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Artificial intelligence-powered remote monitoring of patients with chronic obstructive pulmonary disease

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Chronic obstructive pulmonary disease (COPD) has recently become the third leading cause of death following heart disease and cancer. Acute exacerbation of COPD (AECOPD) can be prevented by early detection of deterioration and timely treatment, which can effectively lower the severity of exacerbation and prevent hospitalization.[1]

Remote patient monitoring (RPM) is essential for inpatient and outpatient care settings for COPD [Supplementary Figure 1, http://links.lww.com/CM9/A562]. Artificial intelligence (AI) technologies implemented in RPM settings can help anticipate exacerbations and allow early therapeutic intervention.[2]

AI-enabled Technologies for Remote Monitoring of COPD Patients

Globally, healthcare policies encourage telehealth-care-supported self-management of long-term conditions.[3] Recent advances in sensors, miniaturized processors, and wireless data transmission technologies have allowed the assessment of environmental, physical, and physiological data or signals in different environments without the restriction of patient activity. Meanwhile, AI empowers sensors to achieve a better understanding of patient conditions. Here, we present both body-worn and contactless sensors for RPM and related AI technologies.

Physical activity monitoring

Today, many intelligent sensing technologies are capable of continuously tracking body motions and detecting various activities of daily living (ADL), such as sitting, walking, and sleeping. Being able to measure physical activity levels can potentially help identify the disease stage at which physical activity becomes limited, understand the relationship between physical activity and clinical characteristics, and ultimately drive innovative clinical procedures to predict patient risk and provide more effective interventions on time.[4]

One critical paradigm for RPM is the monitoring of physical activity. An accelerometer[5] is a widely used sensor for monitoring patients' vigorous activities, used in almost every consumer wearable device (ie, wrist band, smartwatches) and smartphones. The accelerometer is a small-scale micro-electro-mechanical system device and a *de facto* standard for physical activity monitoring. A study presents an early RPM system with a small-waist-worn unit that can process and classify the collected physical activity data.[6] Another study[7] demonstrated the feasibility of inferring physical activities by combining sensors available on a smartphone (accelerometer, gyroscope, and gravity sensor) using machine-learning algorithms. It involves collecting a relatively large dataset for training the classifier, extracting features from the data, and using a machine-learning algorithm to classify the activities into the following categories: walking, running, sitting, standing, climbing stairs, and going downstairs. These experiments show an average accuracy of above 86%.

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Using camera-based sensors with action recognition techniques[8] is an attractive alternative solution for remote tracking of COPD patients' ADL because of their unobtrusive nature. Camera-based sensors send live ADL video streams to processors using algorithms for classification. A typical deep learning algorithm for this case is called a convolutional neural network. With proper training and model tuning, the model can achieve an accuracy of approximately 80%. Continuous detection of ADL can also help monitor other diseases that affect ADL, including Alzheimer's disease and Parkinson's disease.

Audio symptoms monitoring

Recent studies have provided several efficient solutions for audio symptoms monitoring. For example, a recent work[9] presented a real-time low-power wireless respiratory monitoring system with cough detection to measure coughing frequency. This system uses a microphone and an AI-based audio analysis algorithm to perform automated cough detection. The system is in the form of an on-body sensor patch and achieves good results. Another study[10] presented four audio-only cough monitors using an artificial neural network to detect cough after signal processing.

A few studies[11] on wheeze sound analysis have demonstrated that wheeze signals have sufficient information for patient categorization according to the severity of COPD. Various machine learning algorithms such as support vector machine have been implemented to build the classifier, which achieved an average sensitivity of above 90% and an average accuracy of above 85%.

Audio-based cough detection systems powered by AI algorithms[12] are now increasingly applied in RPM. These techniques are also becoming increasingly important in the study of other audio symptoms caused by COPD.

Environmental sensors

There are various available air quality sensors. The World Air Quality Index team conducted a thorough evaluation and comparison of different air quality sensors, most of which are based on the same working principle: an infrared light source (laser) with a photodetector placed on the opposite side. The detector measures the light scattered by the dust or haze particles in the air chamber. Most sensors on the market can measure dust larger than 1 μm, and provide particulate matter density readings.

A low-cost sensor called DHT22 is widely used to monitor temperature and humidity.[13] DHT22 uses a capacitive humidity sensor and a thermistor to measure the surrounding air and generate a digital signal on the data pin. It can achieve 0% to 100% humidity readings with 2% to 5% precision and ±0.5°C resolution for the temperature range from –40 to 80°C.

Pulse oximetry

A wearable finger pulse oximeter was used for pulse oximetry measurement.[14] It is a thin clip-like device placed on a thin body part, such as the finger, ear lobe, or across the foot for infants.

The basic principle is based on the change in the amount of light absorbed during an arterial pulse.[15] Two light sources located in the visible red-light spectrum (660 nm) and infrared spectrum (940 nm) alternately illuminate the area under test. The amount of light absorbed during these pulsations is related to the oxygen content in blood. The microprocessor embedded in the system calculates the ratio of these two spectra absorbed, and compares the results with the saturation value table stored in the memory to obtain the pulse oximetry.

Respiratory rate

There are many sensors available on the market for respiratory rate measurement. One such device is an electrocardiogram (ECG) sensor. Many studies[16] have shown that the respiratory rate, and even the respiratory wave morphology, can be approximated by ECG-derived respiration. This method detects the frequency by measuring the size of R-wave in QRS signals. The preliminary study showed a precision of over 97%.

Another more appealing approach[17] is contactless sensing using Doppler radar, which transmits radio waves and senses the signals reflected from the chest. The chest wall movement induced by the respiratory system is remotely monitored and captured as a waveform signal. A time-domain autocorrelation model is then applied to process the radar signals for a rapid and stable respiratory rate estimation.

Predicting COPD Exacerbation with RPM

It is worth noting that most of the COPD exacerbations symptoms can be detected remotely by the sensing technologies described previously, such as using respiratory sensors to capture vital signs[18,19] and pulse oximetry[20] wearable/non-wearable devices for monitoring physical activitiy. Such technologies have great potential for the proactive management of patients at risk by providing a data foundation for monitoring the flare-ups of physiological measures and symptoms. A previous study[21] described a COPD exacerbation prediction method using respiratory signals. This method uses a machine-learning technique called decision tree forest to predict early AECOPD. The detection accuracy was 78.0% and 75.8% of the detected episodes and reported exacerbations, respectively.

Prospect

AI technology has rapidly advanced in recent years with several promising applications in COPD. For example, AI-assisted computed tomography (CT) and other imaging diagnoses are helpful for an accurate diagnosis of COPD. The use of CT scans at different levels can measure the airway diameter and tube wall thickness, which can help accurately identify the stage and clarify the progression of COPD. The various wearable and contactless devices discussed in the previous sections will be further improved, enabling more effective RPM in practice.

AI is expected to have a significant impact on the overall COPD remote monitoring market. In the future, COPD patients will be able to enjoy more hospital-grade medical care services in the comfort of their homes or outpatient facilities.

Patients with complex and urgent hospitalization needs will receive more effective care in smart hospitals equipped with intelligent monitoring devices. Assisted by AI-empowered tools, caregivers can better plan and coordinate care efforts according to patients' individual demands, leading to better outcomes at lower costs.

Conclusion

RPM is crucial in patients with COPD. With the development of sensors and AI technology, RPM can effectively reduce economic and medical burdens. With AI technology, the remote monitoring system integrates the data obtained from various medical devices and sensors and analyzes them to understand the conditions, determine trends, and generate early warning signals to help the medical team monitor and treat patients more effectively.

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Conflicts of interest

None.

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