Review of Research on Gesture Recognition Based on Radar Technology

Yaoyao Dong[1(✉)] and Wei Qu[2]

[1] Graduate School, Space Engineering University, Beijing 101416, China
jndy940123@163.com
[2] Department of Electronic and Optical Engineering, Space Engineering University, Beijing 101416, China

Abstract. In order to know the development context of radar gesture recognition and predict the possible future development trends, the research and development of gesture recognition based on radar technology in recent years was sorted out. Focusing on key technologies such as dynamic gesture information perception, gesture echo signal preprocessing and feature extraction in radar gesture recognition technology, and classification algorithms for gesture recognition, the relevant literature published at home and abroad is summarized and existing methods are summarized. The performance of the system is analyzed and evaluated; the problems to be solved in the research direction are sorted out and the future research directions are prospected. The results show that radar gesture recognition technology has made great progress in human-computer interaction applications. With the deepening of related research, the gesture recognition system based on radar technology will develop towards intelligence.

Keywords: Human-computer Interaction · Gesture recognition · Machine learning

1 Introduction

In recent years, with the advancement of artificial intelligence and machine learning technology, the relationship between Human-Computer Interaction (HCI) technology and people's daily life has become increasingly close. Traditional contact human-computer interaction methods such as keyboards and mice have been unable to meet the needs of people's lives. Researchers have begun to devote themselves to the development of new non-contact human-computer interaction methods, including gesture recognition, voice recognition, face recognition, and eye iris. Recognition etc. Among them, gesture recognition, as a very important interaction method in the new human-computer interaction, is one of the most powerful and effective methods in human-computer interaction [1]. With the help of this interactive technology, users do not need to operate redundant devices, they can naturally control electronic devices through the movement of fingers and palms [2], and then complete the information exchange between humans and electronic devices such as computers.

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Early gesture recognition technology mainly used wearable electronic devices to directly detect and obtain spatial information of human hands and various joints. Among them, more representative devices such as data gloves, using sensors such as accelerometers and gyroscopes [3], can be enriched by operators. In addition, wearable devices based on optical marking method [4] also have good detection performance and robustness. However, the above two gesture recognition technologies are complicated to operate and the equipment is expensive, and they have not been widely used in daily life. Then, gesture recognition technology based on visual images has gradually developed. Compared with wearable gesture recognition systems, visual gesture recognition technology abandons additional wearable systems, allowing users to interact with humans with bare hands [5, 6]. Visual gesture recognition technology is mainly used by computers to detect, track and recognize user gestures through video input devices (cameras, etc.) and computer vision technology to understand user intentions [7]. Although the high-resolution camera enables the recognition rate of visual gesture recognition technology to be as high as above [8, 9], the technology is largely limited by light conditions, and there are also security issues of privacy leakage.

With the rapid development and wide application of radar technology, radar gesture recognition technology has become an important branch of human-computer interaction technology research [10]. Compared with traditional optical sensors, radar sensors can work normally in severe weather conditions such as rain, snow, fog and haze, or under dark conditions, and have the advantages of all-weather and all-weather; secondly, radar sensors can be embedded in the equipment, thereby improving the reliability and design flexibility of the equipment; in addition, the radar signal also has a greater advantage in privacy and security, which can effectively protect user privacy information. In view of the above advantages, the research of gesture recognition based on radar technology has been paid more and more attention. This technology is also a popular direction of computer vision research at present and in the future.

Gesture recognition can be roughly divided into two categories: static gesture recognition and dynamic gesture recognition [11]. This article mainly combs and summarizes the research on radar-based dynamic gesture recognition and related technologies in recent years, and discusses the shortcomings of existing methods. And the next research direction.

2 The Key Technology of Radar Gesture Recognition

Generally, gesture recognition based on radar technology can be divided into 3 major steps: First, the radar sensor is used to collect the user's dynamic gesture information; then, certain preprocessing operations need to be performed on the received radar echo signal to maximize the extraction of the target Gesture features and remove interference signals; finally, according to the gesture feature set, select the appropriate algorithm for gesture recognition. The basic process of a gesture recognition system based on radar technology is shown in Fig. 1. This article takes the radar gesture recognition step as the main pulse to analyze the key technology of gesture recognition.

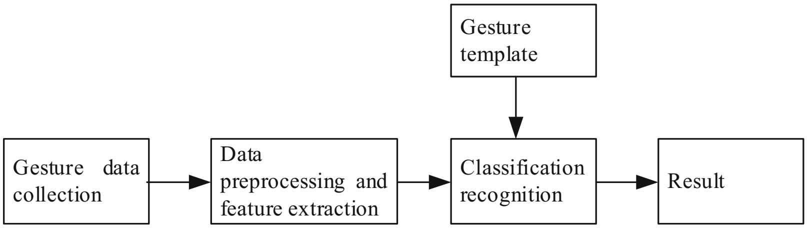

Fig. 1. Block diagram of radar gesture recognition process

2.1 Gesture Data Collection

As the premise foundation of the radar gesture recognition system, the collection of gesture data is directly related to the performance of the entire system. At present, for the radar gesture recognition system, the radar transmission signals used by the researchers can be mainly classified into two categories according to the frequency band: one is concentrated in the K-band and below, and the other mainly uses millimeter waves. Regardless of the frequency band, most of the radar signal waveforms currently used are continuous wave (CW) systems, which are favored by researchers for their advantages of low power consumption, miniaturization, and high reliability.

Sample Radar Sensors Based on K-band and Below
Aiming at the K-band or even lower frequency range, researchers such as Xiaomeng Gao of the University of Hawaii used a quadrature Doppler radar sensor with a carrier frequency of 2.4 GHz, the radar working in the ISM band to collect gesture information and extract zero-crossing from its baseband signal. The features are drawn into strip-shaped feature graphics to distinguish different gestures [12]. In 2016, Fan T et al. constructed a radar sensor working at 5.8 GHz with a coherent zero-IF architecture with symmetrical subcarrier modulation, responsible for the collection of hand movement information [13]. In the same period, Youngwook Kim et al. of California State University used a Doppler radar with a frequency of 5.8 GHz and an antenna beam width of 60° to detect 10 common gestures [14]. The following year, the team used low-power radar to identify three gestures, and achieves an average accuracy rate of 99% on the test sets by using deep learning network [15].

Qifan Pu of the University of Washington and others designed a gesture recognition system named as Wise. The system used the 2.4 GHz wireless signal in daily life, and it can realize the perception of gesture information in the whole room through the difference of Doppler frequency shift of echo [16]. In addition, Matthew Ritchie of the University of London, UK, used the 24 GHz Ancortek radar system to repeatedly detect four different gestures of six people for up to 3000 times [17]. The radar signal frequency was also 24 GHz. Pavlo Molchanov of NVIDIA research center and others used the frequency modulated continuous wave (FMCW) with four antennas (one transmit and three receive antennas) radar sensor, combined with optical camera and time of flight (TOF) depth sensor and other sensors to carry out gesture recognition research in the car [18].

Radar Sensor Based on Millimeter Wave

Compared with gesture recognition systems based on low-frequency wireless signals, millimeter-wave radar sensors are easier to miniaturize and can be embedded in the device, greatly improving the integration and reliability of the device. At the same time, the millimeter wave signal has a stronger ability to capture tiny movements due to its extremely short wavelength, it has good Doppler resolution, and it can effectively identify the subtle movements of the finger. Researchers such as Ismail Nasr use a 60 GHz transmission frequency, two-transmit antennas and four-receive antennas FMCW radar sensor, used SiGe technology to achieve the detection of target gestures [19]. Xuhao Zhang used a frequency modulated continuous wave radar sensor with a working frequency of 77 GHz to provide dynamic gesture detection for the driver's gesture recognition assistance system [20].

Choi Jae-Woo of the KAIST School of Electrical Engineering in South Korea used the FMCW radar with a frequency of 60 GHz developed by Google to perceive 10 kinds of gesture information, and cooperate with the Long Short-Term Memory (LSTM) algorithm of deep learning. The recognition rate is as high as 99.10% [21]. Both Li Chuyang and Wang Yalong of the University of Electronic Science and Technology of China used a millimeter-wave radar with one transmit antenna and four receive antennas to construct a sample database of 3,200 gestures [22, 23], providing a large number of samples for later data processing. In addition, Google's Soli project publicly demonstrated the use of FMCW millimeter-wave radar chips in the 60 GHz frequency band to realize close-range micro-motion gesture recognition [24, 25].

2.2 Gesture Data Preprocessing and Feature Extraction

The main purpose of radar gesture signal preprocessing is to convert a one-dimensional gesture signal into a two-dimensional signal containing both time domain and frequency domain information. Considering that in addition to the information of the target gesture action, the received radar echo signal also contains other irrelevant objects and environmental noise and other irrelevant interference information. For the interference signal in the echo signal, a certain signal processing algorithm is used for the received data preprocessing is performed to ensure that interference information is removed while maximizing the retention of key gesture information [26]. The purpose of feature extraction is to remove redundant information in gesture data, and extract as much as possible the feature quantity that can meet the discrimination of different gestures. It is used as a feature that can well characterize the motion characteristics of dynamic gestures from the preprocessed data. The vector process is an important part of the good work of the gesture recognition system. Because the excessive redundancy of the gesture data will seriously affect the difficulty of training the classifier and extend the training time, which is a very unnecessary time loss for practical applications.

Based on Classical Time-Frequency Analysis

The classical time-frequency analysis method mainly includes Fourier Transform (FT) and a series of transform methods derived therefrom, which has an important position in the field of signal processing. Yu Chenhui used Short-Time Fourier Transform (STFT) to process the gesture echo signal, and extracts the envelope characteristics of the time-frequency map, including the maximum value, average value and variance of the time-frequency envelope curve. The time-frequency characteristics of wave signals are classified [27]. Wang W and Liu Ax proposed a human motion recognition model based on Channel State Information (CSI), using WiFi frequency band signals, analyzed the impact of multipath effects on human motion, and proposed the use of wavelet transform or time frequency analysis is used to recognize human gestures to obtain characteristic parameters [28].

WiGest is a product made by Khaled A. Harras team of Carnegie Mellon University. It used Received Signal Strength Indication (RSSI) information received by WiFi, then they used wavelet transform to identify dynamic gestures with the rising edge, falling edge, pulse and other features of the gesture signal [29]. Zhang used the Short-Time Fourier Transform to analyze the time-frequency of radar echo signal, and then constructed the positive and negative ratio of Doppler frequency offset and the duration of gesture action as features [30]. Kim used STFT to calculate the Doppler spectrum of radar signal, and used the Doppler spectrum image as the input data of convolution neural network for gesture recognition research [14]. Wang draw lessons from arctangent algorithm mentioned in communication signal processing, it can linearly solve the Doppler phase shift, thus obtaining the motion information of dynamic gesture. However, there are also problems with the pure arctangent algorithm. When the target motion amplitude is too large, the demodulation signal truncation and phase ambiguity will occur. In view of this, the team extended the arc tangent algorithm and proposed the extended differentiate and cross-multiply (DACM) algorithm. By introducing differential and integral operators, the truncation problem in phase demodulation was solved, and the complex baseband signal phase was phase continuous change, thus realizing linear demodulation of large dynamic range motion [31].

Based on Radar Signal Processing and Analysis Method

For the shortcomings of the classic time-frequency analysis method, the researchers derived a series of methods for radar signal processing on this basis. For radar signals, Schmidt R used 2-Dimensional Fast Fourier Transform (2D-FFT) to estimate the range of gesture targets and Doppler parameters, and used Multiple Signal Classification (MUSIC) algorithm [32] estimated the angle parameters of the gesture target, and the gesture action data is presented in the form of distance, speed and angle parameter changes. LIN discussed the mixing and modulation principles of FMCW signals in the article [33]. Li G used the Orthogonal Matching Pursuit (OMP) algorithm to analyze the FMCW radar echo signal, and obtained the micro-Doppler time-frequency trajectory as the characteristic input vector [34]. Wang used FMCW radar to collect gesture signals, obtained distance and speed through radar signal processing, and mapped the corresponding signal amplitude into a parameter map. Finally, the parameter graph is used to represent the gesture at each moment, and the parameter map is input into the deep learning network for feature extraction and classification [35]. However, this method is only sensitive to the radial change of the gesture, which limits the angle feature extraction sensitive to the lateral change, thus greatly limiting the application range of gesture recognition. Pavlo Molchanov introduced the estimation method of the range-Doppler map of the FMCW radar for vehicle gesture recognition, and the method of fusing radar sensor and depth sensor data [18]. Dekker processed the one-dimensional signal of the gesture into a Doppler-time spectrum and used the real and imaginary parts of the Doppler-time spectrum as the two-channel classification and recognition input data [36].

Based on radar signal processing and analysis, Wang Yong constructed a Range-Time Map (RTM), Doppler-Time-Map (DTM) and an Angle-Time-Map (ATM), synchronized the three kinds of data of the same gesture action and construct a gesture action multi-dimensional parameter data set [37]; in the same year, the team proposed a Two-Stream Fusion Neural Network (TS-FNN) based on multi-parameter images of FMCW radar signals gesture recognition method, which used gesture signals to generate distance-speed parameter graphs and angle-time parameter graphs and establishes TS-FNN for feature extraction and fusion, retaining the gesture lateral and longitudinal motion parameters [38]. Zhou Zhi used wireless channel state information and terahertz radar signals to obtain data sources, and used gesture radial velocity to characterize gesture behavior [39], but the author directly calculated a distance scalar value to represent gesture feature information at every moment. This makes the feature extraction incomplete (lack of speed and angle information), thereby reducing the accuracy of gesture recognition. Wang Jun et al. performed matched filtering, Fast Fourier Transform (FFT) of LFMCW radar echo of gesture target in turn Transform (FFT) and coherent integration processing are used to obtain the two-dimensional distribution in Range-Doppler (RD) domain, which is used as the input feature vector of subsequent deep learning network to realize automatic feature extraction and recognition of gesture actions [40].

2.3 Gesture Classification and Recognition Algorithm

The classification and recognition algorithm of gestures is the last and most important step in the research of gesture recognition. Radar gesture signals are processed by data preprocessing and feature extraction, and the echo signals are converted into abstract representations. Then, machine learning technology is used to realize the gesture classification and identification. Machine learning can not only quickly process data, predict and classify problems, but also has great development potential in the field of pattern recognition including gesture classification.

The vision-based dynamic gesture recognition algorithm is relatively mature. For the gesture recognition algorithm based on radar technology, researchers are also improving step by step. For the radar system gesture recognition technology, the current mainstream recognition algorithms include template matching-based methods, methods based on statistical learning and methods based on deep learning.

Radar Gesture Recognition Algorithm Based on Template Matching

Dynamic Time Warping (DTW) is the most commonly used template matching method in radar gesture recognition. The DTW algorithm is an algorithm commonly used in speech matching, and currently has certain applications in image processing. The algorithm is based on the nonlinear regularization method of dynamic programming, and it uses regularization functions to describe the time correspondence between the template to be tested and the reference template, so as to solve the similarity of the two time series [41]. When using DTW algorithm to recognize gestures, a series of reference templates need to be recorded in advance, and then the similarity between the gesture to be tested and the reference template is matched and calculated, and the template gesture with the highest similarity is recorded as the recognition result. The DTW algorithm has the characteristics of less training sample demand and high accuracy. Zhou Zhi used DTW method to classify multi-modal signals. Taking 10 gesture signals collected by terahertz radar as an example, the effectiveness of the analysis and recognition system is verified. The experimental results show that the recognition accuracy is above 91% [39]. Plouffe et al. used DTW algorithm to recognize dynamic gestures, and the recognition rate reached 96.25% [42].

However, the DTW algorithm also has certain limitations, including problems such as high computational complexity and poor robustness. Especially when dynamic gestures are more complex and the number of training samples is large, the recognition rate will drop significantly. Therefore, the optimization research of the original DTW algorithm came into being. Ruan X et al. improved the search path and the matching process, and then used the distortion threshold algorithm to control the process of matching the gesture to be measured with the reference gesture in real time. Compared with the traditional DTW algorithm, the improved DTW algorithm reduces the processing time 15% [43].

Radar Gesture Recognition Algorithm Based on Statistical Learning
Statistical learning is a theory that abstracts probability statistical models from data and uses the models to analyze and predict new data. For the field of radar gesture recognition technology, statistical learning-based methods are widely used in Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Hidden Markov Model (HMM) and other methods.

SVM is a supervised learning model based on statistical learning theory. Its principle is to map the input sample feature vector to a high-dimensional feature space through a kernel function, perform linear classification in the high-dimensional space, find the optimal separation hyperplane, so that the training samples can be most separable. Zhang et al. extracted two kinds of micro-Doppler features from the time-frequency spectrum of the echo signal, and used the SVM algorithm to classify these four gestures. The experimental results on the measured data showed that the classification accuracy of this method was higher than 88.56% [30]. Liu Zhao et al. used the segmented FFT signal processing method to convert the one-dimensional gesture signal into a two-dimensional gesture image, combined with the SVM algorithm to learn and classify the two-dimensional gesture signal, with an accuracy rate of 90.25% [44].

KNN is based on the training data set and calculates the k training instances that are closest to the new input instance, and the category with the largest number of k is the prediction result for the new input instance [45]. Xu Xian et al. applied traditional K-nearest neighbor algorithm and capacitive sensor to realize gesture recognition, which effectively improved the recognition success rate compared with ordinary threshold recognition methods [46]. However, in the process of gesture recognition, if there are a large number of gestures that need to be recognized, the traditional KNN algorithm training group data will be too large, which will affect the recognition efficiency. Chen Jiawei used the improved KNN algorithm to extract the features of the gestures that need to be recognized in the gesture recognition, and encode the gestures according to the extracted feature values, so that each gesture has a unique code, effectively reducing the amount of data in the training group, and it improved the success rate of gesture recognition by 5% [47].

Hidden Markov model is a typical probability and statistics model, which is usually used to describe Markov processes with hidden states. HMM can effectively capture the correlation in time series. Since gesture action is a time sequence, HMM has been widely used in the field of gesture recognition. When using HMM to recognize dynamic gestures, a separate HMM model needs to be trained in advance for each gesture, and then the probability of each HMM model producing the gesture to be measured is solved. The gesture corresponding to the HMM model with the highest probability is the recognition result.

Based on the self-developed 77 GHz millimeter-wave radar chip, Texas Instruments used the Hidden Markov Method to achieve an average classification accuracy of 83.3% for 6 medium motion amplitude gestures [48]. However, the speed energy distribution feature used in this paper is not enough to accurately represent a variety of gestures with many categories and similar features. Using the features extracted from the CSI, Wei Wang et al. proposed to use the Hidden Markov Model to build a CSI activity model containing multiple motion states, thereby completing the recognition of dynamic gestures [49]. Wang X et al. used the AdaBoost classifier to detect the user's hand, then they used particle filtering for tracking, and finally completed gesture recognition based on HMM [50]. This method has a significant improvement in recognition accuracy, but the computational complexity is extremely large and cannot meet the real-time requirements.

Radar Gesture Recognition Algorithm Based on Deep Learning

In recent years, deep learning has achieved remarkable results in computer vision, speech recognition, natural language processing and other fields. It has become one of the research fields that scholars pay attention to. Now it has become one of the most successful combination of big data and artificial intelligence. Deep learning is a kind of unsupervised learning. It can not only automatically extract features in images, but also automatically learn higher-level features, which overcomes the subjectivity and limitations of manual feature extraction [51]. The algorithms involved in deep learning methods in radar gesture recognition technology mainly include Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).

According to different dimensional processing methods, convolutional neural networks can be divided into two-dimensional convolutional neural networks (2-D CNN) and three-dimensional convolutional neural networks (3-D CNN). CNN is also called the two-dimensional convolutional neural network. It is one of the most basic network structures in deep learning. It usually consists of a convolutional layer, a pooling layer, and a fully connected layer. At present, CNN has achieved great success in the fields of face recognition and target detection, and it is also rapidly emerging in the field of radar gesture recognition technology.

Wang Yong used the method of convolutional neural network classification based on the distance, Doppler and angle multi-dimensional parameter features of gesture actions, which can achieve an average classification accuracy of 95.3% for 6 kinds of large motion amplitude gestures [37]. However, in this article, the multi-dimensional parameter features combined with distance spectrum, Doppler spectrum and angle spectrum are used. Among them, distance spectrum and angle spectrum are difficult to accurately characterize the micro-motion gestures with insignificant distance and angle changes. Therefore, the combination of range spectrum and angle spectrum features will deteriorate the representation ability, which is only suitable for gesture representation with large motion range. Researchers such as Dekker B used the real and imaginary parts of the Doppler-time spectrum as the input data of the two channels. Then, the author used the network structure of the convolutional layer, the pooling layer and the fully connected layer to extract the features of the image, and they used softmax classifier completes the gesture classification, the classification accuracy rate of 99% is reached on the test set [36]. Sruthy used the two receiving antennas of continuous wave Doppler radar to generate the in-phase and quadrature components of the beat signal, and they mapped the two beat signals to the CNN model, so that the accuracy of gesture classification exceeded 95% [52]. Pavlo Molchanov used optical, depth and radar sensor data fusion to recognize typical driving gestures through heterogeneous image registration and three-dimensional convolutional neural networks [53].

Recurrent Neural Network (RNN) is a type of recurrent neural network that takes sequence data as input, recursively in the evolution direction of the sequence, and all nodes are connected in a chain. In recent years, some scholars have adopted the combination of CNN and sequence model to recognize dynamic gestures. Infineon, a chip supplier of Soli, uses a long cycle full convolution neural network method based on sequence based range Doppler feature image training for gesture recognition, which can achieve an average classification accuracy of 94.34% for five micro-motion gestures [25]; Soli team adopt end-to-end cyclic neural network method based on distance Doppler features to classify gestures, which can achieve an average classification accuracy of 87% for 11 kinds of small and medium motion amplitude gestures [26], but the above two recognition systems based on RNN use the original range Doppler features, which is difficult to characterize the micro hands. Choi J used the distance Doppler sequence generated by data processing as the input of the Long Short-Term Memory (LSTM) network, enabling the gesture recognition system to successfully recognize 10 gestures with a classification accuracy rate of 99.10%. At the same time, the recognition accuracy rate of new participants' gestures was 98.48% [21]. However, this method has the best performance on small data sets. When the number of training samples is large, the computational efficiency will be greatly reduced.

From the current radar gesture recognition algorithm based on deep learning, the commonly used methods have their own advantages and disadvantages. In order to facilitate comparison and selection, Table 1 summarizes the different gesture recognition methods.

Table 1. Comparison of common radar gesture recognition algorithms

Common algorithms	Advantage	Disadvantage
DTW	Less training sample needs, high recognition accuracy	High computational complexity and poor stability
SVM	Can effectively solve small sample, high-dimensional, non-linear problems, and has strong generalization ability	When the number of training samples is large, the efficiency is low
KNN	The algorithm is simple and easy to understand	Need to take up a lot of storage space, time complexity is high
HMM	Can effectively capture the correlation in timing	The training process is more complicated, the training time is long, and the amount of calculation is large
CNN	No need to extract features manually, weight sharing	Requires a lot of training data and high computational cost
RNN	Can be used to describe the output of continuous state in time, with memory function, weight sharing	Poor parallel computing power and large amount of calculation

3 Existing Problems and Development Direction

The radar-based gesture recognition system does not require the human body to wear additional sensors and it is not affected by light conditions, it can also work normally around the clock. And the radar signal has good penetrability, even if the radar sensor is embedded inside the electronic device, the system can perform gesture recognition stably. This technology is becoming more and more mature. In addition, it is closely related to the fields of medical assistance, smart cars, and robots. It is an inevitable trend that radar technology gesture recognition will develop toward intelligence. The use of radar technology for dynamic gesture recognition has achieved certain results, but there are still some problems to be solved.

3.1 Radar Gesture Recognition in Complex Scenarios

Aiming at the K-band or even lower frequency range Compared with the complex application environment, the experimental scenes of the existing research are relatively simple, and there are not too many interfering objects within the transmitting range of the radar. In practical applications, due to the complexity of the actual application environment, the detected gesture signal sample data is often mixed with various noises. Therefore, more complex experimental scenarios can be considered in future research work to ensure that the system can still maintain stable recognition performance in the presence of other active human bodies and body movements.

3.2 Multi-view Data Fusion of Multiple Radar Sensors

Among the existing research results, most researchers use separate radar sensors for dynamic gesture information perception and have achieved good results. It is a potential direction worthy of research in this field to design a recognition system with higher accuracy and stability by fusing multiple radar sensors with multi-view and multi-scale data.

3.3 Radar Gesture Recognition Under Multiple Users

Most existing gesture recognition systems cannot recognize gestures performed by multiple users simultaneously. Different from recognizing a single user's gestures, this type of problem needs to consider the extraction of different gesture features and the construction of gesture models. In addition, due to differences in personal habits, proficiency and time, different users perform specific gestures differently. Therefore, the development of a multi-user gesture recognition technology that considers these individual differences is another future research direction in this field.

3.4 Higher Requirements for Training Data

Radar gesture recognition algorithms have high requirements for the quality and quantity of training samples. Sample data with quality and quantity is the premise and basis for effective recognition of dynamic gestures. In the process of radar collecting gesture signals, some data is lost. Aiming at the problem of poor data quality, studying how to improve the robustness of the model and maintaining a high recognition rate is one of the research directions to be carried out. Aiming at the problem of insufficient number of samples, on the one hand, the researchers should improve the learning efficiency of the model, capture the effective information in the sample and improve the classification and recognition ability; on the other hand, the researchers should enhancement and simulation data generation to expand the sample library.

4 Conclusion

The development of radar gesture recognition technology has brought a new way of human-computer interaction. The user can complete the interactive function without direct contact with the computer. This allows the user to successfully get rid of the shackles of external wearable devices such as data gloves, so as to improve the flexibility and naturalness of human-computer interaction. With the advancement of science and technology, intelligent radar gesture recognition system is an important development direction in the future. Machine learning is the core technology of artificial intelligence. Combining machine learning with radar gesture recognition is a good solution. In this paper, the methods of gesture recognition based on radar technology are summarized, sorts out the problems that need to be solved, and lays the foundation for the next step of research. It has certain reference significance for promoting the gesture recognition methods and research based on radar technology.

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