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Review

Wearable sensors for activity monitoring and motion control: A review

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ABSTRACT

Wearable sensors for activity monitoring currently are being designed and developed, driven by an increasing demand in health care for noninvasive patient monitoring and rehabilitation training. This article reviews state-of-the-art wearable sensors for activity monitoring and motion control. Different technologies, including electromechanical, bioelectrical, and biomechanical sensors, are reviewed, along with their broad applications. Moreover, an overview of existing commercial wearable products and the computation methods for motion analysis are provided. Future research issues are identified and discussed.

1. Introduction

During the past decade, new wearable sensor technologies have been developed for wide applications. Wearable sensors can benefit patients, such as those with orthopedic or neurological diseases, with improved diagnosis, treatment, and personalized clinical management [1]. Moreover, wearable sensors provide continuous monitoring and measurements of physical activities for patients in the recovery process, such as strength training and practicing degenerated skills [2].

These sensors can be mounted to different parts of human body, for example, the chest, waist, and upper and lower limbs, and can even be worn in pockets or shoes or adhered to the skin to collect data quickly and conveniently for the human motion of interest. In addition, sensors are integrated into wearable devices, such as orthoses and exoskeletons, applicable for patients with hemiplegia, elderly people, and workers, with the purpose of assistive control.

To date, few articles have reviewed wearable devices for activity monitoring and tracking [3–5]. For example, Tokuçoğlu [6] has reviewed wearable systems for monitoring physical activity in medical applications, focusing on their use in health care. Khakurel et al. [7] has provided an overview of the applications of wearable technologies in the workplace. However, even fewer articles have paid attention to various technologies and application scenarios such as daily activities, medical rehabilitation, and industrial assistance, as well as to commercial products available for use in these areas.

In this article we review state-of-the-art wearable sensors for activity monitoring and tracking, including technologies, computing algorithms, and applications. Moreover, existing commercial wearable products are listed and their performance compared.

2. Wearable sensing technologies

Many wearable sensors have been developed over the years and can be classified by signal source into three major categories: electromechanical sensors, bioelectrical sensors, and biomechanical sensors, as shown in Fig. 1. Sensors that detect limb motion and collect kinematic and kinetic information include accelerometers, encoders (angle, angular velocity, linear acceleration, angular acceleration, inclination angle), inertial measurement units (IMUs) with even more kinematic data, and foot switches and pressure insoles.

Sensors that detect central nervous system (CNS) activities can be divided into invasive and noninvasive. Invasive bioelectrical signals mainly include cortical electroencephalography, cortical neural recordings, invasive peripheral nerve recordings, and invasive electromyography (EMG). Noninvasive measurement methods mainly include surface electromyography (sEMG) and surface

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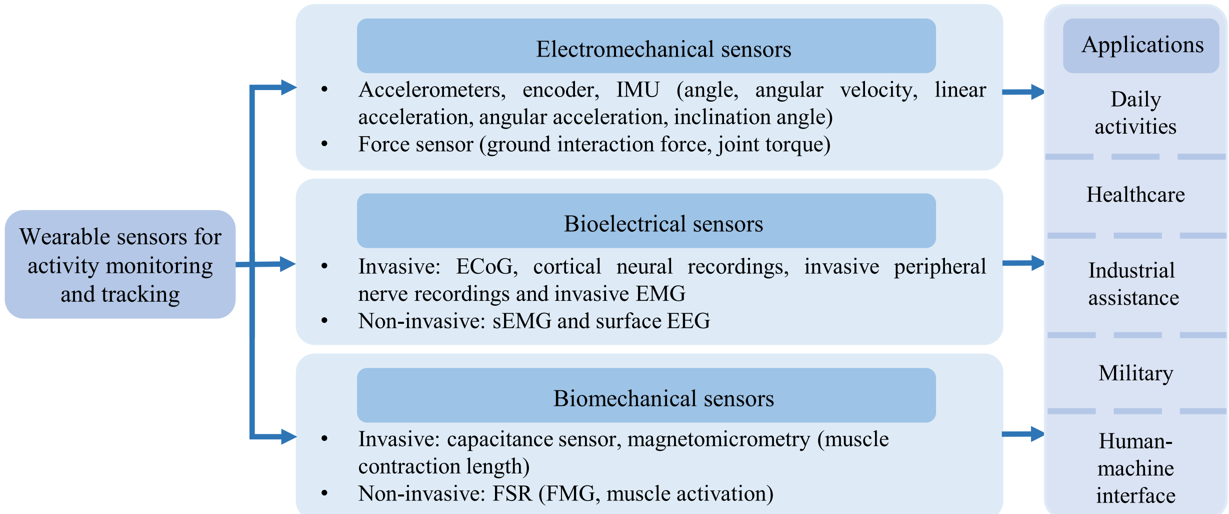

Fig. 1. Classification of wearable sensors for activity monitoring and tracking.

electroencephalography (EEG). Sensors developed on biomechanical principles to detect biomechanical activities such as muscle contractions include force-sensitive resistor (FSR, noninvasive), capacitance sensors, and magnetomicrometry (invasive).

An overview of the sensors in these categories is listed in Table 1. In the following sections, we examine each type's development and applications.

2.1. Electromechanical sensors

Electromechanical sensors convert human movements into kinematic and kinetic parameters. This type is the most commonly used, spanning from medical care to sports medicine to supporting daily activities. Compared with sEMG signals, electromechanical sensors have good stability and high repeatability but also experience hysteresis. Moreover, their performance is prone to mechanical gaps, wearing misalignment, and other issues, which can aggravate the hysteresis and downgrade performance.

A typical sensor of this type is the accelerometer, which has been used extensively in gait analysis [26,27]. For example, accelerometers are installed on the lower limbs and back to measure accelerations during walking [28,29]. The phase of lower-limb motion can be determined by analyzing the acceleration data obtained [30]. Other wearable sensors, such as magnetoresistive sensors and gyroscopes, can be integrated with accelerometers to provide more information about human gait [8–11,13, 14,31,32]. Gyroscopes usually are used to measure the angle and angular velocity of the lower-limb joints [33–35].

The combination of IMU with foot switches and pressure insoles enables more accurate gait detection, developed with more complex algorithms [36,37]. Yang et al. [38] have proposed an adaptive gait phase detection model based on three IMU sensors and two foot switches for monitoring unsteady walking and various activities (e.g., walking, running, stair ascent and descent, squatting). Their results showed that the accuracy of the proposed gait detection model in the measured activities reached 99.0%. Su et al. [39] have proposed a deep convolutional neural network (CNN) model to classify five gait phases according to IMU and foot switch information. In the offline evaluation of gait phase recognition, their model shows an accuracy of ∼97%.

2.2. Bioelectrical sensors

Bioelectrical sensors detect the electrical potential of nerve cells. The signals are filtered and amplified for interpretation of CNS activities. Invasive sensors are electrodes directly implanted into the neural information source (e.g., cortical neuron recordings, EMG) or neural signal pathways (e.g., invasive peripheral nerve recordings). Invasive electrodes provide signals more accurately and reliably than do noninvasive ones.

Many clinical studies with invasive neural sensors have been conducted, with promising results [40]. For example, Raspopovic et al. [41] have proposed an activity monitoring system based on an implanted neural interface that integrates sensory feedback into a sensorimotor loop. This system can improve the wearer's mobility, agility, and fall prevention in dynamic tasks. However, the current invasive neuro-sensing technologies can cause direct physical harm and some unknown risks to the human body; therefore, more development and clinical research are needed.

Among the noninvasive neural sensors, EEG caps, which are commonly seen in laboratory settings and tests, can easily be interfered with, especially during the process of walking [42–44]. The neuronal pulse signals of the cerebral cortex have a natural distortion after passing through the skull and scalp. Artifact detection and removal methods from scalp EEG remain an active area of research, as none of the existing methods are complete or universal.

The sEMG sensors are the most commonly used neural sensors for activity monitoring. The sEMG sensors cover surfaces specific to muscle activities occurring during movements, as shown in Fig. 2. The sEMG signal has the advantages of small delay, high fidelity, and convenient measurement. Whereas a few studies have adopted sEMG sensors in gait detection [15–20,45–47], in general, EMG-based systems are less commonly used for this purpose because their performance is poor due to, for example, electrode position changes, sweat on the skin, and muscle variations.

One model based on SVM obtained good results, with a 96% accuracy in detecting swing and stance phases [48]. Fricke et al. [49] have compared three different classification methods-K-Nearest Neighbors (KNN), CNN, and SVM–to automatically classify EMG patterns according to potential gait disorder. The automatic classification of normal and abnormal EMG patterns during gait was possible with high accuracy when using CNN (91.9%) but not with SVM (67.6%) or KNN (48.7%). Joshi et al. [50] have proposed a

Table 1
Overview of wearable sensors for activity monitoring and control.

Sensor category	Characteristics	Sensor types	Examples								
			Author [Ref.]	Integrated system	User groups	Tests	Type	Location	Data	Algorithm	Note
Electromechanical signal	kinematic and kinetic data High stability, high repetition, but high hysteresis	IMU, encoder (angle, angular velocity, linear acceleration, angular acceleration, inclination angle), force sensor (ground interaction force, joint torque)	Kreil et al. [8]	Special shorts for the integration of FSRs	Healthy participants	Lab	FSR	Ankle	Acceleration; angular velocity	Threshold algorithm	FSR can provide information that is not accessible to motion sensors
			Liu et al. [9]	N	Healthy participants	Lab	Inertial sensor	Toe	Angular velocity	Machine learning (ML)/Hidden Markov Model (HMM)	Recognition rate of the model is 91.88% despite the differences in age, height, and weight
			Chen W. et al. [10]	N	Healthy participants	Lab	IMU	7 plantar positions; instep	Acceleration; plantar pressure	ML/support vector machines (SVM)	Method can successfully classify the phases of gait with an accuracy of approximately 94%
			Potluri et al. [11]	N	Healthy participants	Lab	IMU	64 plantar positions; calf	Acceleration; angular velocity; magnetic field strength; plantar pressure	ML/SVM/K-means/ANN	Verify that ML methods, especially ANN, performed well in gait phase detection with high accuracy
			Rattanasak et al. [12]	N	Healthy participants	Lab	Plantar force sensor	5 plantar positions	Plantar pressure	ML/KNN	Method provided an 81.43% accuracy for gait phase detection and can control the transtibial prosthetic effectively at the maximum walking speed of 6 km/h
			Rahimi et al. [13]	N	Patients with Parkinson's disease (PD)	Home	3-axis accelerometer, 3-axis gyroscope	Head, trunk, pelvis, upper arms, wrists, thighs, shanks	10 joint angular velocities, 48 joint angles	PCA	PCA analysis compared across trials for the walking task indicated large intertrial variability
			Ding et al. [14]	Lower-extremity exoskeleton robot	Healthy participants	Lab	IMU	Instep	Acceleration; angular velocity	Threshold algorithm	Compared to the force plate, the mean time errors of toe-off and heel-strike detection are −10 and 19 ms
Bioelectrical signal	Detect CNS system activities Small delay, high fidelity, easy distribution, but poor stability	EMG, sEMG, EEG sensors	Tsurushima et al. [15] and Kawamoto et al. [16,17]	Hybrid assistive-limb robotic exoskeleton suit	Patients with stroke	Lab	EMG, angle sensor, IMU, plantar pressure sensor	Hip, thin-muscle EMG, foot plantar	Mean step length, average step rate; single-leg support time; maximum distance walked lasting for 6 min; Berg Balance Scale score	Proportional control	Patient performed a more natural walk with more step length than his normal walk
			Gupta et al. [18]	Lower-limb prosthesis	Patients with amputations	Lab	Single-channel EMG	FL, BF	Average identification accuracy	Continuous terrain identification method	Feature selection algorithm significantly improved identification accuracy as compared to PCA technique
			Chen et al. [19,20]	Knee-ankle-foot robot	Patients with stroke	Lab	EMG, encoder, force sensor, IMU	EMG: thin and shank muscle, IMU: waist, thighs, shanks and feet	Angular velocity, angle and muscle activations	Hidden Markov Model	Activation level of the major leg muscles s reduced as indicated by the EMG signals, and normal gait pattern is maintained during the test
			Liu et al. [21]	Lower-limb exoskeleton	Healthy participants	Lab	EMG sensor	EMG: thin and shank muscle		Metric-learning-based temporal convolution network	Model's accuracy of gait phase recognition is 96.22%, which is better than LSTM's 91.20%
Biomechanical signal	Perceiving physiological activities from muscle contraction Intrusive sensors need relevant surgery	FSR (noninvasive) Capacitance sensor, magnetomicrometry (invasive)	Ogris et al. [22]	N	Healthy participants	Lab	FSR	Forearm muscle	Manipulative arm gestures recognition	KNN (mean and variance are used as features, with window size 30 and step size 15)	For all classifiers, overall accuracy of the FSR system is in the middle between the accelerometer and the gyro
			Islam et al. [23,24]	Upper-body exoskeleton	Factory workers, elderly people, or people with weak muscle Strength	Lab	FSR band	Upper arm	Payload estimation	SVM	Mean value of absolute error varies from 0.14 kg to 0.37 kg, and mean value of relative error varies from 0.07 to 0.17 for the participants
			Esposito et al. [25]	Prosthetic hand	People with upper-limb amputations	Lab	FSR with rigid dome	Forearm muscle	Quantitative comparison between EMG and FMG (Pearson's correlation coefficient r)	Proportional control of prosthetic hand	The r scored 0.9286 (p value < 0.0001). All participants reported no appreciable differences between EMG-LE control and FSR control of the prosthesis

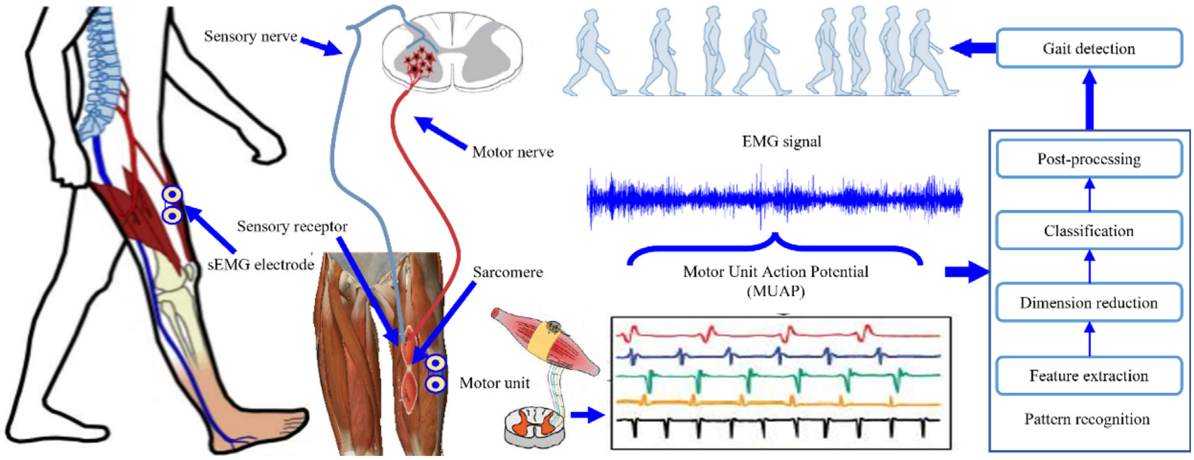

Fig. 2. Gait detection with sEMGs.

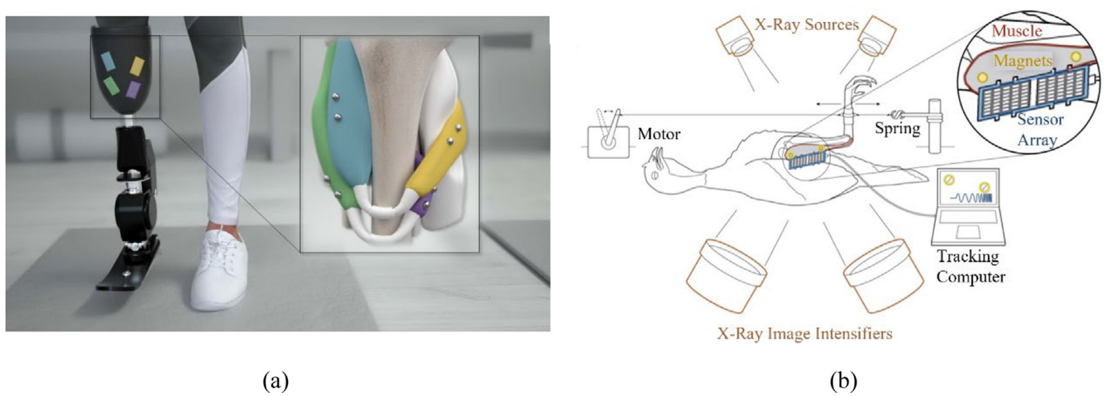

Fig. 3. Magnetomicrometry for motion intention detection. (a) Application in transtibial prosthesis. (b) Experimental verification on birds [51].

linear discriminant analysis control system that can recognize eight gait phases through eight EMG electrodes under the user's foot. Due to the complexity of data acquisition and processing and the sensitivity of moisture between the sensors and skin, the method based on EMG was less popular.

2.3. Biomechanical sensors

In recent years, attempts have been made to use biomechanical sensors, such as muscle contraction information accompanying the movement process, to detect human motion and recognize motion intention [51–56]. Biomechanical sensors have been developed using biomechanics principles to detect changes or deformations of muscles and the skeletal system. This type of sensor can detect human motion more effectively.

Taylor et al. [53,54] have proposed a sensing method, magnetomicrometry (shown in Fig. 3), which tracks changes in tissue length wirelessly according to the relative position of the implanted magnetic beads. Their work indicated that fast and accurate muscle measurement can be achieved for animals. Esposito et al. [25] presented a non-invasive FSR that can sense the mechanical force exerted by the underlying contracting muscles. The muscle simultaneous recordings showed a high correlation between the FSR output and the EMG linear envelope.

3. Wearable sensor applications

3.1. Daily activities

Wearable motion trackers, which continuously monitor the user's movement in real-time, are increasingly used in health care. One reason is that they can motivate users to perform more exercise while providing feedback on their activities [57]. The other is their enabling of wearers to become aware of the level of their activities, which can ensure that users maintain adequate activities for a healthy life.

A variety of motion trackers are available, including 3-axis accelerometers, magnetometers, and gyroscopic sensors. Wrist-wearable devices are most commonly used for tracking daily activities. These devices measure activity signals such as motion, acceleration, rotation, and gestures.

Accelerometers are most commonly used for daily activities [58]. sEMGs and FMGs also are used for gestures' recognition [59]. Because the palm side of the wrist noticeably deflects during finger flexion gestures, an array of piezoelectric contact sensors can be used to measure this deflection. Wrist-based devices have been utilized in research settings to monitor sleep quality [60].

Generally, gyroscopes, accelerometers, and magnetometers are combined in the same device, namely IMUs, for more accurate motion tracking. For example, gyroscopes can respond quickly to changes and are more reliable when measuring angles, whereas magnetometers have poor accuracy when moving rapidly but show no deviation over time [61].

3.2. Medical rehabilitation

Wearable sensors can be used for medical rehabilitation and patient care [62–64]. Motion sensors and posture detection devices can monitor patients with balance problems and PD or patients undergoing rehabilitation [65–68]. The motor symptoms of PD have hypokinetic and hyperkinetic features. The autonomic involvement and loss of postural reflexes can be seen in the later stages but also can be seen earlier in patients with atypical Parkinsonian syndromes. When motion and position sensors are used together, falls can be detected or predicted. Patients with a history of falls or with no falls have different locomotion patterns. These findings are indicated by studies of patients using wearable motion sensors [69]. Galvanic skin activity and electrocardiography can be recorded with wearable sensors in a patient's own environment to disclose autonomic abnormalities. Using motion sensors to monitor motor symptoms gives better information than does patient use of a diary. Thus, more satisfactory planning of treatment can be possible.

Multiple sclerosis (MS) affects younger people in their productive age. Therefore, maintaining a certain level of physical activity is essential for a good quality of life. Several performance scales have been defined to measure physical activities such as gait, hand movements, fatigue, vision, and spasticity [70]. Traditional methods of evaluation include questionnaires, observation, and activity timing, all of which are time consuming and imprecise. On the contrary, motion sensors and actigraphs can offer more precise information [71]. Commercially available devices have been used to record step numbers and temporal parameters of gait such as stride, swing, and step times [65].

Sedentary behavior seems more common in patients with MS who have mobility disabilities than in those without [66]. One study assessed sedentary behavior with an actigraph, finding a significant correlation between disability and self-reported disability status scale scores but no significant correlation between cognitive function and sedentary behavior [72]. Brain atrophy and sedentary behavior also should be investigated further.

3.3. Workplaces and industrial exoskeletons

In addition to health care, wearable sensors are being applied to the workplace to improve working conditions and reduce work-related injuries. These sensors have the potential to improve employees' work efficiency and health status. Working posture in some jobs, such as computer-related work, construction, and mining, can cause a large amount of physical tension in the back which, if continuing for a long time, can cause lower-back disease [73,74].

To reduce the risk of work-related musculoskeletal diseases, innovative wearable technologies that do not interfere with workers' activities can improve biomechanical risk assessment, adapt to all working conditions, and overcome the limitations of the current standardized methods. These technologies include IMU, instrument gloves, and sEMGs, although new tools have emerged in other research laboratories and workplaces [75]. Wearable systems based on intelligent footwear with which the reverse dynamics analysis can be carried out are very promising [76,77]. Artificial muscles that can contract, expand, and rotate reversibly under external stimulation can be embedded with microsensors to implement effective feedforward prediction control [78–80].

In industry, wearable devices are needed to provide external assistance to workers carrying or lifting heavy objects. Luo et al. [81] have designed a wearable stooping-assist device that can reduce the strain from a stooping posture and prevent risk of low-back injuries. Chu et al. [82] have tested exoskeletons for shipyard workers to help improve working conditions by reducing the muscle tension in lower-limb muscles and supporting vertical loads, which can help prevent musculoskeletal diseases. Although exoskeletons have certain limitations, such as lifting capacity and maximum walking speed, testing over several hours showed improved work efficiency and the potential prevention of muscle diseases [7].

3.4. Other applications

Wearable devices are commonly used in other fields as well, such as military and human–machine interfacing. Military wearable devices cover a range of locations according to their behavioral characteristics, such as a head controller [83], smart gloves [84,85], a lower-limb exoskeleton [86,87], smart shoes [88], and wearable suits [89,90]. For example, Schlenker et al. [89] have developed FlexiGuard, a biological telemetry system used to monitor the physiological conditions of soldiers, rescue workers, and firefighters. This system can improve the personal safety of monitored personnel during training and tasks. Basic settings include heart rate, body surface temperature, motion tracking (accelerometer), and sweat (humidity) sensors.

Wearable sensors also have applications in human–machine interfaces, for example, to measure artists' stress level and repeatability training [91–95]. Kusserow et al. [94] have proposed a wearable sensor system to measure the pressure response mode of professional musicians under public performance conditions. Otterbein et al. [95] have proposed wearable technology for artistic movement descriptors using force-sensing resistors, which investigated how artistic tools and methods can inform the development of this technology. Nam et al. [93] have proposed a dance training system that senses the pressure on the foot while dancing and extracts ankle movement. The exergame enables students to watch a teacher's dance from all directions by using an avatar and obtaining the effects of exercise and education by repeatedly practicing the avatar's dance.

4. Commercial wearable devices

Many wearable sensor products currently are available in the marketplace to meet increasing interest and applications (shown in Fig. 4). Table 2 summarizes most of these wearable devices and sensors.

The most common commercial sensors are the wrist-worn triaxial accelerometers. These commercial systems use proprietary algorithms that typically rely on inertial or rotational signals greater than a set threshold and are then defined as active counts. For example, Fitbit Flex is a smart watch for sports tracking, including steps, distance, calories burned, active minutes, hourly activity, and stationary time. Similar products include Jawbone Up, Nike FuelBand, Xiaomi Mi Band, and Huawei Zero. However, when walking speed is slow and accelerations during leg swing are small and irregular, the methods for step counting with wrist- and trunk-worn sensors may be inaccurate, as for people with hemiparetic gait.

In practical use, peak acceleration and angular velocity of the leg occur in the swing phase during the gait cycle, which is most easily measured with leg-worn sensors. A magnetometer can be added to evaluate the direction vector of spatial orientation. Therefore, linear acceleration, angular velocity, and heading angle relative to magnetic north can be obtained from any known object position, as the combination of accelerometer, gyroscope, and magnetometer is the most commonly used IMU (e.g., Vicon Blue Trident, XSens, TracPatch, APDM).

Heart rate signal often is fused with the inertial signal measured from commercial wrist sensors to provide information about metabolic information. For special requirements, wireless sensors can incorporate ECG, EEG, or EMG signals; piezoelectrodes can measure, for example, foot pressure and force myogram (FMG); biosensors can continuously monitor glucose; and sensors can measure temperature. Sensor information can be supplemented and given context by smartphone- or smartwatch-based reports. For instance, Movesense Medical developed a

Table 2
Typical commercial wearable sensors.

Product	Country	Sensor	Integrated system	Usage	Measured data	Specification	Pros and cons
Vicon	UK	IMU	N	Home, lab, outdoors, underwater treadmills, swimming	3-axis acceleration, 3-axis angular velocity, and 3-axis direction/position	Battery life: 12 h; Weight: 9.5 g; Charge time: 1.5 h	Waterproof, various application occasion; unable to measure muscle activity
Fitbit Flex	USA	Accelerometer	N	Sweat, rain, and splash proof, but not swim proof or showerproof (IP68)	Steps, distance, calories burned, active minutes, hourly activity, and stationary time	Battery life: up to 5 days; Charge time: 1-2 h	Low price and portable; unable to analyze gait and muscle activity
XSens	NL	IMU	Y	Home, laboratory, outdoors, IP68 water resistant rating	3-axis acceleration, 3-axis angular velocity, and 3-axis direction/position	Battery life: 1 day, 70 mAh; Charge time: 1 h; Weight: 11.2 g	Waterproof, various applications; support to build developer's own applications; unable to measure muscle activity
SENS	DK	Accelerometer	N	Home, laboratory, hospital	3-axis acceleration	Battery life: 90 days	User-friendly patch allows each individual to replace it as required; data automatically transferred to the cloud
TracPatch	CA	Accelerometer, temperature sensor, and step counter	N	Indoor and outdoor	Range of motion, ambulation, exercise, and wound site temperature trend data	N/A	First wearable orthopedic device; TracPatch cloud allows for unlimited data collection and storage; unable to analyze specific gait and muscle activity
Movesense	FIN	IMU, ECG sensor	Y	Home and clinical environment; water and shock proof	3-axis acceleration, 3-axis angular velocity, and 3-axis direction/position; heart rate (bpm); R-R intervals; single-channel ECG (nonmedical); Bluetooth heart rate profile	Weight: 9.4 g	Open source; heart condition can be monitored; unable to measure muscle activity
APDM	USA	IMU	N	Indoor and outdoor; water resistant and dust tight (IP64)	3-axis acceleration, 3-axis angular velocity, and 3-axis direction/position	Battery life: 12 h; Weight: 25 g	Various applications; unable to measure muscle activity
Noraxon	USA	IMU, EMG sensor	N	Indoor and outdoor; water resistant	3-axis acceleration, 3-axis angular velocity, and 3-axis direction/position; raw EMG	Battery life: 8 h; Charge time: 4 h; Weight: 19 g	Measures muscle activity; unstable, high cost, uncomfortable, and complex
BioX Bands	DK	IMU, FSR	Y	Indoor and outdoor	3-axis acceleration, 3-axis angular velocity, and 3-axis direction/position; 8-channel FMG; muscle contraction intensity	Battery life: 8 h	Indirectly measures muscle activity; general-purpose upper- and lower-limb movement detection and gesture classification; low cost

lightweight medical ECG and movement sensor for tracking human health at home and in the clinical environment. The Noraxon device can continuously collect various data within a unified software platform and simultaneously can supplement the integration of EMG, force, pressure, motion, and high-speed video. The TracPatch device passively collects wound site temperature trend data in addition to range of motion, ambulation, and exercise data during a patient's episode of care. The BioX Sensor Band, combining IMU and FSRs, can detect limb motion, muscle strength, and gestures accurately and conveniently.

5. Computation methods

On the basis of the measured data, gait phase detection and human gait feature recognition can be achieved through various analysis technologies. Various methods can be used to determine gait events during walking [4]. The simplest computation method for gait detection is based on threshold values; different threshold algorithms are proposed to extract certain features of the gait phases, time–frequency analysis method, or peak heuristic algorithms, which are also a branch of the threshold method in case the derivative crosses zero [14,96–101].

Fig. 4. Typical commercial wearable devices for activity monitoring and tracking. (a) Vicon; (b) Fitbit Flex; (c) XSens; (d) TracPatch; (e) Movesense; (f) APDM; (g) Noraxon; (h) BioX Bands.

ML is used widely for classifying gait stages in offline and real-time data [102,103]. Many gait phase recognition methods have been proposed on the basis of different ML methods, such as the HMM, CNN, and neural networks (NN) models [104,105]. For instance, HMM has been used in many applications as a branch of ML [9,19,20]. Roth et al. [106] have presented a HMM-based stride segmentation approach to evaluate the gait segmentation performance of 28 patients with PD, finding that the proposed HMM achieved a mean F1 score of 92.1%.

Many methods for gait phase parameters based on ANN have been developed. Evans et al. [107] have developed a hybrid method combining with a Feedforward NN and an HMM to increase the number of detected gait phases to five. Their tests showed that the average detection accuracy was 88.7% within 23 ms. In another study, three-layer NN was embedded into HMM for classification of six gait stages, and training data were marked with a rule-based detection method [98]. The accuracy of this method reached 98.11%, and the sensitivity, 94.32%. This hybrid method is computationally complex for model training but is highly efficient for real-time detection. Wang et al. [108] have applied the Long-Short Term Memory (LSTM) neural network to gait phase recognition based on IMU data. Their results have indicated that the gait phase transitions estimated from the proposed LSTM network can successfully approximate human intention, with an accuracy of 97.8%.

ML-based methods are an effective method for gait tracking [109,110]. Many studies have shown that offline detection is successful, but real-time detection is not remarkable because the parameter matrix and computational times are too large.

6. Discussion

In this article, we reviewed wearable sensors and their applications. Many nonwearable sensor-based devices exist, for example, motion capture systems, which are most suitable for gait analysis in the laboratory environment. Motion capture includes an image processing-based system and a floor sensors-based system to capture gait. However, it is impossible to capture data on human gait outside the laboratory with daily activities. Wearable sensors can be used flexibly not only in the laboratory and hospitals but also in the home and outdoor natural environments.

The use of wearable sensors within the health care system is rapidly increasing, mainly driven by the clinical demand for diagnosing and monitoring treatment. It is expected that wearable sensors will be incorporated into treatment practices over time, changing from decision support to full-scale medical devices. This transformation demands high-quality data with high reliability and a data infrastructure that allows for immediate processing and presentation of real-time data to health care providers and patients. At the same time, iterative design processes including all stakeholders – with the patient at the center – must be performed to ensure high compliance when using these new treatment modalities. Design issues such as battery life versus frequency sample must be addressed and tailored for specific medical conditions to allow for a full-scale transformation from hospital to at home solutions. The need will be most obvious for patients with neurological or musculoskeletal diseases, but all medical fields can benefit from increased knowledge on a disease's impact on motion and thereby on patients' quality of life.

Our review reveals that highly integrated and multimodal measurement is challenging and requires extensive studies. IMU is the most commonly used wearable sensor to measure human kinematics and kinetics, while sEMG is the main noninvasive technique used to evaluate muscle functions. On the other hand, FMG is being studied as an alternative to EMG [51,53,54]. Most reported works have adopted single-modality sensing technologies. Multimodality sensing that collects different types of motion data simultaneously is promising for obtaining more accurate and reliable results and yet remains challenging, requiring additional extensive studies. Multimodality sensing relies on new computation methods and algorithms, particularly ML and artificial intelligence, but will enable intelligent control of wearable devices such as robotic exoskeletons and active protheses. Moreover, data-driven activity modeling and motion reconstruction must be investigated further.

7. Conclusion

Wearable devices are used widely in various fields, from daily activities to medical rehabilitation and industrial assistance. Our review provides an overview of wearable sensors, including their technologies and applications. We focused on wearable sensors for activity monitoring in health care and rehabilitation and extended our examination to sensors for other applications, such as the human–machine interface and motion control in industry, the military, and art. We collected information on commercial wearable sensors, which can facilitate researchers' selection of devices for further studies. From this review we identified a few key research topics, calling for future research for new sensors, methods, and algorithms.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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