

Editorial

Wearable Electronic Systems Based on Smart Wireless Sensors for Multimodal Physiological Monitoring in Health Applications: Challenges, Opportunities, and Future Directions

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1. Introduction

Driven by the fast-expanding market, wearable technologies have rapidly evolved [1] and now have groundbreaking potential to empower people to make well-informed decisions about their lifestyles, thus enhancing the quality of their lives and creating a healthier society. Bridging the gap between these cutting-edge technologies and enhanced quality of life for all people around the world is an essential prerequisite for making responsible, inclusive, and sustainable progress, helping propel the forward movement of humanity by opening new frontiers and expanding future horizons, leaving no one behind.

Owing to their ability to monitor the physiological and/or pathological status of the human body in a sophisticated yet non-invasive way, wearable technologies are increasingly being adopted for health maintenance and disease prevention (e.g., physical activity monitoring), as well as for disease assessment and management of a pathological condition (e.g., remote monitoring) [2]. To keep up with the high speed at which wearable technologies are advancing, we need to unlock and unleash their full potential for shaping a better quality of life for present and future generations. This can be propelled by promoting more widespread acceptance and adoption of these novel technologies that need to be more affordable and accessible to everyone, thus facilitating the collection and analysis of a huge amount of information, known as big data, but at the same time ensuring data privacy and security.

Nowadays, the utilization of advanced wearable electronic systems allows for the recording, processing, and monitoring of a large variety of health parameters, thereby enabling capturing, and then processing, a plethora of health information from the human body. The personalized data generated from wearable electronic systems can be integrated into wireless communication networks, thus allowing for remote health monitoring and data sharing. In the era of the Internet of Things (IoT) [3], the collected big data can be used along with artificial intelligence (AI) and machine learning (ML) techniques to improve the quality as well as the costs of healthcare services, such as supporting disease diagnosis and personalized clinical decision making through the use of the valuable information from large healthcare databases [4].

Although wearable technologies are continually advancing to become more mature and pervasive with improved performance and reliability, it is worth noting that each form of wearable sensor technology has its own pros and cons, depending on the constraints and requirements of the specific application. Therefore, the adopted technological solutions should be carefully tailored to fit the needs of the selected health application [5].

To meet the unprecedented challenges and unique opportunities brought about by the extraordinary evolution of these technologies, the most ambitious target consists of integrating multiple wearable electronic devices to develop powerful multimodal wireless



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sensor platforms. These can be used for wellbeing monitoring and the full assessment of various pathologies for a personalized medicine. The use of a modular architecture for the multimodal systems enables flexibility in integrating additional sensors, thereby allowing the achievement of more functionality when needed. Additionally, today's sensors are smart electronic devices that are capable of data storing/processing and wireless communication in order to allow computations to be performed locally on edge devices or remotely in the cloud. Sensor platforms should be built by targeting the best trade-off among all of the considered factors, which may be high performance, fast response, high reliability, low cost, compact size, being lightweight, minimal invasiveness, comfort and easiness in wearing, portability, durability for long-term healthcare monitoring, low power consumption, environmentally friendly materials, green manufacturing process, adequate computational and data storage resources, high-speed data transfer, or high level of both data security and privacy protection. Due to the diverse nature of the competencies required to handle these key aspects in this fascinating but also challenging research area, it is mandatory to take a multidisciplinary approach that integrates knowledge, expertise, and perspectives from various disciplines, including engineering, medical, and basic science fields.

With the aim of contributing to the widespread diffusion of these amazing and powerful technologies in an effective and responsible way, the objective of this Editorial is to underline the importance of using a multidisciplinary approach in order to bridge the gap between technological advancements and enhanced quality of life. To this end, crucial challenges and potential solutions are discussed by considering the advantages and the limitations of the available wearable electronic devices and the stringent requirements of the clinical practice, together with the potentialities and the possible issues arising from the use of health-related big data.

2. Device Technologies and Medical Applications

As an illustrative example, Figure 1 shows a schematic representation of a wearable multimodal wireless sensor platform that integrates various smart sensors, with each of them targeting a specific body part, source of information, and/or symptom. The adopted technological solutions are, typically, selected to meet the needs of the target clinical applications that require the integration of multimodal signals for the prevention, early detection, diagnosis, and staging of pathologies of a different nature and with various symptoms. A wide range of potential clinical applications can be considered, such as neurological pathologies (e.g., stroke, Parkinson's disease, Alzheimer's disease, and multiple sclerosis), other pathologies with common motor symptoms (e.g., hepatic encephalopathy and orthopedic diseases), acute and chronic pathologies with cardiovascular or respiratory symptoms (e.g., heart failure, arteriosclerosis, hypertension, diabetes, chronic obstructive pulmonary disease, and COVID-19), and nervous or psychiatric disorders that might be either temporary or chronic (e.g., stress, drowsiness, depression, and anxiety). Different sensing wearable technologies can be incorporated to detect and quantify a broad range of symptoms of the considered pathologies by collecting multimodal information.

When the analyzed pathology or condition involves the presence of motor symptoms, among the main candidate wearable sensor technologies for human movement analysis, inertial measurement units (IMUs) stand out as an effective solution that has gained a leading role during the last two decades. They are very powerful, small, lightweight, and relatively inexpensive, and can be easily worn on proximal as well as on distal body parts, such as the forearm, hand, and fingers, and are thus able to easily move the analysis out of the lab, when compared to the stereophotogrammetric counterpart [6]. Owing to recent technological advancements, IMUs have become suitable for integration into wearable devices in clinical settings, also allowing for the capturing of motion-related data in natural unconstrained environments, especially when they are integrated into commercial devices, such as smartphones and smartwatches. Wearable solutions based on IMUs have been extensively used for quantitatively analyzing different motor tasks and related symptoms,

such as gait, tremor, or bradykinesia (i.e., slowness of movement) [7–9]. Despite their extensive use in the field of neurological pathologies, the broad applicability of IMUs has also been reported for a variety of non-neurological conditions, highlighting their ability to capture relevant motor symptoms even when they are not the prominent manifestation of a pathology.

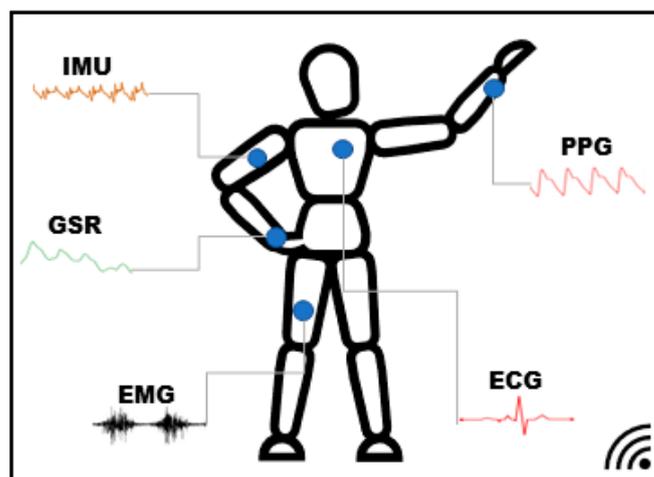


Figure 1. Schematic illustration of a wearable multimodal wireless sensor platform. Different types of wearable smart sensors are wirelessly embedded into the platform to allow for the collection and processing of multimodal data.

For what concerns the assessment of nerve and muscle function, electrophysiological monitoring of muscle activity, referred to as electromyography (EMG), enables reliable sensing of the muscle contraction mechanisms. EMG is the superposition of the action potential trains generated by multiple motor units (i.e., muscle fibers innervated by the same motor neuron), and it has been widely used for many applications, including health monitoring. Clinical applications are often based on invasive recordings using needle electrodes able to record the activity of few motor units within the target muscle, known as intramuscular EMG. However, in the case of wearable technologies, the use of non-invasive measurements is strictly needed, in order to allow for prolonged monitoring, to facilitate the movement of the subject, and to open up the possibility of easily recording the EMG signal in clinical applications from multiple target muscles [10] and/or from multiple locations on a single target muscle [11]. In this scenario, surface electromyography (sEMG) is the only viable solution to fulfil the demands of the wearable applications. To date, sEMG measurements have involved the use of silver/silver chloride (Ag/AgCl) electrodes in the form of pre-gelled adhesive patches to be attached to the skin over the target muscle. Although this solution is widespread in research and clinical practice, the use of temporary electrodes together with bulky recording devices reduces patient comfort and makes it difficult to record the EMG signal for a prolonged period of time. Therefore, the need to develop innovative sEMG recording devices that can be embedded into wearable electronic systems, including processing capabilities (e.g., data compression [12]), is evident. Recent research has gone in the direction of designing wearable sEMG solutions, which include electrodes that are printed or integrated into flexible supports, which also include interconnects [13].

In cardiac and vascular conditions, the frequent measurement of vital signs is often needed in risky situations, such as the periods following a cardiovascular acute event or cardiac surgery, to monitor the patient's evolution and minimize hospital readmission events. Despite the widespread use of wearable electrocardiography (ECG) sensors as a standard reference measurement for quantitative cardiac assessment [14], there is now growing interest in the photoplethysmography (PPG) technique. PPG is a non-invasive optical technique for checking the functionality of the circulatory system [15], which

measures a signal that is proportional to the amount of hemoglobin present in a volume of tissue underlying the optical probe. The PPG technique has been in clinical practice for decades to assess the cardiac function at the peripheral level, with sensors placed over distal parts, such as fingers, ear lobes, and the forehead. The popularity of these devices is essentially due to their non-invasiveness, cheapness, easiness in use, and comfort for the user. Despite the cardiac rhythm and the percentage of blood oxygenation, the PPG has been extensively used for the determination of derived parameters, such as blood pressure and arterial stiffness, that usually require trained personnel and dedicated devices and setups [16]. There are already PPG-based commercially available tools that monitor parameters related to heart rhythm and the state of the arteries, with applications in conditions such as hypertension, diabetes, and hypercholesterolemia (i.e., high cholesterol), besides the natural aging of the arteries [17].

Among the possible signals that can be recorded, health assessment could greatly benefit from monitoring quantities that are related to the user's current state, such as those coming from physiological information. In recent years, increasing attention has been paid to the measurement of the acute physiological responses to mental, emotional, or physical challenges that a subject encounters during the execution of any kind of task. Different markers have been explored for assessing these kinds of physiological responses, including electrodermal activity, features related to heartbeat patterns, blood pressure, and respiration activity [18]. All of these quantities can be modified by the presence of pathologies or be due to the activity of the sympathetic nervous system, in the presence of acute stressful events. Among the various solutions, wearable technologies, including the measurement of electrodermal activity, assessed using galvanic skin response (GSR) sensors, and heart rate patterns, as measured via ECG or PPG sensors, have been widely exploited for monitoring the user's current state [19,20]. The assessment of the status of the patient's health condition in a non-invasive and fast way also paves the way for personalized state-dependent therapies, especially in the field of neurorehabilitation, where the frustration of the patient during the therapy might be one of the main obstacles to a functional recovery.

3. The Potential of Machine Learning in Healthcare

In order for these wearable electronic systems to provide innovative support to medical decisions, there is a need to properly and accurately process the large and heterogeneous amount of information that is gathered. Thanks to the strong improvement in the computational capabilities of modern electronic devices on all scales, the integration of data processing functions within the smart sensor platform, including the integration of ML into the data processing scheme, does not constitute an obstacle anymore. The fast advancements in the fields of AI and ML have indeed conveyed the central role of these techniques, and their potential for providing technical support to clinical decision making is more evident. The integration of ML algorithms with wearable sensing technologies has constituted a trend in the scientific literature of the last decade, and the number of published scientific articles on this topic has been increasing year by year. More specifically, ML algorithms trained using health-related data have shown their potential to detect and classify various diseases, and to even stage specific symptoms associated with different pathological conditions [21]. This ML-based technological approach has the potential to greatly improve healthcare, since it allows the monitoring of the evolution of many diseases, thus facilitating more informed medical decisions and supporting the choice of the most appropriate therapeutic paths. This is possible because wearable smart sensors enable a potentially seamless monitoring of the status of a patient, leading to a more reliable and continuous description of their condition. Despite the huge potential of ML in this field, there are drawbacks, challenges, and bottlenecks that require careful attention [22]; for example, the nature of ML techniques constitutes a potential challenge in itself, since the proper training, testing, and validation of these techniques is often based on the presence of large and representative datasets, which are not always available, especially in the case

of rare diseases. Moreover, biomedical signals and health-related data are subject to high inter-individual variability, and this might constitute a drawback in the construction of robust and representative datasets, able to account for all of the possible manifestations of a pathological condition. Furthermore, considering that wearable sensor platforms are currently being developed for facilitating remote application in real-world scenarios, the unconstrained and uncontrolled measuring conditions constitute an unavoidable source of noise in the gathered data that could significantly affect the accuracy of ML algorithms. These considerations, in addition to the privacy issues related to the collection of sensitive personal health-related data, constitute a bottleneck that needs to be overcome to enable the widespread adoption of ML use with wearable sensor data in routine clinical practice.

4. Perspectives and Conclusions

While innovative wearable technologies able to capture personalized health data are constantly expanding, the present challenge for the scientific and medical community is to understand how we can best use the information coming from these technologies to make a substantial difference in our lives. These health technologies need to simultaneously be usable and affordable, resonating both with the personal wellbeing goals of the patients and with the needs of the medical doctors and therapists. Meeting the challenges posed by the proliferation of the wearable technologies and the associated huge influx of health-related data requires a multidisciplinary team of researchers from engineering, medical, and basic science fields. This interdisciplinary research area needs to bring together technical specialists from different disciplines (e.g., electronics, biomedical instrumentation, bioengineering, sensing techniques, wireless technologies, computer science, microsystems, physics, and materials science) to meet clinical needs in a broad spectrum of medical fields (e.g., neurology, cardiology, and orthopedics), thus enabling the translation of technological advancements into human progress in an effective and responsible way. Even though many off-the-shelf commercial solutions are available, they may not be optimized for specific pathologies, target body parts, or dominant symptoms, mainly because of their general-purpose use; therefore, the development of custom prototypes, tailored to specific clinical scenarios and needs, is often required [23]. This holds true not only for already-identified clinical scenarios, where wearable solutions already exist and a scientific effort to bring about performance optimization is warranted, but also for finding solutions in fields where wearable and portable applications are still in their infancy or are even far from being thought of. For example, the monitoring of cardiovascular, neurodegenerative, or oncologic diseases could benefit from information provided using a breath analysis system [24], especially if a wearable device is envisaged [25]. Another example of great practical importance is patients undergoing nuclear medicine therapy, where it is essential that the treatment be personalized [26]; to achieve this ambitious goal, gamma radiation sensors might be exploited as a wearable monitoring system for the assessment of the absorbed dose in target lesions and organs at risk. With regard to this engaging scenario, one of the main aims of the pillar Health of the SAMOTHRACE project (Sicilian Micro and Nano Technology Research and Innovation Center) is studying, prototyping, and developing innovative wearable devices and multimodal sensor platforms for clinical application using a multidisciplinary strategy, thus contributing to bridging the present gap between the great potential of wearable technologies and their actual translation into clinical practice.

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