracking, and prediction of COVID-19. In their review many ML techniques were used (Please refer to Table I to VI in the paper [17]). The techniques include: Support Vector Machine (SVM), Deep Learning, AI, Linear Regression (LR), netMHC & netMHCpan, and Neural Networks (NN). One of the main challenges that researchers faced when diagnosing using ML techniques was the lack of relevant data that are made accessible to the public. Lack of data meant researchers had to use techniques like data augmentation, transfer learning, and fine-tuning models to improve prediction accuracy. Though these methods worked well in some cases, more data would make these models more robust [17].

Kalkan et al. [18] presented a respiratory monitoring system using time domain analysis. The sensor is a rapid humidity (RH) based on a low deposition-temperature film, which demonstrates an ultrasensitive, ultrarapid-response ionic-type sensor. The unique of this sensor material is the key to its high sensitivity. With the unique situation of voids interconnected and perpendicularly oriented to an open film/ambient interface, the water vapor can diffuse in and out of the sensor rapidly and uniformly. The ability to control film thickness (i.e., diffusion length) with deposition time also enables minimizing response time with ultrathin films. A signal rise/fall of more than 5 orders of magnitude occurs in about 0.2 s or less, pointing out the strong and very rapid response to the 20%–90% respiration rate variation making the sensor suitable to capture small variations in breath.

In 2021, Li et al. [19] presented a respiratory monitoring approach for measuring shortness of breath with WiFi signals.

The approach is called Wi-COVID. Wi-COVID is based on frequency spectrum analysis of the WiFi signals. The prototype uses a WiFi sensing receiver and a Raspberry Pi, which provides an easy installation and a cheap alternative for COVID-19 patients and practitioners. To make Wi-COVID economically attractive, instead of complicated devices or the use of laptops to capture the signals, the use of a simple Raspberry Pi will act as access point. The results are transmitted in real-time to a Cloud server where we configure a visualization tool that allows the medical practitioner to monitor the patient in real-time and verify current and historical respiration values. Fig. 13 present the experimental setup of the approach in [19].

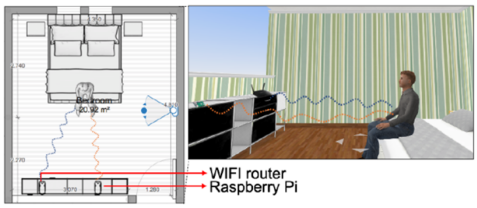

Fig. 13. Wi-COVID experiment setup for COVID-19 patients[19]

Table III shows a summary of the different contactless approach surveyed in this paper.

V. Research Trends

As can be seen during this review paper, the majority of the application for respiration, heart, and sleep monitoring are based on signal processing techniques. However, there is increasing popularity of machine learning techniques for this purpose. We believe there are multiple research trends that can be explored in remote healthcare monitoring. (1) Instead of manually collecting the data from the sensors or perform off-line estimations, we believe that new approaches will consider exploiting the advantages of current sensors and networks. This kind of approach will be the base for future work in which multiple sensors can independently interact with each other to perform estimations. (2) Incorporating physical phenomenon knowledge to sensing will increase the accuracy of multiple applications such as vital sign monitoring. Also, self-configured sensing system will provide a way to minimize human intervention and training data. Deep learning may bring more opportunities for vibration-based systems, which simplifies the deployment and makes the systems configuration-free. (3) While signal processing is fast and computer-economic, the use of more advanced machine learning techniques based on the signal processing features may provide useful information to infer the health status of the subject. We envision that machine learning will be applied as a routine in future health monitoring.

VI. Conclusion

Currently, one of the major complications of COVID-19 disease is the rapid and dangerous respiration and pulmonary function deterioration that can lead to critical conditions and death. This pandemic has placed new demands on the health systems world, asking for a novel, rapid and secure way to monitor patients in order to detect and quickly report patient's symptoms to the healthcare provider, even if they are not in the hospital. While tremendous efforts have been done to develop technologies for in-home monitoring, there are still gaps that need to be covered. In this paper, we surveyed some advances on in-home monitoring for respiration, heart and sleep monitoring. We studied the types of sensors used and the different data analysis techniques available to understand and process remote and stream data. We expect this survey enables researcher to find new trends and gaps for improving the current state-of-the-art of in-home healthcare monitoring.

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TABLE I
CONTACT APPLICATIONS FOR HEALTH MONITORING (PART I)

Paper	Sensor	Monitoring application	Data analysis technique	Evaluation	Year
[1]	Wearable	Respiration	• Frequency & time domain analysis with spirometer	N/A	2009
[2]	Wearable	Respiration	• Frequency – Bland-Altman Diagram	N/A	2018
[20]	Wearable	Respiration	• Frequency domain analysis by microcontroller configuration	Error 6.65%	2019
[21]	Wearable	Respiration	• Frequency Domain Analysis / Fiber Bragg Gratings (FBG) sensor	N/A	2020
[22]	Wearable	Respiration	• Respiration modulation with frequency analysis	N/A	2019
[23]	Wearable	Respiration	• Time domain analysis	N/A	2017
[24]	Wearable	Respiration and heart	• Frequency domain analysis / FlexPock Magnetic Induction Device	N/A	2015
[3]	Wearable	Respiration and heart	• Time Analysis based on response times.	N/A	2017
[25]	Wearable	Respiration and heart	• Time domain analysis / Arduino LilyPad	XX	2018
[4]	Wearable - Body-Contact	Respiration and heart	• High-pass filters and time-frequency analysis	N/A	2019
[5]	Non-wearable - Body-Contact	Respiration and heart	• Frequency-filtering method	N/A	2018
[26]	Non-wearable - Body-Contact	Respiration	• Fuzzy logic	Mean error 6.17%	2008
[27]	Non-wearable - Body-Contact	Respiration	• Digital processing algorithm / Magnetic Resonance Imaging (MRI)	N/A	2013
[28]	Non-wearable - Body-Contact	Respiration	• Body pass localization / Peak detection algorithm	Error 3.3%	2014
[6]	Non-wearable - Body-Contact	Respiration	• Frequency domain analysis of mean-shifted	N/A	2017
[29]	Non-wearable - Body-Contact	Respiration	• Normalization, Frequency domain analysis	Error $\sim$5 bpm	2018
[7]	Non-wearable - Body-Contact	Respiration	• High pass filter/ DWT analysis / Frequency-based method	Error 4.51 bpm	2018
[8]	Non-wearable - Body-Contact	Respiration	• Band-pass filters / Signal Double-Envelope Calculation	N/A	2020

TABLE II
CONTACT APPLICATIONS FOR HEALTH MONITORING (PART II)

Paper	Sensor	Monitoring application	Data analysis technique	Evaluation	Year
[30]	Wearable	Sleep	• Time-frequency analysis	N/A	2017
[9]	Wearable	Sleep	• Band-pass filter and Dual threshold peak detection algorithm	Error 5%	2016
[31]	Wearable	Sleep	• Time domain analysis method	Error $\sim$ 2%	2017
[10]	Wearable	Sleep	• Movement detection algorithm based on threshold	N/A	2018
[11]	Wearable	Sleep	• Motion's scale algorithm	Error 6.3%	2016
[12]	Non-wearable - Body-Contact	Respiration and heart	• Deep Learning and Neural Network	Error 6.66 msec	2020
[32]	Wearable	Respiration and heart	• Approaches with time frequency analysis and machine learning	N/A	2020
[13]	Wearable	Respiration and heart	• Graph mining algorithm technique	N/A	2018
[33]	Wearable	Respiration and heart	• Logistic & Linear Regression	N/A	2018
[14]	Wearable	Respiration and heart	• Random Forest Regression(RFR) / Gradient Boosting Regression(GBR) / Adaptive Boosting Regression(ABR)	BP range 98-138 mmHg	2019
[15]	Wearable	Respiration	• Random Forest Regression(RFR) / Decision Trees	N/A	2021
[16]	Wearable	Respiration	• Linear Regression	Error RR satisfactory in minimal movements	2018
[34]	Non-wearable - Body-Contact	Respiration	• Linear Regression	N/A	2017

TABLE III
CONTACTLESS APPLICATIONS FOR HEALTH MONITORING

Paper	Sensor	Monitoring application	Data analysis technique	Evaluation	Year
[17]	Contactless	Respiration	• Neural Networks (NN), Artificial Neural Networks (ANN) and Naive Bayes, Support Vector Machines (SV), Deep Learning	N/A	2020
[35]	Contactless	Respiration and heart	• Linear Regression	Error 3.2%	2014
[18]	Contactless	Respiration	• Time-domain analysis	Error 0.2 s	2004
[36]	Contactless	Respiration	• Time domain analysis	Error 1.59 bpm	2019
[19]	Contactless - WiFi	Respiration	• High-resolution spectrum analysis	N/A	2020
[37]	Contactless	Respiration	• Frequency domain analysis	N/A	2014
[38]	Contactless	Respiration and heart	• Normalization and multichannel frequency analysis	N/A	2008

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