

Human Activity Recognition Methods

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Human activity recognition (HAR) can effectively improve the safety of the elderly at home. Many researchers have studied HAR from different aspects, such as sensors and algorithms. HAR methods can be divided into three categories based on the types of sensors: wearable devices, cameras, and millimeter-wave radars.

Keywords: human activity recognition ; small-scale datasets ; PCA

1. Introduction

The World Health Organization reports that 42% of people over 70 might fall at least once a year ^[1]. By 2050, the proportion of the world's population aged over 65 is expected to increase to 21.64% ^[2]. As the world's most populous country, China has accelerated its urbanization process in recent years and its original family structure has changed. A large number of empty nesters have appeared in both urban and rural areas of the country. Empty nesters are vulnerable to safety hazards at home due to old age and limited mobility. Especially for those empty nesters living alone, an unexpected fall can result in death in the worst-case scenario. Research shows that timely help can save the lives of those who fall ^[3]. However, existing medical resources are infeasible to meet the massive demand for elderly home care due to the significant number of older adults. In this circumstance, various sensors and technologies have been applied to monitor and recognize the activities of the elderly at home to improve their home safety through technical means. Among these technologies, human activity recognition (HAR) is a key technology for home safety monitoring of the elderly. Although HAR is promising, it still faces many challenges. For example, its recognition accuracy is unsatisfactory and not convenient enough for users ^[4].

2. Human Activity Recognition Methods

Many researchers have studied HAR from different aspects, such as sensors and algorithms. HAR methods can be divided into the following three categories based on the types of sensors: wearable devices, cameras, and millimeter-wave radars. The advantages and disadvantages of different sensors are shown in **Table 1**. In addition to the reasons listed in the table, cost is also an important and realistic factor influencing users' choice. For example, the camera-based method is usually cheaper than the millimeter-wave radar-based method, but the millimeter-wave radar-based method can better protect user privacy. The cost of a wearable device is usually more than the cost of a single camera, but users may need multiple cameras to monitor different rooms while one wearable device can fulfill a user's needs. Therefore, in the se-lection of monitoring methods, it is often necessary to consider the actual situation and needs of users.

Table 1. Advantages and disadvantages of different sensors.

Types of Sensors	Advantages	Disadvantages
Methods based on cameras	♦ High accuracy and robustness	♦ Limited application scenarios
	♦ Non-contact and comfortable	♦ Difficult to use in a dark environment
	♦ Avoid manual use	♦ Privacy issues

Types of Sensors	Advantages	Disadvantages
Methods based on wearable devices	♦ Privacy protection	♦ Inconvenient
	♦ Easy to collect data	♦ Uncomfortable
	♦ Various types of sensors can be chosen	♦ Limited battery capacity
		♦ Difficult for the elderly to use
Methods based on millimeter-wave radars	♦ Privacy protection	♦ Difficult to collect data
	♦ Non-contact and comfortable	♦ Easily affected by noise
	♦ Avoid manual use	♦ Limited location of installation
	♦ Not affected by the light condition	

HAR based on cameras has been popular in the past. Some researchers separated the image background from the human and then used machine learning or deep learning to extract features [5][6]. Espinosa et al. [7] separated the person in the picture from the background and extracted the ratio of length to width of the human body to recognize standing and falling. In addition, some researchers extracted human contour features and recognized activities through changes in contour [8][9][10]. Rougier et al. [11] used an ellipse rather than a bounding box on HAR. They suggested that the direction standard deviation and ratio standard deviation of the ellipse can better recognize the fall. Meanwhile, Lai et al. [12] improved this method by extracting the picture's features and using three points to represent people instead of using the bounding box. In this way, the changed information of the upper and lower parts of the human body can be easily analyzed. With the development of computer technology and deep learning, Nunez-Marcos et al. [13] proposed an approach that used convolutional neural networks (CNN) to recognize the activities in a video sequence. Khraief et al. [14] used four independent CNNs to obtain multiple types of data and then combined the data with 4D-CNN for HAR. Compared with other methods, visual methods have better recognition accuracy and robustness, but the performance of cameras will decline rapidly in the dark environment. Having the camera based in certain places, such as bedrooms and bathrooms, will significantly violate personal privacy and bring moral and legal problems [15]. As a result, the usage of traditional cameras as sensors for HAR has been abandoned in recent years. Although researchers including Xu and Zhou [16] have promoted 3D cameras, they have a limit on the use distance and can only be used within 0.4–3 m, which is not suitable for daily use.

Wearable devices are also widely used for HAR, based on the principle that acceleration changes rapidly when the human body moves. There are many methods to measure the change of acceleration, such as accelerometer [17][18], barometer [17], gyroscope [19][20], and other sensors. In 2009, Le et al. [21] designed a fall recognition system with wearable and acceleration sensors to meet the needs of comprehensive care for the elderly. In 2015, Pierleoni et al. [22] designed an algorithm to analyze the tri-axial accelerometer, gyroscope, and magnetometer data features. The results showed that the method had a better performance on the recognition of falls than similar methods. In 2018, Mao et al. [23] extracted information and direction by combining different sensors, and then used thresholds and machine learning to recognize falls with 91.1% accuracy. Unlike visual methods, wearable devices pay more attention to privacy protection and will not be disturbed in a dark environment. However, wearable devices need to be worn, which reduces comfort and usability and is challenging to apply to older adults. In addition, the limitations of the battery capacity of wearable devices makes it difficult for them to work for an extended period. To address these disadvantages, Tsinganos and Skodras [24] used sensors in smartphones for HAR. However, this method still has some limitations for the elderly who are either not familiar with or do not have smartphones.

With the development of radar sensors, there has been an emergence of HAR using millimeter-wave radar data [25]. Compared with other methods, radar data can better protect personal privacy and is more comfortable for users. The key to using radar to recognize human activities is to extract and identify the features of the micro-Doppler signal generated when the elderly move. In 2011, Liu et al. [26] extracted time–frequency features of activities through the mel frequency cepstrum coefficient (MFCC) and used support vector machine (SVM) and k-nearest neighbor (KNN) to recognize activities with 78.25% accuracy for SVM and 77.15% accuracy for KNN. However, the limit of supervised learning is that it can only extract features artificially and cannot transfer learning. Deep learning does not require complex feature

extraction and has good learning and recognition ability for high-dimensional data. Sadreazami et al. [27] and Tsuchiyama et al. [28] used distance spectrums and time series of radar data combined with CNN for HAR. In 2020, Bhattacharya and Vaughan [29] used spectrograms as input of CNN to distinguish falling and non-falling. In the same year, Maitre et al. [30] and Erol et al. [31] used multiple radar sensors for HAR to solve the problem that a single radar sensor could only be used in a small range. Hochreiter et al. [32] proposed a long short-term memory network (LSTM) to solve the problem of gradient vanishing and gradient explosion. Wang et al. [33] used an improved LSTM model based on a recurrent neural network (RNN) combined with deep CNN. Their work recognized radar Doppler images of six human activities with an accuracy of 82.33%. Garcia et al. [34] also used the CNN-LSTM model to recognize human activities. The authors proposed an approach to collect data on volunteer activity by placing a non-invasive tri-axial accelerometer device. Their innovation lies in two aspects: they used LSTM to classify time series and they proposed a new data enhancement method. The results show that their model is more robust. Bouchard et al. [35] used IR-UWB radar combined with CNN for binary classification to recognize falling and normal activities with an accuracy of 96.35%. Cao et al. [36] applied a five-layer convolutional neural network AlexNet with fewer layers on HAR. They believed that features could be better extracted by using fewer convolution layers.

Although deep learning has a strong learning ability and high accuracy in HAR, it needs a large volume of data for training purposes. Due to the particularity of the elderly, it is difficult for them to generate some high-risk activities for data collection.

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