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Digital Twin Smart Home Using Robust Mat Monitoring System with Multi-Modality Deep Learning Analysis

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Digital twin attracts numerous attentions in the creation of Metaverse because of its capability of real-time projecting the physical world into the digital counterpart, thereby providing a more intelligent, immersive and comprehensive communication between the physical and virtual world. To construct a digital-twin smart home, versatile Internet of Things (IoT) sensors are required to monitor real-time home-related information. Conventional IoT sensors are mostly based on resistive or capacitive mechanisms which rely heavily on power supplies. Self-powered sensors based on triboelectric mechanisms can be potential candidates to address this issue. However, the practical deployment of triboelectric nanogenerator (TENG) based self-powered sensors are still hindered by some intrinsic limitations, such as unstable output in response to the changes in environmental conditions and user behaviours. In this work, we develop a robust triboelectric mat with high tolerance to environmental and user behavior variations. The triboelectric mat consists of an interdigital electrode (IDE)-designed environment-insensitive in-home mat array and a two-channel entry mat at device level. At data analytics level, time-domain analysis and multi-modality deep learning (DL) are utilized. Furthermore, leveraging the comprehensive sensor information and VR technique, a digital-twin smart home is successfully visualized.

1. Introduction (Times New Roman 10pt)

In the era of artificial intelligence of things (AIoT), metaverse and digital twin are two popular concepts that attract increasing attention from both industry and academia.[1] It is of great interest to introduce digital-twin smart homes into metaverse to realize a more intelligent, immersive and comprehensive communication between the physical world and the virtual world.[2] To construct the perception layer of a smart home, numerous diverse sensors with distinct functionalities are blooming to monitor versatile home-related signals.[3] Among them, triboelectric nanogenerators (TENGs) based mat sensors have contributed substantially to providing human activity monitoring functions.[4] However, the practical deployment of TENG mats has been hindered by their unstable output in response to environmental changes and inevitable variations of user behaviors.[5,6] Herein, we develop an all-TENG-based robust mat monitoring system enabled digital-twin smart home with high tolerance to environment and user behavior variations. In the device level, interdigital electrodes (IDE) design is used for environment-insensitive TENG mat array and multi-modality sensory information is generated from a two-channel entry mat. Concurrently, multi-modality deep learning (DL) is exploited for enhanced identity recognition accuracy in the data analytics level. The IDE design allows the ratiometric readout from the TENG mat array to cancel the commonly experienced variations. Monitoring the user at arbitrary positions is achieved because of the easy spreading out of IDE design in a 2D plane and the interval arrangement of the mat pixels. A TENG entry mat is specially designed to accurately record weight information using a hierarchical structure, and the hierarchical mat is combined with a one-electrode mat to form an identity recognition system. With multi-modality DL analysis, the recognition accuracy has been enhanced compared with the single channel DL analysis. Furthermore, a digital-twin smart home is enabled by the mat monitoring system in VR. The information in the smart home is projected to VR to construct a duplicated counterpart in real-time and implement mutual interactions, including access authorization, position, walking trajectory, dynamic activities/sports, etc. A multi-user skipping scenario is successfully realized in the digital-twin smart home.

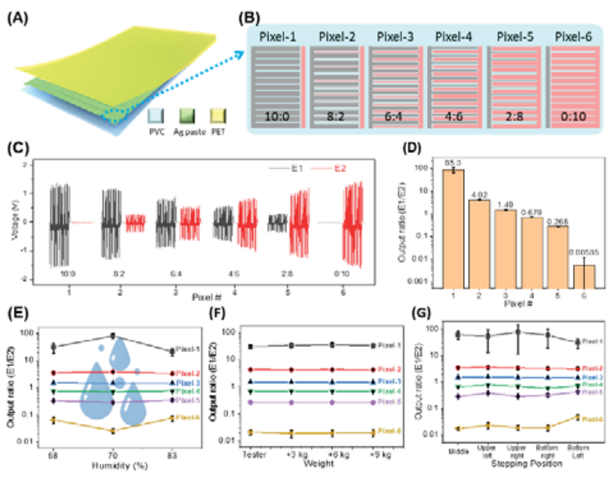

Fig. 1 (A) Structure of a single mat pixel. (B) Diagrams of six IDE patterns with different finger width ratios in one mat set: (C) Triboelectric outputs from two output electrodes of 6 individual pixels. (D) Corresponding output ratios (E1/E2) extracted from C. (F) Output ratios under varying humidity. (G) Output ratios under varying contact weight. (J) Output ratios from different stepping positions (middle, upper left, upper right, bottom right, bottom left).

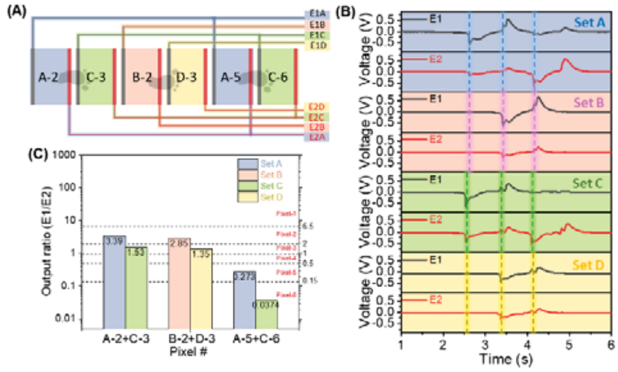

Fig. 2 (A) Schematic illustration of interval arrangement of four sets of mats for arbitrary walking monitoring. (B) Triboelectric output of the four sets (8 electrodes). (C) Corresponding output ratios when a user walks along the mat array with a manner of one step two pixels.

2. Design and characterization of environment-insensitive triboelectric mat

The large-scale, environment-insensitive in-home mat array is constructed from four sets of mats and each set contains six pixels, resulting in a total of 24 (4 × 6) pixels. One set of mat is illustrated here for characterization first. Fig. 1A shows the sandwiched structure of a mat pixel. The electrode designs of the six pixels have varying IDE ratios. Screen printing technique is employed here to guarantee precision and uniformity of the six diverse IDE patterns as well as the mat scalability. Fig. 1B shows that the width ratio of the two IDE fingers varies from each pixel in one set. Grey color and red color are utilized to differentiate two IDE fingers (E1 and E2). The triboelectric output ratio of the two IDE fingers in each pixel is theoretically the same as the IDE width ratio because TENG output is proportional to electrode area under the same triboelectric area, thus providing a way to distinguish the six pixels.

To characterize one set of mat, six pixels with varying IDE finger width ratios are connected in parallel with all E1 connected together and E2 connected together, resulting in only two electrode terminals. Fig. 1C shows the triboelectric output voltages of the six pixels from two electrode terminals when a user steps on and off the six individual pixels. Correspondingly, the output ratios E1/E2 for six pixels are presented in Fig. 2D. The six ratios are distinguishable. To verify the environment-insensitivity of this mat set, the triboelectric output ratios of the six pixels under different circumstances are investigated in Fig. 1E-G, including various ambient humidity, user weights, and stepping positions. Under different humidity, the output ratios keep constant in each pixel and are distinguishable between pixels (Fig. 1E). Regarding different user weights, when a user (50 kg) holds different weights, the triboelectric output increases accordingly while the ratios keep unchanged and are distinguishable for six pixels (Fig. 1F). Regardless of the stepping positions, the results show that the six pixels can be successfully distinguished (Fig. 1G). Therefore, the ratios of each pixel are stable and distinguishable under changing environments and users' stepping manners, contributing to

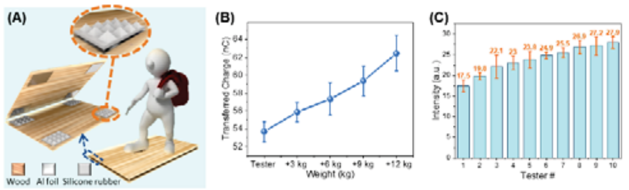

Fig. 3 (A) Configuration of the weight sensing mat containing four silicone rubber-pyramid units. (B) Relationship between the obtained transferred charge and the individual (50 kg) holding varying weights of objects from 3 kg to 12 kg. (C) The measured result of 10 users with different weights when connecting the sensing mat to MCU.

environment-insensitive and user-friendly mats.

Next, we explore the application for position sensing and walking trajectory monitoring. We need to ensure the pixels covered by two consecutive steps are from different sets of mats, so that four sets of mats with eight electrode terminals are introduced in Fig. 2A. Fig. 2B illustrates the generated triboelectric output signals of the four sets of mats with eight output electrode terminals and taking the ratios of the negative peaks of each mat set regarding the walking sequence. The calculated ratios in Fig. 2C are all within the defined range of the ideal ratios, indicating the feasibility of this mat array arrangement for arbitrary walking trajectory monitoring.

3. Mat integration and applications

3.1 Multi-modality DL analysis for enhanced identity recognition

To enhance mat functionality, we introduce a weight sensor for healthcare applications. We apply the contact and separation mode TENG with elastomer and Al as the triboelectric materials and Al as the electrode material. The optimal structure and elastomer for negative triboelectric materials are found to be the pyramid&sphere mixed structure and skin-like elastomer, respectively (Fig. 3A). The output performances are shown in Fig. 3B&C. Fig. 3B illustrates the weighing results of a user (50 kg) holding increasing weights. The transferred charge increases almost linearly with the increasing weight. Towards practical system, we connect the weight sensor to MCU. Fig. 3C shows the obtained results of 10 users with different weights recorded by MCU, indicating the ten weights can be distinguished.

Next, the environment-insensitive mat (as the information mat) and the hierarchical weight sensor (as the entry mat) are integrated to realize more versatile practical applications. Aiming at constructing a digital-twin smart home with novel functionality of identity recognition and access authorization, DL is integrated to analyze the gait information generated from a two-channel entry mat. Fig. 4A shows a typical step of normal walking on the entry mat including stepping on, standing still and stepping off process. Specifically, the entry mat is composed of a top one-electrode mat attached to a bottom hierarchical weight sensing mat (Fig. 4B) where the top one-electrode mat is fabricated with the same materials as the mat array. Thereby, the generated signals during one step are obtained from two output channels separately, i.e., the top one-electrode mat and the bottom hierarchical mat. Ten users participate in data collection. Both signals from the top one-electrode mat and the

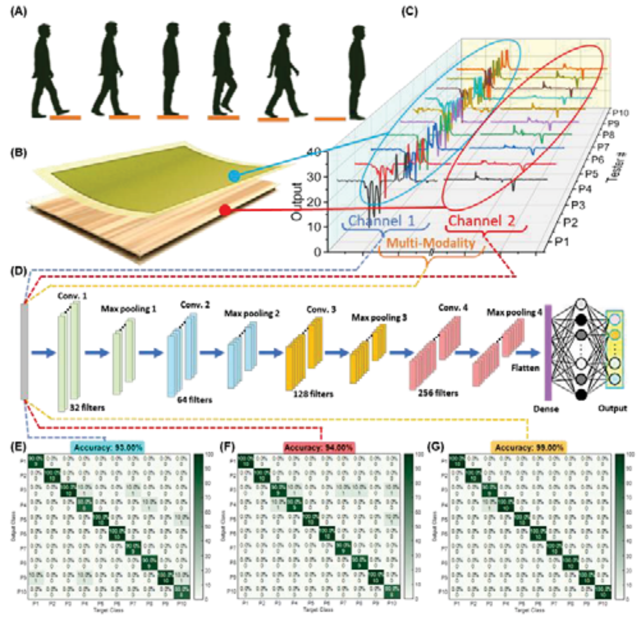

Fig. 4 (A) Schematic illustration of a normal walking step including stepping on the entry mat, standing still and stepping off. (B) Configuration of the entry mat. (C) Corresponding outputs from the two channels during ta normal walking step for 10 users. (D) Structural illustration of the convolutional neural network (CNN). (E)-(G) Confusion maps obtained using (E) channel 1 only, (F) channel 2 only, (G) multi-modality analysis of channel 1 and channel 2.

bottom hierarchical mat are collected by the two analog-to-digital converter (ADC) channels from an MCU, and the generated signals in one step are recorded in real time in terms of two separate channels, as shown in Fig. 4C. To collect dataset for DL, the 10 users all repeat the one-step walking motion for 50 cycles with 1600 data points collected from each channel per cycle. Finally, 50 samples are collected for every user in each channel and randomly divided into training set (80%) and testing set (20%). The DL analysis model is based on a convolutional neuro-network (CNN) (Fig. 4D). For the input layer, initially, the samples from channel 1 and channel 2 enter separately, and the classification accuracy is 93% and 94% respectively in identifying 10 users. Fig. 4E and F show the corresponding confusion maps of the two channels. We next show that improved accuracy can be achieved when the multi-modality sensory information including both channels enter the input layer together. We fuse the two different kinds of sensor signals in data-level feature. Because the two channels from MCU are collect into same format, we directly combine the two-channel signal into the input data with 3200 data points per cycle. By entering such multi-modality sensory information into the training model, relationships between the two different channels are supposed to be considered, and more features of gait information may be extracted as well. It is proven that the classification accuracy for multi-modality analysis reaches a higher value of 99% as shown in Fig. 4G. Although identity recognition has been extensively explored in smart homes either using triboelectric mats or triboelectric socks, a feasible strategy to further improve the classification accuracy has been effectively proposed here.

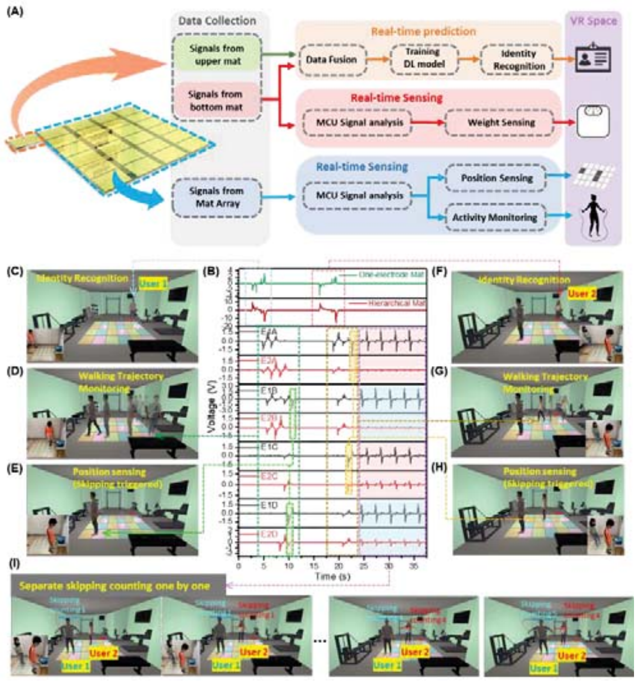

Fig. 5 (A) Overview of the proposed system involved the signals flow for identity recognition, weight sensing, arbitrary position monitoring and activity monitoring. (B) Generated triboelectric signals of two users when entering smart gym, walk to skipping positions, stand still one by one followed by skip together. (C) User 1 walks on the entry mat for identification. (D) Walking trajectory of User1 avatar in VR space. (E) Skipping command triggered in VR space when D-2 and B-1 are detected in sequence. (F) User 2 walks on entry mat for identification. (G) Walking trajectory of User 2 avatar in VR space. (H) Skipping command triggered in VR space when C-2 and A-1 are detected in sequence. (I) Separate and one-by-one skipping counting in VR space when the two users skipped on their triggered pixels.

3.2 Digital-twin smart home application

To better visualize the multi-functionality of the integrated map, a digital-twin smart home is developed via the interactions between real space and VR space. Fig. 5A describes the system working schemes which enables four functionalities, i.e., identity recognition, weight sensing, position sensing, and activity monitoring. The first two functionalities are based on the entry mat that outputs multi-modality sensory information with two kinds of triboelectric signals. One is from the top one-electrode mat and the other is from the bottom hierarchical mat. The multi-modality signals are collected and fused together in real time, followed by being sent to the DL trained model for identity prediction. The signals from the bottom mat are processed for real-time weight sensing. Likewise, when the individual walks on the large-scale mat array, the generated triboelectric signals are collected and processed by the MCU in real time for position sensing as well as activity monitoring which can be reflected in VR space. In the skipping application, the generated triboelectric signals are plotted in Fig. 5B with respect to the two output terminals from the entry mat and the eight output terminals for the four-set mat array (10 output channels in total). Initially, User 1 steps on the entry mat for identity recognition (signals shown in light blue frame in one-electrode mat and hierarchical mat). The corresponding avatar appears in VR space indicating successful identity recognition (Fig. 5C). Next, User 1 walks on the mat array to the targeted positions for triggering the skipping command in VR space (Fig. 5D and E). The signals generated during this walking trajectory are marked in the dark green frame, and the two inner light green frames indicate the triggered skipping command signals on D-2 and B-1. Then, User 1 stands still and no triboelectric signals are generated for all the ten channels until User 2 comes in. Similarly, User 2 steps on the entry mat in the real space first for identity recognition (signals shown in light red frame), and the successful recognition is displayed as a woman avatar appears in VR space (Fig. 5F). Next, User 2 walks to the other skipping command triggering positions, during which the generated signals are marked in the dark yellow frame with two inner light yellow frames indicating the command signals triggered from C-2 and A-1 in sequence. Fig. 5G and H display the corresponding walking trajectory and skipping triggered positions in VR space respectively. After the two users stand still, they begin skipping together in the real space and the corresponding avatars respond in VR space with accumulated counting concerning each user. The two blue shadowed frames in Set B and D represent the skipping signals from User 1, and the red ones in Set A and C stand for User 2. The counting number is accumulated separately for the two users by considering the positive peaks in the corresponding mat sets following the time sequence. The signals are shown in blue and red shadowed frames, and the final accumulated counting number in Fig. 5I is consistent with signals for both users, showing the perfect real-time interaction between the real space and VR space.

3. Conclusions (Times New Roman 10pt)

In summary, we have proposed a robust TENG based mat monitoring system, consisting of an environment-insensitive in-home mat array via unique IDE design and a two-channel entry mat with multi-modality sensory information. Specifically, owing to the unique electrode design of IDE and the resulted ratiometric readout method, the in-home large-scale mat array can achieve accurate position sensing and walking trajectory monitoring. It has successfully overcome the intrinsic limitations of TENG devices by eliminating the influence of environment condition changes and stepping manners. Meanwhile, by introducing four sets of mats, arbitrary walking trajectories can be precisely detected even when two pixels are covered during one step. When integrated with DL for identity recognition, the multi-modality DL analysis of two channels (bottom hierarchical mat and upper one-electrode mat) has successfully enabled accuracy improvement from 93%/94% for one respective channel to 99% with multi-modality analysis. Hence, the proposed strategies in device and data analytics level for robustness enhancement can be strong references for the development of TENG devices and DL analysis.

Enabled by the mat monitoring system, a digital-twin smart home is developed via duplicating the real-time status of physical home space to digital world, regarding the user access authorization, position, walking trajectory, dynamic activities, etc. The generated signals are analyzed using DL or time-domain analysis for the construction of a digital counterpart that is visualized in VR simultaneously. The skipping application in digital-twin smart home shows the feasibility of monitoring two users on the mat at the same time. The developed digital-twin smart home is good evidence for the technical convergence of digital-twin, AI and VR. Therefore, it is of great potential that a more comprehensive, efficient and immersive environment is going to be established in the Metaverse to benefit the whole society regarding living, working and learning.

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