Advanced Electronics and Artificial Intelligence: Must-Have Technologies Toward Human Body Digital Twins

Yanning Dai, Jiaqi Wang, and Shuo Gao*

1. Introduction

The concept of a digital twin (DT), which refers to the establishment of a virtual representation of a practical object, was first officially proposed by NASA in 2010 to address the working issues of flight engines, which play a significant role in Industry 4.0 and relevant fields, where the real-time monitoring of complex systems and the prediction of their future status in diverse conditions are required. For example, in the manufacturing industry, DTs affect the entire product lifecycle management (PLM). Conventional approaches for PLM are extraordinarily time-consuming and complicated in terms of their design, manufacturing, service, and operations. However, DTs can extract digital information and overlay physical products with virtual models. In this way, companies are capable of managing their products digitally throughout the overall product lifecycle. Furthermore, DTs are applied to urban planning in the form of interactive platforms. With the captured real-time 3D and 4D spatial data, DTs establish digital models for urban environments.

Inspired by the successful utilization of DT technology in industries, biomedical researchers are focused on building DT models for the human body. This includes the digitization of the musculoskeletal nervous system, which can not only provide medical staff with patients’ vital physiological information (e.g., blood glucose and respiration rate) in real time but can also report patients’ potential body changes when certain drugs are delivered. Nevertheless, it is challenging for current mainstream technologies to achieve this goal for the following two reasons. First, the human body can be regarded as a complex system whose status involves the comprehensive interaction between different tissues, organs, and subsystems. Medical tests usually examine one or several types of human body information, which may satisfy the diagnosis of certain diseases; however, they are insufficient to adequately represent the working mechanisms of human bodies. Further, most of the tests are discrete in the time domain, indicating that the continuous changing trend of indexes is not available. Second, it is difficult to establish relationships between different types of human body information. For example, the principle responsible for the control by the neuronal system on the musculoskeletal system is still vague, and only limited body movements can be explained.

During the past decade, there have been rapid developments in the fields of material science and fabrication technologies, and there has been an exponential increase in the number of reports on fundamental theories and applications. Advanced electronic devices exhibit desirable attributes such as small volume, biocompatibility, and low power consumption. Diverse multifunctional wearables and implantables have been demonstrated to monitor multidimensional human body information, which are essential, but they have been omitted in conventional measurements, indicating the potential to provide must-have elements for modeling human bodies. In addition, emerging artificial intelligence (AI) methods have proven to be useful in the determination of nonlinear relationships between multimodal data and in finding hidden links for historical and real-time information, based on which the future body status could be potentially forecasted. Some state-of-the-art works have used recurrent neural networks (RNNs) to predict users’ motion strategies in a new environment after partially recording their daily activities and reinforcement learning (RL) has now...
been applied to simulate the metabolism of drugs in an individual.\textsuperscript{13–15}

Although human body DTs have not yet been developed, many fundamental building blocks are now being prepared and are under construction. In the following sections, we first briefly review state-of-the-art wearable and implantable electronics and AI methods, which can monitor and analyze human body signals at all times and places, and then we provide different perspectives on new and advanced experience and services that are enabled by human body DTs.

2. Wearables and Implant-Based Human Body Signal Retrieving

The journey toward understanding the highly complex human body system can be traced to the Han dynasty of China, when Huangdi Neijing was composed. Since then, there have been many attempts globally to create a foundation for modern medical science. Although there have been tremendous achievements, and many of them are now extensively used in biomedical research, a comprehensive recognition of the mystery of the human body is still under way, indicating the difficulty in establishing corresponding DTs. As briefly explained earlier, advanced electronics and machine learning algorithms have paved the way for the study of the human body. In this section, new material-based wearables and implants for retrieving multidimensional human information are explained.

2.1. Wearables

Compared with commercial wearable electronics, which are capable of monitoring basic human body signals and postures (such as heart rate, blood oxygen, and walking), novel materials and microelectromechanical systems (MEMS) technology-enabled advanced wearables not only offer higher detection accuracy, but also enrich information dimensions.\textsuperscript{16–18} Later, we explain the advanced wearables from the perspectives of locomotion, physical signs, and external body fluid detection, which represent the overall performance of the musculoskeletal nervous system under different in vivo conditions.

In the study by Zhao et al.,\textsuperscript{19} a multisensory fusion-based locomotion–recognition technique was presented. The authors developed a pair of insole force-sensing systems (48 channels for each foot) to read plantar stress distribution as well as an electromyography EMG-based intention detection system. The different signals were merged at the feature level, and a support vector machine (SVM) method was used to classify five different locomotion modes with an accuracy of 96.53%. In the study by Camargo et al.,\textsuperscript{20} the inertial measurement unit (IMU), goniometer, and electromyogram (EMG) data were merged. The extracted time and frequency features were processed using both a dynamic Bayesian network for user intention estimation and a feedforward neural network for environmental parameter regression. Low error rates of 0.70 ± 0.15% and 3.55 ± 0.85% were eventually obtained for steady state and transitions, respectively, validating the feasibility of using the fusion of wearable sensors in locomotion classification. Yoon et al.,\textsuperscript{21} developed a flexible skin-type sensing device to measure the human metacarpophalangeal joint flexion. The sensing end was a capacitive strain sensor assembled as a silver nanowire (AgNW)/polydimethylsiloxane (PDMS) elastomer/Ag ink-sandwiched structure, providing a stable response under a uniaxial strain of up to 50%. The data acquisition, transmission, and processing modules, that is, sensors, interconnect bridges, and processing circuit boards, were assembled in a discrete manner to customize the geometric characteristics of the user’s hand.

Although good results have been obtained, the use of multiple devices increases the complexity of the system and may place a heavy burden on users. A potential solution is to decrease the types and numbers of sensors while increasing device performance and using more smart algorithms. To this end, Liu et al.,\textsuperscript{22} designed an advanced motion-tracking device that offered an integral-free velocity detection function enabled by incorporating microtiaxis flow sensors with microtiaxis inertial sensors. The proposed method obtained a high dynamic motion detection accuracy by avoiding the accumulated integration errors in traditional IMUs. The experimental results of capturing boxing and kicking actions using a single device validated the feasibility of single-device-based locomotion classification.

Another alternative solution to reduce the physical load of wearing multiple sensors could be to integrate sensing materials into cloths directly, implying that users can enjoy freedom of motion while providing body motion information for diverse purposes. In recent years, textile-based electronics have demonstrated good potential in various applications, such as sensing,\textsuperscript{23–25} display,\textsuperscript{26} and energy harvesting.\textsuperscript{27,28} In the field of human locomotion detection, textiles are generally used as resistive-type strain-sensing materials, where the transverse and longitudinal fibers are processed into resistance filaments.\textsuperscript{29} When a slight deformation occurs, changes in the conductive area will result in material resistance variations. For example, in the study by Shi et al.,\textsuperscript{26} a large-area textile touch sensor was demonstrated using a weave of transverse low-resistance silver-plated yarns and longitudinal high-resistance carbon fibers. The developed sensor could be used on clothing as a keyboard that recorded the input letters of users. In the study by Yang et al.,\textsuperscript{30} graphene-based strain sensors were knitted into polyester fabric clothes for human movement detection. The transverse and longitudinal graphene textile fibers exhibited different tensile properties, enabling their woven conductive networks to detect strains in diverse directions. The sensor exhibited a maximum gauge factor of –26 (with a strain range within 8%) in the transverse direction and –1.7 in the longitudinal direction (with a strain range within 15%). To enhance the strain-sensing sensitivity of resistive-based textile sensors, Liu et al.,\textsuperscript{25} introduced microstructures along textile fibers, which significantly magnified the local strain. The fabricated sensors could successfully distinguish between fast and slow squatting and leg lifting. Thus, it can be concluded that the current textile electronics technology can support the goal of highly wearable locomotion sensors with full potential.

Physical signs, such as heart rate and respiration rate, can indicate our physiological condition and can be used together with locomotion analysis to provide a deeper understanding of body status. Physical sensors based on optical, mechanical, and capacitive methods have been widely reported in the literature to obtain heart rate, pulse, respiration rate, blood oxygen...
saturation, blood pressure, and temperature. In the study by Lochner et al., a fully organic optoelectronic device that measures both human pulse and arterial blood oxygenation using a mix of red (626 nm) and green (532 nm) lights, as shown in Figure 1a, is reported. Compared with the conventional single-light detection mechanism, the mixed light could compensate for the signal loss caused by the differences in the central frequencies of distinct proteins, giving rise to an accurate pulse rate and oxygenation measurement with errors of 1% and 2%, respectively. Although such devices have demonstrated encouraging experimental results, in practical applications, the wearing methods (based on adhesive tape or mechanical straps) result in poor adhesion between the sensing material and the human skin, which decreases the signal-to-noise ratio of the system. To overcome this issue, Kim et al. introduced the epidermal electronic system (EES) technology, which uses pure van der Waals forces to establish conformal integration with the skin. This technique supports mechanical- and capacitive-based sensing mechanisms. For instance, in the study by Son et al., an epidermal sensing system was developed to measure physical signals (skin tremor frequency and temperature) in patients with Parkinson’s disease.

The system was constructed using a silicon nanomembrane (Si NM)-based mechanical strain sensor, an electroresistive temperature sensor, and a flexible random access memory array made of gold nanoparticles (Au NPs). All of the system modules were integrated into an elastomeric hydrocolloid patch, resulting in intimate mechanical contact with the patient’s skin via van der Waals interactions. The proposed system provided a temperature sensitivity of 0.086 Ω°C−1 and an effective gauge factor of ≈0.5. Therefore, biocompatible organic materials and advanced attachment technologies ensure a high sensing performance as well as a good user experience.

Wearable devices usually monitor signals at the skin or in the shallow tissues, and it is challenging to obtaining “in-depth” information. To address this issue, Wang et al. developed an ultrasonic device that is based on rigid 1–3 piezoelectric composites assembled using soft components, as shown in Figure 1b. This device offers better acoustic coupling with soft biological tissue compared with isotropic piezoelectric actuators. The proposed technique allowed ultrasonic waves to reach 4 cm under the skin with a detection accuracy comparable with that of commercial equipment, satisfying the utilization requirement.

Figure 1. a) Device description (top) and working principle (bottom) of the full organic optoelectronic device for the pulse and arterial blood oxygenation measurement. Reproduced with permission. Copyright 2014, Springer Nature. b) Device architecture, utilization demonstration, and detection mechanism for the ultrasonic device proposed in the study by Wang et al. Reproduced with permission. Copyright 2018, Springer Nature. c) Device structure (left) and photograph (right) of the temperature drift-compensated pH sensor. Reproduced with permission. Copyright 2018, Springer Nature. d) Conceptual description of sweat-powered electronic skin proposed in the study by Yu et al. for the monitoring of biomarkers. Reproduced with permission. Copyright 2020, AAAS.
for monitoring cardiovascular events at different body locations. The success of wearable physical sign detection has triggered the generation of multimodal studies that investigate the correlation between motion information and physical signs.

Sweat contains many chemicals that are associated with health conditions. Hence, the development of wearable chemical sensors is of significance. In the study by Bariya et al., moisture-impermeable nitrile-based gloves were proposed to enable the collection of sweat from the fingertips, palm, and back of the hand. The harvested sweat could be further analyzed using chemical sensors installed in the glove to recognize the percentages of different elements such as ions, heavy metals, xenobiotics, and nutrients. Nakata et al. reported a flexible Schottky barrier-based charge-coupled device (CCD) that could be attached to the skin for pH value detection. By integrating a temperature sensor near the pH-sensing area (as shown in Figure 1c), the sensitivity drift due to the temperature change could be calibrated, and a high pH detection sensitivity of 240 mV pH⁻¹ was given. In the study by Gao et al., multiple chemical sensors were assembled in a flexible wristband for the simultaneous measurement of glucose, lactate, and electrolyte (e.g., Na⁺ and K⁺) concentrations in human sweat. Using a built-in signal-processing unit, real-time data collection and analysis could be conducted. The device achieved sensitivities of 2.35 nA μM⁻¹ and 220 nA mM⁻¹ for the glucose and lactate sensors, respectively. Lee et al. proposed a wearable sweat glucose sensor for precise drug dosage control in patients with diabetes. Real-time measurement and calibration of ambient conditions, including pH, temperature, and humidity, were integrated to minimize the measurement error caused by activity changes in glucose oxidase (GOD). He et al. developed a silk fabric-based sweat sensor to detect highly sensitive health-related biomarkers. Owing to the intrinsic porous and hierarchical woven structure of silk fabrics, the sensor offered good water wettability and rich active sites for biomarkers. A high sensitivity (of 6.3 nA μM⁻¹) for glucose concentration detection was obtained. Koh et al. reported a wearable microfluidic system for sweat volume and composition sensing that harvested sweat in its internal channels and responded to chemical markers of interest through color changes. Subsequently, photographic and colorimetric means were applied to obtain quantitative results. The system was able to hold the saved sweat for ≈125 h, with negligible color fading. In the study by Yang et al., a laser-engraved graphene (LEG)-based chemical sensor and a multiplexed LEG-based physical sensor were assembled in a glove to determine the temperature, uric acid, and tyrosine, together with the respiratory and heart rates. It was proven that this wearable system had the potential to evaluate gout levels in physically trained and untrained subjects. The chemicals in sweat can also be used to power wearable systems. Yu et al. presented a battery-free fully perspiration-powered electronic skin (PPEGS), as shown in Figure 1d. Lactate biofuel cells (BFCs) were used to harvest energy from sweat, and a biosensor array consisting of biosensing films and biocatalytic nanomaterials was used to monitor key metabolic biomarkers (e.g., glucose, urea, NH₄⁺, and pH). The harvested energy could support both chemical detection and wireless communication modules for more than 60 h. In addition, the PPEGS could respond to muscle contraction, indicating its potential for locomotion classification.

2.2. Implants

It is either challenging or impossible to precisely monitor the internal conditions of the human body (such as human skin and fat) using conventional technologies, not only to protect organs, but also to prevent external instruments from probing the internal environment. Therefore, mainstream technologies use indirect means, such as computed tomography (CT) and ultrasound, to analyze the desired in vivo objectives, failing to obtain accurate and long-term detection. In contrast, novel implantable devices can make direct contact with internal targets, retrieving the desired information from the source. In this section, we explain how traditionally “impossible tasks” can be accomplished. The use of implantable devices to monitor the three most important body components, namely, the skeleton, visceral organs, and body fluid, which mainly provide functions for body support, powering life activities, and regulating the internal environment, are discussed.

Cai et al. presented an integrated and implantable musculoskeletal biointerface adhered to the bone surface to monitor bone health, promote bone rehabilitation, and analyze gait. The front end consisted of a metal foil-based pressure sensor, a negative temperature coefficient (NTC) thermistor-based temperature sensor, a microscale inorganic light-emitting diode (μ-ILED)-based optical stimulator, and an antenna for energy harvesting and wireless data transmission. The device worked under a power consumption of less than 11 mV, achieved resolutions of 14.3 με and 10 µK for strain and temperature detection, respectively, and the optical stimulation covered the range from 5 to 20 Hz. A successful in vivo monitoring experiment was carried out in rat femurs.

A. D. Mickle et al. designed a bio-optoelectronic implantable device for bladder state monitoring and bladder function modulation, as shown in Figure 2a. The device was composed of a thin and soft strain gauge for sensing bladder filling and voiding and a pair of μ-ILEDs for optogenetic neuromodulation. The control signal and power supply were both wirelessly conveyed by the magnetic coupling effect. Conventional electrical stimulation techniques can easily cause discomfort and injury. In contrast, this device, which features softness and real-time monitoring, provided closed-loop optogenetic neuromodulation that avoided any detectable harm or distress. Results of the in vivo experiments in rats indicated that the device enabled the effective sensing and modulation of bladder activities.

Sim et al. presented an epicardial bioelectronic patch fabricated using soft rubbery materials for electrocardiogram (ECG) monitoring, cardiac strain, temperature sensing, electrical pacing, and thermal ablation, as shown in Figure 2b. The patch, which was attached to the epicardial surface of the heart, contained a 5 × 5 rubbery transistor array for ECG mapping and electrical pacing, a strain sensor that detected strain from 0% to 30%, a temperature sensor, and a heater for thermal ablation. A mechanoelectrical transducer was designed for energy collection and conversion from heartbeats. Compared with the present techniques, which are composed of rigid materials that change the cardiac shape or hinder the heart from beating, this patch, which exhibits softness and deformability, performed the
functions in a gentle manner. The capabilities of the patch were verified experimentally using a beating porcine heart.

Williams et al.[53] presented an optical nanosensor made of an antibody-functionalized carbon nanotube (CNT) complex to detect ovarian cancer biomarkers. The sensor detected human epididymis protein 4 (HE4), which is a biomarker for ovarian cancer, using an antibody-nanotube complex. The signals were transmitted to an external detector via NIR emission. Current serum-based methods cannot detect HE4 during the early stages of cancer, thus delaying treatment. The sensor successfully measured HE4 in murine models, indicating its potential for early-stage cancer detection.

Li et al.[54] demonstrated a wireless, flexible, and implantable sensor for nitric oxide (NO) detection (as shown in Figure 2c), which is crucial for monitoring neurotransmission, immune responses, cardiovascular systems, etc. An implantable sensor consisting of degradable materials, including a copolymer of poly (L-lactic acid) and poly (trimethylene carbonate) (PLLA-PTMC), a gold (Au) nanomembrane, and a poly (eugenol) film, was used to measure the concentration of NO by amperometry. Compared with mainstream techniques, such as colorimetric measurement, which cannot provide continuous measurements, and rigid material-based implantable sensors that require surgical retrieval and which increase the risk of infection, the sensing system provided real-time NO monitoring with a wider sensing range, more stable performance, and full degradation characteristics. NO was successfully detected in both in vitro and in vivo experiments.
Boutry et al.\textsuperscript{[55]} presented an implantable pressure sensor that sensed the pulse rate to monitor artery patency (as shown in Figure 2d) with flexibility, wireless, biodegradability, and battery-free characteristics. The sensor contained two fringe-field capacitors fixed around the artery to detect the pressure caused by arterial pulsation and a bilayer coil structure to measure the change in the resonant frequency of the inductor–capacitor–resistor (LCR) circuit and transmit the data wirelessly. Using existing techniques for blood flow monitoring, such as external Doppler evaluation, observational methods, and wired and/or rigid material-based implants, it is challenging to detect the blood flow accurately and continuously and/or perform additional removal surgery that may be required. The proposed implantable sensor, which overcomes these problems, provides robust and real-time measurement. Experiments performed in a custom-made artificial artery model and in rats showed satisfactory results.

Liu et al. proposed an implantable optoelectrochemical micro-probe for real-time optogenetic interference and dopamine monitoring.\textsuperscript{[56]} The proposed probe could perform optogenetic stimulation and dopamine detection by controlling specific cells expressing light-sensitive ion channels and detecting the impedance of a poly(3,4-ethylenedioxythiophene) polystyrene sulfonate (PEDOT:PSS)-coated diamond film. A diamond film was used to separate the light sources and the impedance sensor, and a miniaturized circuit module was developed for wireless data transmission. The probe showed reliable performance during in vivo experiments in the mice’s ventral tegmental area (VTA).

3. Machine Learning in Prediction

AI, which is a concept originally used in science fiction, is now becoming a ubiquitous technology in daily life. During the procedure of creating human-body DTs, AI is crucial for abstracting hidden information from the complex and abundant data retrieved by wearable and implantable sensors, and finding relationships between phenomena and inputting information, although sometimes in a nonlogical manner (i.e., black-box issue).\textsuperscript{[57]} In addition, AI can build a virtue representative of a practical object and apply physical laws to predict the performance under different conditions, which has been broadly used in finite-element analysis (FEA) for complicated mechanical structures, for example, engines.\textsuperscript{[58]} In this section, we focus on the milestones in using AI to understand human motion and health status. We start with purely big data-based research and then discuss studies that combine big data and physical models.

Big data-based machine learning algorithms can generally be divided into two categories: traditional methods and deep learning methods. The former extracts features first and then uses random forest (RF), SVM, and artificial neural networks (ANNs) to implement classifications and regressions. In contrast, the latter provides predictions using supervised learning methods, such as convolutional neural networks (CNNs) and RNNs, and unsupervised learning methods, such as K-nearest neighbor (KNN) and RL, which directly process the raw data to find the connections. Both machine learning categories have been used to address complex biomedical issues.\textsuperscript{[59–61]} Among these, medicine effect prediction and locomotion prediction are explained here as examples because they are believed to be challenging and crucial tasks.

Many medicines are on the nanometer scale,\textsuperscript{[62,63]} but NPs induce an immune response when they spread in the human body. Conventional expensive and time-consuming animal experiments can filter only one or several specific characteristics of NPs. Moreover, simulation-based analyses cannot accurately mimic the immune response. In this context, researchers have attempted to use machine learning to predict effects of medicine. In the study by Yu et al.,\textsuperscript{[64]} a tree-based RF feature importance and interaction network analysis framework (TBRFA) was proposed. The authors used the correlation coefficients of all training and test sets to precisely predict the lung immune response and lung load of the NPs. The proposed method adopts a multipath importance analysis to encounter the feature importance bias caused by small datasets. Komorowski et al.\textsuperscript{[65]} used RL to model and verify the best delivery method for intravenous fluids and vasopressors. As shown in Figure 3a, KNN clustering was used to divide the time-series data of clinical strategies for more than 100 000 patients with sepsis in the ICU into 750 states.\textsuperscript{[66]} A separate validation set (containing 500 sets of dosing data) was used to compare the treatment plan developed by the AI with that provided by a clinician. The results showed that the probability that the AI strategy outperformed the clinician strategy was 66.4% (with a 95% confidence interval).

Body locomotion monitoring based on portable sensors is intractable because a large number of sensors and a heavy burden of data processing are required. For example, conventional IMU-enabled techniques use complementary filtering and attitude calculation to obtain the attitude angles of each individual body segment; soft-stain sensor-based methods require careful calibration according to the geometric characteristics of each joint. To alleviate this, deep learning techniques have been developed for efficient full-body motion estimation.\textsuperscript{[62,67–69]} For example, Liu et al.\textsuperscript{[62]} adopted an ANN model to predict the motion of human body segments using IMU data collected from adjacent segments, thereby reducing system hardware complexity. In an example experiment that involves reconstructing thigh motion from shank data during walking and running, an average accuracy of 1.20° was achieved. In the study by Kim et al.,\textsuperscript{[67]} an RNN-based network was built to estimate 3D body motions from temporal sequence data captured by 20 soft strain sensors distributed on human joints. The network was constructed by a sequence of long-short-term memory network (LSTM) layers to encode the spatiotemporal sensor data and several fully connected network layers to decode the kinematic features. In tests with three athletic motions (squat, bend-and-reach, and windmill), the proposed algorithm obtained a high overall accuracy of 29.5 mm, indicating the capability of a deep learning network to simplify the sensor calibration procedures.

The main challenge in purely machine learning-based methods is the lack of detailed process interpretation. To address this problem, researchers have integrated the body’s musculoskeletal nerve model with big data methods. This methodology can offer improved prediction accuracy and lead to the discovery of new body working mechanisms. In the study by Lee et al.,\textsuperscript{[69]} a human skeletal muscle model with RL to simulate the mechanism of muscle activation was combined. The machine learning model included two layers of the RL process, namely, the bone and...
First, the muscle layer used the degree of muscle activation as an input to predict the torque applied to the joints. Then, by performing dynamic simulation, the joint angular acceleration, angular velocity, and angle were calculated, and finally, the body posture and position of each joint were obtained. The algorithm could process a full-body musculoskeletal model with 346 muscles. Doctors could manually modify the number of muscles to predict gait in various situations, such as bone deformities, muscle weakness, contractures, and the use of prostheses. It could also enable doctors to determine which surgical method is suitable for a patient from among several surgical combinations. Park et al. [70] proposed a hybrid control framework that combines data and physical drives tightly within each frame. First, a large amount of motion capture data was used to train the RNN network. The network input was the previous frame of action and target extracted from the action (current speed, direction, etc.), and the output was the predicted next frame of action. The trained RNN model was then combined with the physical model. Based on the RNN network data, the controller generated a prediction frame each time. The result was combined with the physical model and the strategy search of RL to generate a comprehensive motion prediction, and it was finally entered into the physical simulation to enhance its physical feasibility. While generating natural actions, it ensured the ability to interact with the environment. Figure 3b shows that the strategy of playing basketball was learnt.

The combination of the physiological model and machine learning method has also been used in research on mental and neurological diseases with disturbances in the dopaminergic system and CBGTC circuits, such as Parkinson's disease, addiction, and schizophrenia. [71] In the study by Dezfooli et al. [72] cocaine addiction was investigated by creating a computational model based on the dopamine assumption of cocaine addiction and the hypothesis that the brain reward system would boost the encouragement threshold after long-term drug use. The average reward temporal difference and time of drug use were studied using RL, whose output (i.e., the increment of the reward threshold) was then embedded into the drug addiction model. The results were aligned with those of drug-seeking punishment-driven animal experiments. In addition, the cocaine-blocking effect was successfully predicted using the proposed machine learning and physiological model merging methods.

4. Future of Human Body Virtual Representatives

With the above-explained advanced electronics and AI algorithms, rich and long-term human body data can be obtained and used to build human body DTs (as conceptually demonstrated in Figure 4) to address existing global challenges in the health and biomedical domains and introduce novel experiences when interacting with the external world.

For the former, DTs are believed to play a major role in early-stage disease detection and proper rehabilitation training design. The implementation of the first can enable effective and early intervention in diseases, limiting the damage as much as possible and reducing the risk of death and disability. However, the signs of diseases at early stages are not obvious and cannot be recognized by patients or even regular physical examinations. [73,74] With respect to the latter, DTs are essential in conveying users’ intentions into cyberspace and reporting users’ physical and mental conditions to prevent emergent issues.

With human body DTs, the invisible body’s internal environment becomes transparent, and even tiny index changes can be recorded in real time by implantable devices installed surrounding the source. [75,76] For example, as introduced previously, the presence of NO and other desired chemicals, which cannot be detected by conventional techniques such as colorimetric measurement, can now be sensed. This information is processed by AI to calculate the potential for developing severe conditions. If poor results are obtained, DTs can be used to predict the impact of different medicine portions on the lesion site and other...
body components, which will help doctors to develop optimized medicine treatment plans.

In the area of rehabilitation, the training strategy has been proven to be the key factor correlated with rehabilitation progress. For example, in the US and Germany, ≈47% of stroke patients can return to work and regain self-care abilities after undergoing well-designed physical training. However, this number is ≈25% in developing countries. The main reason is that the stroke unit method, which is widely used in developed countries in the design of proper physical training, requires rich medical resources that are not available in developing regions. In addition, physical training is irreversible, indicating that poor rehabilitation progress caused by improper training cannot be corrected. In the future, doctors can input different training strategies into patients’ DT models and determine the best one. DT techniques may even generate better training strategies than existing techniques. DT has the potential to significantly accelerate the rehabilitation process and improve the training effect, relieving physical and mental pain for patients globally.

As the social aging problem intensifies, there is an increasing demand for intelligent assistive devices that return independence to users over their lifetimes. In this context, advanced human–robot interaction (HRI) techniques involving safe, adaptive, and intimate interactions are of utmost importance. Human-assist devices typically utilize two forms of interaction: human augmentation, such as wearable prosthetics or muscle strength-enhancing devices, and a stand-alone service robot that helps to handle delicate tasks such as preparing food items in the kitchen. Soft robots are particularly suitable for these two aims owing to their salient body compliance, sensing sensitivity and the large number of degrees of freedom (DoFs). With the data captured from the human body and soft robot during the interaction, a human DT model can provide robots with more comprehensive user physiological and psychological data, enabling a better understanding of human intentions and emotions. Furthermore, a DT model can enhance the HRI efficiency by predicting user behavior. For example, in a cooperative load-carrying mission, the DT model can predict the changes in human applied force in advance rather than responding after measurement, thereby ensuring natural and rapid interactions.

The metaverse, in which users can communicate with friends and enjoy a fully immersive experience, is currently being developed. The ultimate goal of a metaverse system is to allow users to interact with the virtual environment as they would with a real one. Here, DTs are required from at least two perspectives.
First, highly digitized human bodies can provide essential information that can be used to precisely influence the digital environment. For example, the fingers block the sun and form a shadow on the ground; wind caused by running blows the paper off. All of these details will be used to create diverse extended reality (XR) scenarios and, finally, offer users some semblance of reality. Figure 6 depicts an example of turning a modern living room into an ancient study room, which may improve user concentration. In the meantime, long-term immersive experiences can make users addicted, which may result in physical and mental issues. Hence, DTs allow the system to determine whether a user should quit an entertainment activity. Alternatively, it can even predict how a user’s body condition will change before extensive content is displayed.

5. Conclusion

The pace of today’s technology development is exponential rather than linear. With the continuous maturity of basic science and engineering technologies, the development of human body DTs may be more rapid than expected. The history and current status of human-body research have proven that each small step of deeper understanding can contribute to significant advances in the quality of life. The perspective provided in this article partially unveils the potential benefits of human-body DTs, and the authors strongly believe that their development will positively impact society.

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Conflict of Interest

The authors declare no conflict of interest.

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Shuo Gao received his Ph.D. in electrical engineering from the University of Cambridge, UK, in 2018. From 2017 to 2018, he was a research associate at the University College London, UK. He is currently an associate professor at the Beihang University, China, and his area of expertise is human–machine interactive systems. He has over 100 publications, including books, peer-reviewed journals, flagship conferences, and patents. With respect to his industrial experience, he worked as an optical fiber system engineer at Ciena Corporation, Canada, and from 2012 to 2013, he worked as a technique consultant at Cambridge Touch Technologies Inc., UK.