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PAPER

Design and Application of Scenario-Based Perception of Smart Wearable Device Interaction Method

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ABSTRACT

At the moment, Internet technology is still in a rapid development phase, with more high-performance, low-power processor chips entering the market and the commercialization of the smart wearable device industry accelerating. Virtual reality, intelligent clouds, and other technologies are at the heart of today's wearable technologies. It is a design product that employs cutting-edge technology to provide sturdy functioning and superior safety. However, the current study on smart wearable devices is more related to engineering technology, and there is relatively little research on the interaction behavior and user experience among users, devices, and environments. Incorporating the design object, application context, user experience, and other factors into the design of smart wearable devices can help promote the transformation of smart wearable devices from technology-driven to user experience-driven. Therefore, it is important to introduce the concepts of context-awareness and interaction design in the design of smart wearable devices. Through contextual cognitive theory, the study studies the contextual cognitive features of users, deconstructs and analyzes the interaction and experience of smart wearable devices, and discovers the relevant elements influencing user experience. The theoretical research results are then integrated with the interaction design system to connect the relationships among users, behaviors, scenes, and technologies, and a context-aware system for smart wearable devices based on scene perception is constructed. The influence of different aspects on the recognition accuracy of the system is analyzed, and the results show that the system proposed in this paper has very superior performance in gesture recognition.

KEYWORDS

wearable smart device, interactive system, design, gesture recognition

1 INTRODUCTION

Virtual reality technology, intelligent cloud technology, etc. are all at the heart of today's wearable technologies. Design a product that relies on cutting-edge IT to deliver robust functionality and top-notch safety. Google's smart glasses, released in 2012, are

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often cited as the first truly intelligent wearable device; they combine a number of cutting-edge technologies in order to better serve the demands of its users in terms of communication. The emergence of connected wearables has transformed our perceptions of human interaction and professional interaction. When this technology improves and is used in more contexts, people's routines and habits will change. And, to completely actualize the union of man and machine, these wearable devices will be linked to other smart devices [1–2]. It is worth emphasizing that the ubiquitous Internet is accelerating its mobility. In layman's terms, mobile informatization is the implementation of information applications on various mobile terminals through the integration of telecommunication and Internet communication technologies, with the ultimate goal of doing mobile information work anytime, anywhere [3–4]. Using mobile phones as an example, the mobile informatization trend enables the realization of many informatization software systems already used by the government and enterprises on computers via the usage of mobile phones, changing the latter into a mobile computer. As a result, the proliferation of several mobile carriers opens up more opportunities for the mobile Internet. The operation can be adjusted to local circumstances and time, and the viscosity of people's use of it will also rise quickly [5]. The development of the mobile Internet is getting faster and faster, and more and more PC-side products are beginning to focus on the direction of mobility. In the present mobile Internet sector, a movement has taken place from just implementing one function to implementing cross-platform and cross-device responsiveness. As a result, the key study goal of this area is how to create a caring, practical, and user-friendly mobile carrier and interactive form [6–7]. For many years, WSDs have been expanding the science and technology of wearable and wearable-in-clothes-of-the-body accessories and gadgets. In the 1960s, the MIT Media Lab's innovative technologies began to take shape as ideas and prototypes. Various engagement approaches, including gestures and eye movement operations, can be supported by this technology by integrating multimedia, sensors, and wireless communication into people's clothing [8–9]. One of the most noteworthy early instances of wearable smart devices is the Apple-II 6502 computer prototype, which first appeared in the 1970s and 1980s [10]. In recent years, the forms of wearable smart devices have started to diversify, showing substantial research value and application promise in a wide range of industries, including industry, medical care, the military, education, and entertainment. For example, smart glasses, smart goggles, and smart watches are mainly used in English-language infotainment applications, and smart bracelets are used in sports and health auxiliary products [11]. Some WSDs have evolved from ideas to commercialization, and additional WSDs have been reported as the mobile Internet, new technologies, and high-performance and low-power processor chips have emerged [12]. In 2014, the development and launch of multi-enterprise WSDs broke out, and many technology companies also began to explore and develop in this field. Especially when the interactive control methods of existing smart home devices are limited, people's demand for convenient control methods is more obvious. However, since WSDs can be connected to other smart devices, such as smart homes, through gateways, people can use wearable devices to control other smart devices as an extension and improvement of existing control methods [13]. Although WSDs have the above-mentioned wide range of applications, their main input methods are limited by the size of their touch screens. Because of this constraint, user input on the device is limited to tapping and swiping the touchscreen. And when inputting, the user's finger will cause a large proportion of occlusion on the touch screen, which affects the user experience [14]. The researchers suggested using the non-device touch approach to input the wearable gadget to address this issue. According to the researchers, gestures and noises work together to build a seamless system in human cognition. Gestures are seen as an excellent technique to create a more organic, inventive, and intuitive engagement with WSDs because they are inspired by human interaction [15]. Based on diverse mobile usage scenarios, this study combines individualized requirements into the design and operation experience of WSDs. It examines the particular needs of different use circumstances of products and people from the standpoint of human-computer interaction, and it builds the most direct idea of needs into systems and systems. At the same time, for the emerging hot product of smart watches, the user experience exclusive to wearable smart devices is interpreted through the interaction of software and hardware.

The rest of the paper is as follows: The related work is presented in Section 2. Section 3 investigates the techniques of the proposed work. The experiments and their results are described in Section 4. Finally, Section 5 brings the research investigation to a close.

2 RELATED WORK

WSDs have been known and widely used since the 21st century, but the concept of "wearable devices" appeared in the 1960s [16]. This stage is the embryonic stage of wearable devices; the application fields of wearable devices are few, and the technology is in the stage of exploration and development. Reference [17] researched and invented a small computer and wore it for gambling, which was used to calculate the probability and verify the correct rate. The oldest wearable technology in human history is said to be this tiny wearable computer. Many smart wearable device prototypes based on the Apple II 6520 computer first appeared in the late 1970s. Despite the fact that the majority of them are still in the research and development stage due to technological restrictions, a few devices that have hit the market have contributed to raising awareness of wearable gadgets on a limited scale. Sony's Cassette Walkman, calculator watches, and wearables for the blind that can convert visual information into tactile input are examples of representative items [18–19]. The "father of wearable computing devices" produced the first head-mounted camera in 1981 by merging a computer and a helmet. This indicates that wearable technology has entered a new development period due to the development of science and technology and has begun to be gradually applied in many fields [20]. For example, digital watches, digital hearing aids, head-mounted displays that can store information, badges, and handheld GPS devices that can locate the user's location information through infrared receivers. In 1997, the first International Wearable Computer Academic Conference was successfully held, which marked the true arrival of the era of widely popular wearables. The wearable device in the development period has completed the transformation from a single field to multiple fields and from a single technology to multiple technologies. It shows great development potential in industry, education, entertainment, medical treatment, etc. [21]. Due to the advancement of Internet technology and sensor technology, WSDs began to flourish in the late 20th century. On the basis of realizing functions, more consideration is given to user factors, user-centered design and development, and more attention to the field of health, and consumer wearable devices are slowly entering the lives of ordinary people [22]. The number of wearable medical and health devices is also increasing in the 21st century. The C-Series pacemaker was introduced and manufactured by Vitatron in 2003. With the aid of this tool, doctors may quickly diagnose a patient by obtaining personal information about them in about 20 seconds [23]. In order to help consumers record the exercise process, Nike and Apple collaborated in 2006 to release a wearable gadget. This device records workout data, such as distance traveled, time spent exercising, amount of energy expended, and activity times, on the iPod [24]. In addition, the representative works of the health category in this period include the Fitbit wearable health device launched in 2009 that can monitor the user's walking steps, walking distance, energy consumption, and other data by clipping it to clothes [25]. The introduction of Google Glass in 2013 fueled the consumer market for smart wearables. As the wearable device market expands and heats up globally, products such as smart glasses, smart watches, and smart bracelets have entered the market. Wearable gadgets have also emerged as one of the most recognized and important developments in smart terminals in the information technology area [26].

The wearables business has been dominated by global IT behemoths. Foreign small and medium-sized firms have expanded swiftly and efficiently with the support of health and sports-related products, achieving some level of market awareness [27]. Domestic smart wearables, however, place a greater emphasis on smart watches and smart bracelets. The primary duties are managing health data, keeping track of exercise progress, and monitoring sleep quality. Driven by smart technology companies such as Huawei and Xiaomi, many smart wearable products with high popularity have appeared in the domestic market [28]. In contrast, domestic smart wearable products have been successfully explored in some market segments, and products aimed at special groups such as children, the elderly, or pregnant women have received widespread attention after they were launched. These smart products show great advantages in terms of special populations and personalized needs [29]. At present, smart wearable devices closely related to public life at home and abroad can be roughly divided into entertainment communication, health care, sports vitality, and safety protection [30]. The homogeneity of wearable products is serious, and the innovation is weak. The functions of wearable products currently remain in step count calculation, call reminder, heart rate monitoring, etc. There are a large number of wearable products with the same functions and similar appearances on the market [31].

3 METHOD

3.1 Design of gesture recognition system based on sound perception

This system is a sound perception system that can use the built-in microphones in commercial smart devices to realize finger gesture recognition in interaction. Figure 1 describes the system architecture of the system.

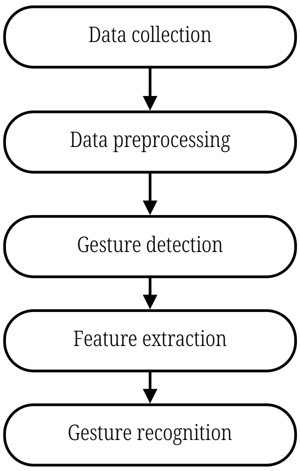

Fig. 1. System work flow

The smart watch gathers sound signals from finger motions in the first module. Due to the smart watch's low computational capability, it sends the captured signal over Bluetooth to the smartphone for further processing. In the second module, the original sound signal is subjected to a bandpass filter to decrease interference from outside sources. Afterwards, we use a unique gesture recognition algorithm to remove the "silent" portion of the audio signal, which is the portion of the audio signal where no gesture occurred. In the feature extraction module, we use a spectrogram and a mel-scale frequency cepstral map to turn the sound data into finger gesture characteristics. This is the last module in which we use a CNN to recognize finger motions. CNN uses spectrograms as well as MFCC to generate visual pictures. The wristwatch or smartphone communicates with the user by invoking the appropriate function in each app, depending on CNN's output.

Following a motion on the back of the hand, the wristwatch continuously monitors the sound signal and sends the recorded sound to a smartphone. The sound of friction on the back of your hand can be heard using the smartwatch's built-in microphone. The raw sound signal captured from the built-in microphone of the commercial smart device is noisy, and in addition to the noise brought by the sensor hardware itself, there are usually noises of different decibels in the environment. Putting the received sound signal into the wavelet transform with a series of filters for analysis, the formula is as follows:

$$x_{\alpha,L}[n] = \sum_{k=0}^{K-1} x_{\alpha-1,L}[2n-k]\, g[k] \tag{1}$$

$$x_{\alpha,H}[n] = \sum_{k=0}^{K-1} x_{\alpha-1,H}[2n-k]\, h[k] \tag{2}$$

Where, $x_{\alpha,L}[n]$ and $x_{\alpha,H}[n]$ represent the output of the αth order.

First, we apply a bandpass filter to the audio input to get rid of low-frequency and high-frequency noise so that finger motions can be reliably identified. Using a weighted sum of the input signals, the FIR filter produces an output signal with the following formula:

$$y[n] = \sum_{i=0}^{N} b_i \cdot x[n-1] \tag{3}$$

$$b_k = b_{n+2-k},\ k = 1,2,\ldots,n+1 \tag{4}$$

Where, N represents the number of finite impulse response filters, and b_i represents the impulse response value of the Nth filter at time i.

This applies a filter to an audio signal to remove noise outside the frequency range. This sets the two cutoff frequencies of the FIR filter output to 6000 and 14000Hz, the stopband cutoff frequencies to 5000 and 15000Hz, and the sampling rate to Fs = 44100Hz. We set N to $N = 112$ in the system based on experimental observations to achieve the desired denoising effect.

Using time-domain signal processing, we can isolate the sound wave that the user's finger made. A considerable rising or falling edge is the major performance of the friction sound between the finger and the back of the hand, which is one of the signals received by the watch. The acoustic signals of various gestures have distinctive, changing patterns that can be utilized to identify finger movements. These shifts are crucial for recognizing the occurrence of finger gestures. We first identify the origin of gestures and then extract valid motion signal segments from the processed sound signal. We developed an input gesture detection method with the ongoing false alarm rate in mind. After dividing the sound stream $y[n]$ into sliding window-sized chunks, we determine the average energy of each window segment.

$$E[n] = \frac{1}{W} \sum_{k=n-W+1}^{n} |y[n]|^2 \tag{5}$$

Where, W is window size.

Each segment contains a sound signal with a sampling rate of 44100Hz for 0.02s. After the signal is processed by the bandpass filter, if no gestures are taking place, the average energy of the window and the average energy of the adjacent windows will only fluctuate within a small range. However, when the window contains the starting point of the action, the average energy $E[n]$ of the window will suddenly increase; that is, the difference $\delta_{Et} = |E[l] - E[l-1]|$ will become significantly larger. In addition, the presence of gesture input will cause the variance of $E[n]$ and δ_{En} to increase.

In the gesture detection process, the system obtains the candidate set of the action start time in the input signal by calculating $arg\ max_n\ \delta_{En}$, and then sets two guard intervals tg_1 and tg_2 on both sides of the gesture sound signal interval estimated by the algorithm. For example, the candidate set of action start time is $\{n_1, n_2, \ldots, n_m\}$, then we subtract tg_1 from each point in the candidate set as the start time of the signal, and add tg_2 as the end time of the signal. That is, the candidate set becomes $\{n_1 - tg_1, n_1 + tg_2, n_2 - tg_1, \ldots, n_m - tg_1, n_m + tg_2\}$. The purpose of doing the above is to capture the complete sound signal during the action.

After detecting gesture input, our designed system obtains a valid sound signal for each gesture. Experimental results show that only using time-domain signals is not enough, so we use time-frequency analysis to extract features. We use the short-time Fourier transform (STFT) instead of the Fourier transform here.

$$STFT\{y(t)\}(m,\omega) = Y(m,\omega) = \sum_{n=-\infty}^{\infty} y[n]\,\omega[n-m]e^{-j\omega t} \tag{6}$$

Where, $\omega[t]$ is window function.

The effect of STFT depends on choosing an appropriate value for the parameter. In the system, we set the Hamming window, the length of the overlapping part is 256, and the length of the FFT is 512. Then, we extract 12 MFCC features, which represent the short-term power spectrum of the sound signal. During gesture feature extraction, we will compute and combine STFT and MFCC coefficients and then convert them to grayscale images. In order to distinguish small differences between input gestures, we utilize a CNN to analyze the image of the extracted features of the sound signal.

In this paper, the CNN model is used to identify various gesture inputs. The sound signal's STFT and MFCC coefficients are used to generate the features of these motions, which are then converted into grayscale images and fed into the CNN model. That's why we've designed this approach to getting input photos so that we can ensure that CNN classification works as expected. LeNet-5531 and AlexNet154 are common CNN structures that we use in our system to construct a CNN structure for mobile devices that meets our application needs. The benefits of LeNet5 and AlexNet are combined in the CNN we use. We use the convolutional layers of AlexNet in conjunction with LeNet's network topology as the primary structure. We employ four convolutional layers, four pooling layers, two fully connected layers, and one output layer in our algorithm. The kernel sizes are two 11×11, five 5×5, and three 3×3, and the pooling size is 3×3. However, if the training set of our CNN model lacks enough data, it can lead to severe overfitting problems. Therefore, we introduce the commonly used methods to avoid overfitting—regularization and dropout—into our system. L2 regularization can only be used in fully connected layers, and we can do it by adding a sign of $1/2\lambda\omega^2$ to the error function of the neural network. Furthermore, we utilize the dropout method at each layer, and during training, we set a fixed dropout probability of $p = 0.8$.

3.2 Design practice

Using a goal-directed approach results in solutions that meet both the user's needs and goals, as well as business and technical needs. The five constituent activities of interaction design proposed in these stages are consistent, namely understanding, abstraction, organization, representation, and refinement, but with more emphasis on modeling user behavior against the definition of system behavior. Table 1 shows the detailed process of goal-oriented design.

Table 1. Goal-oriented design detailed process

Stage	Work Activities	Concern
Research	Define project goals and schedule	Goals, timelines, financial, etc.
	Audit	Marketing plan and brand strategy
	Review current products and work	Competitor, related technology
	Stakeholder interviews	Outlook and risk
	User interview	Behavior, attitudes, etc.
	Understand user needs	Motivation, circumstance
Modeling	Task role	Customer Behavior, Tools
	Customer model	Environment, difficult
	Scenario script	Products for everyday needs
Need	Need	Features, Data, Design, etc.
	Hear the experiencer's story	Achieve the goal
Frame	Element	Information, functions, etc.
	Frame	Object relationships, models, etc.
	Design Experience Framework	Sketches, storyboards, etc.
	Scene script	Adaptive behavior sequences, etc.
	Human-machine interaction	Cater to different scenarios
Detail	Design	Exterior, idioms, interface, etc.
	Concretize	Branding, visualization, etc.

4 EXPERIMENT AND ANALYSIS

4.1 Data collection and experimental setup

We developed four major finger gestures in the previous section: the left swipe, the right swipe, the pinch, and the expand. It's critical to remember that the entire finger movement sequence occurs behind the hand. We created settings with 40 dB of background noise in a library, 50 dB in a laboratory, and 60 dB in a coffee shop. An insufficient data set will result in ineffective categorization training. The training set consists of 15 volunteers' voice recordings. There were 10 males and 5 females, ranging in age from 6 to 60. The finger gestures were performed 30 times by volunteers 1–14. Volunteer 15 was instructed to do each of the 12 multi-finger gestures 100 times to gauge the impact of training samples of varying sizes. We gathered a total of 2880 records from this system. In a natural setting, the participants were able to maintain these movements for three seconds. We just give participants the names of the gestures to employ in the experiment so that we can account for the wide range of user performance. The remaining 20% is then used as a test set, after which the remaining 80% is used as training data.

4.2 Micro-benchmark evaluation

Experiments in three areas are offered to further understand how this system works: preprocessing, gesture detection, and gesture recognition. Following that, we'll look at how the human body influences how finger motions are recognized. We will examine the accuracy of the system's finger gesture detection algorithms in low-noise situations. It is critical to note that detection accuracy is calculated by dividing the proportion of successfully detected gesture signals by the total number of transmitted gesture signals. This study has 14 participants, and the outcomes are displayed in Figure 2. The detection accuracy will be affected by the fact that different volunteers execute the identical actions in slightly different ways and make distinct rubbing noises. The coefficient of friction of the skin affects the segmentation accuracy of the system, while the behavior of performing gestural finger movements does not. For example, in the experiment, we observed that the average recognition accuracy of volunteers 1, 7, and 14 was 97.2%, 97.3%, and 97.6%, respectively, which was lower than that of volunteers 6, 8, and 11. We found that the three volunteers, all women, had smoother skin on the backs of their hands. However, due to rough skin, the segmentation accuracy of volunteers 6, 8, and 10 all reached 100%.

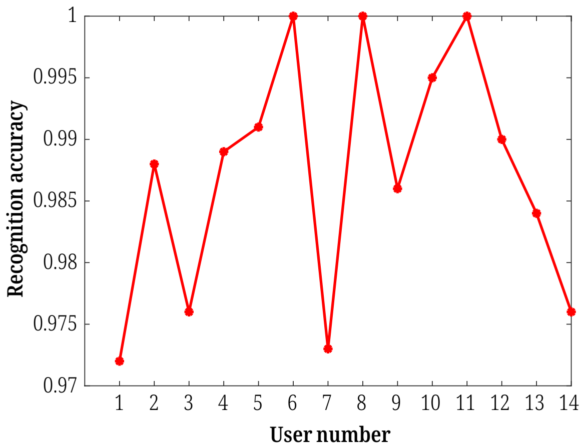

Fig. 2. Volunteer's segment recognition accuracy

By adding a denoising process to the system, the recognition accuracy of volunteer gestures can be further improved. To measure the effect of noise on gesture detection, we plot the accuracy for 30 dB and 60 dB noise levels in Figure 3. Consistent with the expected results, the segmentation recognition success rate can be maintained at almost the same level.

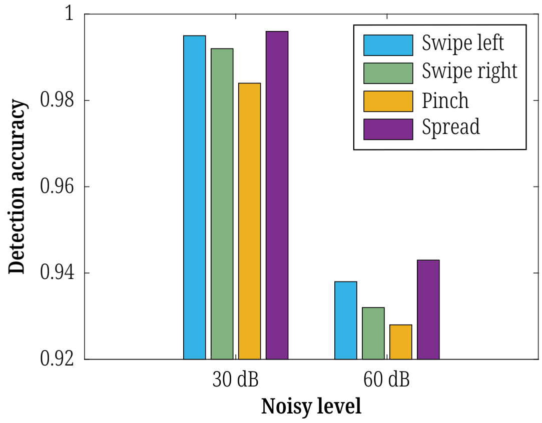

Fig. 3. Detection accuracy of different gestures under different noisy levels

4.3 Performance influence of parameters on system identification accuracy

Next, we study the performance effects of the following parameters on the recognition accuracy of the system, and describe them in detail. It is worth noting that the recognition accuracy of the system uses the average recognition accuracy.

1. User influence: We trained a CNN classifier utilizing a portion of the finger gesture data from volunteers 1–14 in order to assess the recognition accuracy of our system for each user. We determined the overall recognition accuracy for all 12 multi-finger gestures for each volunteer. Figure 4 shows the average accuracy per participant when assessing recognition accuracy using training and test data. The training set contains data for volunteers 1 to 14, and the average recognition accuracy of the known data set is 88.75%. The data of volunteer No. 15 did not appear in the training set; average accuracy for the unknown data set was 83.62%. In contrast, the skin of volunteers' No. 4, 12, and 14 was smoother, and the recognition accuracy was about 85%, which was lower than others. In addition, pinching can achieve an average recognition accuracy of 84%. However, the unfolded recognition accuracy is 58% to 92% because the roughness of the skin surface can significantly affect the recognition results when the user gestures with their fingers on the back of the hand. Still, the overall accuracy of finger gestures is over 80 percent.

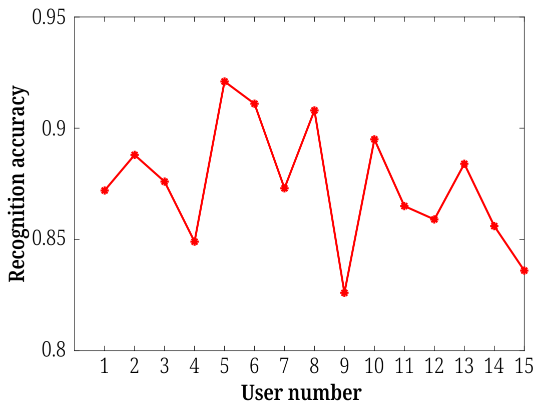

Fig. 4. The influence of different users' postures on the recognition accuracy

2. Influence of training set size: Increasing the size of the training set is known to improve learning performance. We sample the training set 10 times and do a 10-fold cross-validation for the four most fundamental hand motions. As shown in Figure 5, average accuracy rises from 75.5% to 88.6%. A larger training set that includes a wider variety of gesture features will naturally yield better predictions.

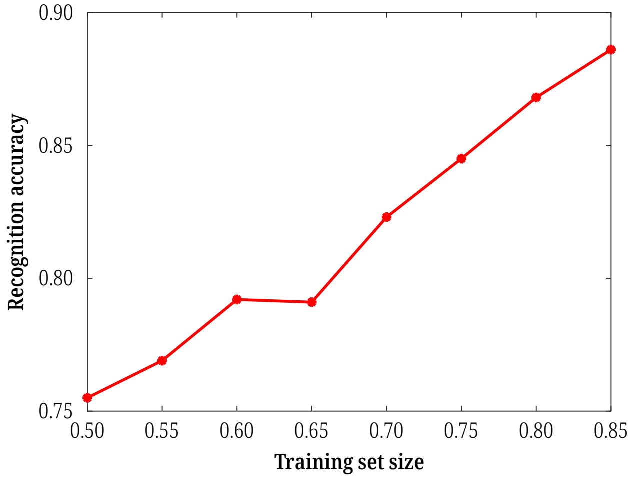

Fig. 5. The effect of training set size on gesture recognition accuracy

3. The effect of training time: Figure 6 examines the performance of various training durations using the same size training set. When the training times are less than 16, as shown in the figure, increasing the training times can considerably enhance recognition accuracy. With enough training time, however, the algorithm converges, resulting in a much slower rate of accuracy improvement. This suggests that for our future studies, it would be prudent to choose a training set size of 20, as this would maintain the computing cost within reasonable bounds.

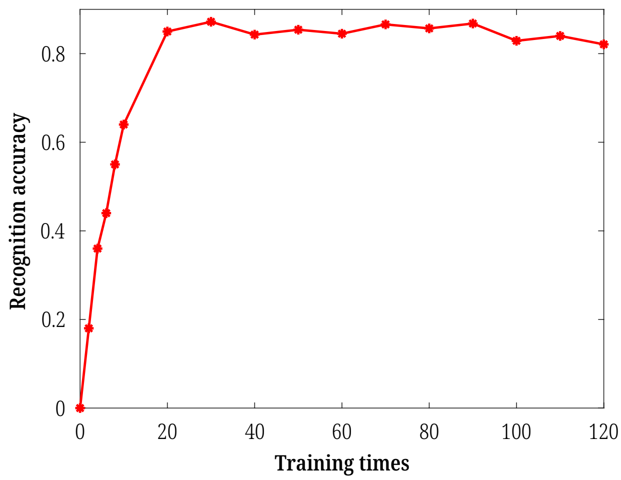

Fig. 6. The effect of training time on the accuracy of gesture recognition

4. The influence of age and gender: The recognition accuracy for various age groups is displayed in Table 2. The experimental findings indicate that children's accuracy is marginally below that of other age groups, which may be related to kids' smaller hands' backs. Additionally, we looked at whether the volunteers' gender had an impact on the volunteers' accuracy of recognition.

Table 2. The recognition accuracy of different age groups

Gesture / Age Groups	Swipe Left	Swipe Right	Pinch	Spread
Children	0.782	0.958	0.805	0.837
Teenagers	0.841	0.848	0.836	0.859
Middle-aged	0.961	0.952	0.937	0.925
Elderly	0.949	0.951	0.956	0.938

The experimental results in Table 3 show that the recognition accuracy of women is generally higher than that of men, which may be because women are more cautious when making gestures.

Table 3. The recognition accuracy of different genders

Gesture / Genders	Swipe Left	Swipe Right	Pinch	Spread
Male	0.852	0.913	0.855	0.870
Female	0.921	0.918	0.885	0.919

5 CONCLUSION

The traditional interaction mode can no longer demonstrate the benefits of hardware, especially when users are interacting with wearable smart devices. Instead, it can become a recalcitrant obstacle that impedes the user experience. Therefore, it is necessary to study how to apply interaction design methods and user experience theory to the design and development of wearable smart devices. Three components of wearable smart device interface design are highlighted based on preliminary research: hardware and action interaction, software and operation interaction, and the combination of software and hardware to improve the operation experience. These three factors will be addressed by extensive consumer and user research, as well as quantitative and qualitative user analysis. Design and investigate the appearance of smart watch products as well as the interaction system of software and hardware under the supervision of demand target orientation. Based on the interaction analysis of smart watches and user research, this paper explores the interaction design ideas and user experience theory applied to wearable smart devices and completes the following work: 1) This paper introduces the research status of WSD at home and abroad and provides a theoretical basis for the design framework. 2) The characteristics of hardware and software are merged during the interaction design stage, and the user experience for smart watches is collaboratively built with effective hardware and software coordination and creatively suggested the development of a sound perception-based design for a gesture detection system before introducing the pertinent ideas. 3) Collect experimental data from 15 volunteers and then evaluate the system's recognition ability. The effect of several factors on the system's recognition accuracy is investigated, and the results demonstrate that the system suggested in this work performs extremely well in gesture recognition.

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