IoT Systems for Real-Time Posture Asymmetry Detection

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Contributor: Monica La Mura , Marco De Gregorio , Patrizia Lamberti , Vincenzo Tucci

The rise of the Internet of Things (IoT) has enabled the development of measurement systems dedicated to preventing health issues and monitoring conditions in smart homes and workplaces. IoT systems can support monitoring people doing computer-based work and avoid the insurgence of common musculoskeletal disorders related to the persistence of incorrect sitting postures during work hours.

digital health | force sensing resistors (FSR) | IoT | monitoring | posture

1. Introduction

In recent years, outstanding growth of the Internet of Things (IoT) was enabled by the parallel progress of sensing technologies, miniaturization of electronic devices, cost reduction, widespread diffusion of consumer electronics, ubiquitous connectivity, and rise of cloud computing. Every technological advancement ideally has the ultimate goal of bringing benefit to humanity, hence the IoT paradigm unveiled the great potential of connected sensor systems for the improvement of the health conditions of all living being [1].

In this scenario of pervasive electronics, many IoT systems have been developed for monitoring vital signs and have later become commercially available. Examples include systems for the monitoring of the heartbeat [2], blood pressure [3], oxygen saturation [4], glucose level [5], breathing rate [6]. The monitoring of vital signs can be achieved by embedding sensors in wristbands, smartwatches, chest straps, or wearable apparel, and provides immediate feedback on the health condition of people that can be used either for anamnestic reasons or to trigger timely intervention in case of sudden events (e.g., heart attacks, strokes, suffocation) [7]. In the long term, health is strongly affected by environmental conditions, hence systems that monitor the air quality in terms of pollution and concentration of harmful particles also fall within the user-centered IoT measurement systems for human well-being [8]. In a broader context, considering the improvement of people's general well-being, sensors, and IoT systems can be employed to monitor the perceived ambient conditions and eventually operate to set parameters, such as temperature and humidity, according to personal preferences [9][10][11][12]. Moreover, connected sensor systems also enable health preservation by doing environmental surveillance for safety reasons, for example, by checking constantly for the presence of smoke or toxic substances [13][14] or by performing structural health monitoring [15][16].

Figure 1 recaps the main examples of IoT measurement system applications designed to improve human well-being.

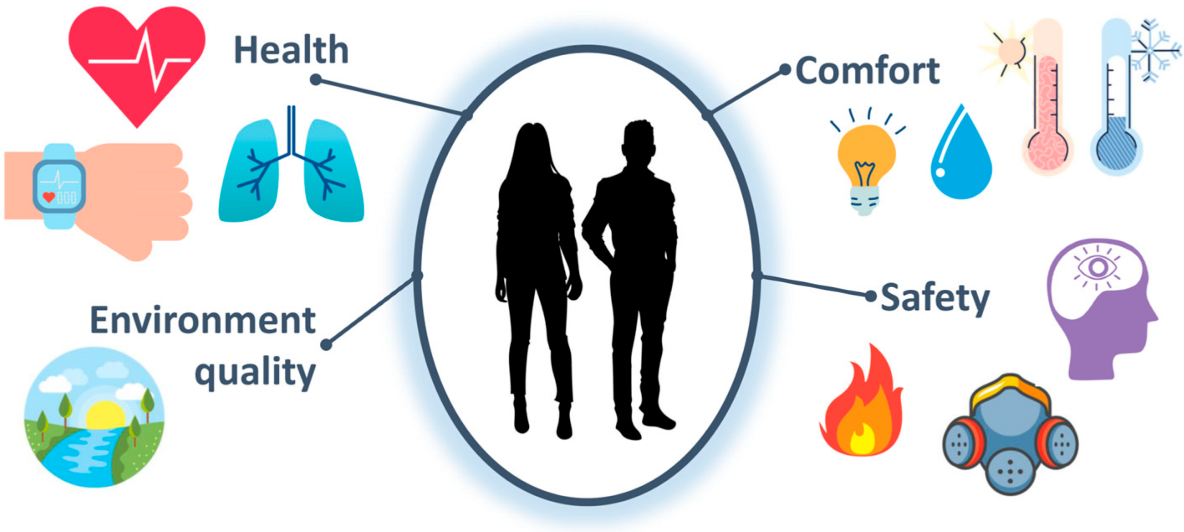

Figure 1. User-centered applications of IoT measurement systems for the improvement of human well-being based on the monitoring of vital signs and environmental conditions.

IoT measurement systems find application either in wearables or in smart homes and buildings, which include home and work environments. In wearable systems, sensors are embedded in clothes, fabrics, or accessories that the user carries on-body and are, therefore, suitable for monitoring vital signs and movement of all people. In home and work environments, sensors are hosted in the furniture or assembled in self-standing systems, therefore, they interact with the person either directly (e.g., sensors embedded in chairs) or indirectly (e.g., location systems detecting people's presence in the room). Systems designed for home environment are generally aimed at the assisted living of elders. Systems designed for work environments target the preservation of the health and safety of workers. For example, in the context of smart homes and assisted living, Stern et al. [17] recently described a system for in-bed posture recognition by convolutional neural networks based on the pressure data acquired from a pressure mat positioned on the mattress aimed at investigating the relation between the sleeping positions and the insurgence of pressure sores in bedridden people. Leone et al. [18] developed a posture recognition machine learning algorithm for the classification of four postures: Standing, sitting, bending, and laying down. Concerning the monitoring of workforce health conditions, Lind et al. [19] overviewed the available systems based on motion capture instruments to collect kinematics data for the prevention of work-related musculoskeletal disorders.

Many jobs of the present time involve the use of personal computers for a long time. Typically, computer-based jobs require people to sit during work hours, enhancing the risks correlated to sedentary lifestyles. Among these, the problems related to a prolonged incorrect sitting posture are largely diffused and represent a health issue that many people around the world must deal with. The negative effects of prolonged bad sitting postures include musculoskeletal disorders involving the hip joints, lumbar area, upper back, shoulder blades, shoulders, and neck [20]. The condition of persistent loading on the intervertebral disks associated with poor postures is also responsible for the insurgence of low back pain [21], which affects people of all ages and is one of the main causes of absence from work [22]. Back pain is especially frequent in people with scoliosis, a pathological curvature of the spine that can cause chronic pain and prolonged asymmetric postures is, therefore, even more relevant for people who suffer from this condition. Although the incidence of scoliosis is not gender-related, it is found that female subjects are more likely to experience a progression of the spine curve [23]. The wide interest in posture-related health issues has originated several proposals for monitoring the workers' sitting behavior.

In the past, different approaches to monitoring the sitting postures of long-time sitting workers were investigated in the context of the IoT applications for health risks prevention. Originally, several systems were proposed based on video analysis, though they never took place due to privacy issues. Then, textile sensors were largely considered for the development of smart fibers and wearables that could analyze the person's posture by relying on dedicated posture classification algorithms. More recently, thanks to the widespread diffusion of low-cost and well-performing pressure sensors, the first solutions were replaced by sensor array-based systems.

2. IoT Systems for Real-Time Posture Asymmetry Detection

Before the explosive growth of embedded system technology and IoT, several implementations of sitting posture monitoring systems involved the acquisition of video recordings for an offline or real-time image analysis based on computer vision techniques [24][25][26][27][28]. These solutions were soon abandoned due to poor acceptability, as they required performing video recordings and for privacy issues. Thanks to the widespread diffusion and cost lowering of sensors, the easiest and more affordable way to assess the sitting posture is now based on pressure sensors.

Already in 2001, a 'sensing chair' for the classification of static postures was described [29], based on commercial pressure distribution sensors, allowing posture classification by exploiting pattern recognition algorithms already used in image processing techniques for computer vision.

In 2010, Meyer et al. [30] proposed a pressure sensing mat made of 240 sensing elements, capable of relieving the pressure applied over a surface by measuring the change of the capacitance between two electrodes made of conductive textiles and separated by a compressible dielectric spacer. The static pressure measurement was then used to recognize 16 sitting postures.

The eCushion presented in 2013 [31] is based on a textile pressure sensor made by placing on top and bottom of an eTextile (a composite yarn made of fibers coated with conductive polymer) fabrics coated by conductive buses. The posture monitoring system includes a cushion supplied with a 16 × 16 array of sensitive elements, an Arduino-based data aggregator, and a data analysis module. The seven-posture classification relies on a dynamic time warping-based algorithm. However, different weights, sizes, and sitting orientations impair the recognition algorithm performance.

Later on, in 2016, Zemp et al. [32] evaluated the accuracy of five different machine learning techniques for sitting posture classification based on a set of features extracted from 16 force and acceleration sensors applied to the seat pan, backrest, and armrests of an office chair. The goal was to analyze the sitting behavior, in terms of static position assumed during work, as well as of number and frequency of position shifts, in order to assess the level of comfort or discomfort perceived and eventually develop strategies for low back pain prevention.

The system proposed by Suzuki et al. [33] uses a commercial pressure mat made of a 16 × 16 pressure sensor array to generate a report about the sitting behavior, informing the user on the predominance of a particular sitting posture based on the distribution of the person's weight on the chair seat. However, the report is generated after a sitting session, and therefore, does not provide real-time feedback on the assumed position.

In 2017, the smart cushion presented in [34] employed a 5 × 8 FSR sensor grid to recognize 15 sitting positions, although by working on the feature selection and the classification algorithm, Liang et al. managed to achieve good results by reducing the number of operated sensors down to 10.

More recent systems employ a reduced number of sensors and achieve a higher success rate in the identification of the sitting posture. For example, a system for the combined monitoring of the sitting posture and the electrocardiographic activity was proposed very recently by Pereira et al. [35], to recognize eight sitting positions by means of three load cells and monitor the heartbeat by means of conductive nappa leather dry electrodes, and the system proposed by Roh et al. in 2019 [36] identifies with excellent classification accuracy six different postures by using four low-cost load cells.

A system providing feedback on the assumed posture was proposed by Kim et al. [37] in 2018. The described real-time sitting posture correction system is based on textile pressure sensors, which return a different capacitance based on the applied pressure. The measurements acquired at 10 different points (six on the seat and four on the backrest) of the chair were used to identify seven different positions based on an ad hoc decision algorithm. The system is capable of providing real-time feedback on the sitting position by displaying posture changes on the PC monitor.

In 2021, Luna-Perejón et al. [38] proposed a six FSR-based system using a machine learning model based on artificial neural networks trained to identify seven sitting positions, i.e., the neutral correct posture and the six most frequent postures that can create issues in the locomotor system.

Anwary et al. [39] proposed an asymmetric posture detection system based on custom-made pressure sensors made from Velostat, a piezoelectric conductive material coupled to polyethylene foam and placed between two layers of conductive fabric. Four sensors embedded in the seat and two in the backrest provide the data to measure mild, moderate, and severe asymmetry of the sitting position based on a fuzzy logic algorithm. The system provides visual feedback of the sitting posture held during work hours by means of a mobile application, although it does not interrupt the user's actions in case of prolonged severe asymmetry detection.

Nevertheless, despite all the previous works underlining the importance of keeping a correct posture while sitting for long hours, they focused on classifying the sitting posture and eventually providing feedback on the assumed sitting position without raising an alert to invite the user to correct their posture. In 2010, Hu et al. [40] proposed a wireless system for posture monitoring that provided a visual warning in case an inappropriate position was detected for a prolonged time. The system acquires pressure data from an accelerometer, two pressure sensors in the seat, and four pressure sensors in the backrest of an office chair (the number of sensors is limited by the microcontroller capabilities) and is managed by a mobile application that analyzes the sitting posture using a machine learning-based algorithm and sends the stored posture readings to a remote web server.

In the same year, Zheng et al. [41] proposed vibrotactile feedback for posture guidance. The developed system uses seven FSR sensors (five in the chair seat and two in the backrest) to recognize ten sitting postures and activates four vibration motors in case of bad posture, according to a pattern related to the incorrect posture assumed. In this way, not only is the user informed that the position needs to be adjusted but he or she is also guided through the position correction.

In order to understand which kind of warning is more effective and better tolerated, a study was proposed in 2011 [42], investigating different ways of notifying the sitting person about the harmful position held on the chair. The study involved the use of four force sensing resistor (FSR) sensors and had the only purpose of alerting the sitting person of the bad posture assumed by means of graphical, physical, or vibrotactile feedback. Among the considered modalities, the vibrotactile feedback proved to be more effective but also more intrusive, whereas the physical feedback was found sufficiently effective while being also less disruptive, and therefore, better tolerated.

Vibration feedback is included also in the work proposed by Ran et al. in 2021 [43]. In this case, like in [41], four vibration motors are activated according to a specific posture-related pattern to inform the user of the poor posture. In their work, the authors compare seven machine learning algorithms to classify seven different postures, using the data collected from a pressure sensing mat based on FSR sensors.

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