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Advancements in Human Motion Capture Technology for Sports: A Comprehensive Review

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Researchers have been focusing on developing intelligent sensing devices capable of capturing human movements or signals, particularly in sports and healthcare. These signals, encompassing biophysical and biochemical data, are increasingly utilized across various fields for purposes such as sports training, medical diagnostics, preventive healthcare, and rehabilitation. The urgency for real-time health monitoring has been underscored by the coronavirus disease 2019 (COVID-19) pandemic, hastening the demand for portable, flexible sensors enabling remote health signal measurement. Our investigation delves into recent advancements in flexible smart sensor technologies tailored for monitoring crucial signals in healthcare and sports. Within this comprehensive study, we provide an overview of the latest progress in smart sensors and systems engineered to track fitness and health indicators. These encompass a range of signals including electrocardiograms (ECGs), inertial data, motion, heart rate, and biological fluids (such as blood and sweat). Furthermore, we introduce a novel approach involving multimodal and integrated multidimensional sensing systems distinguished by their high sensitivity. Additionally, we elucidate current challenges in the field and offer insights into the future trajectory of smart sensors in capturing vital signals effectively. It is evident that the integration of modern fabrication techniques, stretchable electronic devices, the Internet of Things (IoT), and artificial intelligence (AI) algorithms has significantly augmented the capacity to monitor and utilize these signals for human health monitoring, including disease prediction. Smart sensors and systems that are multidimensional and multimodal might provide a more adaptable and comprehensive solution to meet the escalating healthcare demands.

1. Introduction

In these days of fast technological innovation and elevated concern for health and wellness, the worlds of sports and healthcare are integrating with each passing day.(1,2) With civilization advancing at such a rapid pace, monitoring physical health is becoming increasingly crucial.(3,4) There has been a marked emphasis on monitoring one's health since the beginning of the coronavirus disease 2019 (COVID-19) pandemic, leading to a dramatic surge in the demand for smart sensing devices. Smart sensors used to capture human motion have recently emerged as an

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essential tool for athletes, enabling them to personalize their health tracking and perform at their highest level.[5] The use of data-driven technology to measure and analyze vital signs is having a profound impact on the general population as well as athletes.[6,7] While conventional methods of health monitoring and diagnosis have their uses, they also come with several limitations.[8,9] For example, ambulatory monitoring devices for real-time electrocardiograms (ECGs) may be bulky, laden with cords, and irritating to the skin.[10] In addition, most traditional devices lack portability, making it difficult to seamlessly monitor one's health without disrupting everyday routines. This issue impacts not only sportsmen but also elderly individuals who regularly need to commute with healthcare institutions. It also affects those who participate in consistent physical exercise.[11,12] Athletes, in particular, need smart sensor technology that can adapt to their requirements and effectively track their training programs without hindering performance. These contemporary smart sensors are highly suitable for meeting these requirements because of their adaptability, portability, remote accessibility, and rapid data-collecting capabilities.[13,14] They have versatile applications in several domains, including sports training, medical diagnostics, and rehabilitation.

The introduction of smart sensors has led to substantial advancements and promising opportunities in the monitoring of essential physiological indicators in sports and healthcare.[15] These sensors are crucial for the management of personalized health since they are designed to monitor bioelectrical signals, movement data, and biochemical indications.[16,17] The advent of flexible smart monitoring devices has enabled a continuous monitoring of vital signs, hence expanding the potential for health surveillance. Research has shown that the integration of inertial sensors with adaptable smart sensors enhances training outcomes and diminishes exercise-related ailments.[18,19] These adaptable sensors provide an immediate and uninterrupted monitoring of blood pressure, blood oxygen levels, blood glucose, heart rate, and ECG, while also providing real-time readings.[12,20–22] These advancements have been facilitated by the emergence of pioneering materials, production methods, and adaptable electronics, resulting in enhanced user satisfaction, instantaneous data collection, accuracy, and a wider range of potential uses.[23–25] Moreover, the integration of artificial intelligence algorithms, big data technologies, and the Internet of Things (IoT) enables adaptable smart sensors to provide healthcare professionals with valuable data.[26,27] The advantages of using this integrated approach comprise a notable reduction in the number of hospital admissions, cost savings in hospital stays, and an enhanced utilization of medical resources. Portable smart sensor technology has recently seen an apparent upsurge in research, with the goal of monitoring critical physiological data in medical and athletic settings.[28,29] An indicative of this upsurge is the increasing number of comprehensive evaluations targeting flexible smart sensors to monitor health and fitness.[30,31] Focusing on the development of flexible smart sensors for health and fitness tracking is important, but relying solely on bioelectrical or physical signals for accurate disease diagnosis, health assessment, and sports training presents significant challenges.

The primary signals crucial for capturing human motion in sports applications encompass biophysical and biochemical indicators, exemplifying the inherent challenges in this endeavor. This review aims to explore diverse monitoring approaches, notably, employing flexible, intelligent sensors to procure precise human motion data. Before delving into specifics, it is essential to examine the critical signal monitoring across three main categories: cardiovascular signals detection, human mobility indicators for monitoring, and inertial movement signals detection, as depicted in Fig. 1. In this investigation, we thoroughly evaluate advanced sensors utilized for motion capture or monitoring across each signal category, elucidating their sensing methodologies, application prerequisites, technical attributes, and potential problem-solving strategies. While recognizing the limitations of solely relying on individual signals for accurate health monitoring, we present an innovative perspective by advocating and exploring tools and systems integrating multidimensional and multimodal sensing techniques.

Our work distinguishes itself from previous reviews by providing an in-depth analysis of the latest advancements in motion capture technology specifically tailored for sports applications. We have meticulously compiled and synthesized recent innovations, highlighting emerging trends, the integration of AI and machine learning, and novel applications in athlete performance analysis and injury prevention. The study also provides a comprehensive analysis of the opportunities, limitations, and challenges in the field of smart sensors intended to detect critical

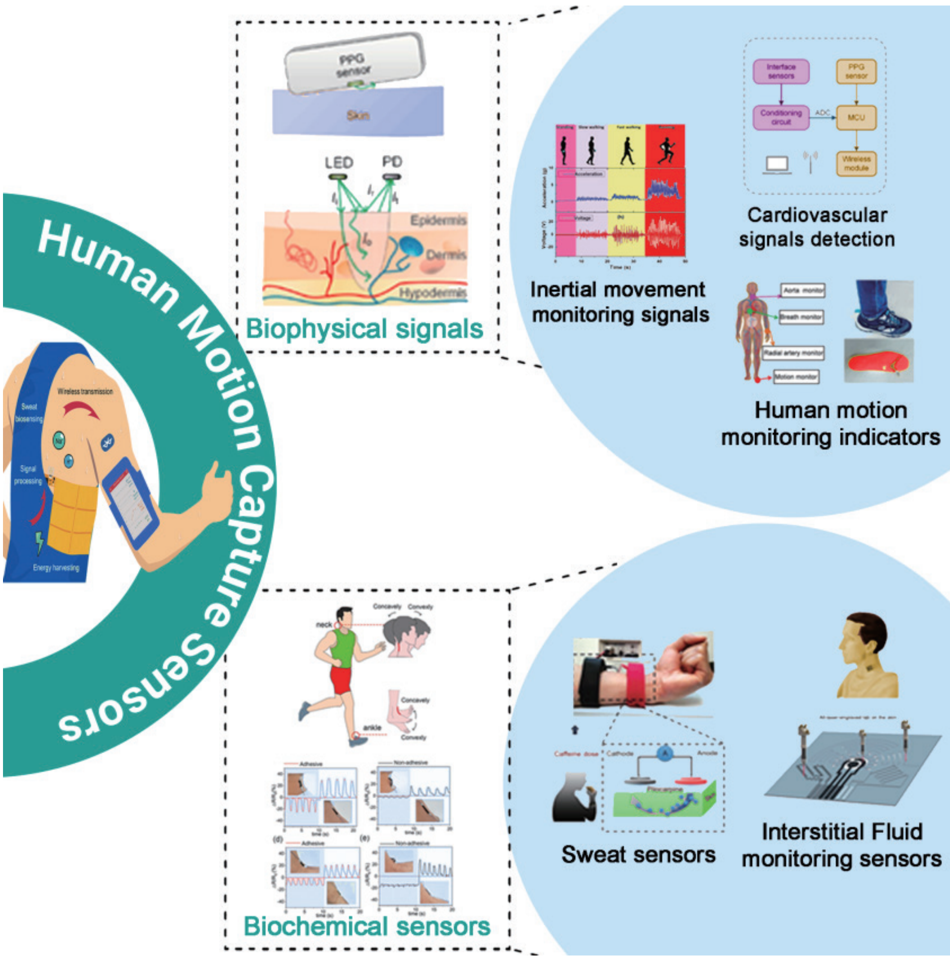

Fig. 1. (Color online) Schematic illustration of human motion-capturing sensing systems and their types, e.g., biophysical and biochemical sensors used to record or sense athlete motions in sports applications.

signals. Our thorough review yields several important findings including (1) a methodical classification of biophysical and biochemical signals to record or capture human motions in sports applications; (2) a thorough analysis of the smart sensing technologies used to monitor each of these vital signals, including their sensing mechanisms, applicability, capacity for problem-solving, and technical characteristics; (3) a novel investigation and careful assessment of multidimensional and multimodal smart sensing devices; and (4) an exhaustive summary of the present issues, constraints, and future directions in the field of smart sensor technologies.

2. Classification of Human Body Signal Detection in Athletes

Smart sensors have changed the sports and health monitoring environment. Diverse kinds of signals are utilized to provide vital information, improving the monitoring of sports performance and the treatment of medical ailments.(32) The three primary signal categories of biophysical, bioelectrical, and biochemical signals are critical components of smart sensors intended for vital sign monitoring.

2.1 Physiological signals

Physiological signals produced by the human body are called biophysical signals, and they can be quantified or observed for several uses, such as applications in sports and medicine. These signals can be used to monitor performance, fitness levels, and health conditions since they include important information about how the body is working. Smart sensors for tracking vital signs in sports and health depend heavily on biophysical signals.(32–34) Hence, this area has seen great advancements and bright futures.

2.1.1 Detection of cardiovascular signals

Sensors are widely utilized to measure pulse and heart rate to assess cardiovascular health. These sensors are usually affixed to various areas of the body, including the fingertips, neck, wrist, and chest.(33) In the field of cardiac health monitoring, developments in optical, pressure, and electrical sensors have made it possible to achieve an accurate and ongoing monitoring. In some investigations, the integration of electrical sensing has even allowed for the detection of the heart's electrical activity. For ECGs, Rodeheaver *et al.* used window-averaging and peak-seeking algorithms to derive heart rates,(35) as shown in Fig. 2(a). The smart integrated system (SIS) has a breathable, perforated membrane that can collect real-time, continuous physiological data. Such data include high-quality ECGs, heart rate, respiration rate, and activities.

Furthermore, Kim and his team developed an innovative and scalable hybrid electronic system that integrates three electrodes, flexible circuits, motion sensors, and wireless transmission modules.(7) The system provides a comprehensive approach to monitoring cardiovascular health in sports and healthcare settings by monitoring ECGs, heart rate, and respiration rate in real time and remotely [Fig. 2(b)]. A pressure sensor can capture the heart rate and pulse directly, in contrast to the ECG, which measures heart rate indirectly. Rasheed *et al.*

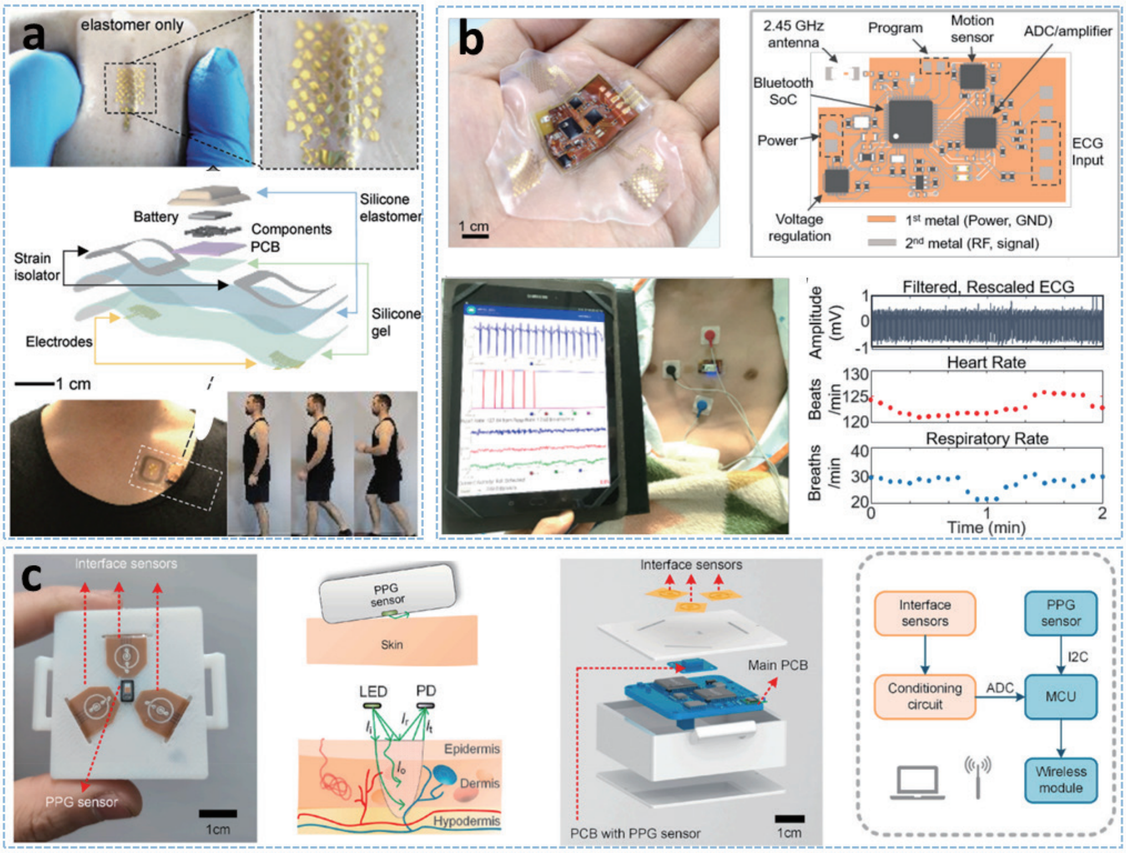

Fig. 2. (Color online) (a) Overview of design, fabrication, and architecture of strain-isolated soft bioelectronics (SIS). Reproduced with permission.(35) Copyright 2021 John Wiley VCH. (b) Schematic and digital image of device design, structural components that describe each functional block, and data acquisition with clinical application on pediatric patients. Reprinted with permission.(7) Copyright 2019 IEEE. (c) Schematic and digital image of the interface sensor with the working principle for sensing skin contact pressure in the middle, with the signal flow diagram of the wearable device. Reprinted with permission.(38) Copyright 2021 Elsevier.

have proposed an innovative approach to creating a pressure sensor that utilizes a piezoelectric charge-gated thin-film transistor (TFT) consisting of a double-gated amorphous silicon TFT sandwiched between a polyvinylidene fluoride (PVDF) piezoelectric sandwich structure.(36) The multipoint monitoring of heart rate is possible with this technology. This is achieved by integrating ultrathin PZT and semiconductor materials into the silicon substrate, allowing for a rapid response time of 0.1 ms and a low detection threshold of 0.005 Pa. A significant advantage of this system is that it can accurately detect arterial pulses at locations such as the wrist and neck. Photoplethysmography (PPG) is the measurement of changes in blood flow across the skin to determine heart rate. Pang and coworkers(37) developed a capacitive sensor that makes use of a microbrush structure. This clever microbrush layout greatly improved the sensor's interaction with bumpy skin, leading to precise positioning on the body.(37) There was also a 1–2-fold increase in signal-to-noise ratio (SNR). The designed sensor was able to pick up on even the most subtle pulsation owing to the ability of microhairs to amplify signals. It is difficult to obtain accurate heart rate and pulse data when using commercially available PPG systems because of their large size and high-power consumption, particularly when the subject is performing intense physical activities or when dealing with optical interference. Smart sensors and the skin are constantly changing in contact, which is the primary source of motion artifacts. Scardulla *et al.* evaluated the impact of contact pressure between PPG sensors and the skin, revealing that it has a greater effect than exercise on skin contact pressure.(25) They observed a Pearson correlation coefficient ranging from 0.81 to 0.95 when contact pressure was maintained at 54 mmHg, with an average percentage error ranging from 2.4 to 3.8%. Wang *et al.*(38) introduced a PI-based interface sensor that employs a reflective PPG sensor and a platinum film thermistor [Fig. 2(c)] to measure the contact pressure between the sensor and the epidermis of the body. The thermistor distinguished pressure by detecting the interface temperature field between the sensor and the skin. By means of its adaptability to irregular surfaces, the sensor facilitates precise heart rate monitoring during physical activities such as weightlifting.(38) Chen *et al.* showed a textile-based pressure sensor that has the ability to monitor epidermal pulses and demonstrates significant promise in further modernizing and standardizing pulse palpation within the realm of traditional Chinese medicine.(39)

As a useful indicator of the effects of neurohumoral factors on the cardiovascular system, heart rate variability provides valuable information. This metric is regularly used to diagnose and prevent cardiovascular diseases, as well as to detect mental stress. Correia *et al.* provided a compelling illustration of this, using data derived from photoplethysmograms (PPGs) and ECGs to examine heart rate variability at rest and during the Stroop colorimetric test, a stress-inducing task.(40) They successfully identified stressors by computing RR and PP intervals, which allowed them to gauge HRV consistency. Pramukantoro and Gofuku also conducted a noteworthy study involving the classification of heartbeats by the extraction of features that are indicative of heart rate abnormalities, particularly RR intervals.(41) After applying the random deep forest model in machine learning to oversampled data, they achieved a remarkable 99.67% accuracy in classifying heartbeats automatically. It is of great importance to be able to monitor cardiovascular diseases early in the course of their development through this achievement. A smart wristband is the most prevalent smart device currently available for monitoring heart rate. The wearability of these products is convenient, comfortable, and discreet. The research field is currently exploring smart clothing for this purpose, which must incorporate the advantages of smart wristbands. The accuracy of monitoring is also an essential aspect of disease prediction, which is why they must maintain a high level of accuracy.

2.1.2 Human mobility indicators for monitoring

Smart inertial sensors are capable of detecting body motion with exceptional precision, but cannot detect movements involving joint bending and swallowing. In spite of this, they provide a wealth of valuable health information that has been used to improve training outcomes and aid in the diagnosis of various conditions, including Parkinsonism, Alzheimer's, and diabetes. A smart strain sensor is affixed to the skin in the form of a patch, which adapts to the movement of the wearer, thereby detecting joint bending. Luo *et al.* devised a piezoelectric sensor based on

PVDF/SWCNTs for sensing purposes, which shows high sensitivity (15.68 kPa^{-1}) and fast response (66 ms).[42] Similarly, Song *et al.* developed an innovative Janus graphene film (JGF)-based convex arch-shaped pressure sensor with a tunable pressure-dependent contact area to monitor the vital signs of the human body such as human body motion, breathing, and arterial pulse [Fig. 3(a)].[43]

Using a multipoint control method, researchers have assessed basketball performance by attaching a sensor to a joint and monitoring changes in force, angle, and motion frequency over time. Wang *et al.* proposed a stretchable, self-healing, and skin-mounted active sensor for multipoint muscle function monitoring.[44] However, these strain sensors may be susceptible to motion artifacts, which may reduce their accuracy. The issue may be mitigated by providing self-adhesive and elastic attributes to the substrate. Wang *et al.* addressed this issue by developing stretchable, adhesive strain sensors that can be attached to the ankle, wrist, and neck,[45] as shown in Fig. 3(b). An innovative dry adhesive layer made of waterborne polyurethane ensures a snug attachment to the skin as well as high sensitivity (GF = 89) and significantly reduced motion artifacts. As sweat accumulates over time, users may experience discomfort and measurements may be compromised. To tackle this issue, Bi *et al.* used conductive fabrics to monitor limb movements.[46] The wrist, elbow, knee, and ankle were covered with a conductive substance by employing a modal/spandex fabric and rGO/carbonated ink/PVA. The data acquired through this approach could potentially be utilized by coaches or in

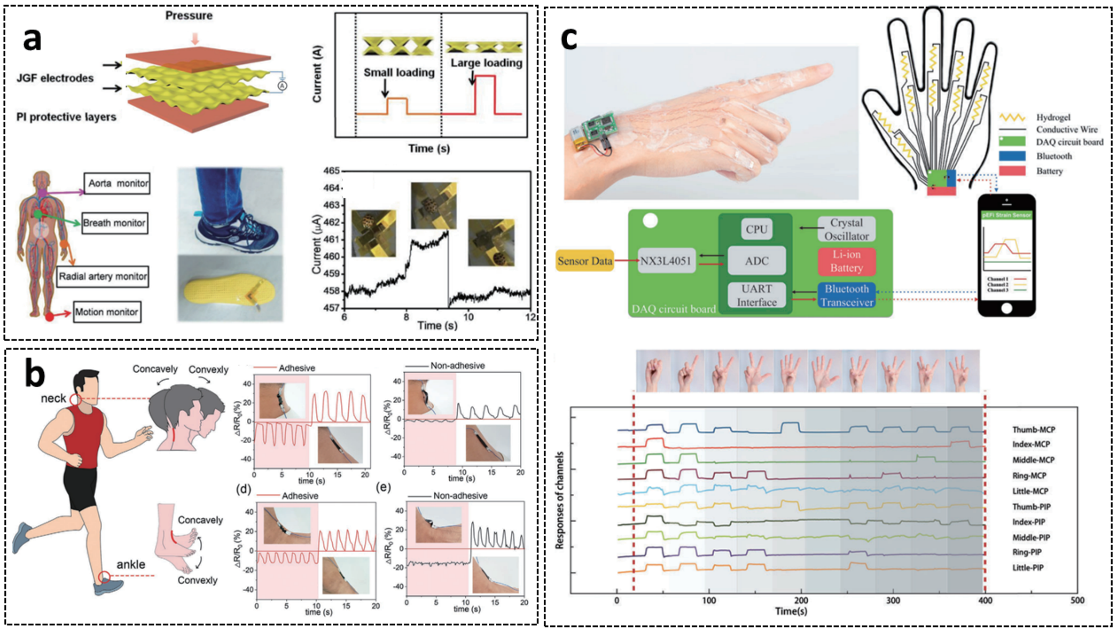

Fig. 3. (Color online) Sensors for detecting human body movements. (a) Schematic illustration of the pressure sensor for monitoring human vital signs. Reprinted with permission.[43] Copyright 2018 John Wiley and Sons. (b) Stretchable and shape-conformal contact strain sensors on the neck and ankle during movements. Reprinted with permission.[45] Copyright 2020 Wiley-VCH. (c) Overview of the soft ionotronic skin (iSkin) system integrating 10-channel hydrogel–elastomer hybrid ionic sensors and a wireless electronic control module. Reprinted with permission.[47] Copyright 2019 Soft Robotics.

specialized algorithms to rectify the posture of collegiate athletes, including those engaged in badminton and basketball.

Tracking physical activity is a must to collect useful health data. Gu *et al.* developed a transparent, smart sensing, highly adaptable soft ion skin technology. It comprises a hydrogel/elastomer hybrid 10-channel ion sensor and a wireless electronic control module,(47) as shown in Fig. 3(c). Hydrogel was applied to an already existing elastomer and allowed to solidify before being treated with benzophenone to create the ion sensor. The resulting hydrogel-elastomer hybrid is extremely stretchy (300%) and highly transparent (95%). This system, when affixed to the hand, is capable of recognizing various movements and wirelessly transmitting the data to a smartphone. This remarkable functionality enables the sensor to aid the deaf and speech-impaired in communicating through sign language. To ensure comfort and softness for users, particularly those who may need to wear such devices for extended durations, such as patients, Zhao *et al.* demonstrated the use of conductive fabrics.(48) Additionally, smart strain sensors have been employed not only to monitor joint movements but also to detect foot motions, serving various purposes, including foot type assessment, sports training, clinical gait analysis, and foot pathology diagnosis. To collect real-time gait data, Mao *et al.* introduced a self-powered portable triboelectric nanogenerator (TENG), which significantly enhanced sensor performance, using 3D printing technology.(49) They embedded this sensor into sneakers to monitor gait and stability during a range of movements, such as *in situ* activities and walking. Liquid-metal-based piezoresistive sensors have also been utilized for measuring plantar pressure. These sensors utilize eutectic gallium indium (EGaIn) within a 3D-printed ABS spiral pattern microchannel as a conductive liquid to detect plantar and ankle pressures within the range of 0 to 400 kPa.(50) The information gathered using these flexible circuits and sensors is transmitted via Bluetooth to the insoles, where it is analyzed by a specialized algorithm. The results of the analysis of the weight distribution during the posture and swing phases indicate that the sensor can effectively differentiate between walking and sprinting. Furthermore, intelligent hosiery, which consists of a signal preprocessing circuit, microcontroller, smart electrode, and triboelectric output voltage, employs the latter as a pressure signal to track plantar pressure. Subsequently, convolutional neural network algorithms are applied to these measurements to derive insights into locomotion and oversee individual health.(51)

Further research is aimed at enhancing the adaptability and mobility of smart sensors. With the advancement of flexible electronics, smart sensors equipped with detection circuits can be seamlessly incorporated into flexible substrates and worn on the body for real-time motion monitoring. However, these smart sensors still face challenges related to motion artifacts. Currently, addressing this issue involves the development of specialized algorithms and the incorporation of filters. Another promising approach is the utilization of self-adhesive substrates, which enable the smart sensor to be securely adhered to the skin. In particular, substrates made from skinlike materials can seamlessly conform to the body, eliminating gaps. The advent of hydrogel materials has resolved the issue of deformability of conductive materials on a large scale, allowing them to be directly affixed to the skin with strong adhesion and excellent tensile properties. In addition to motion artifacts, electromagnetic interference poses another challenge in motion detection. Optical-fiber-based sensors are a viable solution to mitigate electromagnetic interference, although they are less explored compared with the previously mentioned sensors. For instance, Leber and colleagues[52] developed a stretchable strain sensor for detecting bending motions, such as those of knee joints and fingers, by embedding optical fibers into fabrics.

2.1.3 Signals for detecting inertial movement

With a database of information on kinematic and kinesiological mechanics, inertial motion sensors are a jackpot for smart sensors that track vital signs in health and sports. Applications for this plethora of data include injury prediction and motion quality evaluation. An example of a prominent use of inertial motion data is the evaluation of the risk of falling, where data from inertial motion is crucial. From medical diagnosis to sports and rehabilitation to specialized training, the efficient tracking, analysis, and deciphering of such data are crucial. One example is typical stair climbing, which is part of many fitness programs, military drills, and training sessions. Using inertial sensors attached to the feet, Ojeda *et al.* took a novel approach to recording motion data while stair climbing.[19] Researchers found that measuring the distance between feet could help in predicting how likely it is to slip and fall, as well as how ground forces and bounce angles will affect a person's movement. Conventional optical motion and video-based motion tracking systems, which are commonly regarded as the most reliable tools for motion tracking, are burdened by limitations such as the unfeasibility of portability and expensive infrastructure. Nevertheless, these constraints are overcome by employing inertial sensors, which are physically attached to the body. Research results have emphasized that inertial sensors have a remarkable consistency of the gold standard, with correlations surpassing 0.9. Therefore, the movement data acquired by inertial sensors during training can be employed to evaluate athletic performance, offering valuable insights for athletes, coaches, and researchers to enhance training techniques and equipment.

In an effort to alleviate the pain associated with rigid inertial sensors, Ammann and colleagues[53] developed a skin-adhesive patch that combined accelerometers and gyroscopes. A motion-tracking wireless smart patch was created, as seen in Fig. 4(a). An innovative device was utilized to monitor the movement of the arm, and the data was transmitted wirelessly to a computer via Bluetooth. The data processing system obtained an outstanding consistency of 0.95 after evaluating limb movements thoroughly compared with a video motion tracking system. Figure 4(b) shows the stretchable inertial tracking system developed by Lee *et al.*[54] using accelerometers connected by elastic wires resembling snakes on a flexible substrate.

A wide range of body motions were successfully captured using this technology. To keep the device from breaking, a PI network is inserted within the Ecoflex and silicone layers on the outside and inside, respectively. The goal is to keep strain below 20%. Once implanted with a wireless communication module, the device forms a strong bond with the skin, allowing for the immutable tracking of activities such as weightlifting. The results of trials have shown that using flexible packaging methods greatly enhances user comfort and flexibility. A novel gyroscope ball [Fig. 4(c)] built on 3D symmetrical TENG technology was proposed by Shi *et al.*[55] as an alternative to the conventional use of inertial sensors for motion tracking. In addition to its impressive energy harvesting and storage capabilities, this innovative device excels at

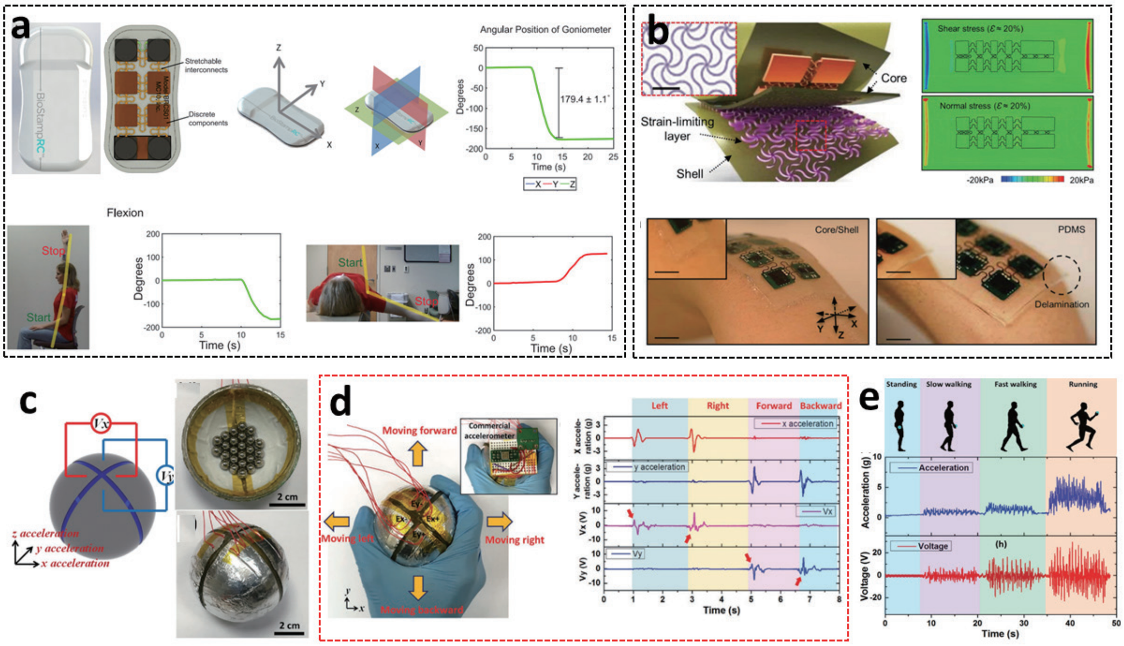

Fig. 4. (Color online) Sensing and recording of inertial signals. (a) Triaxial stretchable electronic sensor used to detect limb movement with multiple degrees of freedom. Reprinted with permission.[53] Copyright 2020 John Wiley and Sons. (b) Integrated electronic sensor that is highly responsive to human stress-strain with a 20% strain limit. Reprinted with permission,[54] Copyright 2015 John Wiley and Sons. (c) Schematic illustration of shape conformal and self-powered rotatory motion detection device used to monitor human activity. Reprinted with permission.[55] Copyright 2017 John Wiley and Sons.

concurrently measuring acceleration and rotation along many axes. Researchers have discovered a correlation between the voltage produced by Ex and the intensity of acceleration when the device's *x*-direction was aligned with the direction of movement (e.g., whether the person was standing, strolling, walking briskly, or running slowly).

However, inertial sensors relying on self-powered mechanisms necessitate an external monitoring circuit. In an effort to streamline complexity and enhance stability and sensitivity, Xie *et al.*[11] introduced an innovative gyroscope design based on the impedance matching phenomenon of TENG for the measurement of relative rotation angles. The system consists of a standalone rotational disk-shaped TENG, a resistive rotation angle sensor, and a light-emitting diode (LED) alarm display. Notably, this design boasts an impressive sensitivity of 67.3 mV per degree, demonstrating excellent linearity between output voltage and rotation angle. Additionally, it offers a rapid response time of just 20 ms within a range spanning 0 to 260 degrees. Notably, this device obviates the need for batteries and intricate management circuits, resulting in a simplified system, and leverages quantized LED indicators to present rotation angles conspicuously.

As individuals age, the risk of accidental falls increases, potentially resulting in fatal outcomes. To address this concern, researchers have employed inertial sensors affixed to the human body to collect motion data, employing filtering techniques to eliminate noise. Subsequently, this data is wirelessly transmitted to a computer and analyzed utilizing a specialized algorithm, allowing for the detection of falls by these inertial sensors. Furthermore, the importance of quality sleep in maintaining overall health cannot be overstated. To assess sleep quality, magnetometer sensors have been utilized to detect minute changes in magnetic vectors associated with millimeter-scale respiratory movements during the night.(56) Following processing by advanced algorithms, this data can be leveraged for sleep quality assessment. In the context of neurodegenerative diseases, such as multiple sclerosis, balance disorders frequently manifest as symptoms. In this regard, Sun *et al.* positioned a BioStamp wireless inertial sensor near the center of mass (COM) on the fifth lumbar vertebra (L5 back) to capture posture fluctuations while standing.(57) The results of comparative analysis with established standards indicate that smart inertial sensors exhibit promise as a diagnostic tool for multiple sclerosis.

2.2 Detection from biochemical signals

Developing and using smart sensors to monitor vital signs in sports and health rely heavily on biochemical signals. The exponential development of these sensors over the past few years has revolutionized our perspective on individual well-being and sporting achievement. Biochemical sensors provide a more comprehensive picture of a person's health than conventional sensors by sensing unique biomarkers and chemicals in physiological fluids, as opposed to commonly measured characteristics such as temperature and heart rate.(37) Electrolytes, glucose, lactate, cortisol, and other indicators may be present. Smart sensors can monitor these biochemical signals and give real-time, individual input that helps with controlling chronic diseases, maintaining general health, and improving athletic performance. When athletes monitor their lactate levels, for instance, they can adjust their training programs to prevent overexertion and injury. Chronically ill people, such as those with diabetes, now have a noninvasive and more convenient way of tracking their glucose levels than with previous blood tests. Smart sensors show great promise in this area, with continuous R&D targeting greater accuracy, less expense, and more user-friendliness. With the continued development and accessibility of these devices, there is great promise for improving sports performance and giving people a new sense of control over their health through the ability to detect problems early and receive tailored treatments.(37) As this development progresses, biochemical signals will remain pivotal, opening up unprecedented perspectives for health and athletic monitoring.

2.2.1 Detection from sweat

Sweat, a vital bodily fluid, holds a wealth of health-related information. Innovative sweat detection sensors, employing various principles, have been engineered to facilitate the continuous, on-site analysis of sweat. For instance, Palumbo *et al.* and Wiig and Swartz devised an electrochemical sensor for the measurement of lactic acid, glucose, and potassium ions via screen printing.(33,34) This sensor was seamlessly integrated into eyeglasses, with data being transmitted to a host device through Bluetooth, allowing the real-time monitoring of sweat markers. The ability to detect ions in sweat holds significance for distinguishing between aerobic and anaerobic exercises. Carbon fibers, commercially modified with a selective sodium ion (Na^+) membrane, exhibit remarkable precision (55.9 ± 0.8 mV/log [Na^+], $N = 3$) in detecting Na^+ within the concentration range of 10^{-3}–10^{-1} M.(58) An electronic tattoo smart sensor made of silver nanowires and molecularly printed polymers was created by Jia *et al.*(59) This sensor can detect lactic acid with a high sensitivity of 0.22 μM. These sensors can be seamlessly incorporated into textiles, paving the way for the development of smart clothing. The future calls for smart flexibility, and Zamarayeva *et al.* have embraced this trend by employing flexible printing techniques to design electrochemical sensors using paper as a substrate.(1)

To enhance the stability of the reference electrode, they ingeniously incorporated a layer of carbon nanotubes (CNTs) between the film and the reference electrode, effectively adsorbing Cl^{-1}. Furthermore, the inhibition of lactic acid diffusion by the PVC film has rendered the detection of lactic acid impervious to the effec of sweat flow, thereby boosting the sensitivity to 3.28 μA/mM. Additionally, these paper-based sweat sensors hold the advantage of being disposable components.(60) Tai *et al.* developed a smart electrochemical differential pulse voltammetry sweat sensing module for drug monitoring, as shown in Fig. 5(a).(61) Sweat caffeine levels were monitored under various conditions, i.e., drug doses and measurement time after drug intake, providing a smart sweat-sensing platform for noninvasive and continuous point-of-care drug monitoring and management. In conjunction with electrochemical sensors, smart sensors that rely on optical sensing techniques are used for sweat detection. A sodium ion, pH, and urea detection system was implemented using an optical sensor that relies on the compound 2-hydroxy-1,4-naphthoquinone, also known as Lawsone (HNQ), in the analysis of sweat samples.(62) The presence of sodium ions was shown to have an impact on the absorbance of

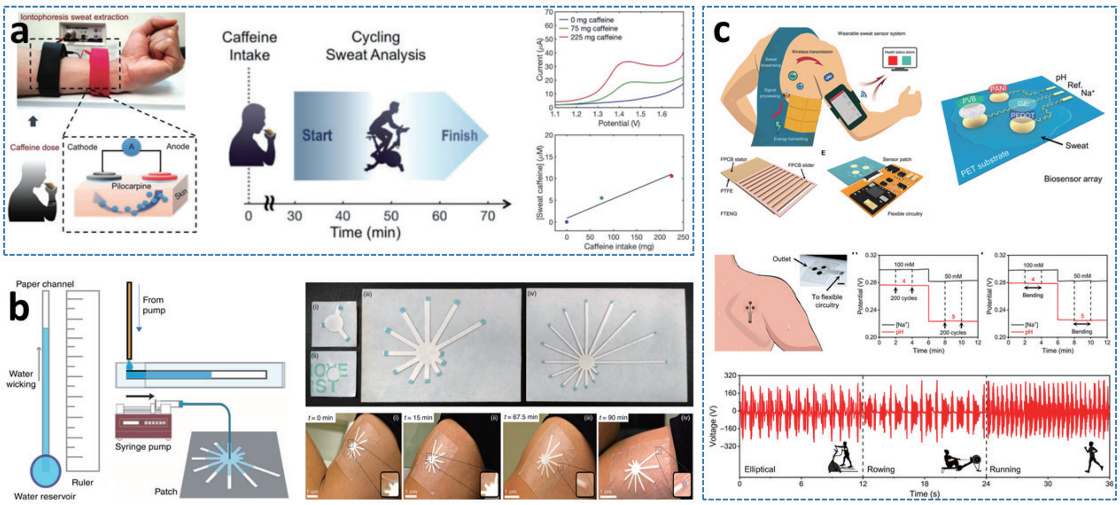

Fig. 5. (Color online) Sweat detection. (a) Schematic of sweat detection of iontophoresis-induced sweat with corresponding results of drug concentration in sweat. Reprinted with permission.(61) Copyright 2013 Wiley-VCH. (b) Sweat patch and paper colorimetric sensor worn on the top-arm surface during exercise. Reprinted with permission.(68) Copyright 2019 Springer Nature. (c) Schematic of the integration of methods for wirelessly transmitting data to a mobile user interface via Bluetooth and incorporating human motion energy harvesting, signal processing, microfluidic-based perspiration biosensing, and real-time health status tracking. Reprinted with permission.(70) Copyright 2020 American Association for the Advancement of Science.

HNQ, whereas the reactivity of HNQ was seen to be diminished by the presence of hydrogen ions. Additionally, the introduction of urea was observed to enhance the interaction between sodium and potassium ions with HNQ. The colorimetric sensor used for sweat detection is a widely employed optical sensor with the notable attribute of visual representation. Zhou *et al.* devised a sweat sensor using colloidal gold nanoparticles (AuNPs) to discern dehydration from overhydration promptly by the observation of color alterations.(63)

Acidity and alkalinity can be measured with the use of fabric-based colorimetric sensors.(64) Methyl orange and bromocresol green were used to determine the pH of sweat, and a lactic acid test was used to quantify the amount of lactic acid. Future research could set the way for the development of smart sensing clothing made possible by incorporating sensors into smart fabrics. The cotton thread and functionalized filter paper colorimetric sensor showed a wide dynamic detection range of 50 to 250 μM and a low detection limit of 35 μM. With the addition of an arm guard, the sensors became much more affordable and convenient to use with a smartphone, which greatly improved their usability.(65) Ardalan *et al.*(66) developed a fluorescent patch for use as a smart diagnostic tool. The materials used to make this patch were medical tape, cotton thread, and filter paper. Glucose, lactate, pH, and chloride were among the analytes that this patch was designed to monitor. A 3D-printed image module with optical filters and ultraviolet (UV)–LED lights was integrated into the smart patch to record the detection data. The user can view the detection outcome on the intelligent terminal once the data has undergone algorithmic processing.

Sweat detection may be used to measure the intensity of training and how well a person is doing throughout training, which can help create personalized training plans. Cai *et al.*(67) used electroluminescence and luminol as the signal material to create the lactic acid sensor. Luminescent hydrogen peroxide is a byproduct of the enzymatic hydrolysis of lactic acid. Because of its luminous quality, the sensor can detect the presence of lactic acid and determine the intensity of the activity. This allows the sensor to zero in on the critical workout intensity threshold. Because too much transpiration may upset the sensitive balance of electrolytes and cause dehydration, controlling sweat production is an important part of keeping the body in homeostasis. Figure 5(b) shows that a sweat rate detector patch may record perspiration in sequential order and conduct independent *in situ* tests in real time.(68) It allows sweat samples to be collected in a sequential fashion and their individual analysis in real time on-site. When saturated with perspiration, the pigmented tip changes color, making it easy to analyze the rate of sweat and the degree of dehydration. Concurrently, the patch is both inexpensive and capable of being mass-produced. Training regimens for athletes, physical exercise programs for rehabilitation patients and older adults, and performance for persons engaged in high-intensity activities, for example, firefighters, could all be improved with the continuous measurement of lactic acid levels in sweat to analyze the lactate threshold, which signifies the shift from aerobic to anaerobic metabolism.(69) A multipurpose sweat platform was developed by Kim *et al.* to measure many physiological indicators, such as stress-related cortisol level, glucose, vitamin C, and sweat rate.(2)

Electrodes embedded in microchannels that come into contact with perspiration were used to monitor changes in electrical resistance, which allowed for the rate of perspiration to be measured. While glucose and vitamin C levels were tracked using fluorescence methods, the concentration of cortisol was assessed using an alternative enzyme-linked immunosorbent assay that made use of anti-cortisol antibody (ACA)–AuNPs.[2] Utilizing near-field communication might lead to the realization of the wireless digital tracking monitoring of the indicated markers. Sweat must be stored since it evaporates very rapidly. According to the study by McCaul *et al.*,[71] the most common method is to add patches that retain sweat to the sensor. In addition to establishing the sweat storage zone, Martín *et al.* used lithography and screen-printing methods to build an electrochemical sensing platform for the epidermis. Rapid and easy sweat extraction and metabolite detection are the goals of this platform design.[72] Electrodes, microfluidic channels, detecting reservoirs, and medical adhesives significantly improved the efficiency of sweat collection.[72] Put together, these parts formed a natural sweat pump that allowed the flexible microchip device to stick firmly to the skin, remaun in constant contact, and rapidly collect perspiration. Consistent and sufficient sweat was supplied by the adopted detector design, which successfully eliminated the presence of initial sweat metabolites that might possibly interfere with correct detection. Song and colleagues[70] created a smart platform that is mass-producible and battery-free. It effectively harnesses body motion power using a freestanding TENG (FTENG) based on flexible printed circuit boards (FPCBs), exhibiting a high-power output of around 416 mW m^{-2}. Figure 5(c) shows the possible applications of the designed battery-free triboelectrically driven system in on-body human trials, where it might power multiplexed sweat biosensors and wirelessly communicate data to user interfaces via Bluetooth.[70] The analysis performed after exercise is the basis of the sweat detection approach discussed previously. Note that sweat sensors may not work for those who do not sweat much or at all, especially in patient groups. In this case, an electric current is employed to inject pilocarpine ions into the skin in order to artificially induce sweating. While a small number of sensors can actively intervene, the majority of sweat sensors merely detect perspiration. We hope to soon make strides in developing more sensors with closed-loop control capabilities.

2.2.2 Monitoring devices for interstitial fluid

Interstitial fluid makes up about 60–70% of all body fluids that is an important part of interstitial fluid.[73] The composition is mostly affected by the cellular environment in which it is found. It is possible to diagnose cytopathology using evaluation results related to the biophysical properties and composition of an entity as a foundation for assessing the health of nearby cells. Several chemical components in the fluid are similar to those in the blood, including glucose, lactate, cortisol, and urea. Therefore, by monitoring health markers in the interstitial fluid, it is possible to assess the number of equivalent indicators in the bloodstream. Reverse ion osmosis (RI) is a process that involves the extraction of chemicals using the potential difference between two electrodes placed on the skin.[73] Charged ions, such as sodium ions, migrate in a certain direction under the effec of an electric field, ultimately accumulating towards the cathode. The cathode, which contains a significant concentration of sodium ions, facilitates the permeation of water over the gradient. Furthermore, in conjunction with water, the neutral species found in the interstitial fluid also demonstrate permeability. In their study, Bandodkar *et al.* presented a comprehensive investigation of a temporary glucose sensor that utilizes a completely printed tattoo-based approach.[74] A set of reverse iontophoresis electrodes, including a reference electrode and a functional electrode, were printed onto the substrate. This printing procedure was conducted using screen-printing techniques. An additional modification was made to the working electrode by adding lactate oxidase. One hour after eating, individuals' blood glucose levels were found to be higher, a phenomenon known as postprandial glycemia.[32] To achieve an accurate and calibration-free glucose level measurement, a two-dimensional array sensor design could potentially be used. Using transdermal refractive index sensing, Lipani and colleagues created a graphene-based glucose sensor array that effectively extracts glucose from interstitial fluid.[75] Their apparatus included a 4 × 4 grid of sensors that facilitated glucose measurement in a noninvasive and path-selective manner. The assessment of glucose levels both pre- and post-lunch and snacks demonstrated that the arranged sensors yielded congruent measurements, therefore validating their capacity to effectively monitor blood glucose levels.[32] The panda electronic tattoo patch sensor was produced by Kim *et al.* using screen printing techniques. This sensor has the capability to detect both the sweat extract from the anode and the ISF extract from the cathode simultaneously, as shown in Fig. 6(a).[76] The correlation between the detection of glucose and alcohol after meal intake and alcohol consumption and the readings obtained from commercial blood glucose meters and breathalyzer equipment was shown to be significant. The extraction of interstitial fluid by the RI approach typically requires a duration of 5 to 10 min, and the pace of extraction is sluggish. Consequently, this technique lacks the capability to perform the real-time detection of interstitial fluid. The advancement in

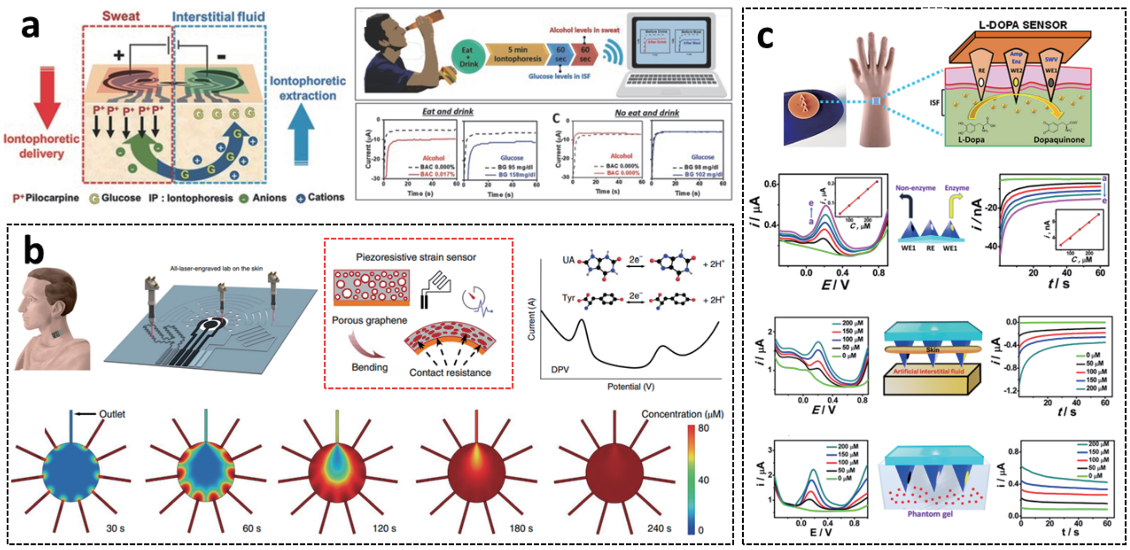

Fig. 6. (Color online) (a) Panda-shaped wearable biosensor for glucose and sweat extraction and detection. Reprinted with permission.[76] Copyright 2018 John Wiley and Sons. (b) Schematics of the sweat sensor for metabolic and nutritional management, which detects UA and Tyr with DPV in which the analyte level is determined from the oxidation peak height. Reprinted with permission.[15] Copyright 2019 Springer Nature. (c) Schematic illustration of a mannequin hand sporting a microneedle sensor for L-Dopa detection and monitoring in ISF using a microneedle sensor. Reprinted with permission.[17] Copyright 2019 American Chemical Society.

microneedle manufacturing technology has addressed the limitation of the reverse iontophoresis technique in real-time interstitial fluid detection. Teymourian and colleagues[77] devised a microneedle apparatus capable of continuously and instantaneously detecting ketone bodies, with a detection threshold as low as 50 μm. The experimental results validated the device's capability to detect ketone bodies, indicating its potential for the continuous and real-time monitoring of diabetic ketosis and ketoacidosis in interstitial fluid. A smart epidermal device that integrates reverse ion introduction with MNs has been created for the efficient detection of significant biomarkers.[78] The presented technology demonstrates the capability to efficiently extract cell-free DNA targets from interstitial fluid (ISF) within a time frame of less than 10 min, achieving a notable capture efficiency of up to 95.4 %.[78] In their study, Ciui *et al.*[29] successfully combined a bandage sensor and a microneedle sensor on an FPCB. This integration allowed for the development of a smart device capable of detecting skin melanoma. The detection process was achieved using wireless human-computer interaction. The concurrent use of unaltered and tyrosinase-modified carbon paste microneedle electrodes on a single sensor array patch enables the simultaneous and autonomous detection of L-Dopa using enzymatic-amperometry and nonenzymatic volumetric dual-mode sensing. The device has the capability to realize the continuous monitoring of the anti-Parkinson's medicine L-Dopa, which plays a crucial role in facilitating the treatment of Parkinson's disease. Yang *et al.* developed a laser-engraved sensor for simultaneous sweat sampling, chemical sensing, and vital-sign monitoring, as shown in Fig. 6(b).[15] Low concentrations of uric acid and tyrosine, which are analytes linked to metabolic disorders and diseases such as gout, are continuously detected by the fluid-detecting sensors alongside respiration rate and temperature. The efficacy of monitoring gout in healthy controls and patients was investigated using a purine-rich food challenge. The antiparkinsonian medication L-Dopa was also continuously monitored by Goud *et al.*[17] using a smart chemical sensing platform based on a microneedle electrode array. They also presented a novel dual-mode sensing technique based on independent electrochemical measurements involving redox and biocatalytic processes. Such multimodal L-Dopa sensing offers built-in redundancy and enhances the information content of microneedle sensor arrays,[17] as shown in Fig. 6(c). In their study, Pu *et al.* used ultrasound as a means to enhance skin permeability and then retrieved interstitial fluid by the application of vacuum pressure.[79] Three electrodes were attached to a microfluidic chip, whereby the working electrode consisted of graphite and AuNPs for glucose detection. This technique, often referred to as sonography, operates on the basis of fundamental idea that ultrasonic waves induce cavitation, leading to heightened skin porosity. Furthermore, the combination of vacuum pressure and ultrasound has been seen to enhance skin permeability. During the detection process, the skin undergoes the generation of micropores, although it is important to note that this occurrence does not result in any harm or damage to the skin. Soto *et al.* developed a transdermal tattoo patch that incorporates microspheres to improve medication delivery capabilities.[80] This innovative patch has the potential for several therapeutic applications and detoxification procedures when combined with the needle-free ultrasonic microsphere technique. The field of interstitial fluid detection has seen significant advancements, enabling the exploration of interstitial fluid as a potential medium for targeted medication administration in the treatment of certain ailments. However, there is a limited number of smart sensors available for diagnosis and therapy that possess the capability of active closed-loop intervention.

3. Summary and Outlook

Substantial progress has been made in smart sensors, and they are now fundamental in the fields of healthcare and sports. This article offers a comprehensive examination of smart sensors used for the uninterrupted monitoring of vital signals in the realm of health and physical activity. The signals included bioelectrical signals such as ECGs, as well as biophysical signals of inertia, body motion, heart rate, and pulse. In addition, biological markers such as perspiration, blood, and interstitial fluid are also taken into account. Finally, this category includes multisignals, which are signals with several dimensions and modes. As research progresses, smart technologies have been endowed with features such as small size, improved accuracy, flexibility, compatibility with living organisms, cost-effectiveness in production, and the capability to provide continuous real-time detection. Hence, these devices provide considerable potential for use in several fields, such as medicine, rehabilitation, and motion analysis. Smart devices equipped with flexible sensors, wireless communication capabilities, and power supply are considered more practical for health and sports monitoring. In the fields of disease diagnosis and prognosis, athletic assessment, and injury alert, these devices play a crucial role owing to their potential to realize the real-time, wireless, remote monitoring of important data. In addition, when combined with AI algorithms and IoT technologies, such real-time monitoring data may support healthcare professionals in developing treatment plans and provide customers with timely alerts. Using visualization software and screens, anyone may see their own health condition in real time.

Recent advances in IoT technology, flexible electronics, (AI) algorithms, and sophisticated manufacturing techniques have led to a dramatic advancement in sensing devices. These developments have paved the way for the creation of smart, portable monitoring devices that can collect data in real time. Nevertheless, flexible smart sensing devices have several obstacles and constraints that must be overcome before they can be brought to market. The ability to accurately track many signals simultaneously, continuous monitoring, connection to the IoT, and predictive and diagnostic capabilities are all part of the list. If flexible smart sensing technologies are to live up to their potential, the following solutions to the problems listed above are required.

3.1 Accuracy

The main factors that affect the accuracy and reliability of communications are power lines and motion artifacts. To reduce the likelihood of electromagnetic interference caused by excessively long power lines, it is preferable to keep the sensor as close to the data processing module as possible while dealing with power lines. Future applications in the domain of motion artifacts might benefit from ultrathin self-adhesive sensors. In addition to being non-irritating and lightweight, these sensors form a strong bond with the skin through van der Waals forces. When the skin moves relative to the sensor, it causes a displacement, which in turn causes motion artifacts. Improving the sensor–skin compliance may be as simple as choosing a base material with the same modulus as skin. The combination of these elements has sparked much interest in creating a signal that can accurately track people even while they are moving about and using the self-adhesive sensors for long periods.

3.2 Multimodality

Accurate diagnoses and forecasts relying on a single indication may be problematic since health is typically linked to several situations. A new generation of sensors that can track many signals at once is therefore urgently required. In the context of cardiovascular disease diagnosis and prediction, this is of utmost importance. Another option, made possible by split manufacturing, is the integration of several sensor components into one integrated sensor. Unfortunately, manufacturing is a major hurdle that must be overcome. In addition, note that strain sensors may frequently detect and respond to several stimuli with only one sensor. An organized structure with an effective sensor system could resolve this dilemma.

Within the framework of continuous, long-term monitoring, energy is a vital subject that requires attention. Power consumption and energy requirements are both increased as a result of the growing number of surveillance goals and processing demands. Reducing computational power use, improving the power supply, or using power management optimization strategies might all be effective in fixing this problem. Reduced power consumption could be a major benefit of self-powered sensors. Additionally, there are several ways in which the human body may provide energy sources, such as via electrochemical, piezoelectric, thermoelectric, and solar devices. On the other hand, keep in mind that these technologies often generate only a small quantity of energy. Thus, future smart gadgets used for health and sports monitoring will need more advanced methods of energy supply, which must be thoroughly investigated and established.

There is promise for the application of vital signal detection systems hosted in the cloud in the context of health diagnosis and prevention, especially for people over 60. However, there are still numerous obstacles to modern cloud-based monitoring systems. The lack of real-time communication between experts and consumers, the insufficient integration of physical and information systems, poor warning accuracy, and insufficient monitoring over the whole life cycle are all problems. Recent advances in algorithms and the addition of extension ports have the potential to effectively solve the current problem of low early warning system accuracy. It should be noted that these steps cannot be taken in isolation to address the fundamental accuracy problem. One possible solution to the problem of data fusion is the digital twin. Also, keep in mind that there is a limit to the transmission distance for communication, which means that data loss, low sampling frequency, and excessive power consumption might occur, especially while the subject is moving. Data processing is an essential post-transmission step for data usability. Most traditional smart gadgets, however, struggle to fully accommodate AI algorithms. The use of offshore servers for intelligent data processing allows for the smooth transmission of data to the cloud, which in turn enables health and fitness early warning systems, real-time monitoring, and diagnostics. Also, the smart devices of family members, community health centers, and hospitals may all work together in perfect harmony with the data stored in cloud-based systems.

3.3 Prediction and diagnosis

Although multimodal sensors and AI algorithms hold great promise for disease prediction and diagnosis, note that the predictive and diagnostic abilities linked to big data and AI algorithms are still in their early stages of development. Data analysis is at the heart of the problem since it is often left to healthcare professionals and does not benefit the end users. In addition, there are still many illnesses for which diagnostic and prediction capacities are inadequate; this is true even in the sports world. The development of smart devices with improved signal monitoring capabilities, in conjunction with healthcare professional collaborations, will pave the way for models that can anticipate and diagnose illnesses. Consequently, it is expected that smart devices equipped to track many signals, in conjunction with new AI algorithms for diagnosis and prediction, will lead to more accurate diagnoses and predictions.

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