A review of AI Technologies for Wearable Devices

Jin chun yu
Mechanical Design Manufacture and Automation, Honors College, Northwestern Polytechnical University, 710072

Abstract: With the popularity of wearable devices, we can collect various data to support a series of innovative applications. The complex and massive data requires stronger data processing technologies. In recent years, artificial intelligence technology has been used to process this rich but complex data. In this paper, we summarize the research of AI technologies for wearable devices, from the aspects of types of wearable devices, collected data, models, and applications. We find that artificial intelligence technology has not only made a breakthrough in performance over traditional methods, but also creates a series of new applications. For the future research directions, we also point out some problems, e.g., the sensor data measurement and classification are not accurate enough, which would inspires the following research to investigate further.

1. Introduction
With the development of semiconductor technology, electronic devices become smaller and smaller in size, but more and more powerful in function. With the popularity of different wearable devices including smart phones, smart wristbands, smart watches, we now have a stronger data collection ability, which can collect a massive amount of sensor data about people's daily life. With more data collected, we can develop a range of applications, such as behavior detection, motion detection, and psychological pressure warning.

While the increase of data volume and type brings us more application possibilities, it also requires a stronger data processing ability. Traditional methods of data processing are unable to meet the processing requirements of new applications. In this case, a series of artificial intelligence technologies have been applied to the data processing with wearable devices. Especially in recent years, with the rise of deep learning [1] methods represented by a series of deep neural networks, more and more artificial intelligence technologies begin to play an important role in various fields, such as image recognition [2], audio processing [3], traffic prediction [4], and have achieved positive performance far beyond traditional methods.

In this paper, we investigate and summarize the latest progress in the research topic of artificial intelligence applied in wearable devices in recent years, from the aspects of different types of wearable devices, collected data, models and applications. We search relevant papers from some distinguished publishers including IEEE, ACM, Springer and Elsevier, through academic search engines such as Google Scholar, using keywords such as artificial intelligence and wearable devices. Compared with other review papers [5-10], we pay more attention to the recent development in the past few years and try to point out the future research directions according to the current research shortcomings.

In this paper, we would firstly summarize the different types of wearable devices in Section 2. Then, we summarize the data collected by these wearable devices in Section 3. Then, we summarize some important AI technologies used in these papers in Section 4. Next, we summarize the different applications based on these data and AI technologies in Section 5. We conclude this paper and point...
out the future research directions in Section 6.

2. Different Types of Wearable Devices
In this section, we categories the different types of wearable devices.

2.1 Smart Phones
Smart phones have many sensors embedded, which collect data about the movements of users. People usually carry their smart phones around in their pockets, which meets the requirements of data collection. Data collection can be used for a wide range of purposes, including movement tracking, fall detection, monitoring of the elder, and recovery training of patients.

2.2 Smart Watches and Wristbands
Smart watches and wristbands are now in general use, with various built-in sensors that monitor users’ daily activity, calorie consumption and heart rate, as well as the quality of sleep, which help users enjoy healthier exercise and better sleep.

2.3 Smart Glasses
The recording and shooting functions of smart glasses may violate others' privacy. However, as long as the purpose is clear and the monitor system is perfect, smart glasses will not become a threat to privacy, but a practical life assistant and medical tool. Google, for example, already plans to introduce contact lenses with built-in sensors which can detect the blood sugar levels of users.

2.4 Smart Clothes and Socks
Smart clothes collect body data from users through fabrics sensors and collection devices, which can be used to monitor users' exercise data and heat consumption. Also, there are smart baby clothes for infants to monitor their physical condition.

2.5 Smart Shoes
Smart sneakers mainly collect users' sports data to help users improve their sports plans better. In addition, some smart sneakers have new motion detection functions, such as Nike's FuelBand SE, which reminds users to stand up and take a move once in a while.

2.6 Smart Earphones
Smart headphones have new methods of applications, such as intelligent voice analysis and processing, which allow users to operate the equipment more conveniently using voice commands. In the future, it may be possible to integrate sensors directly into in-ear headphones to monitor heart rate, body temperature as well as movement.

3. Different Types of Data Collected
In this section, we summarize the different types of data collected by the wearable devices:

(1) Sports data collected by smart phones, watches and wristbands, such as acceleration information, rotation speed, running steps, etc.

(2) Physiological data collected by smart watches, wristbands and clothes, such as psychological heart rate information, blood pressure, body temperature, blood volume, sound pressure, skin temperature, skin conductance, emotional status, sleep quality, fatigue status, general health status, alcohol or caffeine intake, etc.

(3) Environmental data which are collected by smart phones, watches, computers and glasses, such as global positioning system coordinates, magnetic field strength and environmental luminous flux, etc.

(4) Communication data from smart phones and watches, such as call information, SMS information, screen pressure, and use condition of electronic products, etc.
4. Different Models
While many methods have been proposed for the sensor data processing of wearable devices, we focus on three of them in this section, which we believe are among the most effective ones.

4.1 Machine Learning and Ensemble Learning
Machine learning uses experience from data to improve the performance of computer systems, giving them the ability to learn as humans, thus achieving artificial intelligence. In computer systems, experience is often in the form of data, so machine learning is the study of algorithms that generate models from data on a computer, which are known as learning algorithms. With a learning algorithm, we feed it empirical data, and it generates models based on that data, automatically providing judgments when facing new situations. Ensemble learning itself is not a single machine learning algorithm, but is accomplished by building and combining multiple machine learning machines. Through this combination, ensemble learning can often achieve better results than single models.

4.2 Convolutional Neural Network
Convolutional neural network is a neural network with at least a convolutional layer. It generally includes convolution layer, pooling layer and fully connected layer. It is the convolution and pooling layer that make it different from the other neural networks. In the convolution layer, the input data and convolution kernel are cross-correlated and a scalar deviation is added to get the output. Through the convolution operation, the neural network can find the precise location of pixel changes. Pooling is to mitigate the excessive sensitivity of the convolution layer to the position. Like the convolution layer, the pooling layer calculates the output for each element in a fixed shape window of the input data. Different from calculating the mutual correlation between input and convolution kernel in the convolution layer, the pooling layer directly calculates the maximum value or average value of elements in the red window. The generalizations are also called maximum pooling or average pooling, respectively.

4.3 Long Short-term Memory
Long short-term memory (LSTM) is a kind of recurrent neural network, which can better deal with the problems of gradient exploding and gradient vanishing faced by a regular recurrent neural network, and deal with the context dependence of long distance. LSTM introduces the structure of gate, which is input gate, output gate and forget gate. When the input data wants to be written into the memory cell, it needs to be controlled through the input gate. When the input gate is 1, the input data can pass through, otherwise it cannot pass through. Similarly, the output gate controls whether a value in a memory cell can be read smoothly. Finally, the forget gate decides whether to retain the value in the memory cell. If forgetting is confirmed, the value stored in the memory cell will be refreshed.

5. Different applications
In this section, we give a short summary of different applications that are powered by artificial intelligence and wearable devices.

5.1 Monitoring of Motion State Machine
Smart watches and wristbands are used to collect acceleration data of waist, wrist or leg for monitoring falls, warning special cases, monitoring the elder, so that the elder will get timely treatment after falling, improving the quality of life of the elder, and achieve healthy aging.

5.2 Recognition of Sports Behavior
Through analyzing the sports data collected from smart phones and watches, the user is classified into be cycling, running or climbing stairs. It is used for security monitoring, private data processing, positioning and navigation, family behavior analysis, gait analysis and gesture recognition. In addition, for patients with neurodegenerative diseases such as Parkinson's disease, human activity recognition
can be used to compile daily activity logs and detect gait status to assess the patient's condition and progress in recovery.

5.3 Health Care
After collecting physiological data of human body from the integrated embedded intelligent electronic devices or which directly contact with the body, such as heart rate, blood pressure, etc., the data can be used to judge physical condition, health monitoring, chronic disease management and disease prevention for the elder, monitor abnormal conditions of patients with heart disease and detect early signs of disease. For example, smart watches and mobile phones are used to collect physiological data related to Parkinson's disease for scientific treatment and monitoring of Parkinson's disease.

5.4 Pressure Test
Physical and psychological data, such as mood, sleep quality, fatigue, general health, and alcohol or caffeine intake, are collected via smart phones and wristband. It also collects information about users' communications, such as phone calls, text messages and the use of electronic products. All kinds of data collected are used to judge the psychological stress status of users.

5.5 Sports Monitoring
Smart phones collect data on user's physical activity to monitor their health, which aims to avoid excessive exercise and even heart attacks. In addition, it can detect whether the user has reached an appropriate exercise plan and it is suitable for long-term physical exercise users.

6. Conclusion and Future Directions
In this paper, we find that AI technologies have been successfully applied for wearable devices and inspired a various types of applications. However, current methodologies still face many challenges, which need further exploration.

- Inaccurate sensor data measurement
  The data used in the experiment are collected in the laboratory, indicating that when it comes to real data, the effect may be discounted to some extent. Further research can be carried out to evaluate the model with real data. At the same time, the technical model is applied to smart phones to identify real-time motion.

  There is an imbalance in the test data, and the percentage of each exercise in the training data is different. So using the unbalanced data for training may bring negative impact on the results.

- Limitations of wearable devices and sensors
  Due to the limitations of wearable devices and the interference of external environment, the collected data often contain a lot of noise. How to effectively remove noise needs to be further studied.

  Wearable devices are used casually in daily life, and existing algorithms are closely related to the position and mode to place the device. Therefore, it remains to be studied about the methods which are independent of the position and mode to place device and can effectively distinguish features of various behaviors.

  Effective activity identification of wearable devices requires users to wear a large number of devices in different parts of the body, which may cause discomfort and consumes lots of electricity. Video and environmental sensors work under fixed conditions and are not suitable for normal activities.

  The sensor based on video infringes users' privacy, restricts users to a specific location and captures non-target information. Meanwhile, environmental noise will affect the performance of environmental sensor.

- Individual activity differences
  The difference of individual behaviors leads to the low accuracy of traditional model identification. How to effectively eliminate individual differences and make the classification model more widely applicable remains to be studied.
(4) Limited energy supply and storage of wearable devices

The battery and storage resources of wearable devices are very limited, so it is necessary to further study how to effectively control the calculation and storage consumption of the model without losing precision.

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