Research And Application of Wearable Sensor Systems Based on Daily Physical Indicator Collection and Analysis in Elderly Health Assurance

Xuezhi Xu

School of Automation, CENTRAL SOUTH UNIVERSITY, Changsha, China

8207230567@csu.edu.cn

Abstract. In recent years, the popularity of smartphones and smartwatches, along with advancements in IoT and artificial intelligence (AI) technologies, has driven the widespread adoption of wearable sensors. Societally, the aging population has intensified the complexities of chronic diseases, home safety, and mental health issues. Wearable sensors enable home-based health monitoring and alleviate pressure on medical resources. This paper focuses on three sensing technologies: multimodal flexible sensor patches, graphene patches, and spectroscopic sensors. Multimodal flexible sensor patches monitor vital signs such as electrocardiograms (ECG), respiration, and skin temperature; graphene patches detect pulse waves via high-sensitivity pressure sensors to assess cardiovascular health; and spectroscopic sensors utilize optical signals for health monitoring and disease diagnosis. The paper also discusses data processing techniques, highlighting challenges such as sensor accuracy, stability, response time, autonomy, and follow-up response capabilities. Additionally, it explores the future feasibility of hybrid sensor systems combining wearable health sensors with robotics, AI, and smart home technologies.

Keywords: Wearable sensors, elderly health, home-based healthcare, health monitoring.

1. Introduction

In recent years, with the emergence of smartphones and smartwatches, wearable sensors that can be linked to them have become increasingly popular, prompting their continuous development. Meanwhile, the rapid development of technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) has provided strong support for the widespread application and enhanced functionality of wearable sensors. Thanks to their ability to continuously screen biomarkers dispersed in bioanalysates and monitor human physiological indicators, wearable sensors have great potential in the field of monitoring human health.

Nowadays in our society , the problem of population ageing is becoming more and more prominent. On an individual level, older people have limited knowledge of chronic diseases and often ignore early symptoms, leading to aggravation of their conditions. Secondly, in terms of home life safety, the elderly lack sufficient awareness of potential home risks, such as falls. Finally, loneliness is prevalent among the elderly, who often lack social support and mental health issues are easily overlooked. In society, the use of wearable sensors can alleviate some of the pressure brought about by the strain on medical resources and enable home treatment.

Universal smart wearable devices can transmit the health data of older persons to medical institutions or family doctors in real time, which, on the one hand, enables healthcare professionals to respond quickly to emergencies, provide timely medical interventions for older persons and reduce health risks. On the other hand, doctors can have a long-term understanding of the health status of older persons, identify potential health risks and formulate targeted prevention and treatment programmes.

In recent years, researchers have improved various sensors for monitoring human physiological signals to different degrees: Yang Han et al. designed and developed graphene flexible pressure sensors with multilevel branching microstructures for monitoring pulse waves. Pulse wave is an important source of information for assessing cardiovascular health, but it is a non-smooth and weak signal, which requires high sensitivity and stability at the detection end, and they significantly

improved its sensing performance for pulse wave by using the modified HB structure [1]. Matsumura G, Honda S et al. introduced a multimodal healthcare sensor patch system for real-time monitoring of multiple vital signals including skin temperature, ECG, respiration, skin humidity and activity, and providing real-time feedback via a smartphone application [2]. Xiangnan Li et al. developed a sensor patch for Joule-heated sweating and comfortable biofluid monitoring. This biosensor induces profuse sweating in volunteers in as little as 5 minutes with mild thermal stimulation, allowing for real-time assessment of metabolic syndrome risk, including Na +, K +, pH, and uric acid levels [3]. Xiaokang Hu, Yangyang Chen et al. created a wearable regenerative sensing system capable of accurately detecting low concentrations of biomarkers related to specific health conditions in the form of a fabric for the detection of cortisol in concentrations ranging from 1 pM to 10 μM. The sensing system can reproducibly sense cortisol in sweat more than 100 times without any degradation in sensing capability, overcoming the limitations of existing sweat cortisol monitoring systems [4].

The next section highlights the modified HB structure, patch resistance sensing and spectral sensing techniques used in graphene pressure sensors, as well as two data processing and output methods.

2. Key Technologies

2.1. Introduction to the working principle of the sensor

Taking the smart wearable biosensor as an example (Fig. 1), its main body consists of including microfluidic sampler, multiplexed biosensing and data acquisition system for acquisition, identification and transmission respectively. For materials, flexible substrates and body accessories are chosen to enhance wearability, portability and reliability.

Figure 2 shows the mechanism of the biosensor: from left to right, human metabolites react chemically in the biosensing element and generate signals that are sent to the transducer, which is then converted into electrical signals that are sent to the microprocessor unit, and finally converted into electrical signals that are sent to the display device, such as a mobile phone, to complete the data acquisition through the microelectronic components.



Figure 1. Basic structure of intelligent wearable sensors(Picture credit: Original)

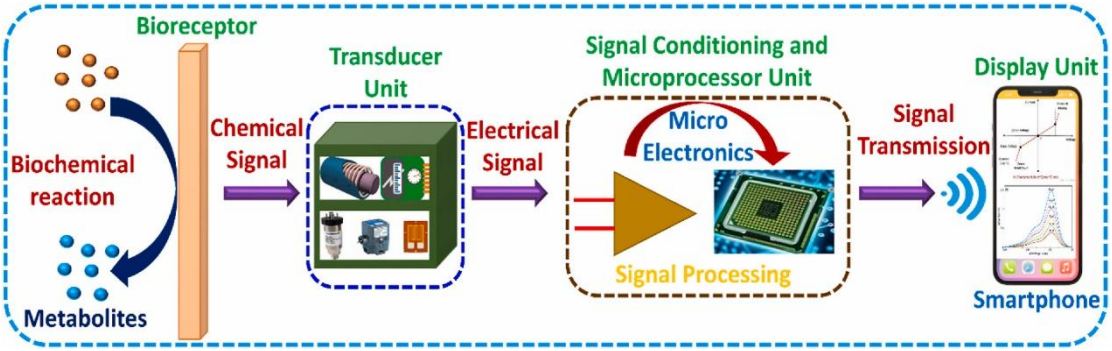


Figure 2. A schematic representation of components of a smart wearable biosensor [5]

2.2. Sensing Technologies

2.2.1 Multimodal Flexible Sensor Patches

The first technology presented is a multimodal flexible sensor patch prepared from a flexible film that can be adhered to human skin [2]. Figure 3 illustrates the basic structure of a multimodal flexible sensor, including temperature sensor, ECG sensor,temperature sensor,strain sensor, humidity sensor, respiration sensor and circuit. The multimodal flexible sensor patch monitors cardiac activity through electrocardiography, respiration, skin temperature and humidity due to sweating, and an accelerometer (ACC) is used to monitor physical activity and posture. The data is then transmitted wirelessly via data processing circuitry on a printed circuit board and a low-power Bluetooth (BLE) module. The signal is finally converted analogue to digital and transmitted to the smartphone via BLE.

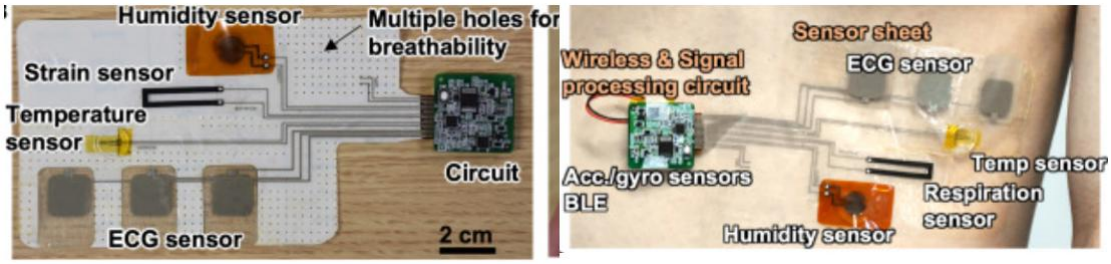


Figure 3. Structure of wearable sensor patch and sensor characteristics [2]

The response and recovery time of the temperature, humidity and strain sensors were tested by touching the sensor surface with a finger and the following results were obtained (Table 1). In particular, the thermal response is relatively slow because the sensor reduces the effect of ambient temperature on the measurement results by carrying a PDMS overlay. Whereas, the humidity and strain sensor data are within the acceptable range. However, under tensile strain applications, the sensor output gradually decreases and takes time to stabilise.

Table 1. Response and recovery times for different sensors

Sensor type	Temp	Humidity	Strain
Response time[s]	20	0.04	0.2
Recovery time[s]	260	14	0.2

Further tests were carried out with the sensor worn by the experimenter outdoors in direct sunlight (Wet Bulb Black Globe Temperature (WBGT) between 29.1°C and 30.4°C) and in an air-conditioned room with temperatures between 21.3°C and 23.1°C. The following data were obtained (Temperatures were also measured from the axilla using a commercial thermometer for comparison). As shown in figure 4, the temperature measured by the patch sensor deviates from the thermometer but shows a similar trend. This suggests that with further data analysis and algorithm development, skin temperature can be used to monitor body temperature trends. The heart rate data (HR) was then extracted from the RR interval (RRI) of the ECG sensor and the respiratory rate data

was extracted from the peak detection of the strain sensor output, respectively. Finally the humidity sensor measures changes in humidity to monitor sweating.

Overall, these sensors are not very sensitive compared to other sensors, but they show high stability in long-term measurements. More importantly, the sensors enable flexible integration of sensors with wireless monitoring, allowing multiple vital signs to be monitored simultaneously in real time. It should be noted, however, that the resistive sensor patch needs to be clinically tested with commercial medical tools to obtain a complete dataset including respiratory rate, skin temperature, and skin humidity.

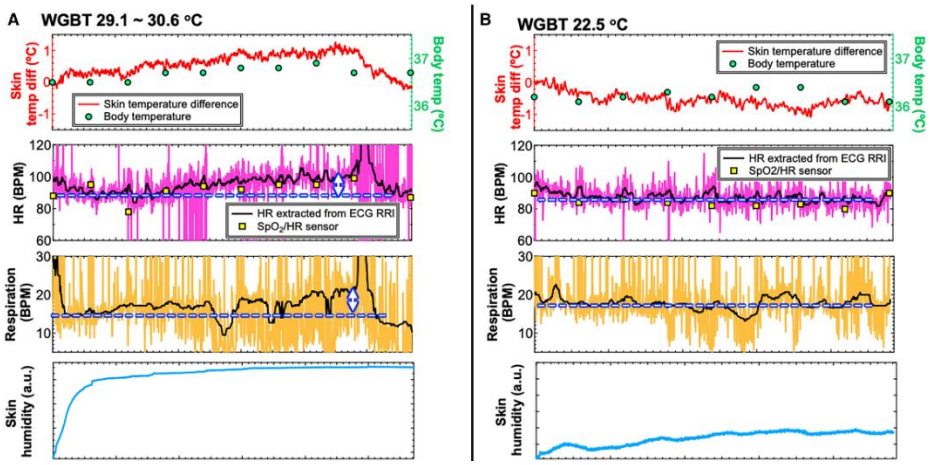


Figure 4. Real-time vital monitoring measured from volunteer at ~30°C and 22.5°C [2]

2.2.2 Graphene Patches

Quantitative analysis of pulse wave can obtain cardiovascular health-related information, such as arterial blood pressure, blood flow rate, heart rate, vascular stiffness, cardiac output, etc., which is a rapid and non-invasive method for diagnosis of cardiovascular diseases. Commonly used pulse wave detection techniques, such as optical sensing, have distortion and limited penetration depth of the acquired signal; ultrasonic sensors and impedance measurement techniques have complex post-processing circuits; and pressure sensing technology can better restore the original waveform of the pulse wave, and at the same time, it has the advantages of low cost of preparation and convenient signal acquisition. Therefore, the realisation of flexible pressure sensors with high sensitivity has become a research hotspot in recent years.

Yang Han, Wang Cerihong, Zhong Hao et al. constructed a graphene HB structure flexible pressure sensor with pulse wave measurement system [1].The HB structure can improve the performance of the device through the template method and the strategy of multilayer stacking. Figure 5 shows the cross-section of the HB structure and the stress distribution of the hemisphere under applied pressure.

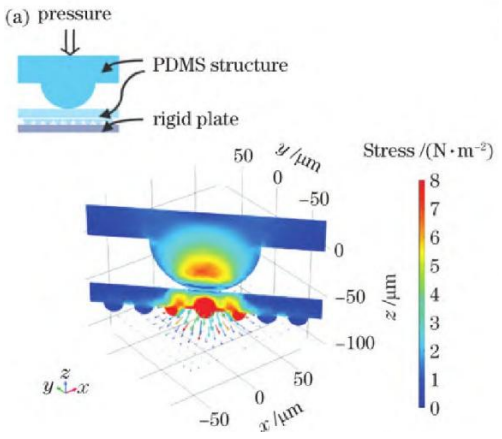


Figure 5. HB-structure cross-section and stress distribution [1]

When subjected to pressure, the HB structure produces two kinds of changes: firstly, it mobilises the deformation of the elastic structure in an orderly manner to increase the number of deformable microstructures in the secondary structure layer and realise self-compensation of the deformation of the secondary microstructures; and secondly, it increases the contact area between the microstructures that are originally involved in the deformation and the bottom surface. This structure synchronously increases the resistance change ability of the sensor from two aspects, so that the pressure sensor with HB structure shows higher sensitivity and larger linear range.

The application of the HB structure not only enables the sensor to combine high sensitivity with a wide pressure detection range, but also has the self-compensating effect of saturating the deformation of the microstructures by integrating multiple elastic layers stacked on top of each other, which results in a reduction of the modulus of elasticity.

2.3. Data Transmission

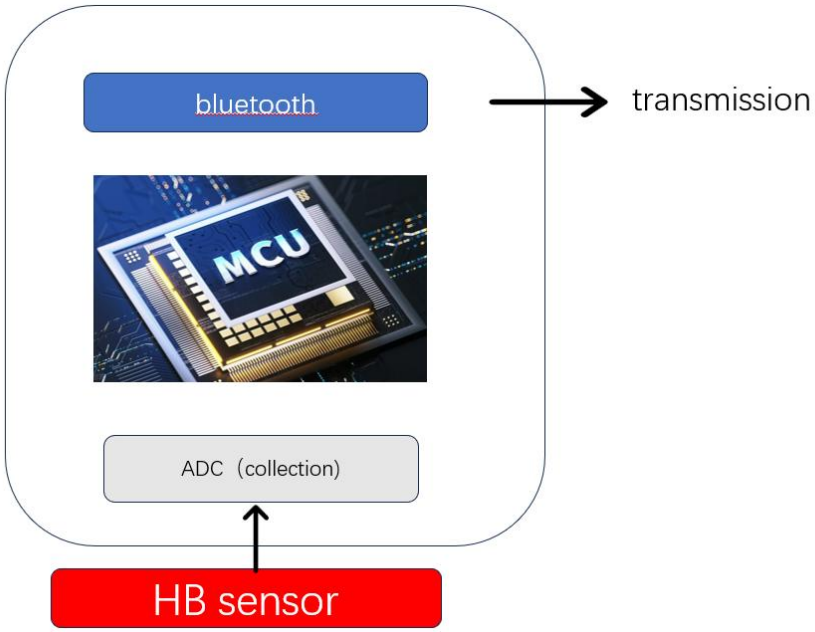


Figure 6. Pressure sensor data acquisition and transmission process(Picture credit: Original)

The main function of the control circuit of the pulse wave measurement system is to realise the acquisition of electrical signals from the sensors and wireless communication, and the system framework is shown in Figure 6.

Firstly, the HB pressure sensor data are collected and converted into digital signals by the analogue to digital converter (ADC); the ADC transmits the conversion results to the microcontroller (Microcontroller unit, MPU) through the serial peripheral interface (SPI) bus. The ADC transmits the conversion result to the microcontroller unit (MCU) through the Serial peripheral interface (SPI) bus; the MCU processes the digital signals and sends the pressure sensor data to the Bluetooth module through the asynchronous serial interface; finally, the Bluetooth module acts as a relay station to transmit the data to the upper computer, which achieves the functions of data display, AI analysis and result report.

2.4. Data Processing and Output

This section focuses on a class of perceptual cuffless blood pressure testing models. The model relies on a flexible pressure sensor to capture a single point pulse wave from the radial artery, and uses a deep learning model based on Transformer for blood pressure classification and a theoretical model based on the M-K equation for blood pressure prediction.

Figure 7 shows the MK equation, which demonstrates the relationship between arterial blood pressure and pulse wave data [1]. The equation states that blood pressure is related to the time

interval between the main wave and the tidal wave in the pulse wave, the amplitude ratio of the P1 peak to the P2 peak in the pulse wave, and the heart rate. However, the disadvantage of the MK equation is that in the original pulse wave signal, there is other information related to physiological features that have not yet been extracted and utilised, and such does affect the accuracy of blood pressure measurement.

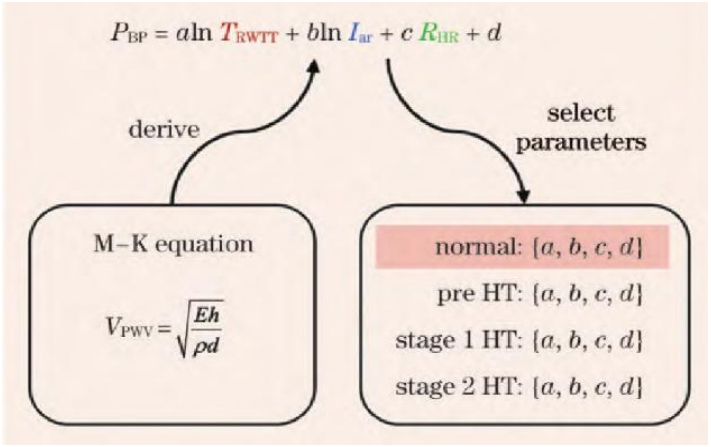


Figure 7. Pressure sensor data acquisition and transmission process [1]

Therefore, the cascade learning idea is introduced into the blood pressure detection model obtained based on M-K equation and proposed (A class-aware model based on Moens-Korteweg equation and Transformers,CAMKformer). The flow of the model for monitoring blood pressure is shown in Figure 8

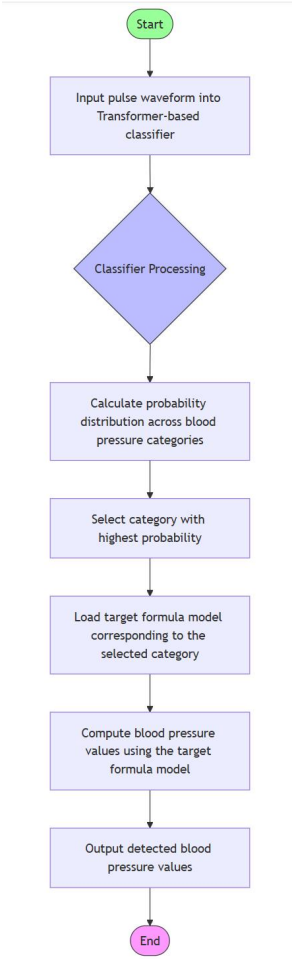


Figure 8. Blood Pressure Testing Procedure(Picture credit: Original)

Compared with traditional machine learning algorithms that only use M-K equations or tree models, the CAMKformer model adds a stage of blood pressure classification of the collected pulse waves before implementing cuffless blood pressure detection. The CAMKformer model also takes full advantage of the complex feature extraction capability of the deep learning model and the strong interpretability and robustness of the theoretical model to achieve the fusion of multimodal pulse-related information, which significantly reduces the error of cuffless blood pressure detection.

3. Applications

3.1. Fall Detection Systems

Purwar A summarised the threshold based wearable fall detection system and machine learning based wearable system for fall detection [6]. Threshold based approach works on the principle that the method detects a fall when the acceleration value obtained from the accelerometer embedded in the wearable device exceeds the threshold boundary value. This approach seems simple with low computational cost and complexity, but the challenge is to find out the appropriate threshold value to distinguish between daily activities and falls. Therefore, machine learning methods are proposed to observe the corresponding effectiveness. Regarding feature extraction, for fall detection systems using wearable devices, features such as mean, standard deviation, tilt angle, and vector magnitude are usually extracted from acceleration signals generated by accelerometers, pressure sensors, or gyroscopes. Static activities such as sitting and standing can be detected with the help of mean values. Dynamic activities such as running, walking, and jumping can be judged with the help of standard deviation. As in the work done by Kimaya Desai et al. the dataset consists of accelerometer and gyroscope readings along three axes [7]. Readings from other daily activities such as running, walking, bending, jogging and squatting were considered in order to identify falls and non-falls.The same two accelerometers and a gyroscope were used for data collection in the study by Diana Yacchirema et al. The publicly available dataset, SisFall, was also used for fall detection [8]. It is important to note that because real-time data from older people is difficult to obtain, existing fall detection systems mainly utilise data collected from younger people. Since both training and testing data used in machine learning algorithms come from the same subjects/individuals data. In real-world scenarios, the subject and sample data may differ making performance degradation, issuing false emergency alarms, and limiting the user's activities.

3.2. Sensors Based on Spectroscopic Technology

Wearable spectral sensors are usually composed of a flexible substrate, a sensing unit and a detection and analysis unit, in the process of use, the target interacts with the sensing unit on the flexible substrate, generating an optical signal, which is converted, amplified, transmitted and processed by the detection and analysis unit, and then the result is presented to the user or the medical personnel through the smart device, so as to achieve the health detection and rapid diagnosis of the disease [9].

The first sensor is a uric acid sensor, which embeds uric acid enzyme into a PVA hydrogel microneedle for low-pain acquisition of uric acid in the ISF and its colourimetric detection, which accurately detects uric acid in the concentration range of 200-1000 μmol/L, with a low detection limit of 65 μmol/L, which is of great significance for the regular uric acid testing of gout patients. The second dermal tattoo colourimetric sensor was prepared from hyaluronic acid hydrogel, which is biocompatible and self-degradable, for ISF monitoring. This sensor releases the chromogenic agent under the skin stratum corneum, is not easily contaminated, has good stability, and can achieve real-time monitoring for 4 days continuously. However, ISF is obtained by a special minimally invasive method, which requires consideration of the biocompatibility and self-degradability of the subcutaneously released colourimetric sensing reagent and the microneedle. There is another gradient-based colourimetric array sensor that has been successfully used for the monitoring of transdermal acetone emission. Detection of markers in wound secretions is extremely

important for wound treatment. In the last one, a core-shell microfibre textile ratiometric fluorescent sensor made by encapsulating hydrophilic ss DNA-single-walled carbon nanotubes in polycaprolactone using core-shell electrostatic spinning technology has excellent resistance to photobleaching. Embedding this sensor into band-aids for real-time detection of H2O2 in wounds is important for the prevention of chronic and pathogenic infections.

4. Challenges and Future Directions

4.1. Future Prospects

4.1.1 Hybrid Sensor Systems

Islam M Mproposes a multi-level fusion network (Figure 6) integrating ConvLSTM, CNN, and attention mechanisms for 97.9% accuracy in activity recognition [10]. However, computational demands remain high.

The multilevel feature fusion architecture contains multiple modules for recognising human activities from multimodal data. Fig. 9 illustrates the multiple modules of the proposed multimodal human activity recognition architecture for smart healthcare applications. Time series data collected from multiple wearable sensors is passed to the ConvLSTM architecture for high-level temporal features. Such an architecture results in accuracy, precision and F1-Score, which are as high as 97.90%, 97.98% and 97.88%, respectively. Although the proposed architecture performs well in both tested deployment scenarios, it still requires significant computational resources to train and perform inference. It should be noted that unimodal data is more common in real-world use cases, and the model still needs multimodal data Venus to be refined.

A similar system that can incorporate numerous wearable sensors and devices is mentioned by Alsadoon A et al. They also proposed the supporting taxonomy (SDD) to test the system in terms of accuracy and effectiveness of monitoring and tracking, and transmission of sensory data within the healthcare industry [11].

In the future, more efficient deep learning architectures may be able to open up new research areas that can handle more complex real-world scenarios. Furthermore, this work can be deployed in multiple user scenarios to facilitate scalable healthcare applications

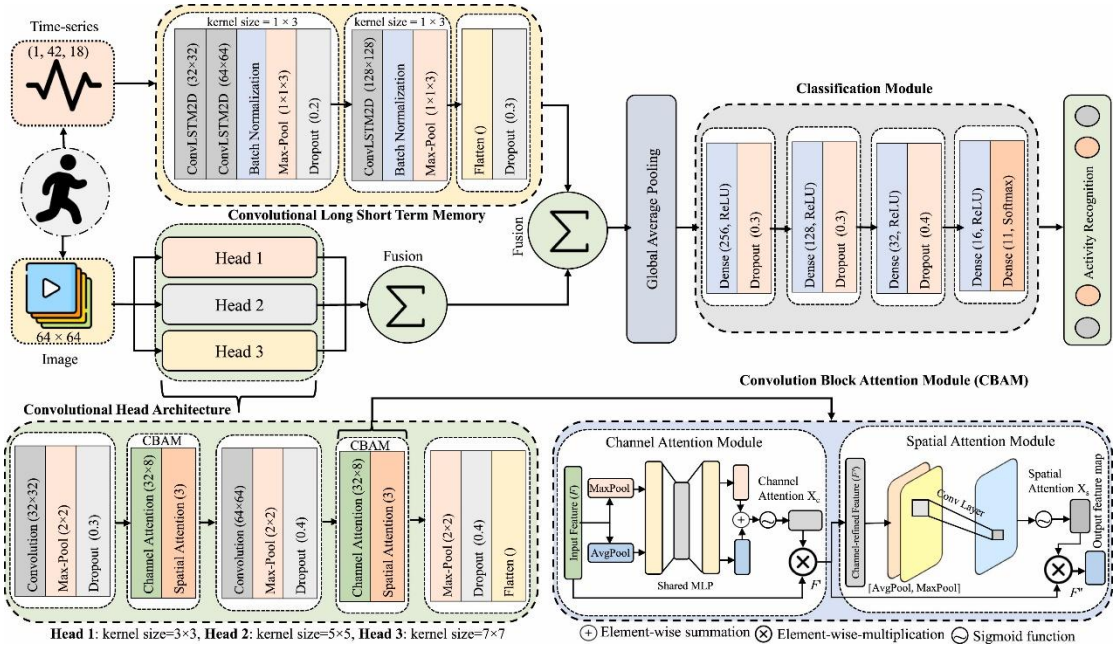


Figure 9. Schematic diagram of the developed fusion architecture for multimodal human activity recognition in a smart healthcare framework [10]

4.1.2 Smart Home Systems

Cantone A A plans to build a complete and fully functional architecture that seamlessly integrates robotics, sensors and artificial intelligence to facilitate continuous health monitoring, emergency response and emotional support for the elderly population and reduce the need for hospitalisation [12]. They used a smart companion robot, QTrobot, that combines sensors and AI to address the complex health management issues of older adults and monitor their health status. Figure 10 shows the appearance of the QTrobot The robot includes the following functions: mood detection, notification of healthcare professionals when encountering abnormal signs, medication reminder, and vital signs query (combining sensors and telegram robot). Not only that, the Telegram bot interface can serve as a bridge between the elderly and the QTrobot. Figure 11 shows the interactive interface of the Telegram robot, which helps the elderly to communicate efficiently with the QTrobot

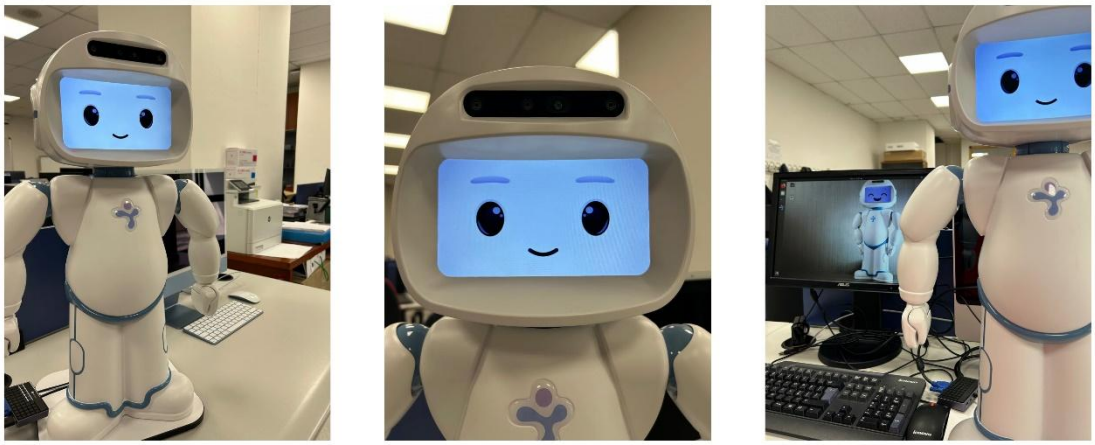


Figure 10. QTrobot in the HCI-UsE lab at the University of Salerno [12]

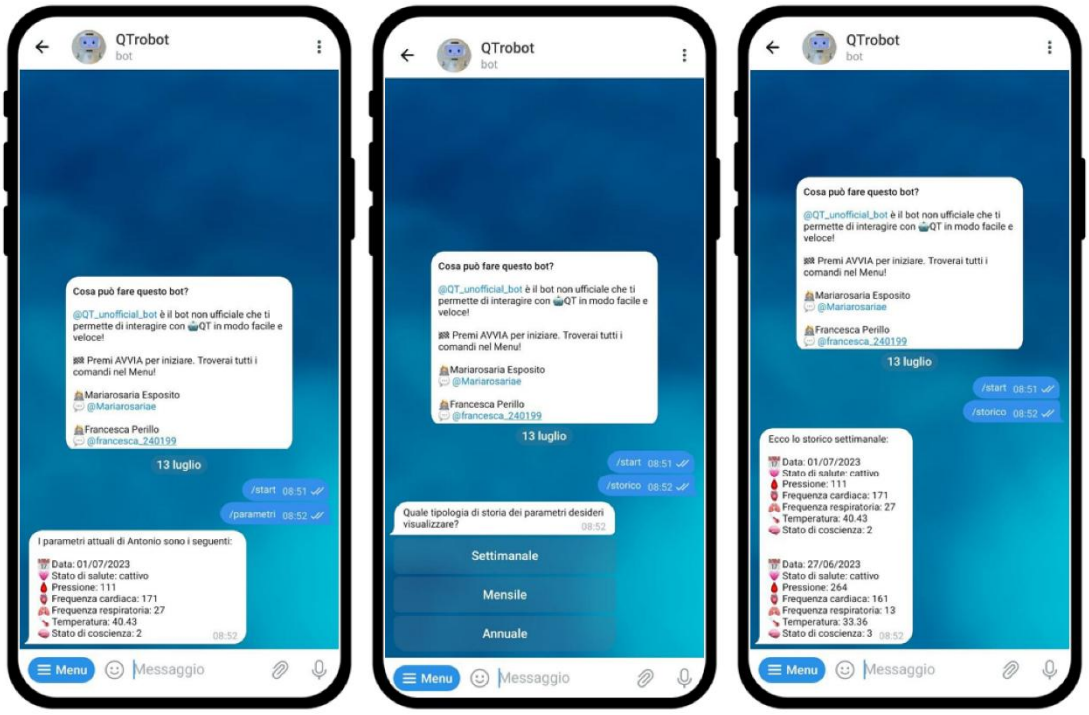


Figure 11. System actors have the ability to access current health status information through two modes: by receiving a list of values for measured vital parameters and by consulting a weekly, monthly, or annual history [12]

The technology has the potential to improve patient-centred care for older people. By providing real-time monitoring, personalised care, and direct communication with caregivers and physicians, the study demonstrates how the integration of robots, sensors, and artificial intelligence can enable patients to become active participants in their care. This integration is expected to promote independence and well-being in older adults, prevent hospitalisation, and allow older adults to remain comfortably at home for longer periods of time.

4.2. Challenges

The future of wearable sensors as a bridge between technology and health monitoring, while promising, faces a number of challenges:

For sensors, there are limitations on their range of action, accuracy (false alarms and omissions), stability, reliability and power.

Sensors operate on a principle that allows them to process only very small amounts of reagents and analytes, so the devices suffer from problems with processing time, contamination and false negatives. The result is that the sensors may detect falls when they are not occurring, or fail to detect falls when they are occurring, leading to false alarms. These errors may cause unnecessary anxiety or lead to a delayed response to a real crisis;

There is limited autonomy for the overall health monitoring system, and some advanced IoT devices could be combined with home automation to provide further assistance, such as automatically switching on lights or calling emergency response teams. Whilst these features are useful, they may not be sufficient to address all fall-related issues, such as the provision of medical care. IoT devices (sensors) can send passive alerts to inform people that a fall has occurred. However, they cannot physically intervene to stop the fall itself. Emergency services or human carers are responsible for responding to the warning and providing assistance. However the subsequent response time after obtaining the data is equally questionable. Whilst it is possible to alert carers or emergency services immediately, the actual response time depends on the accessibility and distance of the responders. However, in cases where local caregivers are not available or are unable to provide assistance quickly, assistance may take longer to arrive.

5. Conclusion

Typical technologies introduced in this paper include multimodal flexible sensor patches, graphene patches and spectral technology sensors. Multimodal flexible sensor patches monitor vital signs such as electrocardiogram, respiration, and skin temperature; graphene patches assess cardiovascular health by detecting pulse waves through highly sensitive pressure sensors; and spectral technology sensors enable health detection and disease diagnosis through light signals. Future challenges include issues of sensor accuracy, stability and response time.

Although wearable sensors show great potential for health monitoring, their autonomy and subsequent responsiveness need to be further improved. By integrating artificial intelligence, robotics and sensor technologies, more efficient health monitoring and emergency response systems for the elderly are expected to be realised in the future.

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