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Intelligent recognition of human motion using an ingenious electronic skin based on metal fabric and natural triboelectrification

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ABSTRACT Various techniques based on electronic or optical signals have been developed to perceive body movements, which is essential in several fields such as healthcare, rehabilitation, and human-computer interaction. However, these signals are obtained externally, not from within the body. In this study, we introduce an electronic skin (e-skin) body motion sensor prepared using organic polymers and metal fabric to detect motion through the body's electro-induction (EI) *via* contact with the ground and shoes or through intrinsic contact electrification of the skin. The device can achieve an EI signal up to 450 V and charge data of 40 V and 2.45 μA when it is detached from the contacted skin. Moreover, the signal can be automatically extracted and trained using the state-of-the-art deep learning techniques. The sensor can accurately track sleep activity with an accuracy rate of 96.55%. This wearable motion sensor can be seamlessly combined with the Internet of Things technology for multifunctional applications, highlighting its potential applications in human activity recognition and artificial intelligence.

Keywords: human activity recognition, e-skin, sleep motion recognition, contact-separation electrification, 1D-CNN

INTRODUCTION

The intensity, frequency, and amplitude of body movements reflect the physical conditions of the human body [1–3]. The ability to perceive and track aberrant motions is crucial for helping people recognize issues and supporting medical professionals in diagnosing and treating patients [4]. Major human movement monitoring systems depend on advanced camera systems [5], laser-based technologies [6], or intricate electronic chips [7]. These systems stress the subject's psyche, have strict guidelines for detecting ambient brightness, and need heavy machinery to be operated by trained professionals. Electronic skin (e-skin) [8,9] is utilized as a sensing device for user identification and human activity identification because of its advantages such as cost-effectiveness, high energy conversion efficiency, and large-scale manufacturing [10–13]. It also eliminates the need for redundant external circuits and offers a voltage output. Typically, it comprises flexible materials [14,15] that can be placed on the surface of the human body to track and record different physiological parameters and human movements.

E-skin is extensively applied in sports, medicine, and human-computer interaction [16–19]. It can also be used to track the rehabilitation progress of a patient, including the restoration of muscular functionality [20]. Moreover, it can improve the interaction experience in augmented and virtual reality systems by accurately tracking hand and body movements [21]. Moreover, e-skin can monitor the activity level, posture, and sleep quality of an elderly individual to offer safe and beneficial care. Zhang *et al.* [22] developed a universal body motion sensor that can sense different movements of the human head, arms, fingers, waist, legs, feet, and toes but necessitates an additional polytetrafluoroethylene (PTFE) film or polyethylene terephthalate (PET) plate for Parkinson's disease (PD) monitoring. Park's group [11] prepared a double-layer nanofiber triboelectric nanogenerator (TENG) by a simple electrospinning process, placed it on an insole, and examined its triboelectric sensing data by deep learning technology. The product can be employed for user and user activity identification but only for user activity monitoring with shoe compression. An additional electrode layer or friction layer would block the final step in the portability of wearable sensors [11,23–25]. Analysis of traditional triboelectric sensor data depends on the manual extraction of surface features from raw data and has limited capacity to process natural data. To track sleep movements, most sensors can only monitor the number of body movements or breathing during sleep, but not the specific sleep posture [26–29]. Thus, developing a more lightweight, smart, multifunctional, and accurate wearable sensor for sleep monitoring has become a new challenge.

Although elastic self-powered e-skins can adhere to human skin without consuming any electricity and realize long-term real-time sensing [30], most e-skins reported in the literature have no breathability due to the use of air-tight elastic rubber or dense semiconductor membranes. This may result in skin discomfort, inflammation, and itching, in particular after wearing over a long time. Thus, developing breathable e-skins is essential, which requires highly breathable materials with intrinsically superior properties. The possibility of fabricating fiber-based devices comprising electrospun nanofibers with outstanding gas permeability and sensing capabilities has been demonstrated

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[31–33]. Nonetheless, further investigation of highly breathable flexible electrodes is still a significant direction in the field of e-skins.

In this study, an e-skin is developed based on metal fabric and natural triboelectrification to detect electrical signals generated by friction between the sole and the floor or friction between the skin and textiles during body movements and variations in body status. The e-skin has two parts, namely, the metallic fabric and the polydimethylsiloxane (PDMS), which has a certain degree of breathability. The sensor has remarkable signal strength and stability due to the stability of the metal fabric and micrometer wire spacing. A cutting-edge deep learning model, i.e., a one-dimensional (1D) convolutional neural network (1D-CNN), is employed for data analysis, which offers an efficient way to extract and train the obtained signal data automatically. Signals may be successfully sent to a computer to track human movements when our bespoke wireless module is coupled. It can offer a way to remotely recognize changes in physiological signals resulting from human state and alert contingencies. It also helps in real-time responses to emergencies involving people, for instance, by remotely detecting flexible wearable e-skin sensor systems to acquire an effective response to a fallen person.

EXPERIMENTAL SECTION

Materials

Stainless steel fabrics (Asada, BS-400/23) with a mesh number of 400 and a wire diameter of 23 μm were procured from Taiwan Dongyuan Screen Printing Equipment Xiamen Branch Co., Ltd. The resistivity ($\rho = 3.5 \times 10^{-7}\ \Omega$ m) and conductivity ($\sigma = 2.8 \times 10^{6}$ S m^{-1}) of the metallic fabric were measured using an M-3 handheld four-probe device.

PDMS and cross-linkers were purchased from Dow Corning. Polyvinylidene fluoride copolymer (PVDF) was procured from Dongguan Zhan Yang Polymer Materials Co., Ltd. Barium titanate ($BaTiO_3$) nanoparticles (~100 nm) were bought from Shanghai Keyan Phosphor Technology Co., Ltd.

Fabrication of the e-skin

Metal fabric substrates were ultrasonically cleaned with acetone, deionized water, and isopropanol in that order for 30 min and then dried under nitrogen flow. A prepolymer solution of PDMS with a mixing weight ratio of base polymer to cross-linker of 10:1 was mixed with PVDF and $BaTiO_3$ powders in a certain proportion to improve the dielectric properties. The weight ratio of PVDF and PDMS/PVDF was 30% unless specifically stated, and those of $BaTiO_3$ and PDMS/PVDF/$BaTiO_3$ were 20% unless specifically stated. The composite material was scraped onto the metal fabric by screen printing and dried in an oven at 80°C for 50 min.

Characterizations

The morphologies of the metal fabric and e-skin were characterized under a 3D laser microscope (LEXT OLS4100), while those of the PVDF and $BaTiO_3$ (BTO) particles were studied using a field-emission scanning electron microscope (FE-SEM, Nova Nano-SEM 230). The e-skin sensor system consisted of a human, an electrical measurement unit, and a ground. An electrode was attached to the human body to connect it to the electrical measurement unit, which included a Keithley 6514 controlled using the LabView program. The electrical measurement unit was grounded.

RESULTS AND DISCUSSION

Structure and operation principle of the e-skin sensor

The design of the e-skin sensor is illustrated in Fig. 1a. An organic mixture (PDMS/PVDF/$BaTiO_3$) covers the metal fabric. Organic and inorganic doping improves the charge sensing, and the metal fabric serves as a conductor and support. It is ultra-simple without a specially designed TENG, and it can be simply attached to the human body (it is attached to the wrist in the picture). A critical component of the e-skin is the large-area manufacturing and high-flexibility metal fabric (Fig. 1b), which makes the device robust and self-conductive and improves the sensitivity and output performance of the e-skin while maintaining its original properties despite vigorous human activity. The e-skin can be worn as a garment or attached to the body with insulating tape. The metallic fabric is soft and has high flexibility, similar to clothing fabric (Fig. S1) due to the porosity, good breathability, and biocompatibility of PDMS, and thus, the e-skin is conformable and can maintain stable wearability during human body movements such as running and waving. In addition, the fabrication process enables arbitrary cutting of the large flexible metal fabric and free printing of polymer gel to cater to different wearable requirements in different environments. Some details of the e-skin sensor are presented in Fig. 1c. The e-skin is quite flexible, shows remarkable robustness and tortuosity, and can be well adapted to wearable needs. Its preparation process is depicted in Fig. S2. PDMS served as an organic adhesive and was mixed with PVDF and $BaTiO_3$. The composite material (PDMS/PVDF/$BaTiO_3$) was scraped onto the metal fabric by screen printing and dried in an oven at 80°C for 50 min.

In Fig. 1d, the left and right sides are the unprinted metal fabric and the printed part of the composite material, respectively. The printed part presents good uniformity and flatness under the electron microscope, and organic and inorganic matter is randomly scattered on the metal fabric surface with Brown distribution (Fig. S3). The metal fabric surface is well-filled and wrapped, as shown under a 3D microscope (Fig. S4). Fig. 1e exhibits the SEM image of PDMS/PVDF/$BaTiO_3$, demonstrating the uniform distribution of PDMS/PVDF and $BaTiO_3$ powders. The outstanding flexibility, biocompatibility, and eco-friendly properties of PDMS make it an ideal e-skin material [34]. In practical applications, PDMS-based wearable sensors have good breathability and long-term durability [35–37]. The incorporation of BTO nanoparticles and PVDF powders into the e-skin film increases the relative permittivity, piezoelectric effect, and surface roughness of the tribolayer, thus improving the charge induction performance. Furthermore, $BaTiO_3$ and PVDF are nontoxic, nonhazardous, and eco-friendly biocompatible materials and do not have physiological effects on the human body or cause skin irritation.

Daily movements of the human body, such as jumping, running, and contact friction, generate frictional electricity, and electrostatic charges are easily released [38–41]. These electrostatic charges can persist for longer periods, leading to a significant buildup of electrostatic potential in the human body. The developed e-skin system for monitoring human motion operates in contact-separation mode by leveraging the coupling effect of contact electrification and electrostatic induction. In

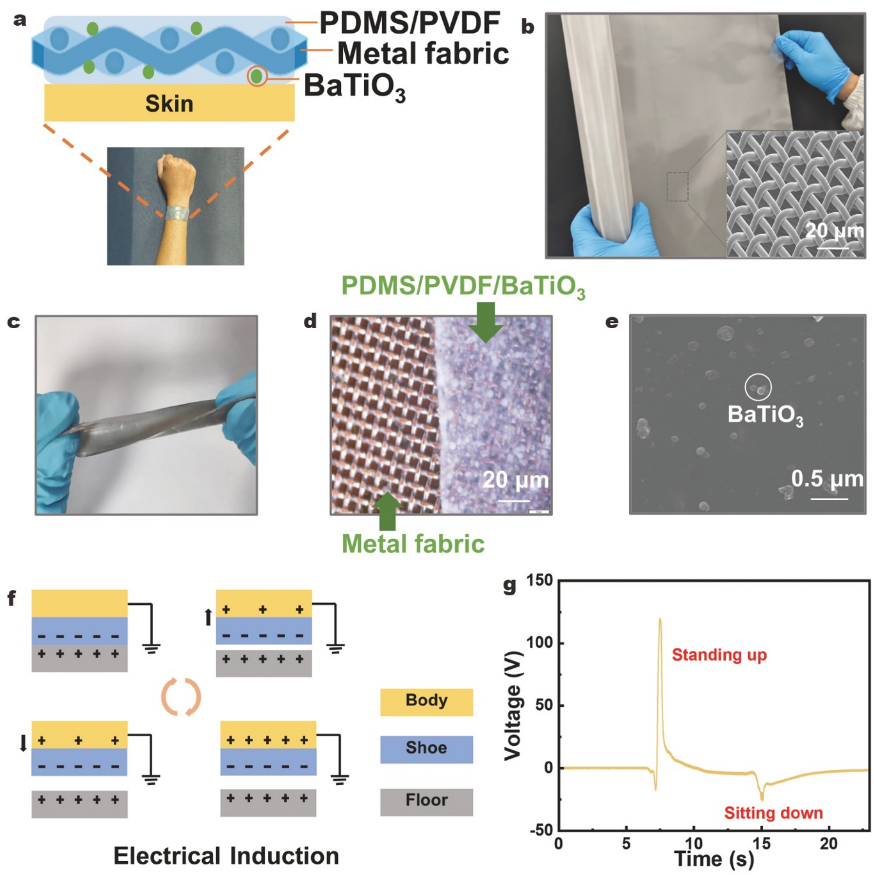

Figure 1 (a) Schematic of the e-skin structure. (b) Schematic of the metal fabric and structure. (c) Physical image of the curved and expanded e-skin. (d) Microscopically unprinted (left) and printed parts (right). (e) SEM image of PDMS/PVDF/$BaTiO_3$. (f) Induction of charges by the electric field on the shoe with the floor. (g) Output voltage of standing up and sitting down.

this system, the human body and e-skin act as the electrodes for TENGs to facilitate electrical charge conduction produced through friction to detect signals. When two layers with different friction materials come into contact, the triboelectric effect induces opposite charges on their surfaces.

In daily life, the friction layers of TENGs during human activities include skin-textile and sole-ground. For skin-textile, nanogenerators can help monitor sleep posture because the generated signal is relatively weak and has a slight difference from the behavior of walking and other motions where shoes cause friction with the ground. Contact electrification (CE) processes are more complex than those of regular TENGs because of the curved surface of the human body and the flexibility of textiles. The contact separation of the skin with the textiles (Fig. S5a) and the sliding of the skin on the textiles (Fig. S5b) are basic processes [22]. However, more complicated processes can also take place due to the irregularity of the body shape and the flexibility of clothes (Fig. S5c, d).

In the sole-ground TENG in Fig. 1f, ordinary shoes become negatively charged upon contact with the ground due to electron accumulation. If the e-skin is an indirect external circuit with the ground, then free electrons migrate under potential difference, thus producing an electrical signal until the distance between the two contact surfaces increases to reach electrostatic equilibrium. When the two friction layers come into contact once more, the friction potential dissipates, leading to the appearance of an opposing electrical signal. Fig. 1g exhibits the motion variation signals collected by the e-skin when standing up and sitting down, and two distinct signal pulses can be detected when these motions occur. Open-circuit voltage (V_{oc}) signals are strong and reach up to hundreds of volts.

Effects of the polymer and electrode on the performance of charge harvesting

The charge-sensing ability of the e-skin sensor depends on the organic polymers used. Good polar materials can sense well the charge of the human body and output electrical signals with enough intensity. The e-skin sensor is employed as a single-electrode TENG, and the finger is used as another contact surface to enhance the charge-sensing properties. When the finger is in contact separation with the e-skin, the sensor harvests the charges and outputs electrical signals. The test system (Fig. 2a) is composed of a frequency control module and a contact-separation module. The e-skin is affixed on the contact-separation module (in the picture), and a finger is placed on it. The system vibrates the e-skin with a certain frequency and amplitude. In these experiments, the contact frequency and spacer distance of the two triboplates were fixed at 2 Hz and 1 cm, respectively. The contact force was 5 N, and the film size was 2 cm × 2 cm.

First, different polymers were investigated as polar materials to study the charge inductivity of the e-skin. The output voltages of different e-skin sensors are displayed in Fig. 2b, and the resulting short-circuit currents are summarized in Fig. 2c. Using

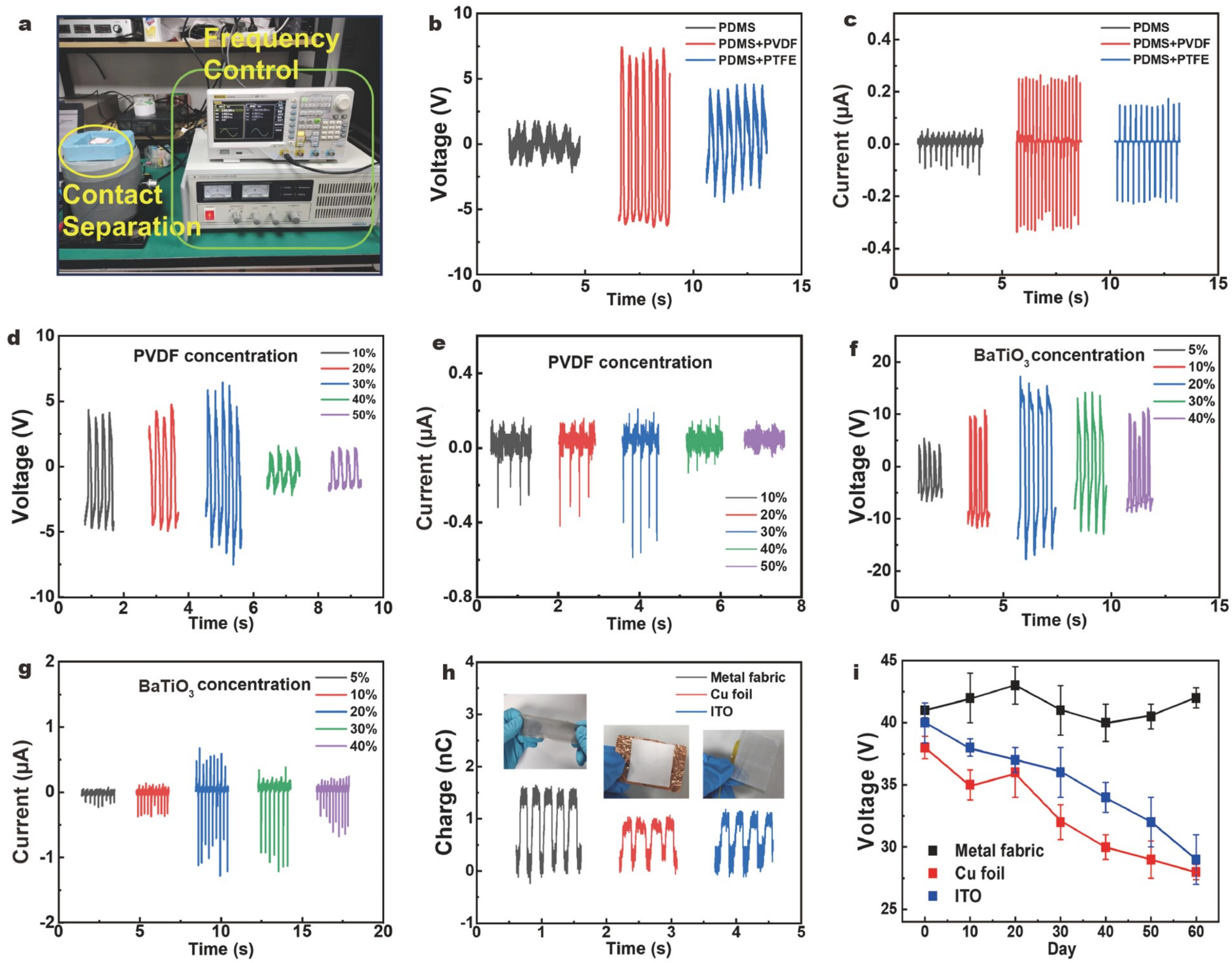

Figure 2 (a) Physical diagram of the experimental system. (b) Output voltages and (c) short-circuit currents of different e-skin sensors with different polymers. (d) Output voltages and (e) short-circuit currents of different e-skin sensors with different PVDF concentrations. (f) Output voltages and (g) short-circuit currents of different e-skin sensors with different BTO concentrations. (h) Charge output performance of e-skins with different electrode materials. (i) Output voltages of the 60-day endurance experiments.

PDMS/PVDF as a polar material, higher voltage and current signals are obtained (14 V and 0.6 μA, respectively). Thus, the combination of PDMS and PVDF has a strong charge-sensing ability for human skin. In addition, we measured the output performance of e-skin TENGs with different PVDF concentrations. In Fig. 2d, the output voltage of e-skin TENGs does not increase continuously with PVDF concentration. Instead, it increases first and then decreases with a further increase in PVDF concentration. The trend of the short-circuit currents follows a pattern similar to that of the output voltages. The maximum values of the output voltage and the short-circuit current are achieved at 30% PVDF. As a high-dielectric organic material, PVDF is suitable for negative electrodes of friction nanogenerators because it can enhance the power generation performance of the film [42,43]. However when the PVDF content is greater than a certain value, the uniformity of film formation and the surface charge density of the film will be affected, causing a decrease in power generation performance. The incorporation of BTO nanoparticles will boost the relative permittivity, piezoelectric effect, and surface roughness of the tribolayer, thus improving the TENG performance [44]. After adding BTO to the polymer and confirming its piezoelectric properties, we measured the output performance of e-skin TENGs with different BTO concentrations. The output voltages of different e-skin TENGs are summarized in Fig. 2f, and the corresponding short-circuit currents are exhibited in Fig. 2g. The output voltage and short-circuit current reach their maximum values (40 V and 2.5 μA, respectively) at 20% BTO. When the BTO concentration is too high, BTO powders cannot be uniformly dispersed in the film, and BTO nanoparticles agglomerate, as shown in the SEM image Fig. S6. Therefore, appropriate BTO concentration can enhance the charge-sensing performance of the e-skin; however, excessive BTO concentration reduces the piezoelectric properties of the e-skin, thereby decreasing its contribution to additional charge generation by polarization [45].

Electrodes play a crucial role in friction nanogenerators by directly influencing power generation performance. The electrical conductivity and chemical stability of a material can influence the efficiency and stability of power generation. A larger surface area can trap more mechanical energy and thus produce more charges. The distance between the electrodes can impact the efficiency of electron conduction. A smaller electrode spacing can reduce the path of electron conduction and boost the power generation efficiency. In this work, a metal fabric with a large specific surface area and micrometer spacing was used as an electrode. A larger specific surface area can trap more charges, and a smaller electrode spacing can decrease the path of electron conduction and enhance power generation efficiency. We chose the commonly used Cu electrode and indium tin oxide (ITO) electrode and studied them using the above system. From Fig. 2h, the charge-sensing ability of the metal fabric is more prominent. During the 60-day endurance experiment (Fig. 2i), the metal fabric output is maintained well, but the output signal of the other two electrode materials is attenuated to approximately 70%. The results may be because the metal fabric is wrapped in a polymer, and they are tightly connected to each other and cannot easily fall off and be damaged. The performance of the walking motion signal was tested every 10 days without encapsulating the e-skin. In Fig. S7, the e-skin sensor still outputs a stable signal and retains the shape of the signal.

Monitoring the performance of leg movement and human fall

Based on the working principle of TENGs, the electrical signal produced relies on the friction material, which in turn greatly influences the size of the electrical signal produced. We selected several common shoes as negative friction layers and used ethylene vinyl acetate (EVA)/rubber polyethylene (PE) or thermoplastic polyurethane (TPU) sole materials to examine their ability to track human movements (Fig. S8). The shoes and wood ground act as the two friction layers, while the human body and the e-skin sensor act as the electrodes and are attached to the skin. The shoes with TPU soles exhibit the maximum electrical signal V_{oc} of 170 V. For soles crafted with PE and rubber, the V_{oc} values are 48 and 150 V, respectively. Also, the effect of different ground materials on e-skin signals was explored. The TPU, selected as the primary material for shoe soles, was the negative friction layer, while three commonly used materials (tile floor, wood floor, and cement floor) were selected as the floor-side friction layer of the TENG. The TENG produces an optimal electrical signal V_{oc} of 230 V on tile floors. On wood and cement floors, the TENG with a positive friction layer of TPU produces electrical signals with voltages of 150 and 170 V, respectively (Fig. S9). It is demonstrated that common shoes and floor materials can be utilized as friction layers of TENGs to detect human body movements.

In our experiments, the electric signals produced are suitable for human body stances in shoe-floor friction pairs. Different body movements produce distinct signals. Using the TPU-wood floor friction pair, we can determine the signals of walking, running, and jumping. As shown in Fig. 3a, b, the signal frequency for running is considerably greater than that for walking, which is ascribed to the faster movement speed for running. Furthermore, the positive and negative signals from running are asymmetrical, i.e., the size of the friction when the shoe contacts and separates from the ground is different. Similarly, jumping signals differ significantly in frequency and amplitude from walking and running signals (Fig. 3c). During jumping, the contact separation between the shoe and the floor creates greater friction on the contact surface of the shoes and the floor due to the greater external force applied to the floor, leading to a higher electrical signal (V_{oc} = 400 V). The observation also demonstrates that during running and jumping movements, the pressure exerted when the shoes make contact with the ground (negative voltage) is greater than when they separate from it (positive voltage), causing a higher negative voltage, as shown in Fig. 3b, c. Based on the output frequency and amplitude, real-time monitoring of walking/running/jumping can be achieved for monitoring of exercise.

Proof-of-concept applications were performed to track body shaking and abnormal movements in patients with PD. Fig. 3d plots the signals that mimic tremors and walking quivers in patients with PD. The shaking frequency of the body can be measured, and these characteristics can be used to monitor the patient's status and study the effect of different treatments. Compared with conventional acceleration-based systems to monitor patient movements, our e-skin sensor can detect changes in body posture at any time; whereas acceleration-based systems can only monitor the movement of the attached part of the body. However, the intricate nature of PD signals may pose challenges for the 1D-CNN in feature extraction. Before using the 1D-CNN for feature recognition and data analysis, it might be required to manually extract prominent features to reduce processing complexity.

Another proof-of-concept experiment was monitoring the recovery of people with leg injuries. During recovery, the amount of force that a patient can exert on the leg increases, which creates a larger signal that can be detected using the e-skin sensor. Fig. 3e plots the signal strength produced by healthy people with legs of different weights while walking and running normally. Heavier people put more pressure on their shoes, thus generating a stronger voltage signal. Fig. 3f exhibits voltage signals on the legs of a person weighing 70 kg at different pressure levels. The voltage is proportional to the pressure (as indicated by the red line in Fig. 3f). Recovery from injury, which is important to leg health, can be measured using a linear relationship.

The developed e-skin sensor can also be used as an emergency fall alert system for the elderly for real-time detection of falls during walking. The sensor can provide timely alerts and rescue, thus reducing the risk of injury and helping seniors and people with special needs to stay independent and comfortable for longer periods of time. This attribute is imperative to enhance their quality of life and safety. When an elderly individual falls, their body makes contact with a surface, such as the floor, leading to the redistribution of static electricity from the body and thus generating an output electrical signal. In this work, we examined the ability of the e-skin sensor to identify fall motion. In Fig. 3g, when the test person stands still on a surface, signals are generated, but when falling down, there is a clear sharp signal decrease. In Fig. 3h, once falling down occurs, the walking signals are immediately transferred to the falling down signals. Fig. 3i shows a recorded example of the signals resulting from falling down and getting up. Between the two peaks of the signal, a no-signal phase, where the test person lies on the ground and does not move, cannot be observed. Thus, the occurrence of a fall down can be recognized by the e-skin sensor in real time on a daily basis, providing a unique way to monitor accidents.

Artificial intelligence (AI) recognition system for sleep motions

Human sleeping motions are rolling over, bending of legs, raising of hands, sitting up, and so on. In real life, all sleeping movements occur simultaneously, and some cannot be adequately described using anatomical terms because they are a composite of several individual movements. Thus, we used customary terminology such as lying on one's side and bending

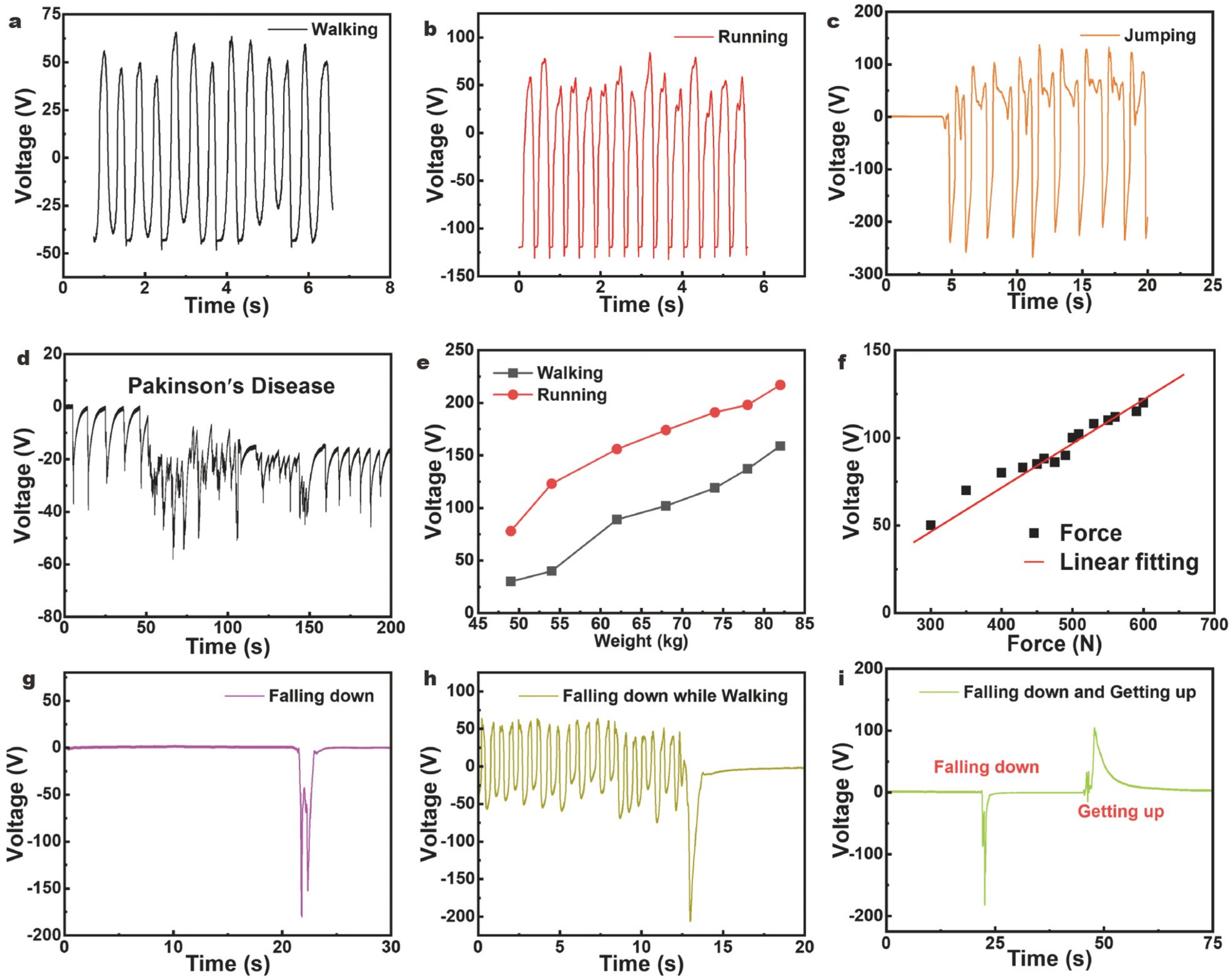

Figure 3 Output voltage of different motions with the TPU sole and the wood floor acting as the friction layers: (a) walking. (b) running, (c) jumping. (d) Voltage generated by body shaking mimicking that of a person with PD. (e) Voltages are generated by people with different weights during normal walking and running. (f) Plot of the voltage intensity *versus* the force placed on the leg mimicking an injury. Output voltage of falling down motion behavior, with the TPU sole and the wood floor acting as the friction layers: (g) falling down, (h) walking with sudden falling down, and (i) falling down and getting up.

one's knees. The measured voltages below using the e-skin sensor are generated solely by the CE between the skin and clothes unless otherwise specified because the sleeping motions do not contact the floor.

Fig. 4a displays the measured voltages generated by lifting and falling of the hand. In our experiments, hand motions were detected by charge sensing between the arm skin and the sleeve of the clothes. The lifting of the hand exhibits a gradual and slight signal compared with the falling of the hand because the falling of the hand is faster. The heavy fall of the hand exhibits a higher signal; in the case of greater force, the contact area between the hand and bed is larger, leading to more charges. Rolling over occurs in many ways during sleep; therefore, we used the e-skin sensor to sense one motion (Fig. 4b). Lying on the side of the body yields obviously larger signals than returning back in the first peak of the signal; in the two other peaks, lying on the side of the body results in a slightly higher signal than returning back. The process of charge generation cannot be easily studied due to the irregular shapes of the clothes. However, movements can be detected based on regular signals. The signal in Fig. 4c is due to the motion of falling from the bed, and this process is accompanied by large areas of skin and textile friction. Thus, the signal intensity would be high, reaching 90 V. This evident characteristic spike can be utilized to track bed drops. Fig. 4d plots the voltage produced by leg motions, and signals can be produced by the CE between the leg skin and the trousers by the CE between the foot and the bed.

Each individual has static charges on their body, and when two individuals come into contact, the former's static charge induces an electrostatic field on the latter (the person being tested). As a result, the e-skin can detect output signals, with regular electrical signals being observable upon tapping the measured individual's shoulder by another person. The output signal in Fig. 4e indicates the response when an individual places their hand on the body of the tester at the shoulder. In this case, electrostatic charge is transferred between individuals, causing the production of sharp pulses with high amplitude and short width. Similarly, we gathered e-skin detection signals by tapping different areas of the test individual's body, as shown in Fig. S10. The results show that although similar waveform signals are produced when contacting other parts of the tested individual's body, the detected signal waveforms vary depending on the

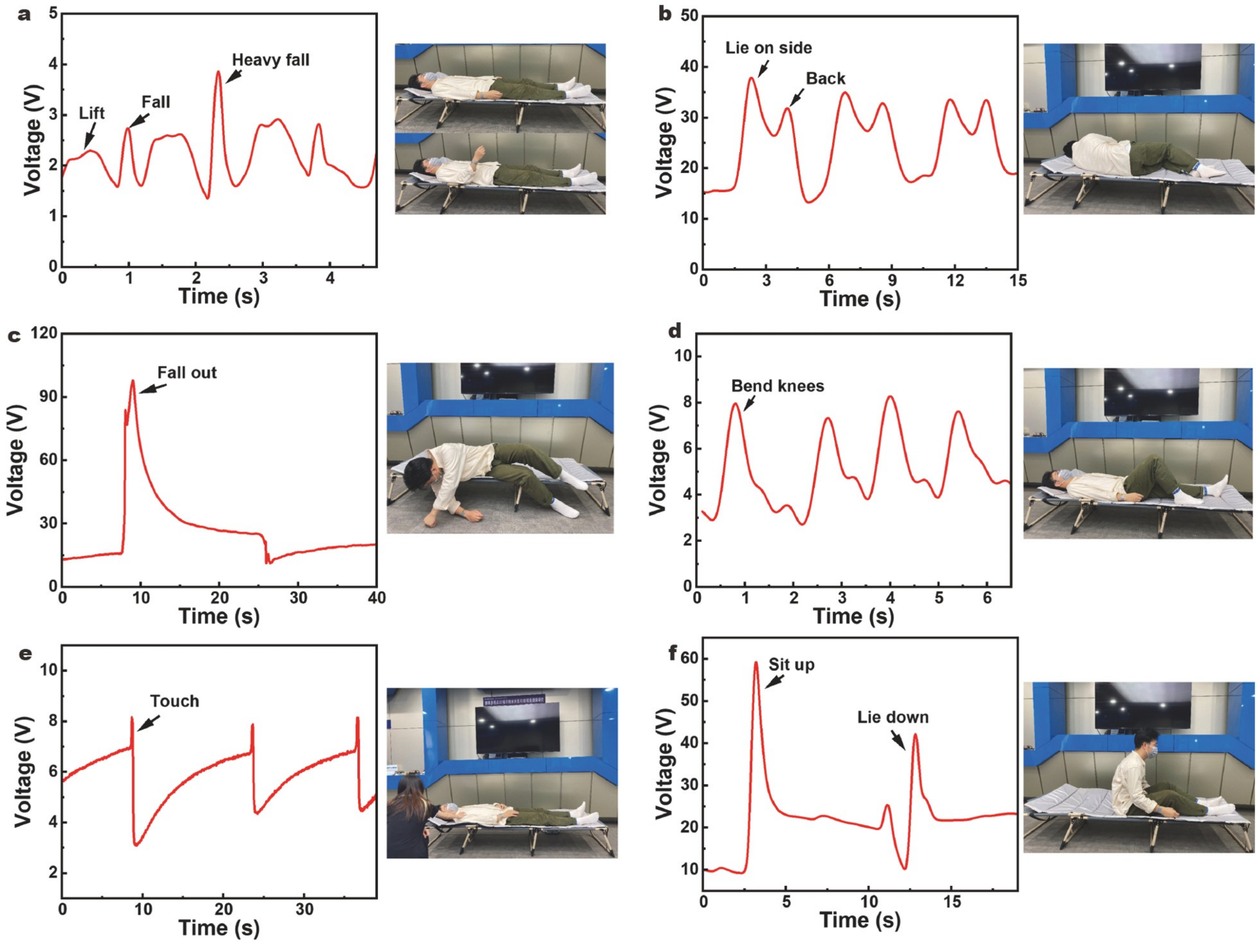

Figure 4 Output voltages of different types of sleep motion behaviors, with the rubber sole and wood floor acting as the friction layers: (a) hands up and down, (b) turn over, (c) fall out, (d) bend knees, (e) touch, (f) sit up and lie down.

specific area being contacted. Moreover, these results indicate that this action generates a distinctive signal pattern that can be easily distinguished from other actions. In Fig. 4f, two single-signal pulses are captured while sitting up and lying down. The forces applied to the bed during the sitting up-lying down process determine the signal pulse magnitudes, and the behavior's time interval determines the separation between the two pulses. Our studies demonstrate that the corresponding signals from CE between a person's skin and textile can be utilized to monitor behavioral fluctuations besides being characterized to recognize relevant behavior of a human body in bed.

Sleep is one of the basic daily behaviors of human beings, and the quality of sleep is important for judging human health. Based on the World Health Organization, sleep body movements often reflect the stress and emotional state of a person [46]. Frequent body movements represent poor sleep; therefore, people do not get enough rest daily, leading to a vicious cycle. Hospitals use polysomnography to determine sleep quality. The head, chest, hands, and feet of the patient need to be covered with electrodes to record electroencephalogram (EEG), eye movement, and electromyogram (EMG) signals [27,47,48]. However, the operation is complex, labor costs are high, and the normal sleep of the patient is severely affected. Thus, the developed e-skin can be employed as a sensing unit for human sleep movement recognition and can be combined with AI to design and prepare a self-powered wearable sleep posture monitoring system (Fig. 5a). The human body and e-skin act as the electrodes for TENGs in this system, facilitating the detection of conducted electrical charges generated through friction. Assuming identical potentials across the human body, only one e-skin (e.g., attached to the wrist) is needed for monitoring different actions.

We developed a wireless detection real-time monitoring system that combines the ability of human movement monitoring and remote data transmission. The hardware comprises three main parts: a signal conditioning circuit, bluetooth, and a microprogrammed control unit (MCU). Participation patterns for each part are depicted in Fig. 5b. The output voltage signal of the e-skin is stabilized at 0–3.3 V through the signal conditioning circuit, which enables it to connect to the analog-to-digital converter (ADC) serial port (comes with MCU). The ADC module is used to convert the signal to a digital signal, which is transmitted to the computer through the bluetooth module. The signal is then passed into the trained deep learning neural network for recognition.

In traditional methods, waveform parameters, including amplitude, frequency, hold time, and peak interval, are extracted manually. However, satisfactory recognition accuracy cannot be reached because of the poor effect of these methods on the

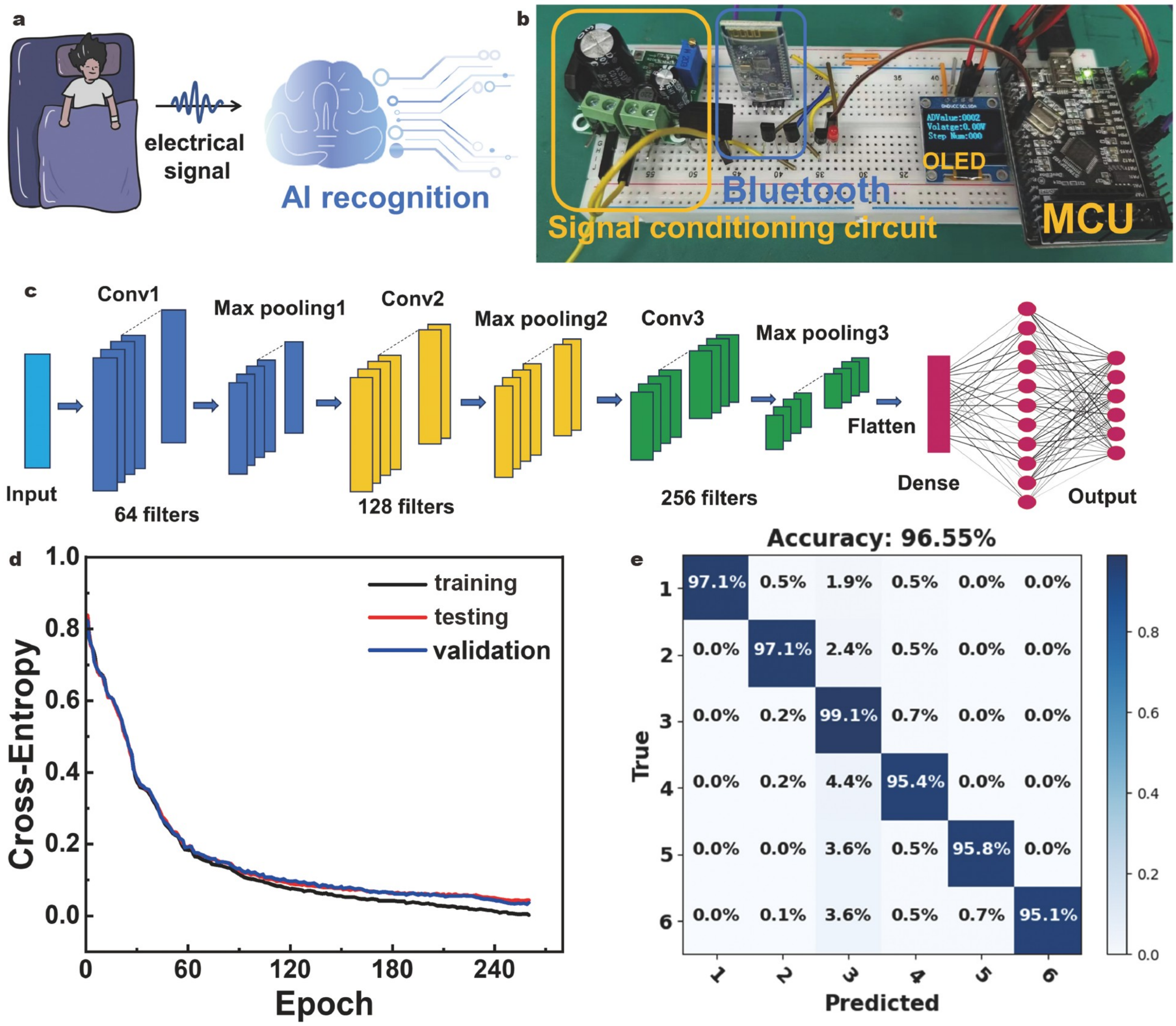

Figure 5 (a) Schematic of the e-skin sensor system with AI motion recognition. (b) Physical drawing of the wireless signal transmission system. (c) System architecture of the 1D-CNN for sleep motion recognition. (d) Cross-entropy curves for training, validation, and testing. (e) Confusion matrix of test results.

recognition of features with small changes. Moreover, the artificial extraction of waveform parameters does not satisfy the requirements of current smart automation. As a consequence, the state-of-the-art deep learning techniques can be utilized to train neural networks to process e-skin sensor outputs with complex features. Moreover, 1D-CNN can be used as a potential deep learning method, which uses convolutional layers to automatically extract information from e-skin sensor outputs without requiring manual feature extraction from the user. When the user conducts any activity during sleep, such as lifting hands, turning over, and bending legs, the e-skin sensor affixed to the wrist generates different output signals for each area of the skin in contact with the fabric and the pressure. The data acquisition (DAQ) analog signal acquisition voltage acquisition module can collect the voltage signal output by the e-skin. To reduce the influence of the instantaneous electrostatic discharge pulse on recognition accuracy, sequential complete waveform signals, including amplitude, frequency, hold time, and peak interval, are adapted. The e-skin sensor collects 100 s (200,000 data points) of data from each user's sleep activity (raising hands, turning over, falling off the bed, bending legs, touching, and sitting up). The tested individual performs a repeated action within a duration of 100 s, and the obtained 1D time-series data are collected and recorded in csv files (e.g., "raising hands.csv"). Then, the initial data are segmented into fixed-length segments together with their corresponding labels. These segments can either be consecutive or overlapping. The dataset is then divided into three: 60% training set, 20% validation set, and 20% test set. The training set is used for model training, the validation set helps tune hyperparameters and monitor model performance, and the test set assesses the generalization capability of the model. Finally, the processed dataset is introduced into a CNN model for training purposes. During this process, a batch training technique is used, where 16 segments are simultaneously inputted to improve efficiency and stability.

The system architecture of the 1D-CNN model consists of three convolutional layers, three maximum pooling layers, and two fully connected dense layers (Fig. 5c). After encoding and normalizing the 2D data of the resulting time series, the CNN model is used for analysis. The model is trained with 260 epochs, and the batch size is 16 to guarantee optimal degree and speed. The classification cross entropy is employed as the loss function, Adam is used as the optimizer to train the model, and the dropout value is 0.5 to avoid overfitting. In training, feature extraction in the original data is conducted through the three convolutional layers, and the extracted features are passed to the fully connected layer. Dense layers that are fully connected can identify various activity signals. Following the training of several neural networks on the training set, the verification set is employed to compare and evaluate the performance of each model. The various models in this context are mostly associated with neural networks that match different hyperparameters, while they can also refer to neural networks with entirely distinct topologies. The obtained cross-entropy curve is illustrated in Fig. 5d, and the 252nd model has the minimum cross entropy (0.034). In recognition of different sleep activities, the accuracy is 96.55%, which is confirmed by the confusion matrix (where 1 to 6 indicate lifting hands, rolling over, getting out of bed, bending legs, touching, and sitting up, respectively) in Fig. 5e. The configuration of the structural parameters of the CNN model is shown in Fig. S11.

This system is especially helpful for elderly people who live alone or in nursing homes. For instance, family members or caregivers can be alerted in time to provide necessary help in case of emergencies, such as falling from the bed. Based on this, we further developed a fall alarm system. When AI detects the characteristic waveform of the fall-out signal, it sends a short message from the cloud to the recipient's mobile phone and the location of the monitored person. The fall alarm message received on the phone is exhibited in Fig. S12. The exact GIS position and the timing of the fall are included in the message. More features and short message service (SMS) recipients can be added by users to the system. To help deliver emergency services on time and prevent missing the ideal moment for rescue, the medical staff is included as the information recipient. It is worth mentioning that despite the conformability and good breathability of the developed e-skin, long-term wear may lead to physiological reactions such as sweating, which can cause bacterial growth and inflammation. From our perspective, addressing this issue involves developing novel antibacterial materials that can be incorporated into the developed wearable device. In addition, integrating sterilization and disinfection strategies into the device, such as incorporating ultraviolet micro-light emitting diodes (LEDs) into the e-skin, might be beneficial.

CONCLUSIONS

The rapid development of information technology and intelligence in human civilization has resulted in the growing desire for the development of e-skins, which are smart extensions of human skin. In this study, we develop an e-skin sensor based on a metal fabric to detect human motion by measuring the charges generated by movements. Analysis of signal intensity and patterns can allow motion identification because of the distinct charge-generating mechanism of various motions. It is useful for tracking tremors related to PD, recuperating from leg injuries, and detecting falls with a real-time alert system. A deep learning model (a 1D-CNN) is employed to extract complex features from the e-skin sensor affixed to the wrist without user intervention. The model achieves approximately 96.55% accuracy in sleep body movement recognition, demonstrating the possibility of e-skin sensors in human movement recognition and safety systems. Our developed portable e-skin sensor has great application potential in the field of healthcare.

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1 Godfrey A, Conway R, Meagher D, *et al.* Direct measurement of human movement by accelerometry. Med Eng Phys, 2008, 30: 1364–1386
2 Minassian A, Kelsoe JR, Miranda A, *et al.* The relationship between novelty-seeking traits and behavior: Establishing construct validity for the human behavioral pattern monitor. Psychiatry Res, 2022, 316: 114776
3 Kirking B. Angle measurement stability and cycle counting accuracy of hours-long duration IMU based arm motion tracking with application to normal shoulder ADLs. Gait Posture, 2023, 100: 27–32
4 Jarchi D, Pope J, Lee TKM, *et al.* A review on accelerometry-based gait analysis and emerging clinical applications. IEEE Rev Biomed Eng, 2018, 11: 177–194
5 Xing Q, Hong R, Shen Y, *et al.* Design and validation of depth camera-based static posture assessment system. iScience, 2023, 26: 107974
6 Zhang X, Xu Z, Liao H. Human motion tracking and 3D motion track detection technology based on visual information features and machine learning. Neural Comput Appl, 2022, 34: 12439–12451
7 Zarka N, Alhalah Z, Deeb R. Real-time human motion detection and tracking. In: 3rd International Conference on Information and Communication Technologies: From Theory to Applications. Damascus: IEEE, 2008. 1–6
8 Zheng Y, Yin R, Zhao Y, *et al.* Conductive MXene/cotton fabric based pressure sensor with both high sensitivity and wide sensing range for human motion detection and e-skin. Chem Eng J, 2021, 420: 127720
9 Guo Y, Yin F, Li Y, *et al.* Incorporating wireless strategies to wearable devices enabled by a photocurable hydrogel for monitoring pressure information. Adv Mater, 2023, 35: 2300855
10 Ye G, Jin T, Wang X, *et al.* Multimodal integrated flexible electronic skin for physiological perception and contactless kinematics pattern recognition. Nano Energy, 2023, 113: 108580
11 Shrestha K, Pradhan GB, Bhatta T, *et al.* Intermediate nanofibrous charge trapping layer-based wearable triboelectric self-powered sensor for human activity recognition and user identification. Nano Energy, 2023, 108: 108180
12 Bulathsinghala RL, Ding W, Dharmasena RDIG. Triboelectric nanogenerators for wearable sensing applications: A system level analysis. Nano Energy, 2023, 116: 108792
13 Yang JC, Mun J, Kwon SY, *et al.* Electronic skin: Recent progress and future prospects for skin-attachable devices for health monitoring, robotics, and prosthetics. Adv Mater, 2019, 31: 1904765
14 Guo Y, Li H, Li Y, *et al.* Wearable hybrid device capable of interactive perception with pressure sensing and visualization. Adv Funct Mater, 2022, 32: 2203585
15 Zhang M, Yang W, Wang Z, *et al.* Highly compressible and thermal insulative conductive MXene/PEDOT:PSS@melamine foam for promising wearable piezoresistive sensor. Appl Phys Lett, 2023, 122: 043507
16 Sanderson K. Electronic skin: From flexibility to a sense of touch. Nature, 2021, 591: 685–687
17 Bai Z, Wang X, Zheng M, *et al.* Mechanically robust and transparent organohydrogel-based e-skin nanoengineered from natural skin. Adv Funct Mater, 2023, 33: 2212856
18 Liu Y, Yiu C, Song Z, *et al.* Electronic skin as wireless human-machine interfaces for robotic VR. Sci Adv, 2022, 8: eabl6700
19 Zarei M, Lee G, Lee SG, *et al.* Advances in biodegradable electronic skin: Material progress and recent applications in sensing, robotics, and human-machine interfaces. Adv Mater, 2023, 35: 2203193
20 Banitaba SN, Khademolqorani S, Jadhav VV, *et al.* Recent progress of bio-based smart wearable sensors for healthcare applications. Mater Today Electron, 2023, 5: 100055
21 Chugh V, Basu A, Kaushik A, *et al.* E-skin-based advanced wearable technology for health management. Curr Res Biotechnol, 2023, 5: 100129

22 Zhang R, Hummelgård M, Örtegren J, *et al.* Sensing body motions based on charges generated on the body. Nano Energy, 2019, 63: 103842
23 Wu J, Wang H, Su Z, *et al.* Highly flexible and sensitive wearable e-skin based on graphite nanoplatelet and polyurethane nanocomposite films in mass industry production available. ACS Appl Mater Interfaces, 2017, 9: 38745–38754
24 Zhang Y, Tao TH. Skin-friendly electronics for acquiring human physiological signatures. Adv Mater, 2019, 31: 1905767
25 Wei S, Liu Y, Yang L, *et al.* Flexible large e-skin array based on patterned laser-induced graphene for tactile perception. Sens Actuat A-Phys, 2022, 334: 113308
26 Perez-Pozuelo I, Zhai B, Palotti J, *et al.* The future of sleep health: A data-driven revolution in sleep science and medicine. npj Digit Med, 2020, 3: 1–5
27 Kwon S, Kim H, Yeo WH. Recent advances in wearable sensors and portable electronics for sleep monitoring. iScience, 2021, 24: 102461
28 Yoon H, Choi SH. Technologies for sleep monitoring at home: Wearables and nearables. Biomed Eng Lett, 2023, 13: 313–327
29 Yin J, Xu J, Ren TL. Recent progress in long-term sleep monitoring technology. Biosensors, 2023, 13: 395
30 Wei X, Li H, Yue W, *et al.* A high-accuracy, real-time, intelligent material perception system with a machine-learning-motivated pressure-sensitive electronic skin. Matter, 2022, 5: 1481–1501
31 Yang W, Liu H, Du H, *et al.* Robust and superelastic spider web-like polyimide fiber-based conductive composite aerogel for extreme temperature-tolerant linear pressure sensor. Sci China Mater, 2023, 66: 2829–2842
32 Sun H, Bu Y, Liu H, *et al.* Superhydrophobic conductive rubber band with synergistic dual conductive layer for wide-range sensitive strain sensor. Sci Bull, 2022, 67: 1669–1678
33 Wang J, Liu H, Yue X, *et al.* Large-scale fabrication of conductive yarn with synergistic conductive coating for high-efficient strain sensing and photothermal conversion. Mater Today Nano, 2023, 24: 100427
34 Qi D, Zhang K, Tian G, *et al.* Stretchable electronics based on PDMS substrates. Adv Mater, 2021, 33: 2003155
35 Liu S, Jun S, Zhang S, *et al.* Advancements in electrospun nanofibrous membranes for improved waterproofing and breathability. Macromol Mater Eng, 2023, 2300312
36 Li Z, Zhu M, Shen J, *et al.* All-fiber structured electronic skin with high elasticity and breathability. Adv Funct Mater, 2020, 30: 1908411
37 Gu X, Li N, Gu H, *et al.* Polydimethylsiloxane-modified polyurethane-poly(ε-caprolactone) nanofibrous membranes for waterproof, breathable applications. J Appl Polym Sci, 2018, 135: 46360
38 Anaya DV, Zhan K, Tao L, *et al.* Contactless tracking of humans using non-contact triboelectric sensing technology: Enabling new assistive applications for the elderly and the visually impaired. Nano Energy, 2021, 90: 106486
39 Xing F, Jie Y, Cao X, *et al.* Natural triboelectric nanogenerator based on soles for harvesting low-frequency walking energy. Nano Energy, 2017, 42: 138–142
40 Wang S, Gao J, Lu F, *et al.* Human motion recognition by a shoes-floor triboelectric nanogenerator and its application in fall detection. Nano Energy, 2023, 108: 108230
41 Park JH, Wu C, Sung S, *et al.* Ingenious use of natural triboelectrification on the human body for versatile applications in walking energy harvesting and body action monitoring. Nano Energy, 2019, 57: 872–878
42 Behera R, K. E. A review on polyvinylidene fluoride polymer based nanocomposites for energy storage applications. J Energy Storage, 2022, 48: 103788
43 Xia W, Zhang Z. PVDF-based dielectric polymers and their applications in electronic materials. IET Nanodielec, 2018, 1: 17–31
44 Li Z, Wang X, Hu Y, *et al.* Triboelectric properties of $BaTiO_3$/polyimide nanocomposite film. Appl Surf Sci, 2022, 572: 151391
45 Tao X, Jin H, Ma M, *et al.* Significantly enhanced performance of triboelectric nanogenerator by incorporating $BaTiO_3$ nanoparticles in poly(vinylidene fluoride) film. Phys Status Solidi (a), 2019, 216: 1900068
46 Vandekerckhove M, Wang Y. Emotion, emotion regulation and sleep: An intimate relationship. AIMS Neurosci, 2018, 5: 1–22
47 Boe AJ, McGee Koch LL, O'Brien MK, *et al.* Automating sleep stage classification using wireless, wearable sensors. npj Digit Med, 2019, 2: 131
48 Fabbri M, Beracci A, Martoni M, *et al.* Measuring subjective sleep quality: A review. Int J Environ Res Public Health, 2021, 18: 1082

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Conflict of interest The authors declare that they have no conflict of interest.

Supplementary information Supporting data are available in the online version of the paper.

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基于金属织物和自然摩擦带电的电子皮肤对人体运动的智能识别

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摘要 目前已开发出各种基于电子或光学信号的技术来感知身体运动, 这在医疗保健、康复和人机交互等领域至关重要. 然而, 这些信号都是从身体外部获取的. 本研究中, 我们制备了一种电子皮肤(e-skin)人体运动传感器, 它利用有机聚合物和金属织物的组合, 通过人体的自然电荷感应(EI)来检测运动. 该电子皮肤可获得高达450 V的人体电势信号. 此外, 该信号可通过最先进的深度学习技术自动提取和训练. 该传感器能准确识别睡眠活动, 准确率约为 96.55%. 这种可穿戴运动传感器可以与物联网技术无缝集成, 实现多功能应用, 展示了其在人类活动识别和人工智能方面的潜在用途.

