WEARABLE TECHNOLOGY

https://aber.apacsci.com/index.php/wt/index

2020

Volume 1

Issue 1

ISSN 2810-9783

ISSN 2810-9783

01

9 772810 978206

Asia Pacific
Academy of Science Pte. Ltd.

Asia Pacific
Academy of Science Pte. Ltd.

Editorial Board

Volume 1 Issue 1 • 2020

Wearable Technology

Asia Pacific
Academy of Science Pte. Ltd.

Table of Contents

Editorial

Original Research Article

Review Article

Wearable Technology (2020) Volume 1 Issue 1, *pp.* 1.
doi: 10.54517/wt.v1i1.1678

Editorial

Wearable technology, also known as wearables, smartwear, skin electronics of fashion technology, is a category of hands-free electronic devices that can be worn as accessories or embedded into clothes or skin surface. The usage involves all kinds of industries such as medicine, sports, apparel, health monitoring and management, and artificial intelligence.

As a new journal focused on wearable technology, we hope to provide a good communication platform for scholars and experts from various industries. It is our honor to invite Prof. Jun Qiu from Tsinghua University and Prof. Pibo Ma from Jiangnan University to write articles involving different fields for the first issue. Prof. Jun Qiu lab reviewed the strategic choices for high-quality development of smart wearable sporting goods industry. In this article, a strategic policy of people-oriented is established, focusing on research and development, and scientific management. Prof. Pibo Ma and his team pointed out that the type, structure and weaving method of the conductive yarn were important factors which affect the performance and wearing comfort of knitted sensors, and the electrical characteristics of two-dimensional extension and three-dimensional deformation in the strain stretching process of knitted sensors determined the effective strain sensing range.

Furthermore, we collected several other excellent articles on application of wearable technology and mechanisms or models about this technology, hoping to show an overview of this rapidly developed subject.

Editor-in-chief

Dr. Zhen Cao

Wearable Technology (2020) Volume 1 Issue 1, *pp.* 2–8.
doi: 10.54517/wt.v1i1.1617

Asia Pacific Academy of Science Pte. Ltd.

ORIGINAL RESEARCH ARTICLE

Research status and progress of intelligent wearable system for first aid based on body area network

Wei Han, Junchao Wang, Yang Zhou*, Yingying Jiang

* *Emergency Department, Shenzhen University General Hospital, Shenzhen 518055, Guangdong, China. E-mail: 54656085@qq.com*

ABSTRACT

With the rise of electronic health services, wireless body area network (WBAN) technology has attracted great international attention. The body area network can obtain human vital sign parameters in its natural state, and support applications in areas such as clinical diagnosis and treatment, emergency rescue and treatment, and health information services. This article introduces the concept of body area network and the electronic medical architecture of body area network, summarizes the advantages of body area network: In low data rate scenarios, the system power consumption of body area network is much lower than that of other wireless communication standards, providing more choices for special frequency bands for medical equipment (500 MHz to 5 GHZ), thereby reducing the interference problem between different communications; proposing bottlenecks and hot spots of body area network: Ultra-low power consumption requirements of sensor nodes and hardware resource constraints with limited computing power, and data security protection problems in body area network sensor nodes; the application of body area network in emergency scenarios was analyzed, and the hot spots of body area network research in the field of emergency were summarized and predicted: The development of ultra-low-power chips, wearable wireless nodes, intelligent medical terminals, health and monitoring instruments and other devices and equipment.

Keywords: body area network; first aid; wearable system; scene application

1. Research status of emergency intelligent wearable system in body area network

1.1. Background

The diversification and facilitation of healthcare services is increasingly rely on the support of information technology[1]. The medical field is one of the application fields with the widest coverage, the greatest support of information technology, the widest industrial driving area, and the most obvious service demonstration effect[2,3]. With the rise of electronic health services, WBAN technology has attracted great international attention. As the system and application of the integration of biotechnology, sensor network, and Internet, it will lead to the mutual penetration and coordinated development of information technology and other new

ARTICLE INFO
Received: December 26, 2019 | Accepted: January 28, 2020 | Available online: February 15, 2020

CITATION
Han W, Wang J, Zhou Y, et al. Research status and progress of intelligent wearable system for first aid based on body area network. Wearable Technology 2020; 1(1): 2–8.

technologies, the BAN has aroused strong interest in academia and industry around the world since its inception[4]. As shown in **Figure 1**, the BAN can obtain human vital sign parameters in its natural state, and support applications such as clinical diagnosis and treatment, emergency rescue and treatment, and health information services[5], which belongs to the intersection of biomedicine and information science, is a local area network with a communication distance of no more than 3 m through multiple wearable sensor nodes[6,7].

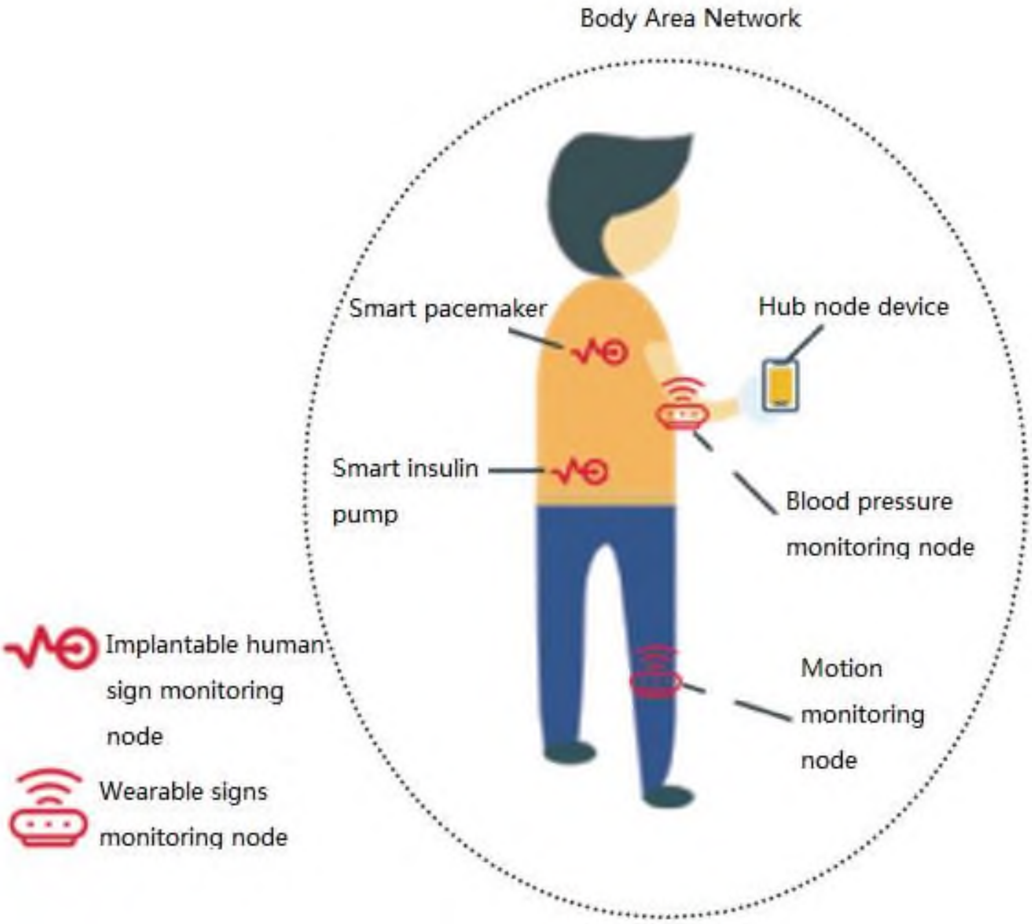

Figure 1. Body area network.

1.2. Electronic health architecture of BAN

The sensor nodes collect vital sign parameters such as blood pressure, heart rate, body temperature, respiration, oxygen saturation, ECG, and the coordinator sends data collected from the sensor node to hospital through the communication network and switching center[8,9], as shown in **Figure 2**, depicting a body area network-based electronic medical architecture diagram. After processing, it can be forwarded to individuals, communities and families, can provide a variety of services such as the mobile clinical, remote diagnosis, health education, health consultation and evaluation, which is extremely effective in alleviating the outstanding contradictions of the current medical shortcomings and low utilization rate[10], rationally allocating medical resources, and significantly improving the level of people's medical and health services, and also the treatment during emergency[11].

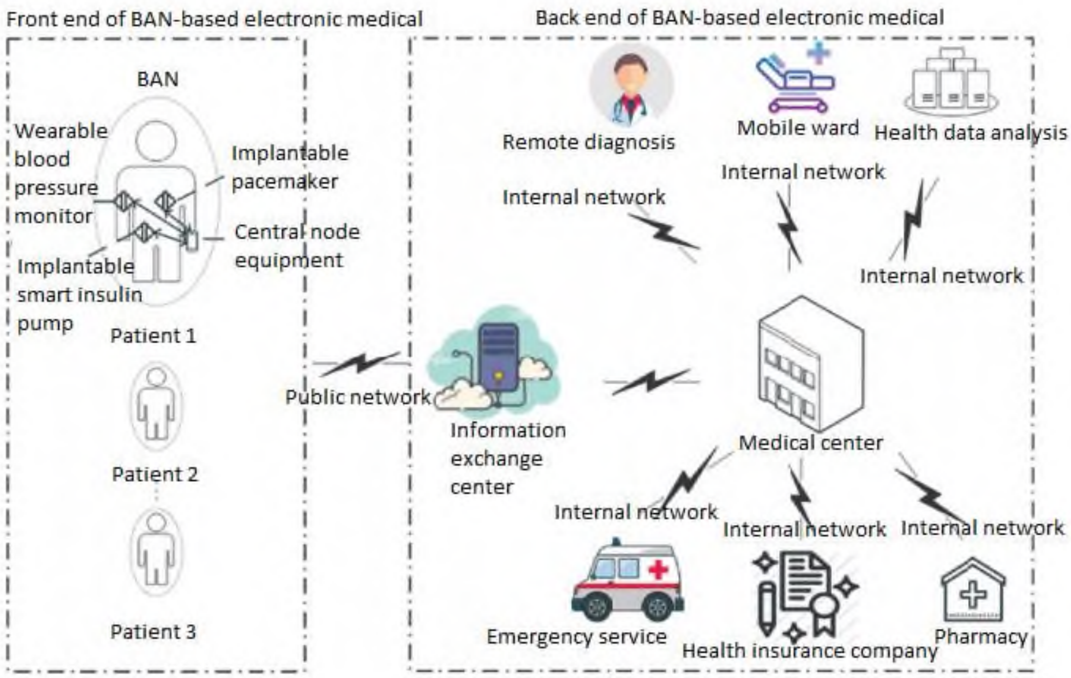

Figure 2. BAN-based electronic medical architecture diagram.

1.3. The application scope and characteristics of BAN

BAN technology can help achieve in the intelligent medical work for people, the digitization of medical information, real-time diagnosis and treatment process, scientific medical process, and humanized service communication[12,13], which can meet the needs of medical health and emergency rescue information, intelligent management and monitoring of public health safety, etc., and at the same time achieve the interaction between individuals and medical personnel, medical institutions, and medical equipment, and achieve the management of personal health by oneself, which enable the early treatment of diseases and the maintenance of emergency rescue information, and promote the informatization and intelligence of management in the medical field[14,15]. BAN can also be widely used in entertainment, sports, environmental intelligence, military and public safety, etc.[16], which is a key area that strongly related to the development of national economy and people's livelihood, and the market demand, which its social and economic benefits are immeasurable[17].

1.4. Advantages of BAN

As shown in **Figure 3**, compared with the standards of other wireless communication, the advantages of the BAN are mainly reflected in the following three aspects. (1) In the scenario of low data rate, the system power consumption of the BAN is much lower, and the battery life is much higher than the standards of other wireless communication. (2) The information transmission of WiFi, Bluetooth, and Zigbee are all concentrated in the 2.4 GHz frequency band, which is easy to interfere with each other and brings additional power consumption overhead[18,19]. While BAN offer more options for medical device-specific frequency bands (500 MHz to 5 GHZ)[20], thereby reducing interference between different communications. At the same time, the BAN system can choose the best channel for communication between the narrowband channel, the ultra-wideband channel and the human body communication channel according to the requirements of different application scenarios[21]. (3) Due to the BAN is aimed at the transmission of human body signs information in medical scenarios, its information sensitivity and privacy are high. Improper information leakage will lead to serious security problems, and even directly affect the safety of users' lives. Therefore, the security protection measures of BAN are also higher and more unique by comparing to other wireless communication standards.

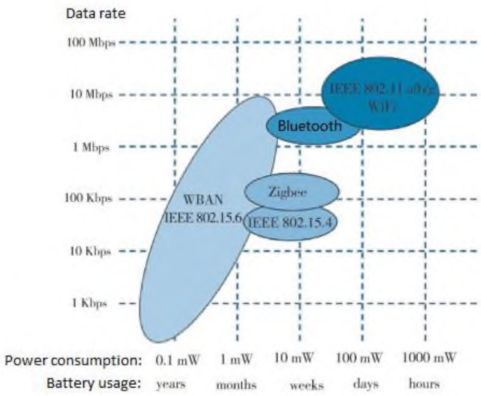

Figure 3. Power consumption and battery usage contrast between BAN and other wireless communication standards under different data rates.

1.5. Bottlenecks and hotspots of the BAN

Compared with other wireless communication networks, the main bottlenecks hindering the large-scale promotion and implementation of body area networks are concentrated in the following aspects. (1) The ultra-low power consumption requirements of the sensor node and the hardware resource constraints of limited computing power[22]. As a basic component of the electronic medical system, the BAN system node is responsible for monitoring and tracking the patient's body parameters for 24 h at anytime and anywhere, the long-term efficient, stable physiological information collection, and data exchange are the basic requirements for achieving its function[23,24]. However, due to the implantable and wearable characteristics of BAN sensor node, it is bound to use a limited power supply and low-power hardware with low computing power[25], and each power supply replacement or charging will have a greater impact on the continuous extraction and tracking of physical parameters[26]. Especially for implantable sensor nodes, each battery replacement will cause great inconvenience and pain to the user. Therefore, under the condition of limited power supply and hardware resources, how to design a long-term, efficient and stable communication design method for ultra-low power consumption BAN sensor nodes has become a hot issue in the field of BAN research[27,28]. (2) Data security protection problems in the sensor node of BAN. The BAN contains a large number of extremely private data information such as various vital signs data, medical diagnosis information, user medical records, etc. Illegal access, modification or information leakage will not only cause greater security risks, but also cause serious threat to the user's life safety, resulting in irreversible social impact[29,30], so the information security requirements of the BAN are higher than other wireless communication networks. (3) The sensor node of BAN and its limited power supply and hardware resource limitations make it difficult for the traditional high-intensity data security scheme to achieve the protection for each data in this scenario[31–33]. Therefore, how to design a safe and reliable encryption algorithm under the constraints of limited hardware computing power, power consumption and area, and establish a reliable environment for data transmission in the BAN, preventing illegal tampering of medical data, and ensure the legitimacy of nodes has become a key scientific problem that needs to be solved urgently in the field of BAN[34,35]. (4) Due to the limitations of low-power communication and data security in the BAN, although the BAN has a good development prospect in the medical field, however, it has always been a major defect in the current clinical application field[36,37].

2. Research progress of BAN intelligent wearable system for first aid

On the basis of solving the low-power and high-reliability communication mechanism and data security problems of the BAN, the wireless signs monitoring system of BAN is developed for emergency scenarios, such as disasters, traffic accidents, public health events, family sudden cerebrovascular accidents and other scenarios, and completes the multi-parameter sign data collection, monitoring and rumination of emergency patients, improves the efficiency of emergency treatment and the speed of diagnosis, and speed up the process of medical informatization. As a bottleneck in the field of BAN research, the breakthrough of its core technology can effectively support the development of a new generation of information technology strategic industries such as information networks (services), wireless communications, semiconductors, etc., thereby driving the development of manufacturing and information service industries such as basic components, communication terminals, and system equipment, and the level of informatization and health care services in the medical industry will be improved. Applications: Smart terminal detection and analysis of physiological data, injury assessment, completion of electronic medical records, transmission of information to the medical cloud information platform through 5G, and the medical cloud information platform transmits hospitals and ambulances inspections, testing analysis and early warning physiological data, injury assessment, and completion of electronic medical records through 5G. It had been reported[38] that advances in BAN wearable systems that improve the current emergency department visit process by monitoring patients after emergency triage, thereby reducing the risk of adverse events. The study proposes a dynamic mathematical decision-making model to determine patient priorities, forming a feedback loop in the emergency department. Coupling of wearables (collecting data) and decision theory (synthesizing organizational information) can help reduce uncertainty in emergency department triage systems. The emergency wearable point-of-care-testing (POCT)[39] can significantly reduce the turnaround time of laboratory test results. POCT devices can test samples on patients directly, including bilirubin meters, pulse oximeters, breathalyzers (for alcohol and cannabinoid testing), transcutaneous blood gas analysis, postoperative glucose, and tumor markers. The use of these devices is very important in critical care medicine and emergency departments. Wearable POCT devices have great promise to meet the needs of current and emerging clinical disciplines.

3. Research hotspots and prospects of BAN emergency intelligent wearable systems

China's research in the field of BAN has just started, and there is a big gap compared with developed countries. At present, there is no theoretical and applied research on BAN in the field of emergency, and it is urgent to carry out relevant research to narrow the gap with the international advanced technology and lay the core technical foundation for the industrialization of the BAN system[40,41]. Information and security technology is a key issue that must be solved to establish a theoretical system and application system of BAN[42]. The cutting-edge research work the author intends to carry out has important academic significance for the exploration of network security technology of BAN and the realization of application-specific integrated circuits; it has high practical application value in reducing the power consumption of wireless nodes, stable and reliable communication, etc., and its successful implementation can promote the development of ultra-low-power chips, wearable wireless nodes, intelligent medical terminals, health and monitoring instruments and other devices and equipment, that can help to form an electronic medical implementation solution that benefits people's livelihood and emergency rescue. It has made direct contributions to the orderly promotion of the deployment and application of remote electronic medical services, and the improvement of the informatization level of medical industry and the level of emergency rescue medical services. The author did extending and deepening on the basis of the original team's work, and the team has a good research foundation in the design of BAN system security solutions, hardware design and emergency rescue application verification[43].

Conflict of interest

The authors declare no conflict of interest.

References

1. Han W, Feng G, Hou S. Reflections on the construction of modern emergency and rescue medicine in the Guangdong–Hong Kong–Macao Greater Bay Area. Chinese Journal of Disaster Rescue Medicine 2020; 8(6): 319–320.
2. Tang X, Dong F, Zhang L, et al. Practice and thinking on the construction of medical and health information standard system in China. China Journal of Health Information Management 2016; 13(1): 31–36.
3. Abidi B, Jilbab A, Mohamed EH. Wireless body area network for health monitoring. J Med Eng-Technol 2019; 43(2): 124–132.
4. Deng S, Gao W, Hu W, et al. Research status and prospect of wireless body area network technology. Sensors and Microsystems 2014; 33(11): 1–48.
5. Wang L, Huang C, Wu X. Research on cross–layer optimization of wireless body area network based on prediction method. Journal of Electronics and Information 2018; 40(8): 2006–2012.
6. Cao H, Leung V, Chow C, et al. Enabling technologies for wireless body area networks: A survey and outlook. IEEE Communications Magazine 2009; 47(12): 84–93.
7. Chai L, Liu W, Wang Y, et al. Exploration and practice of remote consultation system. Information and Computer 2020; 32(7): 74–76.
8. Dong J. Research on health assessment method based on body area network multi–sign information fusion [PhD thesis]. Shaanxi: Xidian University; 2013.
9. Liu C. Research and design of wearable intelligent monitoring system [PhD thesis]. Guizhou: Guizhou University; 2018.
10. Latha R, Vetrivelan P. Wireless body area network (WBAN)—Based telemedicine for emergency care. Sensors 2020; 20(7): 2153.
11. Jin W, Pan W. Design of remote intelligent medical system based on Internet of things technology. Microcomputer Application 2020; 36(5): 113–116.
12. Ling L, Chen L, Zhu Y, et al. Tensor flow intelligent medical service platform design. Fujian Computer 2019; 35(6): 95–96.
13. Chen J, Zhou Y, Zhou X. Privacy—Preserving telemedicine diagnosis system in wireless body area network. Journal of Changchun Normal University (Natural Science Edition) 2018; 37(5): 37–45.
14. Omeni O, Wong ACW, Burdett AJ, et al. Energy efficient medium access protocol for wireless medical body area sensor networks. IEEE Transactions on biomedical circuits and systems 2008; 2(4): 251–259.
15. Qu T, Zhao X, Li B. A real-time monitoring system for human health indicators based on wireless body area network (WBAN). Modern Electronic Technology 2013; (18): 128–130, 133.
16. Liu Y, Song Y. Research on wireless body area network technology. Small Microcomputer System 2013; 34(8): 1757–1762.
17. Wang M, Yang J, Chen H, et al. Research on the development of remote digital health system based on body area network and cloud platform. Computer Science 2012; 039(B06): 195–200.
18. Dellarocas C. The digitization of word of mouth: Promise and challenges of online feedback mechanisms. Management Science 2003; 49(10): 1407–1424.
19. Sodhro AH, Li Y, Shah MA. Energy–efficient adaptive transmission power control for wireless body area networks. Communications Iet 2016; 10(1): 81–90.
20. Abidi B, Jilbab A, Mohamed EH. Wireless body area networks: A comprehensive survey. J Med Eng Technol 2020; 44(3): 97–107.
21. Li Y, Cao X. Research on energy—Saving dynamic routing algorithm for body area networks. Software Engineering 2019; 22(11): 15–17.
22. Movassaghi S, Abolhasan M, Lipman J, et al. Wireless body area networks: A Survey. IEEE Communications Surveys & Tutorials 2014; 16(3): 1658–1686.
23. Peng Y, Zhang S. A power–optimized routing algorithm for wireless body area networks. Electronic Science and Technology 2018; 31(7): 34–37.
24. Sun G, Yu J, Li W. Design and implementation of sensor nodes in wireless body area network. Wireless Communication Technology 2011; 20(2): 31–35.
25. Wu Z, Sun Y, Tan Y, et al. Three–dimensional graphene–based macro and mesoporous frameworks for high–performance electrochemical capacitive energy storage. Journal of the American Chemical Society 2014; 134(48): 19532.
26. Lin W, Lei S, Wei C, et al. Research progress of body area network sensor nodes and wireless communication technology. Journal of Biomedical Engineering 2012; 29(3): 568–573.
27. Al-Fares M, Loukissas A, Vahdat A, et al. Commodity data center network architecture. Computer communication review: A quarterly publication of the special Interest group on data communication 2008; 38(4): 63–74.
28. Wan J, Zou C, Ullah S, et al. Cloud-enabled wireless body area networks for pervasive healthcare. IEEE Network 2013; 27(5):56–61.
29. Zhang Z, Wang H, Vasilakos AV, et al. ECG-Cryptography and authentication in body area networks. IEEE transactions on information technology in biomedicine. Medicine and Biology Society 2012; 16(6): 1070–1078.
30. Wu J, Xu H, Wang J. Design of acceleration data compressed sensing for low power consumption in body area network. Chinese Journal of Biomedical Engineering 2015; 34(6): 677–685.
31. Peng Y, Tian Y, Peng X. An end-to-end medical wireless body area network lightweight authentica-

tion protocol. Computer Engineering 2017; 43(06): 73–77.
32. Wang J, Han K, Fan S, et al. A logistic mapping-based encryption scheme for wireless body area networks. Future Generation Computer Systems 2020; 110: 57–67.
33. Peng N, Jin Z. Research on energy saving strategy of wireless body area network based on forwarding nodes. Journal of Hangzhou Dianzi University 2011; 31(6): 103–106.
34. Gao X, Guo Y, Feng T, et al. Design and implementation of intelligent rehabilitation nursing system based on WBAN. Journal of Sensor Technology 2012; 25(10): 1333–1339.
35. Wang M, Yang J, Chen H, et al. Research on the development of remote digital health system based on body area network and cloud platform. Computer Science 2012; 39(101): 195–200.
36. Zhang H, Du X, Yang J, et al. Development and testing of a body area network wireless ECG monitoring system. Modern Electronic Technology 2014; (4): 37–41.
37. Kasyoka P, Kimwele DM, Angolo SM. Certificateless pairing-free authentication scheme for wireless body area network in healthcare management system. Journal of Medical Engineering & Technology 2020; (4).
38. Nino V, Claudio D, Schiel C, et al. Coupling wearable devices and decision theory in the United States emergency department triage process: A narrative review. International Journal of Environmental Research and Public Health 2020; 17(24): 9561.
39. Wu A. “On Vivo” and wearable clinical laboratory testing devices for emergency and critical care laboratory testing. The Journal of Applied Laboratory Medicine 2019; 4(2): 254–263.
40. Fang X, Luo J. Key technologies and new challenges of body area network. Journal of Internet of Things 2018; 2(1): 64–68.
41. Zou W, Kang F, Du G, et al. Design and interference analysis of physical layer scheme based on frequency band of medical body area network in China. Journal of Electronics and Information 2015; (2): 429–434.
42. Poon C, Zhang Y, Bao S. A novel biometrics method to secure wireless body area sensor networks for telemedicine and M-health. IEEE Communications Magazine 2006; 44(4): 73–81.
43. Han W, Jiang Y, Li J. Comparison of emergency medical service systems in Hong Kong and Mainland China and its enlightenment. Chinese Journal of Hospital Management 2020; 36(12): 1037–1040.

Wearable Technology (2020) Volume 1 Issue 1, *pp.* 9–18.
doi: 10.54517/wt.v1i1.1615

Asia Pacific Academy of Science Pte. Ltd.

ORIGINAL RESEARCH ARTICLE

Research progress of knitted sensors in the field of sports and fitness apparel

Pibo Ma*, Qing Liu, Li Niu, Yutian Li

**Engineering Research Center for Knitting Technology, Ministry of Education, Jiangnan University, Wuxi 214122, Jiangsu, China. Email: mapibo@jiangnan.edu.cn*

ABSTRACT

Knitted sensor has the advantages of lightness, conformity, good strain tensile recovery and formability, which provides a possibility for flexible and non-inductive motion signal monitoring and smart wearable sports health clothing preparation. This paper reviews the preparation methods of knitted sensors, analyzes the influence of yarn types, fabric microstructure and tensile sensing direction on its sensing performance, and compares the advantages and disadvantages of knitted sensors in the fields of life and health, human movement and other fields. It is pointed out that the type, structure and weaving method of the conductive yarn are important factors affecting the performance and wearing comfort of knitted sensors, and the electrical characteristics of the two-dimensional extension and three-dimensional deformation in the strain stretching process of knitted sensors determine the effective strain sensing range. This paper outlines the development opportunities and challenges faced by knitted sensors in the field of sports and health clothing.

Keywords: knitting sensor; knitting technology; conductive yarn; sensitivity; exercise health

1. Introduction

With the development of science and technology and the enhancement of national health awareness[1,2], people's demand for wearable products that can achieve daily sensing and real-time monitoring of human motion data has become increasingly urgent, which has led to the birth of smart bracelets, sports wristbands and other smart wearable devices[3]. At present, these smart wearable devices mostly use gravity sensors, multi-axis acceleration sensors and image sensing technologies to collect human motion information. Although they can better reflect the state of human motion in daily sensing, they still have high hardness, poor elasticity and other technical problems such as poor wearing comfort and lack of motion detail signals[4,5]. Therefore, the development of highly integrated, comfortable and wearable flexible strain sensors to realize human body signal sensing or motion recognition is an important problem that needs to be solved urgently. Knitted strain sensors are made of conductive yarns through different processes to make conductive knitted fabrics or conductive treatment on knitted fabrics to form smart wearable devices with sensing properties. The knitted fabric matrix is light and soft, which can effectively improve the wearing comfort of traditional smart textiles, where the large strain and good stretch recov-

ARTICLE INFO
Received: January 15, 2020 | Accepted: February 14, 2020 | Available online: March 2, 2020

CITATION
Ma P, Liu Q, Niu L, et al. Research progress of knitted sensors in the field of sports and fitness apparel. Wearable Technology 2020; 1(1): 9–18.

ery of the knitted structure meet the requirements of smart sports health sensing monitoring[6,7]. This paper mainly summarizes the preparation method of knitted sensors, comprehensively compares the influence of knitted sensor material types, organizational structure, and tensile direction on its sensing performance, and analyzes the latest application of knitted sensors in the field of sports health. On this basis, its future development is reviewed in order to provide a reference for the research of knitted sensors in the field of sports and health clothing.

2. Preparation of knitted sensor

Knitted sensors are mainly divided into three categories: Resistive strain sensors, capacitive strain sensors and piezoelectric strain sensors, among which resistive strain sensors are the most common in the field of sports and health clothing. Resistive strain sensors mainly use the change of resistance value to characterize the physiological signals of the human body to achieve sensing. At present, there are two commonly used preparation methods: 1) Use conductive yarn to knit directly on knitting equipment; 2) Treat the surface of knitted fabrics[8].

2.1. Fabrication of sensors by knitting technology

Some conductive yarns can be directly knitted by knitting sensors on the knitting equipment. The knitting technology used mainly includes two categories: Warp knitting technology and weft knitting technology. Knitted sensors prepared by different knitting technologies have certain differences in sensing performance, wearing comfort and product appearance.

Warp knitting technology

Warp knitting technology refers to a knitting method in which one or several groups of parallel yarns are inserted into a row of knitting needles along the longitudinal direction and synchronously formed into loops. With warp knitting technology, not only that it can be used to prepare tensile sensors, but it can also be used for the preparation of pressure sensors. Since the coils of the knitted sensor prepared by the warp knitting technology are arranged along the warp direction of the knitted fabric, the product has a flat appearance, a tight weave structure with no floating thread on the back of the intarsia area, resulting in better stability and anti-separation of the fabric as compared to the weft knitted fabric. The warp knitted spacer fabric has advantages in the preparation of pressure sensors due to its good retraction. Zhu[9] studied the influence of fabric structural parameters on the compressive properties of warp knitted spacer fabrics, and the results showed that spacer fabrics with high density, large thickness and single fibre spacer have better bending resistance, which can be used to prepare knitted pressure strain sensors with good recovery. In terms of local positioning weaving, the warp knitting machine is more suitable for whole conductive fabric or strip conductive fabric. However, it offers no advantages in the preparation of small-area positioning sensors.

Weft knitting technology

Weft knitting technology mainly includes flat knitting technology and circular knitting technology.

Flat knitting technology refers to a knitting method in which one or several yarns are drawn from the yarn bobbin and placed on the corresponding knitting needles of the flat knitting machine along the weft direction to form loops. In flat knitting, the technology includes double needle bed flat knitting and four needle bed flat knitting machines. Among the two, the double needle bed flat knitting machine technology is widely used and has strong versatility. However, it has high requirements on raw materials where the yarn raw materials that match the needle type must be chosen, while the four needles bed flat knitting machine technology can be used for the preparation of one-piece molded clothing, which is more suitable for the weaving of complex fabrics. The precise positioning of the sensor can be achieved by using the intarsia function of the computerized flat knitting machine[10]. The flat knitting machine is convenient for the weaving of small knitted products. Through the design of the supporting computer software, socks, gloves, knee pads and other products can be automatically generated, and the size and product shape can be changed according to needs. **Figure 1**[11] is a fully formed sports glove that can monitor finger movement knitted on a double needle bed Shima Seiki computerized flat knitting machine. Knitted fabrics prepared by computerized flat knitting machines are inferior to warp knitting in terms of weft looping and fabric stability, especially when weft and flat fabrics are prone to crimping. Due to the coarse needle number of the general flat knitting machine, the product structure of the flat knitting machine is relatively sparse and the feel is poor.

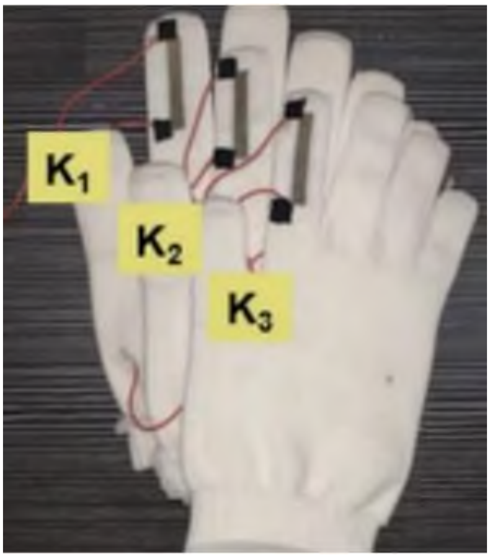

Figure 1. Fully-formed sports gloves knitted on computerized flat knitting machine using intarsia.

Circular knitting technology refers to a knitting method in which the yarns are placed on the corresponding knitting needles of the circular knitting machine in sequence along the weft direction to form loops. The circular knitting technology not only is able to achieve integral molding of knitted products, but also able to achieve the positioning and weaving of multiple sensors. Because this technology has the advantages of high rotation speed, high output, fast pattern change, good fabric quality, few processes, and strong product adaptability, it further provides advantages in the preparation of large-area knitted products and fully formed seamless sports suits. In this, weaving the whole product at one time can reduce the production process and shorten the production cycle. Thinner yarns can also be spun on a circular machine[12,13] with the obtained fabric having good stability. However, there are many floating threads on the back of the conductive area. In order to avoid mutual interference between the conductive yarns, it is generally necessary to remove the floating threads.

2.2. Surface treatment of the knitted fabric

The surface treatment of knitted fabrics is to add a certain proportion of reducing agents, dispersants and binders to conductive substances such as polypyrrole, graphene, nano-silver, etc., and treat the surface of the fabric by dipping, coating, screen printing, etc., thus forming a stable and continuous conductive network layer[14]. This processing method can improve the sensitivity of the sensor, but the overall stability of the sensor is poor. Therefore, the key to the surface treatment of knitted fabrics is to form an interface with good bonding force between the fabric and the conductive material to ensure that the conductive material has good adhesion and is not easily fallen off.

In order to improve the adhesion effect of conductive substances, Lin et al.[15] used plasma pre-treatment to increase the adhesion of polypyrrole on polyester to prevent the falling off of conductive substances and ensure the continuity and uniformity of conductive substances during stretching. Amjadi[16] covered a layer of PDMS on the surface of the nano-silver-coated fabric and prepared a stretchable sensor for finger posture monitoring.

3. Factors influencing the sensing performance of knitted sensors

The main properties of the knitted sensor include sensitivity, linearity, stability, repeatability, hysteresis, etc. The influencing factors include the type of yarn, the structure of the fabric, the direction of tensile sensing, and the interaction force between the coils.

3.1. Type of yarn

In actual production, the type of conductive yarn is a key factor affecting the performance of knitted sensors. According to the different materials, conductive yarns can be achieved in two ways: (1) Using conductive fibers to directly spin yarns; (2) Treat ordinary yarn to make it conductive. According to the actual application, it can be divided into metal conductive yarn, carbon-based conductive yarn and composite conductive yarn[17,18].

1) The difference in conductive yarn affects the sensing performance of the knitted sensor. Yarns with conductive properties such as metal and pure carbon have the characteristics of high sensitivity, but due to their high rigidity and other problems, they are prone to irreversible mechanical damage and permanent structural deformation during weaving or use, with poor stability, especially under a large strain where the rapid elastic recovery is poor, which seriously affects the stability and linearity of the sensing performance of the knitted sensor, and it is difficult to make a tensile sensor. After adding common yarns such as spandex elastic yarn and polyester yarn to the conductive yarn, not only can it increase the shape retention of the fabric, but also improve the performance of the sensor. Zhang et al.[19] used conductive yarn and ordinary yarn to weave an intarsia knitted sensor (see **Figure 2**), and the conductive yarn and ordinary yarn were connected in an intarsia manner, which improved the sensitivity and stability of the knitted sensor.

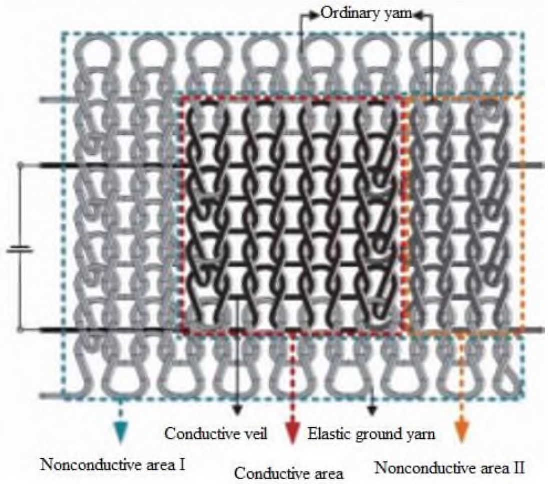

Figure 2. Intarsia stitch.

Using conductive materials such as metals to treat ordinary yarns or blending with ordinary yarns to prepare composite conductive yarns can improve the difficulties faced in knitting. However, in the weaving process, conductive coated yarns are also prone to problems such as conductive material shedding and yarn surface oxidation, which seriously affects the sensing performance. The resistance of blended yarn and the conductive core-spun yarn is relatively large, and there are also problems in sensitivity.

Many researchers have devoted themselves to the development of new conductive yarns using electrochemical methods to improve the problems of easy shedding, easy oxidation and poor sensing performance of the conductive layer on the surface of the existing conductive yarns. However, the relevant technology is not mature at present, and there are few applications in the textile field.

2) The electrical characteristics of different kinds of conductive yarns determine the effective strain range of the knitted sensor. The resistance of metal nano-silver wires is only a few to tens of ohms, which can be used for tensile strain sensors. Liu et al.[20] used 44 dtex nylon silver-coated yarns with circular knitting technology to prepare a tensile strain sensor for monitoring human arm posture. After repeated usage, it still has good sensing performance. Meanwhile, conductive yarns treated with graphene[21], polypyrrole, and conductive nanomaterials have a resistance of several thousand or even tens of thousands of ohms, with high sensitivity and can be used in piezoelectric strain sensors.

Liu et al.[22] studied the influence of parameters such as the thickness of the conductive nanofiber membrane and the material ratio on the sensitivity of the sensor. The results showed that the best sensitivity of the sensor was achieved when the mass ratio of Py monomer to nanofiber is 1:1 and the thickness of the conductive nanofiber film is 48 μm.

3.2. Structure of the fabric organization

The structural organization of the fabric has a great influence on the linearity and sensitivity of the sensor. Han et al.[23] studied the sensing performance of three kinds of weft-knitted structure sensors, and the specific results are shown in **Figure 3**. It can be seen from **Figure 3**. that under the same conditions, the weft plain needle knitted sensor has the best sensitivity and conductivity, followed by the 1 + 1 fake rib knit fabric sensor, while the 2 + 1 fake rib knit fabric sensor was the worst. The overall resistance showed a trend of first increasing and then decreasing. Therefore, the structure of the knitted stress sensor should not be too complicated, and the basic structure should be used. Han et al.[23] also studied the longitudinal electrical properties of spandex weft knitted conductive fabrics. By comparing with Zhang et al.[24], they found that the longitudinal electrical properties of spandex weft knitted conductive fabrics were similar to those of warp knitted fabrics. This shows that there is a difference in the sensing performance of warp knitted fabric and weft knitted fabric. However, both knitted fabrics shares similarity in terms of good sensitivity and linearity. Raji[25] found that the sensitivity of the rectangular sensor is higher than that of the saw-tooth sensor. It can be inferred that the shape of the knitted sensor has a greater impact on its sensing performance, and the knitted sensor with a simple shape has higher sensitivity. The research results of Li, et al.[26] showed that with the increase of the number of longitudinal rows of the conductive coil, the resistance change of the sensor showed an increasing trend while with the increase of the number of rows of the conductive coil, the resistance growth trend of the sensor weakens. The resistance change of the sensor conforms to the law that the knitted fabric coils are parallel in the longitudinal direction and series in the transverse direction. Therefore, the number of horizontal and vertical coils of the coil is closely related to the sensitivity of the sensor. When the number of horizontal columns is constant, the fewer the number of vertical rows the better the sensitivity. When the number of horizontal columns is the same as the number of vertical rows, the conductivity in the vertical and horizontal directions is similar, but the sensitivity in the vertical direction is generally greater than that in the horizontal direction.

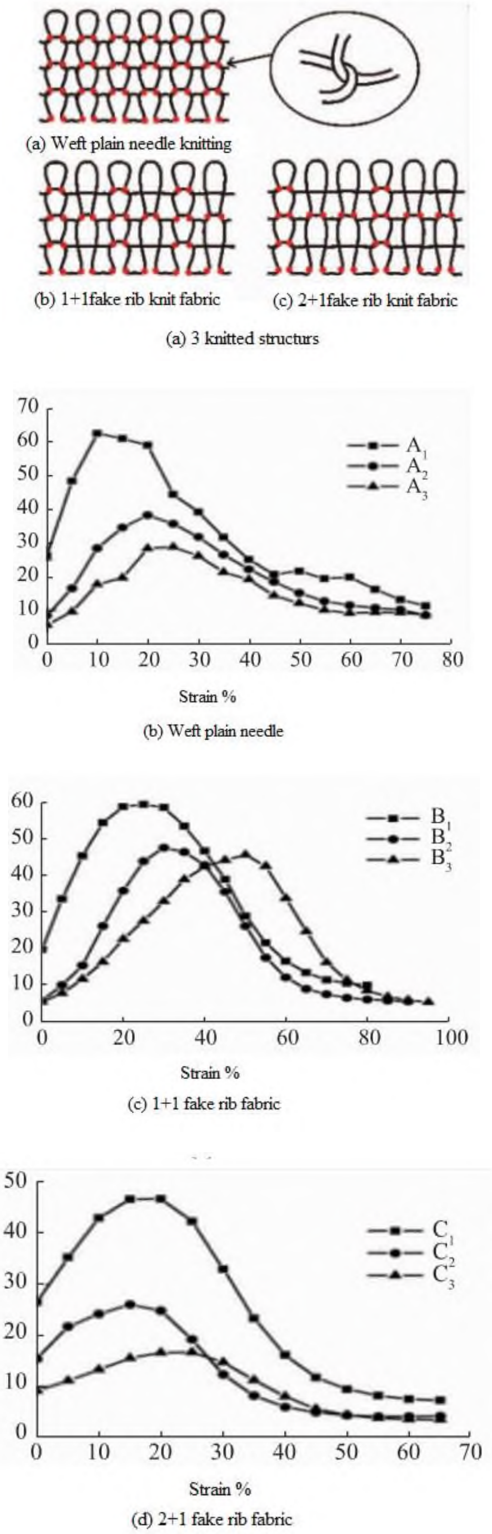

Figure 3. Distribution schematic diagrams of contact points of the three stitches.

3.3. Stretching direction of the sensors

During the actual wearing process of the sportswear, the forces incurred are mostly two-or-multi-directional tension forces from the plane, while shear and curved surface tension forces occur in the three-dimensional direction. Therefore, it is necessary to consider the sensing performance of the knitted sensor in different stretching directions.

At present, the research on the stretching direction of the sensor is mainly based on horizontal, vertical, biaxial and three-dimensional stretching which mimics the actual movement of the human body. However, there are relatively few research examples of testing electrical signal changes in multiple directions with standard experiments.

There are the following differences between horizontal and vertical stretching: (1) In terms of tensile formation, the yarn under horizontal stretching is transferred from the loop column to the loop arc where the yarn is rotated with the degree of displacement seen to be more obvious while the coiled yarn under vertical stretching moves from the loop arc to the loop column. (2) The stretching direction of the sensor is a key factor affecting the sensitivity and hysteresis of the sensor. During horizontal stretching, changes in the hysteresis of resistance between strain stretching and recovery are small while in vertical stretching, the changes in the hysteresis of resistance between strain stretching and recovery are more obvious. In most cases, the rate of change in resistance during vertical stretching is greater than that of horizontal stretching. Xie[27] studied the resistance change of the weft plain needle sensor under the condition of horizontal and vertical stretching, as shown in **Figure 4**. It can be seen from **Figure 4**. that the electrical resistance of the conductive knitted fabric in horizontal stretching shows an approximately linear growth trend with the increase of strain, while the relationship between the changes in resistance and strain increases nonlinearly in vertical stretching. (3) In terms of stretching speed, the increase of stretching speed increases the resistance of the sensor correspondingly but with a slower trend. At lower stretching speed, there is a hysteresis phenomenon that occurs in the change of resistance between strain stretching and recovery[28].

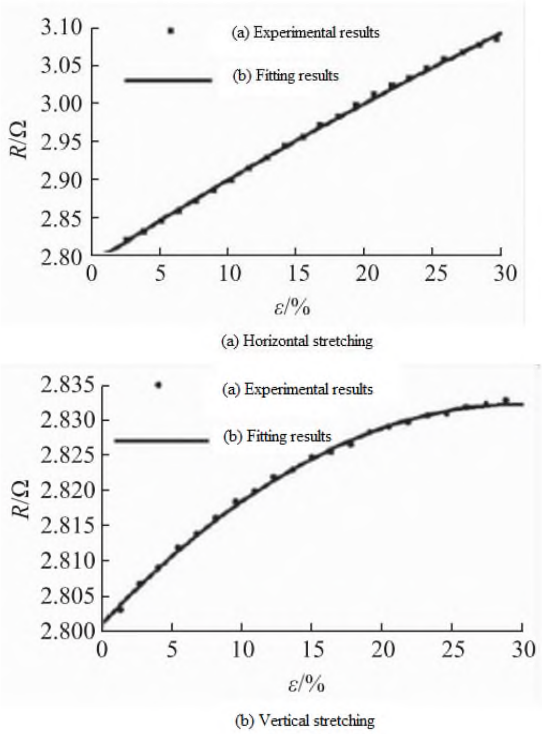

Figure 4. Relationship between resistance and strain of knitted sensor under biaxial stretching.

The three-dimensional stretching direction is closer to the actual perception of the human body when wearing the knitted sensor, and has the common characteristics of horizontal and vertical stretching.

Li et al. wrapped the fabric with small pellets to simulate the motion of the human knee joint, as shown in **Figure 5**. The sensing performance of the knitted strain sensor was evaluated using a three-dimensional curved surface. From this experiment, it was found that the strain sensing range of the three-dimensional surface was 120%, which was twice that of the two-dimensional stretching performed with the two-dimensional test method.

3.4. Interaction force between coils

The interaction force between the coils mainly affects the contact resistance of the sensor. The construction of the equivalent resistance model clarifies the sensing mechanism of the conductive fabric and is used to simplify the coil circuit, and the contact resistance directly affects the accuracy of the equivalent resistance model prediction. (1) Contact resistance is related to the contact force between coils. The interaction force between the coils, coil transfer[29] and changes in the length of the coil would result in a change in the contact resistance. Wang et al.[30] simulated the relationship between contact force and contact resistance by intertwining two silver-coated yarns with each other. From theoretical analysis and experimental research, it was known that the contact resistance decreased with the increase of the contact force. (2) In the case of a small strain, the change in contact resistance between the coils is very small, where its influence on the sensing performance of the fabric can be ignored. Conversely, in the case of a large strain, the contact resistance influences the elongation-strain linearity of the sensor. (3) The overall resistance of the sensor is small due to the close contact between the coils, where the knitted sensor is made of conductive yarn covered with ordinary yarn, and the coils are not separated from each other. If there is contact resistance, or if the exposed conductive yarn produces a small contact resistance, the overall resistance value will increase greatly.

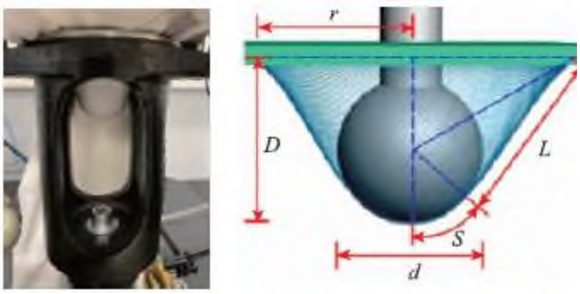

Figure 5. Three dimensional test of knitting sensor.

4. Application in the field of sports and health clothing

Knitted sensors are an important tool for collecting human motion signals. In the development of smart sports and health clothing, knitted sensors play a pivotal role. Its application scope mainly includes three aspects: daily sports protection, professional sports guidance, and sports rehabilitation guidance.

4.1. Daily sports protection

With the continuous enhancement of national health awareness, more and more people are protecting themselves through the monitoring of daily exercise. When the knitting sensor detects abnormal conditions during human movement, it will send out a warning signal to remind the athlete to rest or seek medical attention. Garcia et al[31] developed a wireless and comfortable wearable back motion monitoring system which was prepared by sewing a copper wire with a diameter of 0.14 mm into a piece of elastic fabric with a “T” shape. In addition, an inductive textile sensor was integrated into the back of the bodysuit to monitor back posture. In addition to the protection of the human body’s daily exercise, the monitoring of the human body’s physiological signals during daily exercise is a hot research topic in the field of sports health. Liu et al.[32] used graphene webbing as a substrate to be coated on elastic knitted fabrics to prepare flexible graphene sensing elastic belts. The flexible graphene sensing elastic belts have certain practicability in the collection of human body data for clothing.

4.2. Professional sports guidance

Professional exercise guidance can help athletes perform exercise assessment, improve lack of exercise, standardize exercise methods, control exercise intensity, optimize training effects and reduce physical injuries. Xie[27] used weft knitting technology to weave silver-plated nylon conductive yarns into flexible knitted fabric sensors, which were integrated into smart T-shirts and smart knee pads to monitor elbow, shoulder, abdomen and knee joints, respectively. Physiological signals are used to analyze the resistance changes under different postures, but the specific transmission method of the data collected by the knitting sensor is not clear. To this end, Li et al.[33] prepared a kind of tights that can be used to monitor the motion of the human knee joint based on a flexible sensor of silver-coated conductive yarn. The relationship between the sensors is analyzed, and a portable data module is developed for the collection and output of the sensor resistance signal. The strain resistance signal generated by a single exercise is of little significance for professional exercise guidance, but the analysis of multiple exercise signals is very important for exercise guidance. Based on this, Chow et al.[34] prepared a textile pressure sensing monitoring sock using conductive yarn to connect the communication module at the ankle joint and observe the wearer's foot movement according to the strain image.

4.3. Sports rehabilitation guidance

Exercise rehabilitation guidance can help patients recover more quickly with the scope of monitoring including families and hospitals. The current mainstream method is to achieve auxiliary rehabilitation guidance in hospitals and other medical institutions based on self-monitoring. Lorussi et al.[35] designed a smart wearable system based on the fusion of inertial sensors, fabric piezoresistive sensors and textile EMG sensors. The system is designed in a modular form and consists of separate shirts, pants, gloves and shoes to monitor human activity during post-stroke rehabilitation in daily life, which can help doctors optimize and adjust the training program of patients to assess the daily life and rehabilitation of stroke patients. Han et al.[35] designed flat knitting technology to prepare a seamless glove with sensors embedded in the fingers for finger gesture discrimination. Heo et al.[36] designed a sensing glove coated with AgNW and PDMS, and studied the electrical signal changes of different fingers under different bending conditions to guide the recovery of hand movement health.

5. Conclusions

The research of knitted sensors in the field of sports and health clothing has achieved certain results, but there are still many shortcomings, so it is difficult to be widely promoted. The future research focus and development prospects can be summarized as the following points:

1) Smart sports and health clothing should possess textile wearing quality which is similar to the performance of the sensors. At present, although there are many research results on knitted sensors, most of them were focused on the implementation of functionality, and there is still a lack of research on clothing pressure, breathability, washability and other wearability. 2) Industry standards for specifications should be established. Due to the large differences in the types and preparation methods of knitted sensors, it is difficult to unify the scope of use and data discrimination standards. Therefore, the parameters and specifications of conductive materials should be unified, and while realizing the function, the safety of sensor use should be ensured, and relevant performance, preparation and production standards should be established. In addition, in terms of data transmission standards, reliable and secure smart products can establish public trust. There are currently relevant standard protocols in the transmission mode of Bluetooth; however, as the transmission of data requires multiple transmission networks to complement each other, the security of personal information must be guaranteed. 3) Seamless connection of knitted sensors with other smart components. Limited by the development of science and technology, knitted sensors cannot be used alone at present, and the collected signals still need to be converted by circuits and data processing systems before output can be made. The use of knitting to integrate each intelligent component can effectively overcome the current limitations.

In short, with the current development and the advancement of science and technology, the research and applications of knitted sensors in the field of sports and health clothing are developing towards health comfort, functional diversification, new energy and energy storage methods, intelligent and precise information and lower pricing.

Conflict of interest

The authors declare no conflict of interest.

References

1. Wen W, Fang F. Application and research progress of flexible sensor for smart textile (in Chinese). Journal of Clothing Research 2019; 4(3): 223–229.
2. Li N. Research on wearable health monitoring system based on human motion state recognition (in Chinese) [PhD thesis]. Beijing: Beijing University of Technology; 2013.
3. Pin C. 2020 smart wearable innovation TOP50 (in Chinese). China Internet Week 2020; (16): 12–13.
4. Cai S, Li W, Zou H, et al. Design, fabrication, and sting of a monolithically integrated tri-axis high shock accelerometer in single (111) silicon wafer. Micromachines 2019; 10(4): 1–11.
5. Yang C, Li L. Integration of soft intelligent textile and functional fiber (in Chinese). Journal of Textile Research 2018; 39(5): 160–169.
6. Miao X, Liu Q. Research and application progress of knitting stress sensor (in Chinese). China Textile Leader 2020; (5): 26–30.
7. Cong H, Zhao B, Dong Z. Development status and application prospect of intelligent knitting products (in Chinese). China Textile Leader 2020; (5): 20–24.
8. Jana P. Assembling technologies for functional garments-an overview. Indian Journal of Fibre and Textile Research 2011; 36: 380–387.
9. Zhu F. Research on the structure and properties of knitted three-dimensional spacer fabrics (in Chinese) [PhD thesis]. Hangzhou: Zhejiang Sci-Tech University 2018.
10. Li S, Wu G, Hu Y, et al. Preparation of pressure distribution monitoring socks and related sensing properties (in Chinese). Journal of Textile Research 2019; 40(7): 138–144.
11. Han X, Miao X, Chen X, et al. Research on finger movement sensing performance of conductive gloves. Journal of Engineered Fibers and Fabrics 2019; 14(17): 1–7.
12. Ding H, Wang X, Guo J. Flat knitting remove-loop technology on the application in product design (in Chinese). Journal of Clothing Research 2020; 5(5): 411–414.
13. Jiang G, Gao Z. Development status and tendency of knitting technology innovation (in Chinese). Journal of Textile Research 2017; 38(12): 169–176.
14. Shi J, Liu S, Zhang L, et al. Smart textile integrated microelectronic systems for wearable applications. Advanced Materials 2020; 32(5): 1–37.
15. Lin J, Miao X, Wan A. Influence of plasma pretreatment on structure and properties of polypyrrole/polyester warp knitted conductive fabric (in Chinese). Journal of Textile Research 2019; 40(9): 97–101.
16. Amjadi M, Pichitpajongkit A, Lee S, et al. Highly stretchable and sensitive strain sensor based on silver nanowire-elastomer nanocomposite. ACS Nano 2014; 8(5): 5154–5163.
17. Zeng W, Shu L, Li Q, et al. Fiber-based wearable electronics: a review of materials, fabrication, devices, and applications. Advanced Materials 2014; 26(31): 5310–5336.
18. Wang X, Miao X, Li Y, et al. Progress in application of conductive yarns to knitted flexible strain sensors (in Chinese). Wool Textile Journal 2019; 47(3): 81–84.
19. Zhang Y, Long H. Preparation and performance of intarsia knitting strain sensor (in Chinese). Journal of Donghua University (Natural Science) 2020; 46(6): 889–895.
20. Liu C, Miao X, Wan A, et al. Design and verification of arm monitoring sensor (in Chinese). Journal of Silk 2020; 57(2): 108–113.
21. Shao Y, Wang J, Wu H, et al. Graphene based electrochemical sensors and biosensors: a review. Electroanalysis 2010; 22(10): 1027–1036.
22. Liu C, Zhong W, Wang D. Preparation, performance and applications of polypyrrole/polyolefin elastic nanofiber pressure sensors (in Chinese). Polymer Materials Science and Engineering 2019; 35(6): 94–99.
23. Han X, Miao X. Longitudinal electrical physical properties of spandex weft-knitted conductive fabric (in Chinese). Journal of Textile Research 2019; 40(4): 60–65.
24. Zhang S, Miao X, Raji, et al. Strain resistance sensing property of warp knitted conductive fabrics (in Chinese). Journal of Textile Research 2018; 39(2): 73–77.
25. Raji, Miao X, Zhang S, et al. Knitted piezoresistive strain sensor performance, impact of conductive area and profile design. Journal of Industrial Textiles 2020; 50(5): 616–634.
26. Li L, Au W, Wan K, et al. A resistive network model for conductive knitting stitches. Textile Research Journal 2010; 80(10): 935–947.
27. Xie J. Bidirectional extension of knitted fabric sensor electro-mechanical properties and limb movement for monitoring research (in Chinese) [PhD thesis]. Shanghai: Donghua University 2015.
28. Atalay O, Tuncay A, Husain MD, et al. Comparative study of the weft-knitted strain sensors. Journal of Industrial Textiles 2017; 46(5): 1212–1240.
29. Wang J, Long H. Effect of loop transfer on electro-mechanical properties of conductive elastic wearable knitted sensors (in Chinese). Journal of Textile Research 2013; 34(7): 62–68.
30. Wang J, Long H, Li J. Effect of contact resistance on the electro-mechanical properties of conductive weft plain knitted fabric sensors (in Chinese). Journal of Donghua University (Natural Science) 2013; 39(5): 608–613.
31. Garcia PA, Khoshnam M, Menon C. Wearable device to monitor back movements using an inductive textile sensor. Sensors 2020; 20(3): 1–17.
32. Liu Y, Xiong Y, Yang Y, et al. Stretch sensing performance of flexible graphene sensing ribbon (in

Chinese). Journal of Donghua University (Natural Science) 2020; 46(1): 35–40.
33. Li Y, Miao X, Raji R. Flexible knitted sensing device for identifying knee joint motion patterns. Smart Materials and Structures 2019; 28(11): 1–10.
34. Chow JH, Sitaramams K, May C, et al. (editors) Study of wearables with embedded electronics through experiments and simulations. 2018 IEEE 68th Electronic Components and Technology Conference; 2018 May 29–June 1; San Diego. NYC: IEEE; 2018.
35. Lorussi F, Carbonaro N, De RD, et al. Wearable textile platform for assessing stroke patient treatment in daily life conditions. Frontiers in Bioengineering and Biotechnology 2016; 4: 1–16.
36. Heo JS, Shishavan HH, Soleymanpour R, et al. Textile-based stretchable and flexible glove sensor for monitoring upper extremity prosthesis functions. IEEE Sensors Journal 2020; 20(4): 1754–1760.

Wearable Technology (2020) Volume 1 Issue 1, *pp.* 19–29.
doi: 10.54517/wt.v1i1.1618

Original Research Article

Research on a monitoring and evaluation platform for mountain sickness of grid construction workers based on disease information entropy

Donglai Tang[1*], Ying Yang[2], Ping Li[3], Juntai Tian[1], Hongfei Ye[1], Jin Guo[1]

*[*1]Aostar Information Technology Co., Ltd., Chengdu 610074, Sichuan, China. E-mail: tangdonglai@sgitg.sgcc.com.cn*
[2]Department of Rehabilitation Medicine, People's Hospital of Suzhou High-tech Zone, Suzhou 215000, Jiangsu, China
[3]Customer Service Center, State Grid Sichuan Electric Power Company, Chengdu 610041, Sichuan, China

ABSTRACT

The inaccuracy of acute altitude sickness screening has brought great challenges to power grid construction workers in high-altitude areas. Human vital signs monitoring technology is an effective technical means to prevent people from developing altitude sickness. This paper proposes a monitoring and evaluation platform for high altitude sickness in power grid operations based on information entropy of the causes of the illness. First, the vital characteristics data of workers are collected through sensors such as blood pressure and blood oxygen. Secondly, the collected data is transmitted back to the platform by using the Internet of Things technology. The information entropy establishes an analysis model of altitude sickness and generates personnel evaluation reports and treatment recommendations. Finally, the application results of the platform verified that the preventive effect of the platform is much higher than that of the pre-existing physical examination method.

Keywords: power grid field operation; monitoring and evaluation of altitude sickness; illness cause information entropy

1. Preface

The average altitude of the Qinghai-Tibet Plateau is above 4,000 m. Affected by factors such as high altitude, thin air, low atmospheric pressure, low partial pressure of oxygen, and strong ultraviolet rays in the region, acute altitude sickness has become a major threat to the construction personnel of the power grid in Tibet[1,2]. According to severity, acute mountain sickness is divided into two types: Mild (reactive or acute altitude sickness) and severe (high altitude cerebral edema, high altitude pulmonary edema)[3]. The onset time of acute mountain sickness is short, occurring within hours to days. If it is not treated in time, it will be life-threatening[4].

Surveys and studies performed by High Altitude Sickness Prevention and Control Center of State Grid Corporation of China have shown that when the power grid construction workers, whose original permanent residences were from low altitude areas just entered the Qinghai-Tibet Plateau, were likely to induce acute altitude sickness, with the total incidence of acute altitude sickness of 18.97%, of which the incidence rate of mild and

ARTICLE INFO
Received: January 17, 2020 | Accepted: February 20, 2020 | Available online: March 10, 2020

CITATION
Tang D, Yang Y, Li P, et al. Research on a monitoring and evaluation platform for mountain sickness of grid construction workers based on disease information entropy. Wearable Technology 2020; 1(1): 19–29.

severe altitude sickness was 18.19% and 0.78%, respectively. It can be seen that among those who have just entered the Qinghai-Tibet region to perform power grids operations, experience high and harmful incidence of acute altitude sickness, which further poses a serious threat to their health[5].

Many scholars have done a lot of research on the prevention and treatment of altitude sickness among power grid construction workers. Literature[6] proposed the establishment of altitude sickness analysis software, using ultrasound examination, electrocardiogram and other methods to conduct pre-physical examinations for personnel entering the construction sites in the Qinghai-Tibet area. In literature[7], it was proposed that the method of establishing bone marrow nucleated red blood cell examination and analysis software be used to carry out the pre-analysis of construction workers in the Qinghai-Tibet area.

However, the above-mentioned altitude sickness prevention and control software have no effective method for predicting and screening acute altitude sickness. The only way to prevent and treat altitude sickness is to perform physical examinations on power grid construction workers in advance or to send them to the hospital for treatment after the power grid construction workers developed altitude sickness. Doing so often misses the critical period for the prevention and treatment of altitude sickness and causes permanent damage to the body of power grid construction workers[8]. At the same time, power grid infrastructure construction is often performed in remote areas. When the power grid construction personnel fall ill, power grid companies will not only have to spend a lot of manpower and material resources for treatment but also, the life safety of the patients cannot be guaranteed[9]. Meanwhile, the progress of power grid construction will also be delayed to varying degrees. In recent years, the state has attached great importance to the economic construction of the Qinghai-Tibet region, and the scale of power grid construction has continued to expand. According to statistics, more than 60,000 power grid construction workers enter Tibet and Qinghai regions every year to participate in power grid construction projects. As a result, the number of power grid construction workers suffering from acute altitude sickness is huge. If it cannot be effectively prevented and disposed of, altitude sickness will cause significant economic losses to power grid companies.

The Internet of Things technology has the characteristics of comprehensive perception, efficient information processing, convenient and flexible application, and can realize intelligent supervision and management of power grid operations[10–12]. The Internet of Things technology, especially with the use of mobile internet technology, allows the realization of mobile communication between the grid construction personnel and the back-end systems[13,14]. The use of the technology can provide vital sign data transmission support for the prevention and treatment of altitude sickness for power grid construction workers in the Qinghai-Tibet region.

Given the above background, this paper proposes a monitoring and evaluation platform for high altitude sickness for power grid construction workers based on the data of human vital signs collected and transmitted by the Internet of Things and mobile internet technologies. The platform can collect real-time data of the life characteristics of power grid construction workers and timely analyze the warning risks and provide treatment plans of the said workers in the Qinghai-Tibet region through the information entropy modeling of the causes of altitude sickness to prevent the occurrence of altitude sickness among power grid construction workers in advance. The application results of the high altitude sickness monitoring and evaluation platform for power grid construction workers verify that the prevention effect attained from this platform is much higher than that of the pre-physical examination method, and it can effectively reduce the incidence of high altitude sickness among power grid construction workers.

2. Analysis on the characteristics of altitude sickness among power grid construction workers

Based on the survey of altitude sickness among power grid construction workers of the High Altitude Disease Prevention and Control Center of State Grid Corporation of China, Suzhou High-tech Zone People's Hospital analyzed 452 patients on the illness causes characteristics among power grid construction workers suffering from altitude sickness. From the results, it was summarized that there were 7 types of causes for altitude sickness with characteristic data that can be categorized into 4 categories and 16 subcategories.

Table 1. Analysis on the causes of altitude sickness among construction workers

Cause of illness	Metric	Number of patients	Proportion of patients/%
Original altitude	≤ 1,000 m	415	91.81
Time of construction workers to enter The high altitude area	≤ 5 days	291	64.38
Acclimation time at mid-altitude areas	≤ 2 days	391	86.50
Psychological factors	≤ Class III	215	47.57
Construction labor intensity	≥ Class II	442	97.79
Age	≥ 50 years old	87	19.25
Respiratory infection	≥ mild	142	31.42

From **Table 1**, it can be seen that the causes of altitude sickness among power grid construction workers from high to low include construction labor intensity, original altitude, acclimatization time in mid-altitude areas, time of construction workers entering the high altitude area, psychological factors, respiratory infection and age. Based on this, in the early stage of the grid construction workers entering the high altitude area, the cause of the construction workers becoming altitude sickness patients should be included in the information entropy analysis of the causes of illness and focus on observing the people whose original altitude, acclimatization time in mid-altitude areas and construction labor intensity that exceeded the threshold.

The characteristic data of power grid construction workers suffering from altitude sickness are listed in **Table 2**.

It can be seen from **Table 2** that after the power grid construction workers suffer from altitude sickness, the physical characteristics are mainly composed of 4 major categories and 16 subcategories including respiratory, cardiovascular, digestive and urinary system abnormalities. In this, it is necessary to combine the causes of altitude sickness and the characteristics of altitude sickness data as a joint source for information entropy modeling. When the power grid construction workers have abnormal physical characteristics, effective treatment and rescue are then able to be carried out to prevent such personnel from developing altitude sickness.

3. High altitude sickness monitoring and evaluation platform process

Figure 1 shows the overall process of the monitoring and evaluation platform for altitude sickness among power grid construction workers. The architecture mainly includes three links: data collection and transmission of construction personnel's vital signs, information entropy modeling of the causes of altitude sickness, and evaluation and treatment of the power grid construction personnel.

Table 2. Data sheet of altitude sickness characteristics of construction workers

Category	Name of illness characteristic data	Eigenvalues
Respiratory system	BMI index/(kg·m^{-1})	≥28.3
	Lung function-FVL/L	≥3.47
	Lung function-FEV1/L	≥3.23
	Lung function-FEE25/(L·sec^{-1})	≥4.51
	Lung function-SaO_2 Decrease/%	≥83.9
	Number of breaths/(times h^{-1})	≥35
	Breathing pause time/s	≥10
Cardiovascular system	ECG ST-segment/%	≥40.1
	Diastolic blood pressure/mmHg	≤65
	Systolic blood pressure/mmHg	≥135
	Heart rate ≥ 100 times/min	≥30
	Red blood cells/(pcs L^{-1})	≥10
	Hemoglobin/pg	≥35
Digestive system	Abdominal muscletone/(number of spasms h^{-1})	≥2
	Urine red blood cells/(/ul)	≥50
Urinary system	Urine protein/(mg L^{-1})	≥150

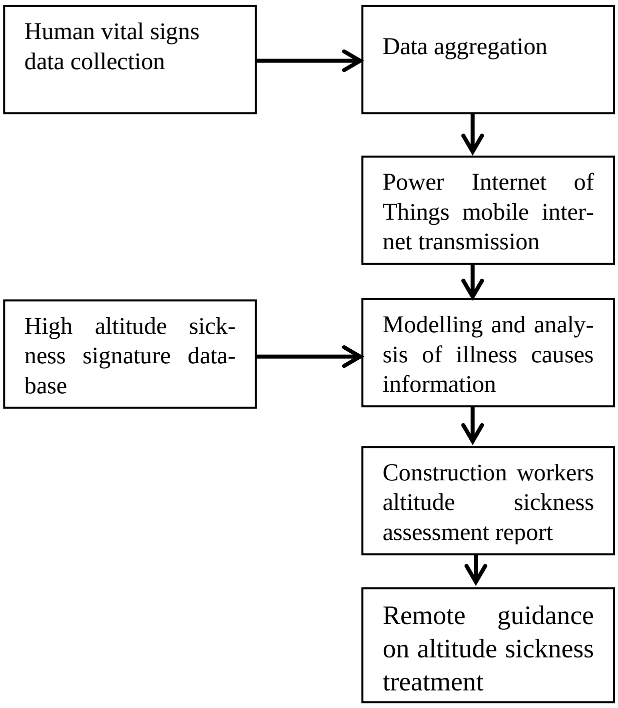

Figure 1. Overall process of altitude sickness monitoring and evaluation platform.

The human vital sign data collection module monitors the personnel's blood pressure, blood oxygen, electrocardiogram and other characteristic data in real-time through the vital sign sensors wearable by the grid construction workers. The data aggregation module uses the data-centric self-organizing algorithm based on the information negotiation sensor network protocol (Sensor Protocols for Information Via Negotiation, SPIN) to realize local aggregation of vital signs data of multiple construction workers. In the mobile interconnection transmission module of the power Internet of Things, the local data is transmitted back to the altitude sickness prevention and control platform of the power grid construction personnel of the power supply company through the 5G network. In the information entropy modeling and analysis of the causes of altitude sickness, experience data of the expert knowledge base can be combined with the collected characteristic data for modeling analysis to generate the risk assessment report of altitude sickness for power grid construction workers. Finally, the wearable video transmission model is used to provide remote treatment guidance for altitude sickness prevention and treatment.

4. Data collection and transmission model of construction workers' vital signs

The power grid infrastructure construction in the Qinghai-Tibet region is mostly in remote areas.

Hence, the collection and transmission of vital signs data of power grid construction personnel mainly consider the reliability and cost of the collection and transmission. In this, the collection model includes two parts: wearable life feature data collection, wireless networking and aggregation transmission of data collected by multiple people in the construction team.

4.1. Wearable vital signs data collection

The vital sign data of power grid construction personnel is collected by wearable vital sign sensors. The sensors are mainly divided into heartbeat, cardiogram, blood pressure, blood oxygen, body temperature, respiratory rate and altitude. Additionally, several life feature collection points are also configured according to the conditions of the construction workers. This multi-sensors data fusion is carried out through neural network, wavelet transform and Kalman filtering technology[15,16] to obtain accurate measurement signals.

In this paper, the multi-sensor data-adaptive weighted fusion estimation algorithm is used to collect vital sign data.

There are n sensors to measure a grid construction worker where the variance of the sensor is ☒$_1$,☒$_2$, ... , ☒$_n$, From the first measurement, the number of measurements is σ, while the estimated true value of the sensor measurement is x_{fa}, and the measurement value of each sensor is x_1, x_2,…, x_n and the weighting factor of each sensor is y_1,y_2,…, y_n. After multi-sensor fusion, the weighting factor of x_{fa} is:

$$x_{fa}{}^{n} = \sum_{\sigma=1}^{n} \binom{n}{k} y_\sigma x_\sigma \tag{1}$$

Assuming that the second group is measured h times, the average variance of the sensor is:

$$\partial^2 = E\left[\begin{matrix} \sum_{\sigma=1}^{n} y_\sigma^2 \left(x_{fa} x_\sigma\right)^2 + \\ 2\sum_{\sigma=1,h=1}^{n} y_\sigma y_h \left(x_{fa} - x_\sigma\right)\left(x_{fa} - x_h\right)\end{matrix}\right] \tag{2}$$

It can be seen from equation (2) that the average variance of the sensor is a multivariate quadratic function about each weighting factor and so has a minimum value. According to the multivariate function theory, to find the extreme value theory, the weighting factor corresponding to the minimum total mean square error can be obtained:

$$y_\sigma^h = 1/\left(\partial^2 \sum_{\sigma=1,h=1}^{n} \frac{1}{\partial^2}\right) \tag{3}$$

At this time, the minimum variance corresponding to the multi-sensor is:

$$\partial_{min}^2 = 1/\sum_{\sigma=1}^{n} \frac{1}{\partial_\sigma^2} \tag{4}$$

The multi-sensor data-adaptive weighted fusion estimate x_{fb} can be calculated from equations above:

$$x_{fb} = \sum_{\sigma=1}^{n} y_\sigma x_\sigma(\partial) \tag{5}$$

It can be seen from equations that through the data fusion of wearable vital signs multi-sensors, the accurate vital signs data of heartbeat, cardiogram, blood pressure, blood oxygen, body temperature and other types of power grid construction workers can be obtained.

4.2. Multi-person wireless networking and aggregation transmission

In the Qinghai-Tibet Plateau power grid construction site, several people are participating in the power grid construction work. If each construction worker occupies a 5G transmission channel, it will cause a waste of resources and an increase in transmission costs[17-19]. Therefore, the data-centric self-organizing algorithm SPIN can be used to achieve local aggregation of life characteristics data of multiple construction personnel.

In the SPIN multi-person wireless network of power grid construction personnel, the geographical location of the construction personnel is randomly arranged, and each vital sign monitoring sensor node will first send a command to request the allocation level to the adjacent base point sensor. If the adjacent base point sensor is the convergence point, then the vital sign monitoring sensor node will receive the level assigned by the convergence point, and the sensor node will send the vital sign information datagram to the convergence point. If the adjacent node sensor is another transit vital sign monitoring sensor, the sensor node will send vital sign information data to the transit sensor. Through the SPIN routing algorithm networking, each sensor node hopes to become a transit node and guides its transmission path to the aggregation node. In order to reduce the loss of node transmission, the vital sign sensor nodes of each construction worker negotiate directly during transmission to achieve the best transmission efficiency. The schematic diagram of SPIN multi-person wireless network is shown in **Figure 2**.

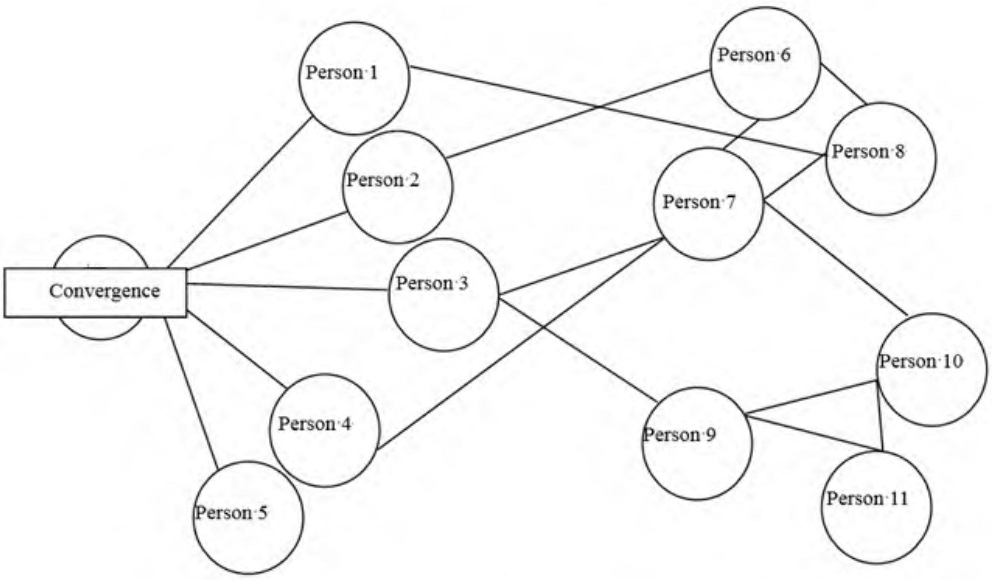

Figure 2. SPIN multi-person wireless networking.

When the vital sign data of each power grid construction worker reaches the convergence point, the 5G network is used to transmit the data to the monitoring and evaluation platform of high altitude sickness for power grid construction workers of the power supply company through the multi-level security architecture of the Internet of Things[20].

5. Causes of altitude sickness information entropy modeling

The information entropy of the causes of altitude sickness mainly involves the traceability analysis of the causes of altitude sickness to power grid construction workers, respiratory system, cardiovascular system, digestive system, and urinary system. Based on the analysis of the characteristics of altitude sickness among power grid construction workers, a two-layer cause of altitude sickness information entropy modeling was carried out comprising of the independent information entropy of the causal factors and the combined information entropy of altitude sickness.

5.1. Modeling of independent information entropy of the cause factors

Traceability modeling of the causes of altitude sickness

The traceability of the causes of altitude sickness mainly includes seven aspects. The range of values for the traceability characteristics of the causes of high altitude disease is listed in **Table 3**.

Table 3. The value range of the traceability characteristics of the causes of high altitude sickness

Cause of illness	Lower limit	Upper limit
Altitude of the original location/m	0	4,000
Time of construction Workers to enter the high altitude area/day	0	60
Acclimation time at mid-altitude areas/day	0	60
Psychological factors/class	1	VI
Construction labor intensity/class	1	VII
Age/years old	18	65
Respiratory infection	No infection	Severe

Let z be the information entropy of tracing the causes of altitude sickness, the altitude of the original location is z_a, the labor intensity of construction is z_b, the acclimatization time in the mid-altitude area is z_c, the time for construction workers to enter the high altitude area is z_d, the psychological factors is z_e, and the respiratory infection is is z_f, age is z_g, and the cause entropy for tracing the origin of altitude sickness is:

$$H(z) = H(z_a) + H(z_b) + H(z_c) + H(z_d) + H(z_e) + H(z_f) + H(z_g) + Hz(z_a|z_b|z_c|z_d|z_e|z_f|z_g) \qquad (6)$$

Respiratory system modeling

There are 7 main aspects of respiratory system modeling. According to the breathing data monitored by the vital sign sensors, the monitoring data such as pauses of more than 10 s are generated by detecting the rapid breathing of a worker and the continuous 3 or 4 rapid breathing to determine the risk of altitude sickness onset. The value range of respiratory system characteristic value is listed in **Table 4**.

Table 4. Value range of respiratory system characteristics

Name	Unit	Lower limit	Upper limit
BMI Index	kg/m	10	50
Lung function-FVL	L	0.5	10
Lung function-FEV1	L	0.5	10
Lung function-FEE25	L/sec	0.5	10
Lung function-SaO decrease	%	0	99
Number of breaths	number/h	5	100
Breathing pause time	s	0	100

Let the information entropy of the respiratory system be x, the BMI index to be x_a, the lung function-FVL to be x_b, the lung function-FEV1 to be x_c, and the lung function-FEE25 to beis x_d, the decrease in lung function-SaO2 is x_e, the number of breaths is x_f, the breathing pause time is x_g and the entropy of respiratory system pathogenesis is:

$$H(x) = H(x_a) + H(x_b) + H(x_c) + H(x_d) + H(x_e) + H(x_f) + H(x_g) + H(x_a|x_c|x_d|x_e|x_f|x_g) \qquad (7)$$

Cardiovascular system modeling

According to the heartbeat data, dynamic electrocardiogram data, and blood pressure data monitored by the vital sign sensors, detection on the whether there are increases in heart rate, blood pressure, red blood cells and hemoglobin as well as whether there are clinical symptoms present such as ectopic arrhythmia, can be used to determine the risk of altitude sickness. The value range of cardiovascular system eigenvalues is listed in **Table 5**.

Table 5. Value range of cardiovascular system characteristics

Name	Unit	Lower limit	Upper limit
ECG ST segment	%	0	90
Diastolic blood pressure	mmHg	20	140
Systolic blood pressure	mmHg	60	240
Heart rate ⩾100 times	min	0	600
Red blood cells	number/L	0	9,999
Hemoglobin	pg	0	9,999

Having set the information entropy of the cardiovascular system as y, the ST segment of the electrocardiogram as y_a, the diastolic blood pressure as y_b, the systolic blood pressure as y_c, the heart rate ≥ 100 times as y_d, the red blood cells as y_e and the hemoglobin as y_f, the source entropy of the cardiovascular system is:

$$\mathrm{H}(\mathrm{y}) = \mathrm{H}(y_a) + \mathrm{H}(\mathrm{y}_b) + \mathrm{H}(\mathrm{y}_c) + \mathrm{H}(\mathrm{y}_d) + \mathrm{H}(\mathrm{y}_e) + \mathrm{H}(\mathrm{y}_f) + \mathrm{H}(y_a|\mathrm{y}_b|\mathrm{y}_c|\mathrm{y}_d|\mathrm{y}_e|\mathrm{y}_f) \quad (8)$$

Digestive system modeling

According to the intestinal peristalsis data monitored by the vital sign sensors, detection on whether the intestinal peristalsis is weak, the intensity of intestinal tension and other clinical symptoms can be used to determine the risk of altitude sickness. The eigenvalues of the digestive system characteristic range from 0 to 60 times/h.

Let the information entropy of the digestive system be p, the abdominal muscle tension (the number of spasms/h) be p_a, and the entropy of the source of the digestive system is:

$$H(p) = H(p_a) \quad (9)$$

Urinary system modeling

According to the blood data monitored by the vital sign sensors, detection on whether there are clinical symptoms such as hematuria and proteinuria can be used to determine the risk of altitude sickness. The range of urinary system characteristic values is listed in **Table 6**.

Table 6. Value range of urinary system characteristics

Name	Unit	Lower limit	Upper limit
Urine red blood cells	/μL	0	9,999
Urine protein	mg/L	0	9,999

Let the information entropy of the urinary system be q, the urine red blood cells to be q_a, the urine protein to be q_b, and the entropy of the urinary system to be:

$$H(q) = H(q_a) + H(q_b) + H(q_a|q_b) \quad (10)$$

5.2. Combined information entropy modeling of altitude sickness

In the information entropy modeling of the causes of altitude sickness, five cause variables of altitude sickness, respiratory system, cardiovascular system, digestive system, and urinary system are independent of each other. The amount of information obtained by observing the five variables should be the same as the amount of information of the five variables observed at the same time is the same. Let the amount of traceability information about the causes of altitude sickness be s_i=s{z=z_i}, the amount of information about the respiratory system is a_i=a{x=x_i}, and the amount of information about the cardiovascular system is b_i=b{y=y_i}, the amount of information in the digestive system is c_i=c{p=p_i}, and the amount of information in the urinary system is d_i=d{q=q_i}, then the information entropy of the causes of altitude sickness, the respiratory system, the cardiovascular system, the digestive system, and the urinary system are:

$$H(z) = \sum_{i\geq 1} s_i \log\frac{1}{s_i} \quad (11)$$

$$H(z) = \sum_{i\geq 1} a_i \log\frac{1}{a_i} \quad (12)$$

$$H(z) = \sum_{i\geq 1} b_i \log\frac{1}{b_i} \quad (13)$$

$$H(z) = \sum_{i\geq 1} c_i \log\frac{1}{c_i} \quad (14)$$

$$H(z) = \sum_{i\geq 1} d_i \log\frac{1}{d_i} \quad (15)$$

If in equations (11) to (15) the base of the logarithm is 2, then the information entropy of the causes of altitude sickness, respiratory system, cardiovascular system, digestive system, and urinary system are expressed as H2(z), H2(x), H2(y), H2(p), H2(q), respectively. At this time, the entropy unit based on 2 is bits. The curve of the entropy function is shown in **Figure 3**.

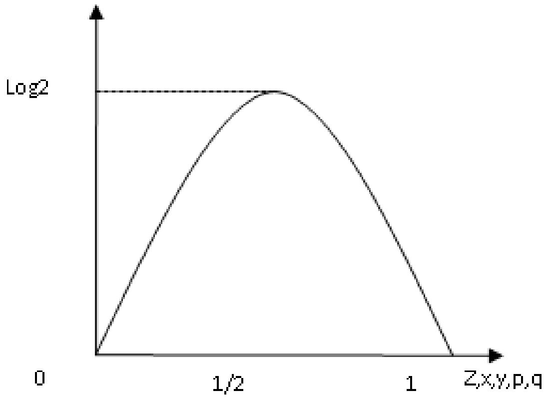

Figure 3. The curve of entropy function of illness source information.

It can be seen from **Figure 3** that the $\log_2$ value of information entropy can be regarded as the amount of information provided by information entropy.

The joint entropy of altitude sickness is defined as the uncertainty of the simultaneous occurrence of five factors traceability of the causes, respiratory system, cardiovascular system, digestive system, and urinary system of altitude sickness. The joint entropy is:

$$H(z,x,y,p,q) = \sum(z,x,y,p,q)$$

$$s(z,x,y,p,q)\ \log\ s(z,x,y,p,q)$$

$$a(z,x,y,p,q)\ \log\ a(z,x,y,p,q) \tag{16}$$

$$b(z,x,y,p,q) = \log c(z,x,y,p,q) \tag{17}$$

$$c(z,x,y,p,q) = \log c(z,x,y,p,q) \tag{18}$$

$$d(z,x,y,p,q) = \log d(z,x,y,p,q) \tag{19}$$

$$H(z,x,y,p,q) = H(z) + H(x) + H(y) + H(p) + H(q) + H(z|x|y|p|q) \tag{20}$$

Conditional entropy H(z|x|y|p|q) can be regarded as the average amount of information lost due to interference and noise on the channel, and can also be regarded as channel noise or dispersion.

The joint entropy relationship and mutual information of the causes of altitude sickness are shown in **Figure 4**.

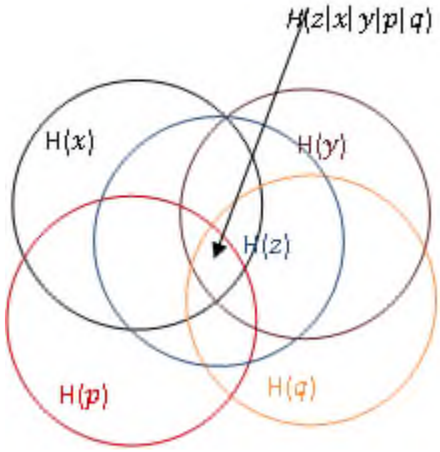

Figure 4. Joint entropy graph of disease source information.

As shown in **Figure 4**, the intersection of H(z), H(x), H(y), H(p), and H(q) is the joint entropy of altitude sickness H(z|x|y|p|q), where the greater the value of the joint entropy of altitude sickness, the greater the difference between the five functions, which means the greater the probability of altitude sickness, to determine whether the power grid construction personnel would have the risk of altitude sickness.

6. Evaluation and treatment of power grid construction personnel

The monitoring and evaluation platform for power grid construction workers can accurately assess the risk of high altitude sickness among the workers after analyzing the probability of high altitude sickness among them based on the information entropy modeling of the causes of altitude sickness. At the same time, when combined with the expert diagnosis database of the altitude sickness patients, it is possible to accurately assess the risk of altitude sickness among power grid construction workers, and generate altitude sickness risk assessment reports and treatment recommendations according to the needs of the construction workers. The level of assessment generated is divided into three categories: mild, moderate, and critical risk while treatment recommendations include stopping work, resting on the spot, intake of glucose, oxygen therapy, and immediate sending to the hospital (see **Table 7**).

Table 7. Risk assessment level and treatment recommendations of altitude sickness

Serial number	Evaluation level	Treatment recommendation
1	Mild risk	Stop work, rest on site, glucose intake
2	Moderate risk	Oxygen therapy
3	Critical risk	Immediately send to hospital

The altitude sickness monitoring and evaluation platform for power grid construction workers send the evaluation report and treatment recommendations to the medical staff at the power grid construction site through the 5G network. The hospital staff on the site can then conduct on-site treatment to the power grid workers who were assessed to be at risk of altitude sickness or send them immediately to the nearest hospital according to the treatment recommendations.

7. Platform application analyses

On-site construction workers of 185 people working on a 330kV line in the Qinghai-Tibet region was selected to conduct analysis on the prevention and treatment of altitude sickness. Before entering the Qinghai-Tibet area, relevant hospitals were arranged to conduct physical examinations on the 185 construction workers, all of whom met the requirements for high-altitude operation.

Before the application of the altitude sickness monitoring and evaluation platform for power grid construction workers, according to the survey performed by the High Altitude Sickness Prevention and Control Center of State Grid Corporation of China, the total incidence of acute altitude sickness among construction workers who have just entered the Qinghai-Tibet Plateau was 18.97% while the estimated number of people at risk of altitude sickness is 35. During the one month of monitoring, the platform found that 33 people were assessed to be at risk of altitude sickness. After the medical staff accompanying the team took measures such as providing glucose intake and oxygen therapy for treatment, the conditions of 27 patients were improved, thereby avoiding the occurrence of altitude sickness among power grid construction workers, and only 6 workers suffered from altitude sickness. The comparison is shown in **Table 8**.

Table 8. Comparison of altitude sickness before and after monitoring and evaluation platform application

Serial number	Construction workers/person	Types	Number of patients/person	Prevalence rate/%
1	185	Estimated incidence	35	18.97
2	185	Actual assessment	33	17.84
3	185	After application	6	3.24

From **Table 8**, it can be seen that before the use of altitude sickness prevention platform for power grid construction workers, among the construction team of 185 people, the estimated incidence of altitude sickness was 35 people, and the estimated prevalence rate was 18.97%. Following actual assessment, there were 33 construction workers with symptoms, and the actual prevalence rate was 17.84%. After using the altitude sickness monitoring and evaluation platform for power grid construction workers, they were evaluated as risky construction workers and treated on-site by medical personnel, with the actual number of patients with altitude sickness to be at 6, and a prevalence rate of 3.24%,signifying a decrease of 14.59% as compared with the method of physical examination beforehand.

8. Conclusions

The altitude sickness monitoring and evaluation platform for power grid construction workers has changed the traditional way of pre-existing physical examination for power grid construction personnel entering Tibet and has realized the transition from altitude sickness treatment of power grid construction personnel to early warning of altitude sickness. The specific implementation of interconnection application reduces the cost of altitude sickness prevention and relief at the construction site, where it not only ensures the health of power grid construction personnel but also improves the efficiency of power grid construction in the Qinghai-Tibet region.

Conflict of interest

The authors declare no conflict of interest.

References

1. Cui J, Yang S. Summary of drug research on improving high altitude working ability (in Chinese). Medical Journal of National Defending Forces in Southwest China 2017; 27(12): 1358–1360.
2. Tian Y, Wang W, Zhang H. An analysis of the incidence and risk factors of acute altitude sickness among visitors to Tibet (in Chinese). Practical Preventive Medicine 2019; 26(8): 975–977.
3. Yuan X, Wu Z, Zha L. The correlation between cardiac function change and sleep quality in patients with chronic mountain sickness in Xining area (in Chinese). Chinese Journal of HealthCare and Medicine 2019; 21(4): 305–308.
4. Liu X, Luo Y. The evolution and the latest progress of the diagnostic criteria of acute mountain sickness (in Chinese). Journal of Preventive Medicine of Chinese People's Liberation Army 2019; 37(10): 188–192.
5. Sun Z, Lin J, Zhu K, et al. Investigation and Analysis on the risk factors of acute high altitude disease in the constructors of high altitude power grid (in Chinese). Medical Journal of National Defending Forces in Southwest China 2016; 26(4): 460–461.
6. Ma S, Shen M, Xia G. Analysis of eight year follow up data of plateau workers by color Doppler echocardiography (in Chinese). Chinese Journal of Industrial Hygiene and Occupational Diseases 2018; 36(8): 607–609.
7. Liu H, Su J, Ma J, et al. The expression of VHL/HIF signaling pathway in the erythroid progenitor cells with chronic mountain sickness (in Chinese). National Medical Journal of China 2019; 99(34): 2670–2674.
8. He X, Feng L, Du Y. Influencing Factors of severe acute mountain sickness (in Chinese). Chinese Journal of Social Medicine 2019; 36(2): 142–145.
9. Wu Y, Bao H, Zhang H. Magnetic resonance and spectrum signal analysis on lumbar vertebra marrow in chronic high altitude disease (in Chinese). Journal of Clinical Radiology 2018; 37(7): 1183–1186.
10. Wang H, Wang D, Yang K. Technical architecture and platform construction of distributed photovoltaic data sharing system based on Internet of Things identification technology (in Chinese). Power System and Clean Energy 2019; 35(8): 69–75.
11. Wang X, Wang L, Wu D, et al. Design about intelligent inspection network scheme of distribution network based on edge calculation and LoRa technologies (in Chinese). Guangdong Electric Power 2020; 33(9): 42–48.
12. Qian H, Jia S, Yang F, et al. Intelligent operation and maintenance technology for relay protection equipment based on mobile Internet (in Chinese). Smart Power 2019; 47(11): 60–66.
13. Ai J, Dang X, Lv Q, et al. Research on full dimension equipment status monitoring system with panoramic function (in Chinese). Power System Protection and Control 2019; 47(16): 122–128.
14. He Y, Liang K, Tan W, et al. Security monitoring system of intelligent substation based on IoT (in Chinese). Telecommunications Science 2018; 34(9): 179–185.
15. Shi Y, Chen C, Luo Y. Design and application of RTU pipeline terminal based on NB-IoT (in Chinese). Transducer and Microsystem Technologies 2019; 38(12): 157–160.
16. Zhang P, Yang M, HE H. Function and application of Internet of Things engine of smart Guangzhou spatiotemporal cloud platform (in Chinese). Geospatial Information 2019; 17(12): 47–49.
17. Zhao N, Wang J, Zhang H, et al. Research and application of remote diagnosis and treatment for cardiovascular diseases based on Internet of Things (in Chinese). China Digital Medicine 2019; 14(12): 80–82.
18. Xie Z, Li D. Research on key technologies of intelligent blood pressure monitoring system based on Internet of Things (in Chinese). China Digital Medicine 2019; 14(12): 36–39.
19. Wang H, Gu S, Wan Y, et al. Research and application of 5G technology in power systems (in Chinese). Guangdong Electric Power 2019; 32(11): 78–85.
20. Konreddy R, He M. How to ensure security in the era of Internet of Things? (in Chinese). Microcontrollers & Embedded Systems 2019; 19(12): 1–3.

Wearable Technology (2020) Volume 1 Issue 1, *pp.* 30–40.
doi: 10.54517/wt.v1i1.1629

Asia Pacific Academy of Science Pte. Ltd.

ORIGINAL RESEARCH ARTICLE

Deep learning-based discriminant model for wearable sensing gait pattern

Qiaoling Tan, Jianning Wu*

College of Mathematics and Informatics, Fujian Normal University, Fuzhou 350117, Fujian, China. E-mail: jianningwu@fjnu.edu.cn

ABSTRACT

In order to effectively improve the accuracy of identifying the gait pattern of wearable sensing data, this paper proposes a new model for deep learning gait mode discrimination that integrates convolutional neural network and long short-term memory neural network, which makes full use of the convolutional neural network to obtain the most local spatial characteristics of data and the long short-term memory neural network to obtain the inherent characteristics of the data, and effectively excavates the hidden high-dimensional, nonlinear, time-space gait characteristics of random wearable sensing timing gait data that are closely related to gait pattern changes, to improve the classification performance of gait mode. The effectiveness of the proposed model in this paper is evaluated using the HAR dataset from University of California UCI database. The experiment results showed that the proposed model in this paper can effectively obtain the time-space gait characteristics embedded in the wearable sensor gait data, and the classification accuracy can reach 91.45%, the precision rate 91.54%, and the recall rate 91.53%, and the classification performance is significantly better than that of the traditional machine learning model, which provides a new solution for accurately identifying the gait mode of wearable sensor data.

Keywords: wearable sensing gait data; deep learning; gait pattern recognition

1. Introduction

In recent years, the construction of a machine learning gait classification model with superior generalization performance based on gait data obtained from outdoor environment has received wide attention in the field of gait pattern recognition research, which is of great significance for the prevention of falls in the elderly, the diagnosis and treatment and rehabilitation evaluation of elderly neurological functional diseases, human identity identification. It now has become a new research hotspot in the research field related to gait pattern recognition[1,2]. In recent years, with the rapid development of advanced data acquisition technology, some advanced data acquisition technologies (such as computer video, wireless radar, wearable sensors, etc.) have been used to collect gait pattern data in outdoor environments. For example, based on gait image data collected by computer video, some scholars have discussed the study of outdoor human

ARTICLE INFO
Received: February 18, 2020 | Accepted: March 25, 2020 | Available online: April 10, 2020

CITATION
Tan Q, Wu J. Deep learning-based discriminant model for wearable sensing gait pattern. Wearable Technology 2020; 1(1): 30–40.

gait pattern recognition in different perspectives[3]; other scholars have discussed the research on gait pattern recognition in outdoor environment containing micro-Doppler feature information based on the gait data obtained by wireless radar devices[4]. While some scholars have also discussed the study on gait pattern recognition in outdoor environment based on gait data of wearable sensors (accelerometer, gyroscope, magnetometer, etc.)[5]. The studies found that the gait acquisition technology of cheap and portable wearable sensor has the advantages of adapting to different outdoor application scenarios and containing rich gait characteristic information, which can better avoid the loss of valuable gait characteristic information by computer video technology due to outdoor environment, human wearing clothing, and the loss of wireless gait detection signal because of the external environmental interference of wireless radar devices, which helps to improve the gait pattern recognition efficiency, and has been widely used in related research in recent years.

Based on wearable sensor data, the application of machine learning algorithms to explore gait pattern recognition models with superior generalization performance has received continuous attention from relevant research, and its basic idea is that it can make full use of the superior data learning performance of machine learning algorithms to obtain more representative gait characteristic information from wearable sensor gait data and improve the gait pattern recognition performance. In the early days, some studies explored the quantitative analysis of wearable sensor data based on traditional machine learning algorithms (such as decision trees, multi-layer perceptual neural networks, support vector machines, K-neighbors, etc.), and tried to construct gait pattern recognition performance with superior generalization performance[6,7]. For example, Bao et al.[8] discussed the gait pattern recognition model of ID3 decision tree based on the gait data of the triaxial accelerometer to identify three gait patterns such as normal walking, jogging, and stair climbing, with an average recognition rate that was only 79%. Tahafchi et al. discussed the application of KNN classification algorithm to obtain and compare data from wearable data of Parkinson's subjects (including triaxial acceleration data, gyroscope data, magnetometer data, and dual-channel non-invasive myoelectric scanner data), and the gait pattern recognition rate reached 91.9%, 87.1%, 80.9%, and 79.9% according to the participants, respectively[9]. In addition, based on the acceleration gait data of wearable sensors, Nickel et al. discussed the research on the construction of gait pattern recognition model based on support vector machine, invisible Markov model and KNN classification algorithm, among which the Equal Error Rate (EER) of support vector machine and invisible Markov model was 10.00% and 12.63%, respectively, and the Half Total Error Rate (HTER) of KNN classification algorithm can reach 8.24%[10,11]. The study found that the traditional machine learning algorithm has the advantages of low computational complexity in processing wearable sensor gait data to recognize the gait pattern, but because of its inherent linear computing model architecture, it is difficult to obtain more representative gait characteristic information hidden in the intrinsic structure of wearable sensor gait data, and it is difficult to support the construction of a gait pattern recognition model with superior generalization performance. In recent years, with the rapid development of emerging machine learning theories such as deep learning and the successful application of image processing, some scholars have tried to explore the construction of deep learning gait pattern recognition model based on the wearable sensor gait data, and its basic idea aims to make full use of the excellent data learning performance of deep learning algorithms to obtain more representative gait feature information from high-dimensional wearable sensing gait data and to improve the gait pattern recognition performance. For example, Zou et al.[12] based on the acceleration data and gyroscope data collected by wearable smartphones, the construction of convolutional neural network and recurrent neural network fused with gait pattern recognition model is discussed, try to obtain the inherent spatiotemporal correlation characteristics information of wearable sensing gait data to improve the performance of gait pattern recognition. The results showed that the accuracy of this method in pedestrian identification and identity authentication is found to be higher than 93.5% and 93.7% respectively. In addition, Ding et al.[13] proposed a gait pattern recognition model based on the long short-term memory algorithm LSTM based on wearable gait data (wearing an inertial measurement unit on the calf to collect angular velocity data), which aims to obtain the time-correlated gait feature information hidden in wearable gait data through the long short-term memory algorithm to detect the gait phase and use the phase marker data to train it. The experimental results show that the recognition accuracy rate can reach 91.4%. In recent years, although the research on gait pattern recognition based on deep learning has achieved good results and positive progress, there is still a lack of a technical means to accurately obtain the more representative time-space correlation gait characteristic information implied in wearable gait data, which seriously restricts the gait pattern recognition performance. Relevant medical studies have shown that gait is a walking posture of the human body, which is closely related to physiological factors such as human nervous system, motor system and psychological cognitive system, and it is a long-term memory process in which various physiological factors interact and influence each other, while the self-recurrent neural network model used in the current study only has short-term memory performance, and it is difficult to obtain long-term temporal correlation characteristic information during gait process. New deep learning models that acquire more representative spatiotemporal correlation gait feature information implied in wearable gait data are urgently needed.

Therefore, based on the wearable sensor gait data, this paper proposes a new model for deep learning discrimination of gait mode that integrates convolutional neural network model and long short-term memory neural network model, which aims to make full use of the convolutional neural network model's superior characteristics of obtaining the most representative feature information characteristics in local space of data and the inherent long-term time correlation characteristic information characteristics of long short-term memory neural network model, and accurately obtain the more representative spatiotemporal correlation gait feature information implicit in wearable gait data, improve gait pattern recognition performance. In addition, this paper selected the HAR data from the publicly available UCI database of the University of California, Irvine[14], and compared with traditional machine learning algorithms and deep learning algorithm models to verify the effectiveness of the proposed model algorithms.

2. CNN-LSTM deep integration learning gait pattern discriminant model

The CNN-LSTM deep learning model proposed in this paper aims to make full use of the excellent characteristics of CNN and LSTM models to obtain the inherent spatial and temporal correlation characteristic information of data structures, respectively, and to deeply integrate the two from wearable sensing gait data (such as acceleration, gyroscope, etc.) to obtain more time-space correlation characteristic information that is closely related to gait changes, and improve the gait pattern recognition performance. That is, it is assumed that the gait pattern needs to be identified as the database $v = \{v_1, v_2, \dots, v_l\}$, among them, l represents the number of gait patterns to be recognized. Suppose the wearable sensor gait time series data is:

$$D = \left(d^1, \dots, d^j, \dots, d^t\right) = \begin{pmatrix} d_1^1, \dots, d_1^t \\ \vdots \\ d_m^1, \dots, d_m^t \end{pmatrix} \qquad (1)$$

In the series data, $d^j = \left(d_1^j, \dots, d_m^j\right)^T$ is the wearable sensing data at time j, while m and t denote the number of wearable sensors and the number of gait pattern time series samples, respectively. In the research, each gait pattern time series data is selected, so that each data segment $h_i = (t_{i-1}, t_i)$ contains gait spatiotemporal feature information, and all selected data segment are defined as dataset $H = \{h_1, \ldots, h_i, \ldots, h_k\}$, and the k is the number of all selected data segment.

In order to accurately identify the gait pattern, we need to construct a model Γ to obtain the vector Y_i containing the gait feature information from each data segment h_i, that is, $Y_i = \Gamma(D, h_i)$. Then, the confidence value set P corresponding to each gait pattern v_i is calculated based on an inference method Ψ, $P: P(v_i/Y_i, \beta) = \Psi(Y_i, \beta)$, is a training parameter set based on the model Γ. Then, by computing the following maximum score value: $v_i^* = \arg\max P(v/Y_i, \beta)$, the gait pattern v_i^*can be obtained accurately, and each gait pattern can be recognized. In this study, we constructed the CNN-LSTM deep fusion learning model as a model Γ, and first use the CNN deep learning model to obtain the local spatial feature information that is closely related to the gait pattern changes from each data segment h_i. On this basis, based on the LSTM deep learning model, the temporal correlation of the local spatial features of the gait data is obtained, and more the time-space feature information related to the gait pattern changes can be obtained, the gait pattern v_i^* is obtained with the maximum probability, and the gait pattern v_i is accurately identified.

The framework of the gait pattern discriminant model based on CNN-LSTM fusion deep learning proposed in the paper is shown in **Figure 1**, which consists of three parts: gait data input layer, CNNLSTM fusion deep learning, and full connection layer.

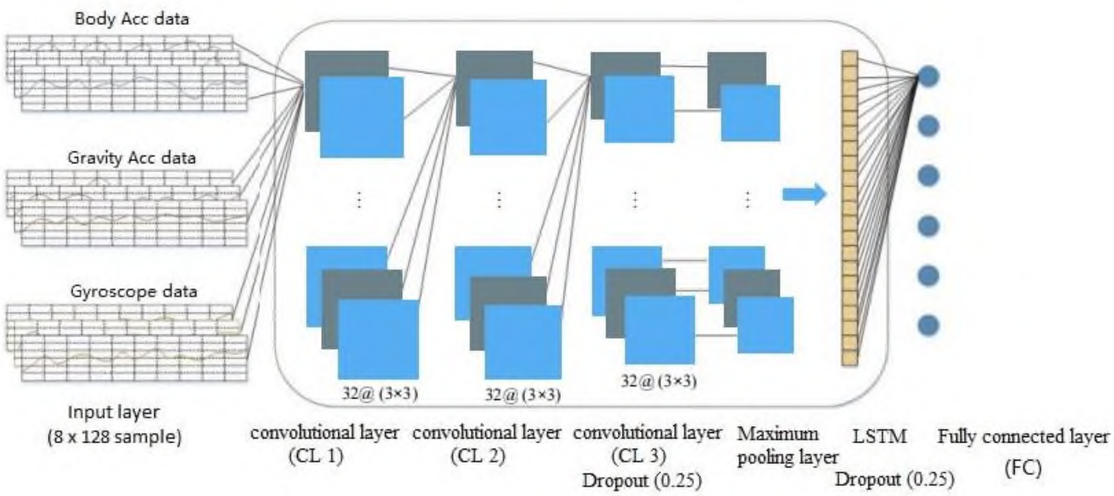

Figure 1. CNN-LSTM network framework.

As shown in **Figure 1**, in view of the time-space correlation characteristics of wearable gait sensing data, the CNN is composed of three convolutional layers (CL1, CL2, CL3), a maximum pooling layer (MP1), and two dropout layers, which accurately obtain the most representative local spatial features inherent in the gait data. In order to accurately obtain the temporal correlation of the most representative local spatial features in the gait data, the LSTM model consists of 32 cells, and in order to accurately obtain the temporal correlation of the most representative local spatial features in the gait data, the fully connected layer is consists of 6 cells, and the gait pattern is identified with the maximum probability.

(1) Extract the most representative local spatial characteristics of gait data based on CNN.

In order to effectively obtain gait feature information, the data of the wearable sensing gait time series at t time t is defined as:

$$d^t = \left(d^t_{BA\_x} d^t_{BA\_y} d^t_{BA\_z} d^t_{GA_x} d^t_{GA\_y}, d^t_{GA\_z}, d^t_{Gy\_x}, d^t_{Gy\_y}, d^t_{Gy\_z}\right) \quad (2)$$

Among them, BA-XYZ represents the three-dimensional human motion acceleration data, GAXYZ represents three-dimensional gravitational acceleration data, and Gy-XYZ represents three-axis gyroscope data. For ease of analysis, selects$t \in \{1, \dots, 128\}$, and its sensory gait data input sequence is defined as:

$$D = (d^1, \dots, d^t, \dots, d^{128}) = \begin{pmatrix} d^1_{BA_x}, \dots, d^{128}_{BA_x} \\ d^1_{BA_y}, \dots, d^{128}_{BA_y} \\ d^1_{BA_z}, \dots, d^{128}_{BA_z} \\ d^1_{GA_x}, \dots, d^{128}_{GA_x} \\ d^1_{GA_y}, \dots, d^{128}_{GA_y} \\ d^1_{GA_z}, \dots, d^{128}_{GA_z} \\ d^1_{Gy_x}, \dots, d^{128}_{Gy_x} \\ d^1_{Gy_y}, \dots, d^{128}_{Gy_y} \\ d^1_{Gy_z}, \dots, d^{128}_{Gy_z} \end{pmatrix} \quad (3)$$

Assuming that the CNN model used to obtain the most representative gait local spatial features has a convolutional layer, each layer of convolutional kernels is defined as: $M_1 \times N_1$, the $l \in \{1, \dots, L\}$ convolutional layer extracts the gait local spatial feature $F^{(l)}$, which is defined as:

$$F^{(l)} = f\left(b^{(l)} + \langle w^{(l)}, d^i, \dots, d^{i+ø-1} \rangle\right), i = 1, \dots, t - ø + 1 \quad (4)$$

Where f(·) represents the activation function, < · > represents the inner product, and $b^{(l)}$ is the bias term; $w^{(l)}$ is a one-dimensional convolutional kernel vector; ø is the length of $w^{(l)}$.

In view of the high-dimensionality, nonlinearity, randomness and low algorithmic complexity of the wearable sensing gait data defined in equation (3), this paper constructs a three-layer one-dimensional convolutional layer, each of which has 32 convolutional kernels, the size of which is defined as 3 × 3, the step size is defined as 1, and the ReLUfunction[15,16] with good nonlinear characteristics is used as the activation function. According to equation (3), the size of the wearable sensor gait input data is defined as 128 × 9, and the gait local characteristic data of the output by the first, second, and third convolutional layers can be obtained, respectively: 126 × 32, 124 × 32 and 122 × 32. To effectively maintain good learning performance and avoid overfitting, build a Dropout layer. In order to effectively maintain the intrinsic characteristics of the gait features obtained by the convolutional layer, reduce its redundancy information, and use the pooling layer to reduce the characteristic dimensionality and increase its spatial invariance[17], the pooling layer that defines the maximum pooling technology obtains the local spatial characteristics P_j that contains more gait change information, which is defined as:

$$P_j = max\left(F_{(j-1)R+1}, \dots, F_{jR}\right), j = 1, \dots, \frac{t}{R} \quad (5)$$

R represents the pooling window size.

Therefore, based on equation (5), the local spatial characteristics with the most gait change information can be obtained from the wearable sensor gait time series data, which lays the foundation for subsequent acquisition of its temporal correlation features. We used this local gait feature as an input to LSTM to extract the dependent characteristics of gait data for a long period.

(2) The temporal correlation of local features of gait data extracted based on LSTM layer

A gait activity can be considered as a long series of time series, and the long-term time-dependent characteristics of local features can be effectively extracted by establishing an autoregressive model RNN. In this paper, in view of the good autoregressive network architecture characteristics LSTM with intrinsic time correlation of dynamic learning time series data[18], the LSTM cell is constructed, including 1 memory cell *C* and 3 gate functions (input i_t, forgetting f_t, output o_t), and the intrinsic long-term time-related characteristics of gait data is extracted in real time, the specific implementation is as follow.

Assuming the gait data sample represented by p^t is processed by the CNN model at the *t* moment as the input term of the LSTM neuron, and when passing through the cell of the LSTM, the useless extracted data information is first discarded by the forgetting gate, and its output is:

$$f_t = \sigma\left(W_f \cdot [p^t, h_{t-1}] + b_f\right) \tag{6}$$

Where σ represents the activation function Sigmoid, W_f is the weight, and b_f is the bias value. The updated data information is then determined by input gate i_t and candidate memory cell $\widetilde{C_t}$:

$$i_t = \sigma(W_i \cdot [p^t, h_{t-1}] + b_i) \tag{7}$$

$$\tilde{C} = tan(W_c \cdot [p^t, h_{t-1}] + b_c) \tag{8}$$

The W_i and W_c refer to weights, and b_i and b_c refer to bias values. The cell update status of the LSTM is then represented by the memory cell C_t:

$$C_t = i_t \cdot \tilde{C} + f_t \cdot C_{t-1} \tag{9}$$

Finally, the output data information h_t of the LSTM unit is determined as:

$$o_t = \sigma(W_o[p^t, h_{t-1}] + b_o) \tag{10}$$

$$h_t = o_t * \tan(C_t) \tag{11}$$

The o_t is the output gate; h_t is the output of the current neuron in time. Specific derivation equations can be referred to reference[19]. By retaining the information that has undergone forgetting and input through the above memory units, the LSTM unit can effectively transmit historical information with a long-time interval to obtain the intrinsic time correlation characteristics of the data. The LSTM layer proposed in this paper consists of 32 cells to process the time signals which expressed as one-dimensional eigenvectors as shown in equation (12).

$$s = [h^1, \ldots, h^t], t \in \{1, \ldots, 32\} \tag{12}$$

The feature vectors s is processed by a fully connected layer composed of 6 cells, and the output is:

$$h = f[Ws + \varepsilon] \tag{13}$$

W is the weight matrix of the fully connected layer; ε is the bias term vector. We set the activation function of the fully connected layer to the Softmax function, and the final output is:

$$v_i^* = \frac{e^{vi}}{\sum e^{vi}}, i \in \{1, \ldots, 6\} \tag{14}$$

The gait pattern v_i is identified with maximum probability by the equation (14).

From the above analysis, it can be seen that the CNN-LSTM model proposed in this paper fully integrates the excellent the characteristics of both CNN and LSTM to obtain the most representative temporal and spatial gait features inherent in gait time series data, reduces the complexity of the learning network structure and the large training cost of the model, enhances the nonlinear fitting performance of the fusion deep learning algorithm, and helps to improve the accuracy and precise in the gait classification of the proposed model.

The neural network model proposed in this paper uses the classification cross-entropy loss function to minimize the classification error rate of the training sample, which is defined as:

$$L(X, D, B) = -\frac{1}{N}\sum_{i=1}^{N}\langle y^{(i)}, \log \hat{y}^{(i)}\rangle \tag{15}$$

D represents the training set, W *re*presents the weight matrix, and B represents the bias value; N indicates the number of training samples, $y^{(i)}$ represents the label of the i^{th} sample, and $\hat{y}$ represents the predicted label and $< \cdot >$ represents the inner product.

3. Experiment and result analysis

3.1. Experimental data acquisition

This paper uses the HAR dataset from UCI database for machine learning proposed by the University of California Irvine. The dataset collected 6 gait patterns from 30 volunteers aged 19 to 48: standing, sitting, lying down, walking, going upstairs and downstairs. Each subject performs two experiments.

Scheme: In the first experiment, the smartphone (with built-in accelerometer and gyroscope) was worn on the left side of the waist; in the second experiment, the subjects placed their smartphones randomly.

3.2. Data preprocessing

In order to effectively eliminate noise interference and obtain more useful gait data, we used a median filter and a third-order low-pass Butter-worth filter (cutoff frequency set to 0.3 Hz) to cancel the noise processing of human acceleration signals and gravitational acceleration signals. Set the window width to 2.56s for sliding window data, window overlap is set to 50%, that each window has: 2.56 s × 50 Hz = 128 cycles, and fast Fourier transform was used to obtain the 17 gait data time-domain and frequency-domain gait features. Therefore, 17 metrics were used to evaluate the eigenvectors in the time and frequency domains, a total of 561 features were extracted to describe each active window (sample point), each sample point is regarded as a gait mode, the metrics are shown in **Table 1** below.

Table 1. Metric table for computing eigenvectors

No.	Function	Introduce
1	Mean	Average value
2	Std	Standard deviation
3	Mad	Absolute median
4	Max	Maximum value
5	Min	Minimum value
6	Sma	Signal Amplitude Region
7	Energy	Square and mean
8	Iqr	Interquartile range
9	Entropy	Signal entropy
10	arCoeff	Autoregressive coefficient
11	Correlation	Correlation coefficient
12	maxFreqInd	Maximum frequency component
13	meanFreq	Frequency signal weighted average
14	skewness	Frequency signal skewness
15	kurtosis	Frequency signal kurtosis
16	energyBand	Frequency interval energy
17	Angle	Angle between two vectors

3.3. Selection of evaluation criteria for gait classification performance

In order to objectively and accurately evaluate the generalization performance of the gait classification model proposed in this paper, the classification accuracy, gait precision, and recall rate commonly used in gait classification related studies were selected as the objective evaluation indicators of gait classification performance.

(1) Accuracy: Used to objectively evaluate the accuracy of the gait deep learning classification model proposed in this paper, which is defined as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{16}$$

TP represents the number of samples that correctly identify gait patterns; *FP* represents the number of samples that incorrectly identify gait patterns; *TN* represents the number of samples in which the correct gait pattern was incorrectly recognized as another gait pattern; The *FN* represents the number of samples of which the gait pattern was incorrectly recognized as the correct gait pattern.

(2) Precision: It is used to objectively evaluate the performance of the gait deep learning classification model proposed in this paper to "truly" identify gait patterns, which is defined as

$$Precision = \frac{TP}{TP + FP} \tag{17}$$

(3) Recall: It is used to objectively evaluate the performance of gait deep learning classification models proposed in this paper for correct recognition of gait patterns, which is defined as

$$Recall = \frac{TP}{TP + FN} \tag{18}$$

3.4. Experiment results

The experiments in this paper are based on Google's open source deep learning framework Tensorflow, the specific experimental platforms are CPU(i5), Python3.7, Keras2.3, and Tensorflow2.1. The number of samples was 10 299, 70% was randomly selected as the training set, while 30% was the test set, and the experimental data is sent to the model training in batches, and the batch size is 32 data samples. The number of training rounds of the model is set to 30 and the adaptive learning rate optimization algorithm Adam is used and the learning rate is set to 0.001.

(1) Optimal structural parameter selection of gait deep learning classification model

In order to accurately optimize and design the structure of the gait deep learning classification model proposed in this paper and improve its performance, this paper first quantitatively evaluates the number of convolutional layers and the number of neurons in the long short-term memory network selected by the proposed model optimization. The selection result of the convolutional neural network convolutional layer is shown in **Figure 2**. From **Figure 2**, when the number of convolutional layers increases from 1 to 3, the accuracy of the model gradually increases. When the number of convolutional layers is 3, the classification accuracy is the largest which up to 92.1%. But when the number of convolutional layers increase to 4 and 5, the classification accuracy decreases significantly. The results show that when the number of convolutional layers is 3, the gait fusion deep learning classification model proposed in this paper can obtain more gait characteristic information closely related to gait pattern changes through the wearable sensing acceleration and gyroscope gait data, which effectively improves the classification performance of the model. However, when the number of convolutional layers increases to 4 and 5, it is difficult to obtain some representative feature information from wearable sensing gait data, which may lose some useful gait feature information and reduce the classification performance of the model.

The results of selecting the number of neurons in the optimal LSTM model are shown in **Figure 3**, and it can be seen from **Figure 3** that when the number of neurons increases from 16 to 256, the selection of different neurons affects the classification performance of the gait pattern of the model.When the number of neurons is 32, the classification accuracy is the largest, reaching 92.3 %.When the number of neurons increases from 32 to 256, the classification accuracy decreases significantly.The results show that when the number of neurons is 32. The proposed model can obtain more time-related feature information closely related to gait changes from the local features of wearable sensor gait data space, which significantly improves the classification performance of the proposed model.

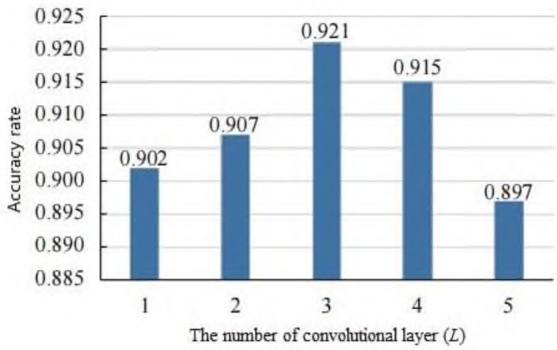

Figure 2. The effect of the number of convolutional layers on classification accuracy.

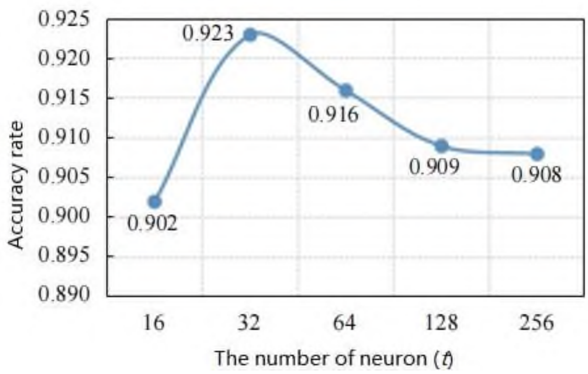

Figure 3. The effect of LSTM neuron number on classification accuracy.

(2) Gait classification performance evaluation results of CNN-LSTM model

The classification performance evaluation results of the CNN-LSTM gait deep integration learning model based on the optimal parameters taken in this paper are shown in **Table 2**. It can be seen from **Table 2** that the proposed model can identify 6 different gait modes with good classification performance, with an average accuracy of 91.45% and an average recall rate of 91.53%. In comparison, the “lying” gait mode has the highest accuracy rate of up to 99%, which shows that the deep-depth learning model proposed in this paper can effectively obtain the time-space gait characteristic information closely related to the “lying” gait mode from the wearable sensing acceleration and gyroscope gait data, can effectively improve its mode identification performance. However, the accuracy of the “standing” gait mode is the lowest, only 80.94%, and the recall rate of the “sitting” gait mode is the lowest, only 81.06%, and these results show that it is difficult for the model proposed in this paper to obtain time-space gait related characteristic information closely related to the “sitting” and “standing” gait mode from the wearable sensing acceleration and gyroscope gait data, which may be due to the gait data acquisition process of wearable single sensor gait collector is difficult to capture the relevant information of the “sitting, standing” gait mode.

Table 2. 6 gait patterns classification results

Gait pattern		Prediction sample						Recall rate (%)
		Lying	**Sitting**	**Standing**	**Walking**	**Going downstairs**	**Going upstairs**	
Real sample	Lying	510	0	24	3	0	0	94.97
	Sitting	3	398	82	1	0	7	81.06
	Standing	0	82	450	0	0	0	84.59
	Walking	0	0	0	472	24	0	95.16
	Going downstairs	0	0	0	1	418	1	99.52
	Going upstairs	0	0	0	0	24	447	94.90
Accuracy rate (%)		99.42	82.92	80.94	98.95	89.70	98.24	

In addition, based on the same gait data, this paper selected a gait classification model based on traditional machine learning algorithms (such as decision tree, KNN, support vector machine, etc.) to further evaluates the superior performance of the proposed model, and its comparative classification performance is shown in **Table 3**. From **Table 3**, the accuracy, precision, and recall rate of the gait deep integration learning model proposed in this paper were the highest, which can reach 91.5%; Secondly, the accuracy, precision, and recall rate of the KNN gait classification model were about 90%, while the accuracy, precise, and recall rate of the support vector machine were all less than 90%, and the accuracy, precise, and recall rate of the decision tree gait classification model were the lowest, which was only 86%.

Table 3. Comparison result of gait classification with traditional machine learning algorithms (%)

Method	Accuracy	Precision	Recall
Decision tree algorithm	86.36	86.31	86.01
Support vector machine	86.09	88.11	85.48
KNN algorithm	90.46	91.06	89.96
CNN-LSTM model	91.45	91.54	91.53

The above results show that the classification performance of the CNN-LSTM gait deep fusion learning model proposed in this paper is significantly better than that of the traditional machine learning gait classification model, and the fundamental reason is that the model proposed in this paper can make full use of the excellent characteristics of the most presentative data obtained by the CNN and LSTM deep-integration learning algorithms, effectively obtain the most representative time-space correlation gait characteristics from wearable sensing acceleration and gyroscope gait data, and significantly improve the gait classification performance. However, the traditional machine learning gait classification model can only obtain local spatial and temporal gait characteristics based on the linear model, and it is difficult to obtain the most representative time-space correlation gait characteristics from wearable sensing acceleration and gyroscope timing gait data, which affects its classification performance.

In addition, in order to further evaluate the effectiveness of the proposed model, based on the above-mentioned same gait data, the proposed model is compared with other traditional deep learning models (such as CNN, RNN[20], LSTM, GRU[21] and other models), and the comparison results are shown in **Table 4**. From **Table 4**, it can be seen that the gait classification performance of the CNN-LSTM model proposed in this paper is significantly better than other traditional deep learning gait classifications performance. In comparison, the gait classification performance of the RNN network model is poor, and the accuracy, precision, and recall rate are only about 70%, which is due to the fact that the RNN network learning model is difficult to obtain the most spatial and time-related gait characteristic information in the gait time series; The accuracy, precision, and recall rate of CNN, GRU and LSTM learning models are about 88%, and although their gait classification performance is better than the RNN network learning model gait classification performance, it is significantly lower than the gait classification performance of the CNN-LSTM fusion learning model mentioned in this paper, and the fundamental reason is that: the gait classification model based on traditional CNN deep learning can only obtain the most representative local spatial gait characteristic information inherent in gait time series data; The gait classification model based on traditional LSTM and GRU deep learning can only obtain the most representative time-correlated gait characteristic information inherent in wearable gait time series data. The limitation of the above two traditional deep learning gait classification models is that difficult to obtain the most representative time-space correlation gait feature information in the wearable gait time series data. However, the CNN-LSTM fusion deep learning gait classification model proposed in this paper can fully integrate CNN and LSTM with excellent characteristics to obtain the inherent spatial and temporal correlation characteristic information of gait time series, effectively obtain the most representative time-space correlation gait feature information of wearable gait time series data, and make up for the limitations of traditional CNN and LSTM deep learning models in obtaining the most representative gait feature information of gait time series data which can effectively improve gait classification performance based on wearable gait sensing data.

Table 4. Comparison results of gait classification with similar deep learning algorithms (%)

Method	Accuracy	Precision	Recall
RNN model	73.94	75.81	67.14
CNN model	88.73	88.84	88.81
GRU model	89.28	89.40	89.35
LSTM model	89.82	90.14	89.72
CNN-LSTM model	91.45	91.54	91.53

4. Conclusions

In this paper, a new model for gait pattern deep learning fusion discriminant based on wearable sensing data is proposed, which can fully integrate the excellent characteristics of the most representative spatiotemporal characteristics of the data obtained by the convolutional neural network and the long short-term memory neural network deep learning model, and effectively obtain the most representative spatiotemporal correlation gait characteristics from the wearable sensor acceleration and gyroscope gait data, significantly improve the classification performance of wearable gait mode. It provides a reliable reference for further research of wearable multi-sensor gait mode deep learning classification.

Conflict of interest

The authors declare no conflict of interest.

References

1. Alemayoh TT, Lee JH, Okamoto S (editors). Deep learning based real-time daily human activity recognition and its implementation in a smartphone. 16th International Conference on Ubiquitous Robots (UR); 2019 Jun 24–27; Jeju, Republic of Korea. NYC: IEEE; 2019. p. 179–182.
2. Prince J, Arora S, de Vos M. Big data in Parkinson’s disease: Using smartphones to remotely detect longitudinal disease phenotypes. Physiological Measurement 2018; 39(4): 044005.
3. Thapar D, Jaswal G, Nigam A, et al. Gait metric learning siamese network exploiting dual of spatio-temporal 3D-CNN intra and LSTM based inter gait-cycle-segment features. Pattern Recognition Letters 2019; 125: 646–653.
4. Seyfioğlu MS, Gürbüz SZ, Özbayoğlu AM, et al. (editors). Deep learning of micro-Doppler features for aided and unaided gait recognition. 2017 IEEE Radar Conference; 2017 May 8–12; Seattle. NYC: IEEE; 2017. p. 1125–1130.
5. Sprager S, Juric MB. Inertial sensor-based gait recognition: A review. Sensors 2015; 15(9): 22089–22127.
6. Watanabe Y (editor). Influence of holding smart phone for acceleration-based gait authentication. Proceedings of the Fifth International Conference on Emerging Security Technologies; 2014 Sept 10–12; Spain. Alcala de Henares; 2014. p. 30–33.
7. Choi S, Youn IH, LeMay R, et al. (editors). Biometric gait recognition based on wireless acceleration sensor using k-nearest neighbor classification. Proceedings of the 2014 International Conference on Computing, Networking and Communications (ICNC); 2014 Feb 3–6; Honolulu. NYC: IEEE; 2014. p. 1091–1095.
8. Bao L, Intille SS (editors). Activity recognition from user-annotated acceleration data. Second International Conference on Pervasive Computing; 2004 Apr 18–23; Linz/Vienna. Berlin: Springer; 2004. p. 1–17.
9. Tahafchi P, Judy JW (editors). Freezing-of-gait detection using wearable sensor technology and Possibilistic K-nearestneighbor algorithm. 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2019 Jul 23–27; Berlin. NYC: IEEE; 2019. p. 4246–4249.
10. Nickel C, Brandt H, Busch C (editors). Benchmarking the performance of SVMs and HMMs for accelerometer-based biometric gait recognition. International Symposium on Signal Processing and Information Technology (ISSPIT); 2011 Dec 14–17; Bilbao. NYC: IEEE; 2011. p. 281–286.
11. Nickel C, Wirtl T, Busch C (editors). Authentication of smartphone users based on the way they walk using k-NN algorithm. Eighth International Conference on Intelligent Information Hiding and Multimedia Signal Processing; 2012 July 18–20; Piraeus. NYC: IEEE; 2012. p. 16–20.
12. Zou Q, Wang Y, Zhao Y, et al. Deep learning based gait recognition using smartphones in the wild. IEEE Transaction on Information Forensics and Security 2020; 15: 3197–3212.
13. Ding Z, Yang CF, Xing K, et al. (editors). The real time gait phase detection based on long short-term memory. IEEE Third International Conference on Data Science in Cyberspace (DSC); 2018 June 18–21; Guangzhou. NYC: IEEE; 2018. p. 33–38.
14. Anguita D, Ghio A, Oneto L, et al (editors). A public domain dataset for human activity recognition using smartphones. Proceedings of the 2013 European Symposium on Artificial Neural Networks; 2013 April 24–26; Bruges; 2013. p. 437–442.
15. Krizhevsky A, Sutskever I, Hinton GE (editors). ImageNet classification with deep convolutional neural networks. Proceedings of the 25th International Conference on Neural Information Processing Systems; 2012 Dec 3–6; Lake Tahoe. Advances in Neural Information Processing System; 2012. p. 1097–1105.
16. Mazilu S, Hardegger M, Zhu Z, et al. (editors). Online detection of freezing of gait with smartphones and machine learning techniques. 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops; 2012 May 221–224; San Diego. NYC: IEEE; 2012. p. 123–130.
17. Scherer D, Muller A, BehnkeS (editors). Evaluation of pooling operations in convolutional architectures for object recognition. 20th International Conference on Artificial Neural Networks; 2010 Sept 15–18; Thessaloniki. Berlin: Springer; 2010. p. 92–101.
18. Wang C, Yang H, Bartz C, et al. (editors). Image captioning with deep bidirectional LSTMs. Proceedings of the 24th ACM International Conference on Multimedia; 2016 Oct 15–19; Amsterdam. 2016. 988–997.
19. Gers FA, Schraudolph NN, Schmidhuber J. Learning precise timing with LSTM recurrent networks. The Journal of Machine Learning Research 2003; 3: 115–143.
20. Fernandez-Lopez P, Liu-Jimenez J, Kiyokawa K, et al. Recurrent neural network for inertial gait user recognition in smartphones. Sensors 2019; 19(18): 4054.
21. Jun K, Lee Y, Lee S, et al. Pathological gait classification using Kinect v2 and gated recurrent neural networks. IEEE Access 2020; 8: 139881–139891.

Wearable Technology (2020) Volume 1 Issue 1, *pp.* 41–55.
doi: 10.54517/wt.v1i1.1614

Asia Pacific Academy of Science Pte. Ltd.

REVIEW ARTICLE

Strategic choices for high-quality development of intelligent wearable sporting goods industry in the new era

***Hengfen Huang*[1], *Jun Qiu*[2,3*]**

[1] *School of Physical Education, Huaqiao University, Xiamen 361021, Fujian, China*
[*2] *Institute of Physical Education and Great Health, Huzhou University, Hangzhou 313000, Zhejiang, China. E-mail: qiujun@mail.tsinghua.edu.cn*
[3] *Division of Sports Science and Physical Education, Tsinghua University, Beijing 100084, China*

ABSTRACT

Use research methods such as survey research methods and literature data methods, and use strategic management theory to analyze the strategic development environment of the smart wearable sporting goods industry. On this basis, the strategic goal of high-quality development of the smart wearable sporting goods industry is clarified. It establishes a strategic policy of people-oriented, focuses on research and development, and scientific management, and proposes a strategic development path for cultivating leading enterprises, developing industrial clusters, and promoting research and development innovation. In order to promote the high-quality development of the smart wearable sporting goods industry in the new era, specific strategic safeguard measures are putted forward in terms of providing talent support for industrial development and improving the legal system for the development of the smart wearable sporting goods industry to achieve high-quality development.

Keywords: wearable sporting goods industry; high-quality development; strategy

1. Introduction

Since 2013, with the upgrading of mobile Internet technology and smart hardware devices, smart wearable sporting goods have become popular all over the world. "The golden key to connect the human body and smart devices" is the most vivid description of smart wearable sporting goods[1]. In the era of mobile intelligent network, a large number of wearable devices such as smart bracelets, smart running shoes, smart clothing, smart wristbands, and smart glasses[2] have appeared in the sports consumer market to better meet people's dual needs for scientific exercise and personalized health services. This also indicates that the smart sports equipment consumption industry that is close to people's lives in the future will be a high-tech innovation industry based on massive data collection and precise calculation and analysis. Today, China's industrial upgrading is accelerating, and the industrial focus is shifting to the tertiary industry. The development of the mobile Internet economy has significantly increased the frequency of people's use of mobile terminals and the time spent on mobile terminals. The collision between

ARTICLE INFO
Received: February 19, 2020 | Accepted: March 30, 2020 | Available online: April 14, 2020

CITATION
Huang H, Qiu J. Strategic choices for high-quality development of intelligent wearable sporting goods industry in the new era. Wearable Technology 2020; 1(1): 41–55.

the healthy sports industry and the mobile Internet makes a variety of smart wearable sporting goods one of the fastest growing product categories in the world's electronic products[3]. It is estimated that from 2020 to 2025, the compound growth rate of the market size will reach 20%. By 2025, the market size of China's smart wearable products is expected to exceed 1,500 yuan. At the same time, smart wearable products have begun to develop in the direction of remote diagnosis and treatment, data cloudification, product verticalization, functional specialization, and diversification of profit models, showing broad development prospects for smart wearable products[4]. In order to better control the development status of the smart wearable sporting goods industry, analyze the achievements and shortcomings in the development process so as to better promote the sustainable and high-quality development of the smart wearable sporting goods industry in the new era, the research starts with the strategic development factors of promoting the smart wearable sporting goods industry, and focuses on the analysis of the strategic environment, strategic policy, strategic goals, strategic choices, and strategic guarantees for the development of the wearable sporting goods industry which are of great significance for the healthy development of the smart wearable sporting goods industry.

2. Analysis of the strategic environment for the development of China's smart wearable sporting goods industry

2.1. Analysis of the policy environment

Since the country proposed the innovation-driven development strategy in 2012, smart wearable sporting goods have been included in the scope of key development of China's high-tech industry, and the annual growth rate of its R&D (research and development) investment has been maintained at 20% above[5]. As early as 2013, the General Office of the National Development and Reform Commission also listed wearable smart products as a key support project in the "Notice on Organizing and Implementing the Special 2013 Industrialization of Mobile Internet and Fourth Generation Mobile Communications (TD-LTE)". In 2015, the state proposed the "Made in China 2025 Strategy", which brought a rare development opportunity to the high-tech smart wearable sports goods manufacturing industry. In the same year, the State Council issued the "Several Opinions on Accelerating the Development of the Sports Industry and Promoting Sports Consumption", which brought huge consumption space to the wearable smart sporting goods market. In 2019, the government work report of the State Council proposed to accelerate the transformation and upgrading of the manufacturing industry to an intelligent, green, and service-oriented manufacturing industry. Among them, the smart wearable products industry was mentioned in the focus areas of benefiting people's livelihood and promoting consumption[6]. In September of the same year, the General Office of the State Council issued the "Notice on the Outline of Building a Powerful Sports Country", clearly proposing to further promote the deep integration of the Internet, big data, artificial intelligence and the sports real economy. It has effectively promoted the R & D, manufacturing and industrial transformation and upgrading of the wearable sports and sports goods manufacturing industry, improved the supply capacity of smart wearable sports goods, and accelerated the quality and efficiency of sports goods services. On September 20, the General Office of the State Council once again issued a document to promote the high-quality development of China's sports industry, encourage financial institutions to support the construction of the sports industry, and make the sports industry truly a pillar industry of the national economy. To sum up, the state has given great policy attention and support to the development of the wearable sports industry in terms of promoting the development of sports, motivating national fitness, improving the development of high-tech and sports industries, and stimulating the consumption economy[7].

2.2. Analysis of technical environment

The full application and market promotion of artificial intelligence technology, 5G technology and Internet of Things technology in the real economy has provided a good technical environment and high-tech technical support for the development of the smart wearable sporting goods industry. Specifically, in: (1) 5G technology provides basic support for smart wearable products, and promotes the iteration and progress of the technical environment. The technical manufacturing of smart wearable sporting goods involves three aspects: Application software, device hardware and artificial intelligence. Smart wearable sporting goods possess powerful information processing functions, and have many high-tech features such as wearability and human-computer intelligent interaction, and need to be supported by chip technology, sensor technology, intelligent interaction technology and battery technology[8]. (2) Chip technology provides high-efficiency digital signal core technical support for wearable sporting goods, and its technical content plays a vital role in improving the hardware platform of smart wearable sporting goods and promoting the development of the entire industry chain. (3) Sensor technology provides physiological sign construction support for smart wearable sporting goods in terms of biosensors, inertial sensors, environmental sensors, etc., and provides direction recognition, positioning and navigation, altitude calculation, speed frequency, etc. for individuals, which can solve the problems related to the user's own activities. The problem of data acquisition can provide users with external environmental information and suggestions in real time[9]. (4) Flexible electronic components provide indispensable sensing technology for the sensitivity of smart wearable sporting goods. (5) Artificial intelligence interaction technology provides voice recognition, eye control and mind muscle feedback control technology for smart wearable sporting goods. (6) Battery technology provides flexible battery life technical support for the chip processor of smart wearable sporting goods. In addition, the development of Internet big data and cloud computing, as well as the development of Internet of Things technology are the technical support environment for the innovation of wearable sporting goods.

2.3. Social Environment Analysis

During the "Thirteenth Five-Year Plan" period, the number of netizens in China increased from 688 million to 989 million, an increase of 43.7% in five years. The overall scale of netizens in China has accounted for about 1/5 of the global netizens. The scale of mobile netizens in China is 986 million, an increase of 88.85 million mobile netizens compared with March 2020, and the proportion of netizens using mobile phones to access the Internet is 99.7%, Among them, the proportion of netizens under 20 years old is 17.1% higher than that of this group; the proportion of netizens over 60 years old is 11.0% higher than that of this group, It is enough to see that the potential consumer group of smart wearable sporting goods in the future will be very large. According to data released by the National Bureau of Statistics in July 2020, in 2020, China's smart wearables shipments will be 107 million units, accounting for about 1/4 of the global smart wearables shipments, a year-on-year increase of 8.1%, it is predicted that in the next five years, the compound growth rate of China's smart wearable products shipments will be 20%. In 2025, China's smart wearable product shipments will reach 266 million units. Products exist to meet the needs of consumers. When wearable sporting goods enter the market as an emerging product, consumers always have a certain time to accept them and put forward reasonable suggestions for improvement. To this end, the author conducts an online questionnaire survey in the online sports community with 3 million users, and summarizes the functional requirements of sports enthusiasts for wearable sporting goods by analyzing 36,800 valid questionnaires (**Table 1**)

Table 1. Sports enthusiasts' functional requirements for sports wearables

Functional requirements of sports enthusiasts for wearable sporting goods	The proportion/%
Wearable sporting goods do not rely solely on time or distance to judge the exercise level or physical condition of sports participants, but must be built into smart wristbands, smart helmets, smart bracelets, smart watches, smart vests, and smart running shoes. Micro-sensors record physical data during exercise, such as heart rate, calories, blood pressure, etc., to quantify the exercise effect of sports participants.	93.3
Wearable sporting goods should pay attention to personal health information in daily life, including sleep, daily activities, etc., and network with professional physical examination centers or health care institutions to become health stewards for healthy exercisers and sick exercisers.	82.6
Manufacturers of wearable sporting goods should invite sports professionals, professional athletes and fitness coaches to join, and through the sharing and interaction of these professional users, meet the needs of many sports participants for scientific fitness.	64.8

Figure 1 shows the trend of users' attention to smart wearable sporting goods at different price points from 2016 to 2020. Among them, the proportion of products priced above 2,000 yuan has dropped significantly, while the proportion of products priced below 1,500 yuan has shown a continuous upward trend, and the attention of products around 500 yuan has basically fluctuated slightly.

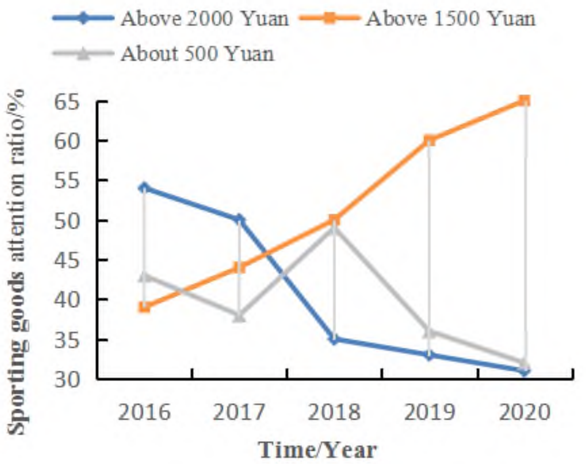

Figure 1. The trend of attention to smart sports wearables at different prices from 2016 to 2020.

In addition, the social network trust of smart wearable sporting goods is an important guarantee for the realization of its own value. According to a survey by iResearch, 36.2% of consumers are relatively optimistic about the use of smart wearable sporting goods, 2% of consumers take a wait-and-see neutral attitude, and 12.6% say they will not use smart wearable sporting goods (**Figure 2**).

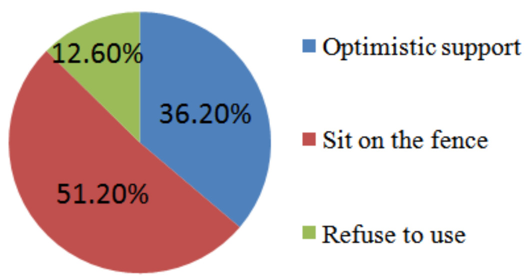

Figure 2. Social trust for smart sports wearables.

The main reason for consumers' lack of trust in smart wearable sporting goods is not only the fear of possible leakage of personal privacy information, but also consumers' concerns about the many uncertainties in the new products themselves. Therefore, how to establish the initial trust of potential consumer groups in smart wearable sporting goods is very important for product manufacturers and distributors. Only by paying attention to the health care and fitness monitoring functions of smart wearable sporting goods, to consumer experience, and increasing publicity, can more and more consumers recognize and accept smart wearable sporting goods.

2.4. Industry environment analysis

The development trend of the smart wearable sporting goods industry

(1) The production scale of the industry is expanding year by year, and the industry activity is rapidly increasing. According to Wearable's "2019

Best Fitness Tracker Buying Guide", fitness data trackers alone hit a $5.4 billion market in 2019. In the future, it is expected to become a new growth point of the global information technology industry after smartphones and tablet computers.

(2) The overall development trend of multinational companies rushing to deploy smart wearable products manufacturing and domestic well-known enterprises accelerating their follow-up has not changed. Google Glass, Samsung Apple smart watch, Intel's wearable processor, FITBIT's health bracelet, SPROUTLING smart anklet, etc. have all achieved rapid industrial entry in the fields of sports, health care and other products. Chinese electronics companies have also increased their investment in capital and technology research and development in the industrial strategic layout of wearable products. Products such as Guoke Electronics GEAK watches, Umicom Omate watches, Yingqu Technology inWatch, and Zhiji Electronics ZWatch have been launched one after another. In terms of smart bracelets, Xiaomi bracelets, Baidu Gudong bracelets, TenghaiShiyangti memory bracelets, ZTE GrandWatch, Huawei Talk Band bracelets, etc. quickly seized market share.

(3) China's smart wearable sporting goods, as an emerging field of electronic consumption, the overall development trend of the industry is good, but the product concept is popular and the market response is relatively bleak. In the industry chain, upstream chip manufacturing, radio frequency technology, and sensor manufacturers have responded positively, but downstream enterprises, due to cost control considerations, have weak investment in brand technology research and development and new product development, resulting in serious product homogeneity and affecting technology upgrades and development. Coupled with the lack of large-scale leading enterprises to drive the integration of the industry chain, the technical strength and brand appeal of smart wearable sporting goods have certain development bottlenecks[10].

Research on the production and sales of smart wearable sporting goods

The innovation of the smart wearable sporting goods industry lies in intelligence, which requires extremely high scientific and technological research and development technology. Under the background of well-known foreign sports giants such as Nike, Under Armour, and Adidas, which have stagnated in the research and development of wearable body hardware products due to production costs and technological investment, domestic enterprises such as Li Ning and 361° have joined the field of sports smart wear in large numbers. According to statistics from the International Data Corporation IDC, in 2019, the shipment of smart wearable sporting goods in China has reached 13.2 million units, a year-on-year increase of 27.8%, and the production output value has reached 14.9 billion yuan. From the perspective of the production and sales rate of sporting goods, the production and sales rate of Huami Technology and Gudong's smart running shoes and smart clothing, and Xiaomi smart sportswear exceeded 90%; the production and sales rate of smart basketball and smart football of Jianji Technology, as well as smart basketball of Yundong Technology and Wanshi Sports Smart Technology is over 92% (**Table 2**). It can be seen that smart wearable products perceive various physiological indicators of exercisers through chips and sensors to help users obtain better training effects, and it is foreseeable that they have a lot of room for growth.

Application of smart wearable sports goods

A total of 1,854 questionnaires were collected through the questionnaire survey on the Questionnaire Star Online, and 62 invalid questionnaires were excluded. Finally, 1,792 valid questionnaires were sorted out and analyzed:

(1) Smart wearable sporting goods are well known and favored by the public. 95.2% of people know and know about smart wearable sports goods, and 65.4% of them have purchased smart wearable sports goods, especially male consumers are more enthusiastic about smart wearable sports goods. This shows that smart wearable sporting goods are popular and favored by the public.

Table 2. Production and sales of domestic smart sports wearable manufacturers in 2019

Supplier	Products	2019 output/10,000 units	2019 sales/10,000 units	Production and sales rate %
Xiaomi	Xiaomi bracelet	171.4	133.5	77.8
Apple	smart watch, smart bracelet	554.3	467.2	84.2
Life sense	smart watch, smart bracelet	19.5	12.7	64.7
BBK Electronics	smart watch	137.6	99.6	72.5
Huawei	smart watch	121.8	107	88.4
mobvoi	smart watch	11.4	8.7	79.2
Erock Sports Smart Technology	smart basketball	12.8	11.9	92.9
Zepp Health	Smart running shoes, smart clothing	167.4	149	90.2
GenGee	Smart football, smart basketball	14.6	13. 6	93.8
CloudFighting	smart basketball	13.8	12.7	92
Codoon Information Technology	Smart running shoes, smart clothing	129.7	118.4	91.4
Beijing Hongqi Shengli Technology	HIPLAY smart basketball bracelet	13.3	11.1	87.4
Li Ning	smart pedometer shoes	9.8	7.4	80.2
Shuangchi	smart pedometer shoes	6.7	5.1	81.3
361°	smart positioning shoes	10.6	7.9	77.3
clouds	smart positioning shoes	7.2	6.2	84.4
Huan Cheng	smart positioning shoes	3.4	2.5	81.3
Foshan Libao Sports Technology Co., Ltd.	smart sportswear	3.8	3.2	84.2
XiaoMi	smart sportswear	5.2	4.7	90.3
body memory	smart bracelet, sportswear	7.5	6.3	84.35

(2) The audience of smart wearable sporting goods tends to be younger. 20–29-year-olds accounted for 35.21%; 30–39-year-olds accounted for 58.45%; 20–39-year-olds accounted for more than 90%, indicating that the younger generation is paying more attention to the current smart wearable sporting goods. usage trends. Due to the advanced consumption awareness of young groups in this age group and their emotional preference for smart wearable sporting goods, the people who pay attention to wearable goods are generally younger.

(3) Sports bracelets and smart watches have become the most popular products in the market. Consumers are more inclined towards sports bracelets and smart watches, with the proportion of the two being 78% and 67%, followed by health trackers, smart earphones, and smart running shoes. On the one hand, smart bracelets and smart watches are light and convenient, with many functions, which can bring consumers more convenience in life and exercise; on the other hand, these two smart devices are closer to people's lives and have strong practicability.

(4) Health monitoring and data recording func-

tions are the core functions of smart wearable devices. 92.24% of consumers think that they are most concerned about health monitoring and data recording functions, and only 7.76% of consumers attach importance to the fashion brand.

(5) Professionalism, cost performance and comfort are the starting points of purchase. Professionalism, cost performance and comfort are the three most important factors, all of which account for more than 50%. In addition, data compatibility and brand awareness accounted for less than 20%, indicating that consumers pay more attention to the function when purchasing intelligent wearable products.

(6) The level of education largely affects the attention of smart wearable sporting goods. Bachelor degree or above accounted for 68%, junior college degree accounted for 18%, and high school and below degree accounted for 14%. It can be seen that the higher the education level, the higher the awareness and acceptance of smart wearable sporting goods.

Through the questionnaire analysis of smart wearable sporting goods, it fully shows that smart wearable sporting goods are loved by the public, especially the advanced consumption awareness of the youth group makes them favored and admired. It can be seen from the survey that the public has a process from cognition to consumption development of smart wearable products, that is, preliminary cognition (low-level stage)-very concerned (intermediate stage)-purchase and consumption (advanced stage). The public understands and is familiar with smart wearable sporting goods from the perspective of health and fashion, and perceives their intelligence and convenience. In addition, the audience with higher education level has higher awareness and acceptance of smart wearable sporting goods, and vice versa. This provides more reference for the technology research and development, fashion comfort and health training of smart wearable sporting goods in the future, which has a broad space for product research and development and sales growth.

3. Strategic goals for the development of the smart wearable sporting goods industry

3.1. Industrial development goals

In 2015, the State Council issued the "Several Opinions on Accelerating the Development of the Sports Industry and Promoting Sports Consumption" clearly stated that, by 2025, the total scale of China's sports industry development will exceed 5 trillion yuan, focusing on the development of sports products with independent intellectual property rights, improving the scientific and technological added value of sports goods, and enhancing the market competitiveness of brand enterprises. In addition, according to the "14^{th} Five-Year Plan Outline and 2035 Vision Outline", during the "14^{th} Five-Year Plan" period, in order to carry out national construction campaigns and build a sports powerhouse, China will expand sports consumption and develop sports industry such as fitness and leisure, outdoor sports, etc. As an important port for accessing national fitness in the future mobile Internet era, the smart wearable sporting goods industry is still in the initial stage of industrial development and the period of infant industry development. In this sense, the smart wearable sporting goods industry has broad prospects for development. (1) From the perspective of its industrial development cycle, the cycle from scientific and technological progress to enterprise investment in research and development, and then to the large-scale development of the industry is about 2 to 3 years. This means that the industry can still experience two rounds of rapid industrial development and expansion by 2025. (2) From the perspective of its sales scale, according to the statistics of the International Data Corporation IDC, by 2025, China's wearable sporting goods industry sales strategy development target shipments are positioned at about 38 million units, and its industry sales will exceed 100 billion yuan. (3) From the perspective of industrial concentration areas, the strategic development planning target area of China's smart wearable sporting goods industry cluster should be established around the Pearl River Delta, Yangtze River Delta, Bohai Rim and Sichuan-Shaanxi regions where the electronic information industry is relatively developed. Today, Shenzhen, Guangzhou, Beijing, Tianjin, Shanghai, Suzhou, Chengdu, Chongqing, Xi'an and other cities have gathered a group of enterprises engaged in the research and development, production and marketing of smart wearable sporting goods, forming large-scale industrial clusters. Only the Pearl River Delta in Shenzhen, as an important production base of China's intelligent wearable sports goods, has produced intelligent wearable products accounting for about 80% of global shipments. It has a complete industrial chain from intelligent chips, sensors, flexible components, terminal equipment to human-computer interaction solution design, product design and marketing in the upstream and downstream of industrial development. It has formed a number of leading enterprises engaged in the production of intelligent wearable intelligent sports goods represented by Huawei and ZTE.

3.2. Technological innovation goals

In formulating the technological innovation and development goals of smart wearable sporting goods, China, it mainly solves the problems of product power consumption and data accuracy in the integration of smart wearable products with 5G and high-tech such as the Internet of Things, and improves the experience of smart wearable sports products by accelerating the special research and development of personal data products.

(1) With the advent of 5G communication technology and the era of the Internet of Everything, the consumer electronics industry, which is dominated by smart wearable sports goods, ushered in new development opportunities. The development of the smart wearable goods industry under the 5G concept can promote glass exterior parts, sapphire and In-depth development of market demand for hardware appearance materials such as ceramics. With the popularization of smart wearable sporting goods, it will become an important port and application terminal of the Internet of Things. It can be seen that 5G interconnection technology has effectively promoted the upgrading and development of smart wearable sporting goods technology, and its impact is huge and far-reaching.

(2) The technological innovation of enterprises should develop in the direction of solving the problems of product power consumption and data accuracy. In reality, many smart wearable sporting goods have problems such as excessive power consumption, weak charging and battery life, low accuracy of exercise reports, and low professionalism. For this reason, the portable demand of smart wearable sporting goods determines that it is necessary to strengthen investment in scientific research and development, rely on new battery technology and flexible materials to reduce the overall power consumption of the system, prolong the charging cycle, and achieve large-scale commercial use.

(3) Accelerate the special research and development of personal data products. Enterprises should create a personalized human digital ecosystem for each user. Under the condition of ensuring data security and confidentiality, the collection, aggregation and analysis of personal exercise and health data will give birth to a larger-scale data industry.

(4) The technological innovation goal of smart wearable sporting goods is to improve the user experience and avoid product homogeneity and popularization. For this reason, enterprises should focus on the research and development and application of core technologies, strengthen the functional optimization design of smart wearable products, and use the Internet to make NFC, Bluetooth and smart terminals seamlessly connected. Voice and somatosensory control are used in the interface of human-computer interaction, and muscle awareness sensing is more used in sensor technology. In short, smart wearable sporting goods must not only make technological innovations on hardware devices, but also achieve powerful functions through software support, big data interaction, and cloud interaction, and create an industrial intelligence core technology system.

4. Strategic policy formulation for the development of smart wearable sporting goods industry

4.1. People-oriented, to meet the growing diverse sports needs of the people

The development of China's smart wearable sporting goods industry must be based on enhancing people's physique and improving the health of the people, and pay attention to meeting the growing needs of the people for the development of diversified sports and fitness.

(1) With the promotion and implementation of national fitness activities, China's mass physical exercise population is on a linear upward trend[11], providing opportunities for the development of the smart wearable sporting goods industry. The survey data shows that 87.5% of the elderly consumer groups pay more attention to the health monitoring function of smart wearable sporting goods; 70.5% of young consumers believe that the biggest functional requirement of smart wearable sporting goods lies in the monitoring of individual sports signs. For 90% of sports health care providers, through smart wearable sports equipment, it will be very important to know one's own exercise environment, exercise calorie consumption, monitor one's full range of physical signs and health data in real time, and provide information services for the physical and mental health care of living individuals.

(2) The development of the smart wearable sporting goods industry can meet the growing demands of the masses for "sports and social interaction". Find fitness and sports partners on social networks and circles of friends through mobile smart wearables, making people's lifestyles richer and more interesting. To this end, sporting goods manufacturers should strengthen the product research and development of smart wearable sporting goods, taking wearable sports products as the starting point, taking advantage of its specialization and individualization, it gradually integrates into mass fitness activities, competitive sports and school sports, and strives to expand the efficient supply of smart wearable sports products and services[12], so as to make sports consumption interactive, sharing, rational and cross-border, which can better reflects the development direction of the sports industry in serving the people.

4.2. Focus on research and development to promote the high quality development of wearable sporting goods industry

In recent years, the structure of China's sports industry has been continuously optimized, the technological content has been continuously improved, and the added value of the sports industry has maintained rapid growth. In 2019, the General Office of the State Council issued the "Opinions on Promoting National Fitness and Sports Consumption to Promote the High-quality Development of the Sports Industry", which has a clear strategic positioning for the development of the sports industry, that is, to promote national fitness and guide sports consumption. The sports industry has become a pillar industry of the national economy. This not only emphasizes that the added value of the sports industry should reach a certain scale in the future proportion of the national economy, but also realize the integrated development of the sports goods industry and other industries, and take the road of high-quality and international development. As a high-tech manufacturing industry, China's smart wearable sports goods are an important part of the high-quality development of the sports industry. At present, China's smart wearable sports products industry has experienced a rapid development period from 2013 to 2015. During this period, there are low-level primary processing stages of imitation, counterfeiting, international brand OEM and OEM production. Development problems such as small operation, fragmentation, low technology content, poor independent innovation ability, serious product homogeneity, extremely low brand premium ability, weak brand equity, and low international influence[13]. In the future, smart wearable sporting goods should focus on R & D investment, enter the golden period of industrial transformation and upgrading as soon as possible, strive to become bigger and stronger, and enhance the market competitiveness of China's smart wearable sporting goods industry.

4.3. Scientific management, standardize the market order of wearable sporting goods industry

It is necessary to adhere to scientific management according to law, establish and improve relevant laws and regulations, improve the supervision and management mechanism, and standardize the market order of wearable sports goods.

(1) Through the formulation and improvement of policies and systems, strengthen the industrial guidance of the smart wearable sporting goods industry, increase the support of technological transformation and scientific and technological funds to the production enterprises of smart wearable sporting goods, guide enterprises to increase investment in industrial research and development, enhance their independent innovation capabilities, and strictly control the risks of homogeneous competition and overcapacity of similar products.

(2) Strengthen the responsibilities of the main body of supervision and the scope of management functions, determine the rights and obligations of various market players, standardize the main behavior of the producers of smart wearable sporting goods, and severely crack down the intellectual property infringement and intellectual property rights in the production of smart wearable sporting goods through laws and regulations. The act of producing and selling counterfeit and shoddy electronic products effectively maintains the market order of the development of the high-tech sports industry.

(3) The government management department should promote the production standardization and quality certification of smart wearable sporting goods, formulate sound national and industrial standards for smart wearable sporting goods, strengthen normalized supervision and inspection and product quality inspection strengthen scientific supervision and standardization in terms of quality.

5. Strategic choice for the development of smart wearable sporting goods industry

5.1. Cultivate leading enterprises and build industry brands

At present, there are many domestic manufacturers of smart wearable sporting goods, and their shipments are also very large. Smart wearable sporting goods represented by Xiaomi bracelet can measure steps, pulse, time, etc. Smart wearable sporting goods represented by Li-Ning sneakers and smart sports vests can measure the stride frequency, gait, heart rate and changing temperature of athletes. However, in the process of industrial development, there are still relatively few leading companies that can lead the research and development and manufacture of wearable sports smart devices. Most of the manufacturing enterprises in the industry are small and micro enterprises, and the phenomenon of OEM and copycat manufacturing is still relatively prominent.

To this end, wearable sports product research and development enterprises must establish a smart wearable sports goods industry chain that conforms to the characteristics of China's sports culture environment. Leading enterprises can drive and incubate a large number of small and micro start-ups through innovation and become a new force in the development of the smart wearable sporting goods industry. Considering that China's smart wearable sporting goods manufacturers are mainly located in Shenzhen, Beijing, Shanghai, Chengdu and other places where the electronic information industry is relatively developed[14], the government needs to guide enterprises to optimize the technological innovation and product structure layout of products. Upgrade and expand, form a leading enterprise of smart wearable sporting goods, form core competitiveness, and build a well-known brand in the industry. For example, Shenzhen-based companies such as Huawei, ZTE, Coolpad, Yingqu Technology, Xiberry Technology, and Yunmi Technology have all stepped up their efforts in the research and development of new smart wearable products. After years of development, a smart wearable sporting goods manufacturing echelon consists of large listed companies, small and micro enterprises and maker teams has gradually formed. The agglomeration effect of industry brands is gradually increasing, and it is becoming an important base for the wearable device industry in China and even the world. Leading enterprises of smart wearable sporting goods must aim at the high-end links of the product value chain. Independently develop and design products, determine effective solutions, provide professional commercial after-sales service, develop new smart wearable products with independent intellectual property rights, continuously improve the usability and stickiness of products, and create a brand effect in the smart wearable sporting goods industry.

5.2. Develop industrial clusters and expand industrial scale

As a new high-tech manufacturing field in China, the smart wearable sporting goods industry has an overall good development trend and broad development prospects[15].

(1) Chinese enterprises engaged in the production of smart wearable sporting goods should achieve vertical integration in the product manufacturing industry chain, that is, they should be able to achieve technological innovation and production supply of production parts such as chips, sensors, and flexible components, and coordinate products downward. The commercial promotion, expansion of sales channels and logistics guarantee has laid a good foundation for consolidating and improving the industrial chain of its own brand.

(2) Enterprises should innovate business models in the design, production and sales of smart wearable sporting goods, improve the core competitiveness of the company's brand, increase innovation and application in the functional experience of products, and enhance the brand technology content of smart wearable sporting goods. In order to guide enterprises in the industry to form core competitiveness as soon as possible, it is necessary to focus on the development model of "new project-industrial chain-industrial base-industrial cluster", build a complete supporting industry cluster, and continuously improve the development level and agglomeration level of the smart wearable industry. Promoting the leading enterprises with significant cluster effect in the region to adjust the production structure, expand the scale of industrial production, form a grape bunch effect, improve the industrial benefits of smart wearable sporting goods, and support qualified large-scale brand enterprises to go out and merge or take shares in foreign smart wearable sporting goods manufacturing enterprises, develop overseas sales markets, and enhance the international competitiveness of the brand. By 2025, a number of enterprises with sales revenue of over 10 billion smart wearable products will be cultivated in Shenzhen, Beijing, Shanghai, Chengdu and other places, and the formation of industrial clusters will be promoted.

5.3. Promote R & D innovation and highlight intelligent technology

Innovation is the lifeblood and driving force of industrial enterprises. Smart wearable sporting goods enterprises should strengthen R & D innovation, increase R & D innovation, and demonstrate the application charm of smart technology.

(1) Realize biometric authentication for smart wearable sporting goods. Sensors based on fingerprint authentication have been widely used in smartphones and laptops. As a personal smart device that provides personalized services, smart wearable sporting goods should provide biometric authentication identities that are more advanced and difficult to tamper with fingerprint recognition, such as sound waves. Recognition and iris recognition, etc., better support the mobile payment function of smart wearable sporting goods, and realize mobile smart payment for users without mobile phones.

(2) Enhance the sports health monitoring function of smart wearable sporting goods. Smart wearable sporting goods must collect and monitor the user's movement data and physiological signs in an all-round way. For example, the athlete's smart vest

can accurately measure various data generated by the user during exercise, such as oxygen consumption, stride frequency, stride length, heart rate, respiration, sweat composition, etc., expanding the breadth and depth of application of smart wearable sporting goods in professional sports. It is necessary to monitor the user's blood pressure, blood sugar and other physiological indicators in real time from the perspective of medical care, the data is uploaded to the mobile cloud service application or the doctor of the medical institution for analysis and feedback, which is used to monitor and improve the medical care of athletes and patients, and to remind the health and safety risks faced by the athletes. Especially in response to the outbreak of the Coronavirus disease in 2020, if smart wearable sporting goods can give full play to expand their physiological sign monitoring functions and big data artificial intelligence, it can not only help users detect infectious diseases in advance, but also assist medical and health care. The agency conducts real-time monitoring and analysis of the dynamic development of the epidemic. In addition, smart wearables can enable telemedicine care, and enjoy timely mobile health monitoring functions for chronically ill patients, which is a new profit growth point for smart wearable medical consulting services in the future.

(3) Make smart wearable sports equipment serves as smart coach. Smart coach is a newly developed function of smart wearable fitness products. Smart wearable sports products give different feedbacks and switch between different types of sports through the collection of exercise data and physiological sign data such as the user's exercise habits, exercise volume, exercise posture, etc. For a period of time, it can formulate scientific exercise plans for users or put forward various suggestions to users based on data to meet the individual fitness needs of users. While improving athletes' sports performance, it can prolong the sports career of athletes and enhance the influence of smart wearable sports on the public to develop scientific sports concepts and healthy lifestyles.

(4) Smart wearable sporting goods should enhance the technological functions of virtual reality and augmented reality. Compared with the traditional human-machine interface interaction, the application of VR and AR technology on smart wearable sports goods can enhance the user's immersive experience and help users better engage in scientific fitness sports.

(5) Add the function of virtual personal assistant for smart wearable sports goods. According to the user's feelings and emotional changes, it provides sports health care guidance, schedule management, and message optimization notification.

(6) Smart wearable sporting goods need to achieve more accurate motion recognition. With the help of various motion sensors such as gyroscopes, accelerometers and magnetometers inside the smart wearable, users can recognize motion accurately in teach and learn health sports and manage health data. The sensors with higher complexity and accuracy reduce user motion calculation errors to within 1%.

(7) Enterprises should deeply implement the integrated application development of smart wearable sporting goods with new technologies such as big data, cloud computing, and artificial intelligence, and improve the innovation capabilities of the equipment itself in the source of key common technologies such as smart chips, precise sensing, and human-computer interaction, design independent operating system for smart wearable sporting goods, etc.[16]

6. Strategic safeguard measures for the development of smart wearable sporting goods industry

6.1. Improve policies to support the development of the smart wearable industry.

In order to better promote the development of the smart wearable sporting goods industry and make it a pillar industry for the development of the national economy.

(1) Governments at all levels need to organize relevant departments to lead the establishment of a

leading group to coordinate the development of the smart wearable device industry in the region. Scientifically formulate the development plan of the smart wearable industry cluster in the region based on the actual conditions, integrate high-tech resources, formulate policies and measures to support the development of the industry in detail, encourage enterprises to strengthen technology research and development, and improve the layout and construction of the industrial chain, make all brand enterprises in the industrial cluster reach a consensus on industrial chain support and regional division of labor, and rationally arrange major application demonstrations and industrialization projects on smart wearable device manufacturing.

(2) Governments at all levels should actively implement the preferential fiscal and taxation policies and industrial support policies of relevant national ministries and commissions to support the development of the smart wearable industry, and actively explore diversified support policies that are suitable for the development of the region and to create an industrial chain and industrial cluster of smart wearable products. Specifically, it is necessary to actively strive for national-level and provincial-level scientific and technological innovation, industrial strong foundation and other special financial support for brand enterprises and science and technology enterprises, and provide corresponding financial support. At the same time, the government should increase efforts to guide financial capital to establish high-tech industry funds, increase financing and support for the smart wearable device industry, expand the scale of industrial development, and enhance the international competitiveness of the industry.

(3) The government should encourage enterprises to increase their independent R & D and innovation efforts. It is necessary to promote enterprises in the industry to focus on innovating research on key common technologies such as smart chips for smart wearable devices, high-performance sensors, human-machine intelligent interaction, and flexible components, and encourage industry backbone enterprises and scientific research institutions to actively integrate into global industrial technologies In the formulation of standards and technical specifications, master the right to speak in the development of the smart wearable device industry. It is necessary to cooperate with enterprises to establish a technical information research center for the development of the smart wearable device industry, give full play to the scientific research, match the cooperation between enterprises and scientific research units, improve the cooperation mechanism of production, education and research, accelerate the transformation efficiency of industrial technology, and promote the high-quality development of the smart wearable device industry.

6.2. Provide talent support for the development of smart wearable industry

As a high-tech industry, the smart wearable industry is a typical knowledge and technology-intensive industry, which determines that the development status and trend of the smart wearable industry is not mainly measured by the large-scale investment of physical capital, but by the real possession and potential of human capital. Without strong human capital as the backing support for industrial development, and without a strong professional talent team, the smart wearable device industry will never be on the right track of high-quality and high-speed development. To this end, the government and enterprises need to do the following work:

(1) The government should attach great importance to the cultivation of intelligent wearable sports equipment professionals, and make overall planning and deployment in terms of scientific research, types of skilled personnel, quantity, and funding. Actively carry out school-enterprise cooperation, create a smart wearable technology innovation laboratory, and cultivate professionals with solid theoretical foundations and outstanding application capabilities; Colleges and universities should add relevant majors, optimize the structure and education model of higher education and vocational education, and cultivate multi-level talents re-

quired by various links in the development chain of the smart wearable industry. Encourage high-tech enterprises and universities to jointly run schools, combine production, learning and research to train backbones and academic leaders for the development of the smart wearable industry; in addition, industrial innovation incentives should be implemented to mobilize people's enthusiasm, and a system and guarantee mechanism for respecting talents and making good use of talents should be formed.

(2) Enterprises should make good use of global resources, introduce technology entrepreneurial talents from overseas who can promote the development of related industries, and promote technological innovation and management innovation in the smart wearable industry chain. To this end, enterprises and related organizations should cooperate to set up special institutions, create overseas professional talent databases, collect information and recruit talents. The government departments should increase funding for overseas returning scientific and technological talents, including the establishment of special funds to attract smart wearable product research and development talents to return to work in China, and to attract more overseas students to return to China for development.

(3) Do a good job in supporting services for talents, adopt more flexible and special policies in the fields of technology, management, skilled talents' work treatment, settlement, and children's enrollment, etc. to promote industrial development, and improve the employment environment and life of talents in related industries environment, in order to promote the flow of talents.

(4) The development of the smart wearable device industry requires not only an excellent scientific research team and skilled team, but also a team of entrepreneurs who dare to innovate and are good at innovation. To this end, the government should select and train a group of enterprise leaders with excellent decision-making, organization, and coordination skills among smart wearable industry manufacturing enterprises, so that they can lead the entire industry to develop in a high-quality direction.

6.3. Improve the legal system for the development of the smart wearable industry

From a domestic point of view, the imperfection of industry standardization regulations is the main reason for the chaos in the smart wearable sporting goods market, which requires strict regulation and refinement of industry standards. China Wearable Alliance officially launched the first smart wearable industry standard system in China in March 2015, which stipulates the safety certification and intelligence standards of smart wearable devices, hoping to guide industry manufacturers to produce products that meet industry standards. Let consumers choose safe and high-quality smart wearable sporting goods, and promote the healthy and sustainable development of the industry. In addition, the use of smart wearable sporting goods involves the privacy protection of personal exercise physiology and health medical data, and the government needs to speed up the formulation and improvement of relevant laws. It is necessary to establish and improve information security supervision regulations to support the development of the smart wearable device industry, strengthen the formulation of industrial control system security standards for information protection, and ensure the network operation security of basic information systems. It is also necessary to ensure the security of user data assets, guide enterprises to standardize the design of the safe use mode of user data, and provide legal protection for the data assets of smart wearable sporting goods. Specifically, the behavior of various stakeholders can be regulated from the data collection, data transmission, data analysis, data preservation and result display of smart wearable devices. Focusing on restricting the behavior of device data acquisition and utilization, obtaining authorization from users and data sources, and do not disclose and violate the user's personal privacy. In terms of data transmission and analysis, it puts forward data protection requirements for communication operators and big data cloud computing service providers, focuses on preventing and punishing malicious acts such as unauthorized data backup, and quickly establishes a benign market order based on the law.

7. Conclusions

With the rapid development of the smart wearable goods industry at home and abroad, it has become an urgent strategic task to actively promote the high-quality development of the smart wearable sports goods industry in the new era. The author obtained first-hand market data through market research, questionnaire survey, etc., and fully understand the development of the entire smart wearable sporting goods industry, and deeply grasp the market acceptance, audience, functional requirements and other aspects of smart wearable sporting goods, and from a strategic perspective, the implementation strategy to promote the prosperity and progress of the smart wearable products industry is proposed, and strive to fundamentally realize the high-quality development of the smart wearable sports products industry. However, compared with developed countries abroad, China's smart wearable sporting goods industry has a late start, a low starting point, insufficient technology research and development, and irregular market order. These problems objectively restrict the development of China's smart wearable sporting goods industry. To completely reverse this situation, we need the joint efforts of the government, enterprises, individuals and other parties.

Conflict of interest

The authors declare no conflict of interest.

References

1. Zhang X, Lu S, Wang Y, et al. Wearable system design for scientific physical exercise of college students. Youth Sports 2019; (8): 124–125.
2. Xiao B, Li Y. The online sales model and management characteristics of sports goods in China. Journal of Beijing Sport University 2015; 38(4): 38–44, 51.
3. Li G, Sun Q. ELES model analysis of the dynamic change of urban and rural residents' sports consumption structure. Journal of Beijing Sport University 2019; 42(1): 98–110.
4. Dong S. Research on the application of physical exercise data in primary and secondary school students [PhD thesis]. Chongqing: Southwest University; 2018.
5. Dong Q, Zhang X, Shen K. Fields, trends and strategies of "Internet + sports industry" development under the background of healthy China. Sports Culture Guide 2018; (5): 74–78.
6. Fu X. Feasibility analysis of wearable devices for guiding scientific exercise and promoting health [PhD thesis]. Beijing: Beijing Sports University; 2018.
7. Deng G. Research on the characteristics of physical exercise behavior of college students in Kunming and the effect of smart bracelets on it [PhD thesis]. Kunming: Yunnan University; 2018.
8. Yu H. Investigation on the current situation of using smart wearable devices in physical fitness of non–sports college students in Changchun [PhD thesis]. Jilin: Northeast Normal University; 2018.
9. Li X. Design and implementation of wearable digital sports–assisted training platform [PhD thesis]. Dalian: Dalian University of Technology; 2018.
10. Chen Y. Research on human action recognition method based on wearable sensor data [PhD thesis]. Dalian: Dalian University of Technology; 2018.
11. Ren B, Dai J, Xia C, et al. Connotation analysis and supply
—Side optimization of China's sports industry structure. Journal of Beijing Sports University 2018; 41(4): 16–23.
12. Li L. Analysis on the development status of China's wearable smart sporting goods market. World of Labor Security 2017; (32): 56, 68.
13. Xie C, Liu Y, Wang Q, et al. Research on the impact of the novel coronavirus pneumonia epidemic on China's sporting goods industry under the new economic normal and its response. Journal of Beijing Sport University 2020; 43(3): 128–134.
14. Zou Y, Tan L. Research on the intelligent development of sporting goods in China: Taking wearable sports products as an example. Journal of Nanjing Institute of Physical Education (Social Science Edition) 2015; 29(4): 87–91.
15. Mao X, Zhou A, Huo D. Research on the theoretical model of the business model of sporting goods enterprises under the new normal economic conditions. Journal of Beijing Sport University 2019; 42(9): 40–50.
16. Wei H, Li C, Liu S. An empirical analysis of the employment effect of China's sporting goods manufacturing exports. Journal of Beijing Sport University 2013; 36(10): 21–26, 32.

Asia Pacific
Academy of Science Pte. Ltd.

Wearable Technology

Focus and Scope

Wearable Technology (WT) is a comprehensive, high-quality international open-access journal that brings together multi-industry features of technology, devices and products in industries and fields such as medicine, sports, apparel, health monitoring and management, and artificial intelligence. It is dedicated to studying the implementation of technology and analyzing the use of products. The journal provides a good communication platform for scholars and experts from various industries, and we welcome the submissions of original research articles, review articles, case reports, commentaries, etc.

The topics of the journal include, but are not limited to:

1. Wearable smart devices
2. Sensors/Controllers
3. Fitness trackers
4. Head-mounted displays
5. Biomedical engineering
6. Systems simulation
7. Digital health
8. E-textiles
9. Intelligent garments
10. Wearable medical products
11. Medical implant products
12. Intelligent electronic devices
13. Technology implementation
14. Mobile Aids

Asia Pacific Academy of Science Pte. Ltd.

Science and technology, an important mainstay for national development strategy all over the time, is the fountain of innovation and value creation, which helping the society beginning its move to the knowledge-based economy step by step.

Under this background, Asia Pacific Academy of Science Pte. Ltd has been born. We are a global market oriented organization serving for scientific research, specializing in scientific research-based services in medical research, environmental life sciences, pollution study, agriculture, materials and engineering research, computer and information technology, industrial development analysis. Through cooperation with universities and research institutions around the world, researches beneficial to human survival, health and future development have been carried out, which accelerate interdisciplinary and international exchanges among researchers and deepen international scientific cooperation.

Asia Pacific Academy of Science Pte. Ltd welcomes the valuable advice and guidance of scholars from around the world, and we look forward to forming a cooperation network of scientific research through such connections.

Asia Pacific
Academy of Science Pte.Ltd.

Asia Pacific Academy of Science Pte. Ltd.
Add：16 Collyer Quay，#12-01，Income At Raffles，Singapore 049318
Tel：+65 91384018
E-mail：editorial_office@apacsci.com
Web：http://aber.apacsci.com