

Retraction

Retracted: Research on Behavior Monitoring of Elderly Living Alone Based on Wearable Devices and Sensing Technology

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] M. Yin, "Research on Behavior Monitoring of Elderly Living Alone Based on Wearable Devices and Sensing Technology," *International Journal of Antennas and Propagation*, vol. 2021, Article ID 4200137, 10 pages, 2021.

Research Article

Research on Behavior Monitoring of Elderly Living Alone Based on Wearable Devices and Sensing Technology

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Human behavior recognition and status monitoring are current research hotspots, especially in the fields of medical monitoring, smart home, and elderly care. With the development of sensor technology, low-power IC chips, and wireless body sensors, miniature sensor networks can be popularized and applied in daily life. Since the energy consumption of sensor networks is a bottleneck problem that limits its development, this paper designs a multimodal collaborative sensing method for the application scenarios of elderly people living alone to reduce energy consumption in the process of daily behavior perception of the elderly. This method subdivides behavior perception into behavior recognition and status monitoring, determines the optimal sensor combination for identifying monitoring different behaviors based on information theory, and then uses a behavior recognition model modeled by a multiclassifier and a status model modeled by a plurality of two classifiers that are used to perceive user behavior. A large number of experimental results show that compared with the traditional sensor network method, our proposed solution can achieve effective sensing while reducing the energy consumption in the process of data transmission and model calculation, thereby prolonging the working life of the sensing network and realizing long-term and reliable daily behavior perception.

1. Introduction

Human behavior recognition [1, 2] and status monitoring are the current research hotspots in the field of artificial intelligence and pattern recognition. Human behavior recognition is classified by the method of obtaining human behavior data and can be divided into behavior recognition methods based on computer vision and behavior recognition methods based on sensor devices. Among them, the main application areas of human behavior recognition based on computer vision include intelligent video surveillance, virtual reality, smart home, user interface, and automobile driving [3–5]. Human behavior recognition based on sensor equipment is mainly used in the fields of medical monitoring, sports medicine, elderly care, and gait analysis [6].

The development of wireless communication technology, sensor technology, low-power embedded technology, and nanotechnology has enabled the integration of miniature sensor networks with our daily life environment, and

the difficulty and cost of developing miniature sensor devices such as wearable smart devices have been greatly reduced. At present, various miniature sensor devices (such as wearable sensors devices) have become very popular. Because they are not restricted by the place of use, they are simple to operate, easy to carry, small in size, beautiful, and fashionable. In the field of mobile health, wearable devices and other miniature sensor devices have become an indispensable part of daily life [7]. These wearable sensor products can detect human sleep and movement and can provide a data reference for our daily life or whether the amount of exercise is reasonable. Human physiological characteristics monitoring systems based on wearable sensors have also been widely used in the medical field. The detected data includes the patient's body temperature, heart rate, brain activity, muscle movements, and other important physiological data [8, 9]. These human physiological data can be obtained through wearable heart rate sensors, temperature sensors, blood pressure sensors, acceleration sensors, and so on. These

sensors can provide a lot of accurate and reliable data about human activities and behaviors. Through the monitoring data provided by the sensors, the nursing staff can know whether the patient is in a relatively healthy condition in real time. If one or more of the physical characteristics of the patient is abnormal during the monitoring process, such as Parkinson's syndrome or sudden heart disease, the monitoring systems will trigger the alarm mechanism that enables the patient to be treated as soon as the unexpected situation is sent.

The development of wireless body sensor networks (WBSN) [10, 11] has greatly reduced the difficulty of developing a mobile human body monitoring system. The sensor nodes distributed in the human body and space form the WBSN through self-organization or multihop. The sensing node in WBSN is used to detect human physiological parameters such as body temperature, blood pressure, and heart rate and send the collected information to the base station or data processing center through the wireless network in a cooperative manner. Commonly used communication protocols in wireless body sensor networks include Bluetooth, WI-FI [12, 13], RFID [14–18], Zigbee, and so on. In various fields, WBSNs have been widely used, including medical care, disease monitoring and prevention, and smart homes. With the more in-depth research and wide application of WBSNs, it will inevitably penetrate into many fields in our real life.

Also, with the development of various technologies, multiparameters, intelligence, miniaturization, and low power consumption have become the main directions for the development of wireless medical sensor nodes, and wireless sensor networks have also been widely used in the medical field. The development of community-wide human characteristics monitoring systems and the establishment of intelligent wards are two of the current development trends in the medical field. The architecture of the physiological characteristic monitoring system based on a wireless sensor network is shown in Figure 1. In Figure 1, the patient's physiological characteristic parameters are collected by wearable sensors, and their data are sent to the monitoring center of the upper computer, and the upper computer determines the patient's health status through the threshold judgment of the parameters.

With the further promotion of the research and application of wearable devices, WBSN composed of multimodal sensors can achieve comprehensive and continuous detection of human behavior through long-term wear in daily life so as to help elderly people living alone, especially those suffering from Parkinson's disease (PD), and provide solutions. At present, not only the continuous detection of human behavior using WBSN through the continuous working mechanism of all sensors in the network consumes a lot of energy and computing resources, but the limited computing resources, wireless transmission, and power of the sensor network also greatly limit WBSN's monitoring and evaluation of PD motor symptoms in daily life. At present, whether it is using wearable sensor devices or BSNs to continuously monitor human behaviors, all sensors or devices in the network will continue to work. Therefore, they

not only consume a lot of energy and computing resources but also greatly limit the BSN's monitoring and evaluation of monitored objects. In order to reduce the resource and energy consumption in the process of user behavior perception, this paper proposes a Parkinson's disease-oriented multimodal collaborative perception method. While the proposed method realizes the perception of user behavior, it minimizes the number of working sensors and the amount of data transmitted, thereby reducing the energy and resource consumption of the entire network.

2. Related Work

Because wearable device-based behavior recognition methods have advantages in many aspects, they have received widespread attention. The acceleration sensor is a necessary sensor for wearable devices, and it is also that the most widely used sensor in human behavior recognition. By analyzing the acceleration of certain positions of the human body, work such as fall monitoring [19], human posture analysis [20], and movement type analysis [21] can be performed. In the human body behavior recognition methods based on the acceleration sensor, two basic issues must be considered first: the number of acceleration sensor nodes and the nodes. In order to improve the accuracy of behavior recognition, early researchers usually used more acceleration sensors to obtain a large amount of human behavior data. Laerhoven installed 30 acceleration sensors on their clothes [22], which are mainly placed on the joints and torso of the human body, and centrally processed the data collected by the acceleration sensors. Subsequently, Kern used 12 acceleration sensors in the behavior recognition experiment, mainly placing the sensors at the joints of the arms and legs, and finally achieved relatively ideal results [23]. In the research work of Varkey, only two acceleration sensors were used, which were placed on the wrist and ankle [24], and Khan only used one acceleration sensor, which was placed on the chest [25]. In the process of behavior recognition, when the number of acceleration sensors is large, in order to reduce the amount of data transmitted by the network in WBSN and reduce the processing of redundant data, an appropriate sensor work scheduling strategy is needed at this time. When the behavior of the human body in a certain state can get the correct recognition result using a small number of sensors, the data of other sensors are redundant at this moment. Zappi solves this problem by dynamically selecting the sensor needed to recognize the current human behavior. The sensor will only be awakened when the current behavior recognition requires data from a certain sensor node [26]. Veltink et al.'s research work shows that a small number of sensor nodes can correctly recognize a behavior set [27]. In the process of behavior recognition, only when the data collected by the current sensor node cannot uniquely identify the current behavior, the system will start a new sensor node to collect human behavior data. Given a specific behavior set, it is easy to select the number of sensors needed and the placement position of the sensors. If a larger behavior set is given and the number of sensors working is also required to be ensured, distributed

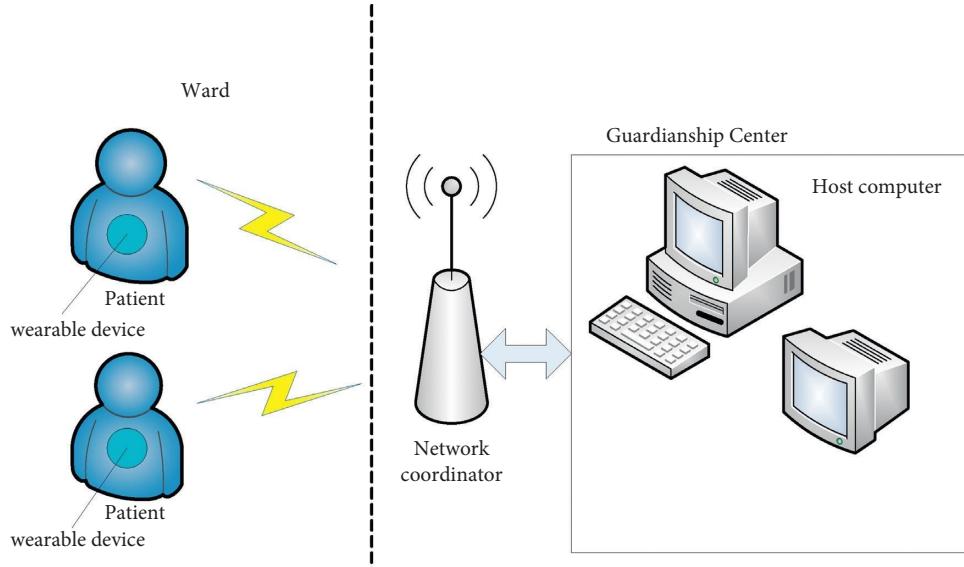


FIGURE 1: The physiological feature monitoring system architecture diagram based on WSN.

recognition mode is a good solution. The distributed recognition mode only needs to collect the node data of some sensors. Ghasemzadeh et al. [28] proposed a distributed behavior recognition method based on string matching. Each sensor node recognizes the current behavior of the human body through the sensor data collected by itself and the processing results of other sensor nodes and sends the generated preselected set of human behavior to neighboring nodes. When there is only one behavior in the preselected set of generated behaviors, this behavior is regarded as the target behavior of the current human body. Yang et al. [29] proposed a distributed human behavior recognition framework based on a low-bandwidth wearable sensor network (distributed sparse classification method). This method uses human behavior sample training motion sequences as prior samples and can mark those behaviors that are not within the recognition range. In the process of using WBSN for data perception, limited computing resources, electricity, and energy have gradually become one of the bottlenecks restricting its application and development and have become hot research topics. Gedik et al. [30] dynamically select a part of the sensor for sampling, while the rest of the sensor data is generated by the probabilistic model trained in advance, reducing power consumption by reducing the number of working sensors. Willett et al. [31] first roughly recognizes the current environment through a small number of sensors and then dynamically activates the sensors based on the recognition results so as to maintain high sampling frequency and accuracy while reducing the number of activated sensors to reduce the overall network power consumption and communication overhead. Ngai and Xiong [32] proposed a method for evaluating the quality of perceived data for the WBSN composed of the mobile phone's own sensors and fixed sensors, dynamically adjusting the sampling rate of the sensor, so as to reduce power consumption while ensuring data quality. In addition,

there are some other types of IoT sensing such as motion sensing [33] by using MIMO radar signals.

However, the currently proposed model not only ignores the collaborative relationship between sensors, but also does not consider the power consumption caused by the complexity of the model calculation process. In order to further reduce the energy and resource consumption caused by behavior perception and model calculation, this paper proposes a collaborative sensing mechanism that uses a multisensor-multiclassification model to identify behaviors and a few-sensor-two-classification model to monitor state.

3. Multimodal Collaborative Sensing Method for Elderly Living Alone

In order to effectively reduce the power consumption in the process of WBSN perceiving users' daily behaviors, this paper proposes a multimodal collaborative sensing method (MMCS-EPLA) for elderly people living alone. The diagram of multimodal collaborative sensing method is illustrated in Figure 2.

3.1. Sensor Selection Method Based on Information Gain. The basis of the method proposed in this paper is to select the optimal sensor combination for behavior recognition and status monitoring models, which not only effectively characterizes user behavior but also reduces the power consumption of WBSN by optimizing the sensor combination and prolongs the lifetime of sensors.

Information gain is one of the commonly used metrics to measure the importance of a node. It is an evaluation method based on entropy. It measures the contribution of feature F to the classification model. It is generally defined as each category set A before and after the feature appears. The difference in the information entropy of the category is shown in the following formulas:

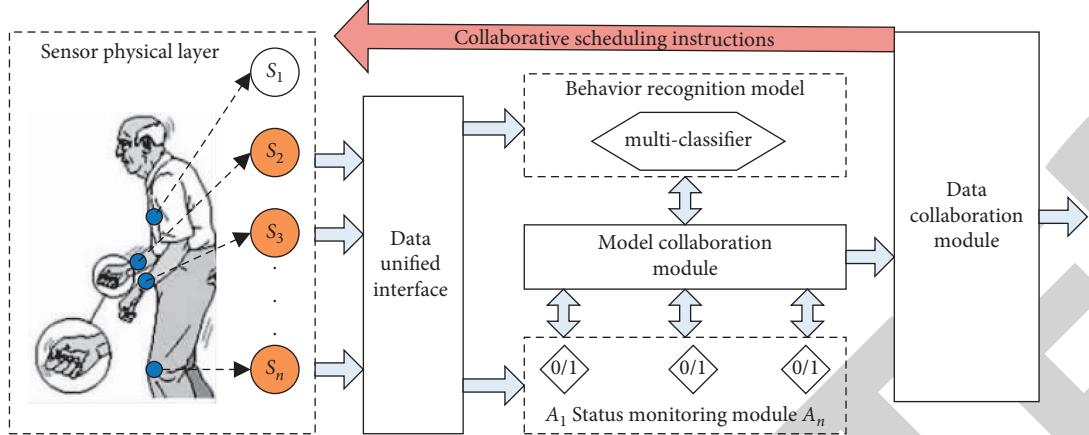


FIGURE 2: The diagram of the multimodal collaborative sensing method.

$$\text{InfoGain}(F, A) = H(A) - H(A|F), \quad (1)$$

$$H(A) = - \sum_{j=1}^m P_r(A_j) \log P_r(A_j), \quad (2)$$

$$H\left(\frac{A}{F}\right) = - \sum_j \sum_v P_r(A_j|F=v) \log P_r(A_j|F=v), \quad (3)$$

where $H(A|F)$ and $H(A)$ are the information entropy of each category when the feature F appears or not, and the probability of each category appearing $P_r(A_j)$ is estimated using the posterior probability. Inspired by the feature information gain, we propose a method to measure the contribution of the sensor, that is, the contribution of the sensor S is measured by the sum of the information gain of its related features, and the calculation method is shown in the following formula:

$$\text{InfoGain}(S) = \sum_j \text{InfoGain}(F_j), \quad (4)$$

where F_j represents the j -th behavior feature extracted from the sensor data.

We use a greedy strategy to combine multimodal sensors in descending order of information gain and find the optimal sensor combination as the sensor that should be activated under this model.

3.2. Collaborative Sensing Model. The multimodal collaborative sensing model for elderly people living alone with Parkinson's disease uses the continuity of PD-related daily behaviors and divides behavior sensing into two submodels: behavior recognition and status monitoring, as shown in Figure 3.

After we use the behavior recognition (multi-classification problem) model to perceive user behavior, we use a simpler status monitoring (two-classification problem) model to determine whether user behavior has changed. Since the lightweight model is used in the status monitoring process, less sensor data and resources will be used, and the overall power consumption of WBSN can be reduced.

Assuming that the number of user behaviors that need to be recognized is m , the task of the behavior recognition model is to recognize what behavior the user is in, which can be characterized by a multiclass classifier (MC). The task of the status monitoring module is to determine whether the user's behavior status has changed, which can be characterized by m binary classifier (BC). It is to be determined which status monitoring model to use based on the result of the behavior recognition model, and the result of the status monitoring model determines whether to call the behavior recognition model.

Let f^{mc} denote the classification result of MC, $f^{mc} = \{1, \dots, m\}$. f_i^{bc} denote the classification result of i -th BC, $f_i^{bc} = \{0, 1\}$. The collaborative working mechanism of the behavior recognition model and status monitoring model is shown in the following formulas:

$$\text{flag}_i^{bc} = \begin{cases} 1, & f^{mc} = i, \\ 0, & f^{mc} \neq i, \end{cases} \quad (5)$$

$$\text{flag}^{mc} = \begin{cases} 1, & \bigcap_{i=1}^m f_i^{bc} = 0, 0, \bigcap_{i=1}^m f_i^{bc} \neq 0, \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where flag_i^{bc} represents the cosign of the i -th BC of the status model and flag^{mc} denotes the cosign of the behavior recognition model.

4. Experiment and Analysis

4.1. Experiment Setup. This paper uses a desktop computer equipped with Intel Core i5-2320 CPU (Quad-Core, 3.0 GHz) and 16 GB RAM as the experimental platform. The system used is Windows 10, and the simulation software is MATLAB 2015b. We use the public data sets MHEALTH [34, 35] and PAMAP2 [36, 37] for experiments, which include daily behaviors of 10 and 9 subjects, including sitting, standing, lying, walking, and going upstairs. The types of multimodal sensors and their wearing positions are shown in Table 1. The sampling frequency of all sensors is greater than 50 Hz, which can meet the requirements of user behavior recognition. All experiments are independently performed, and the results are averaged [38, 39].

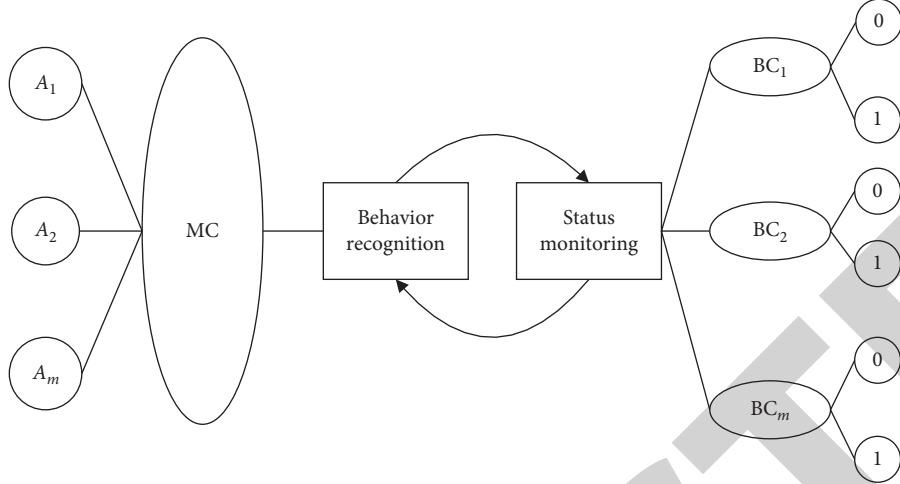


FIGURE 3: The user behavior sensing model.

TABLE 1: Multimodal sensor category.

Data set	Category	Symbol	Position
MHEALTH	Accelerometer	AR	Right wrist Left ankle Chest
	Gyro	GR	
	Magnetometer	MR	
	Accelerometer	AL	
	Gyro	GR	
	Magnetometer	ML	
	Accelerometer	C	
	Accelerometer 1	HAcc1	
	Accelerometer 2	HAcc2	
	Gyro	HGyro	
PAMAP2	Magnetometer	HMag	Dominant side wrist Chest Dominant side ankle
	Accelerometer 1	CAcc1	
	Accelerometer 2	CAcc2	
	Gyro	CGyro	
	Magnetometer	CMag	
	Accelerometer 1	AAcc1	
	Accelerometer 2	AAcc2	
	Gyro	AGyro	
	Magnetometer	AMag	

The early symptoms of PD are prone to abnormalities in the limbs and trunk. The specific manifestations are hand tremor when sitting or resting, sleep disturbance, trunk stiffness when walking, inconvenience in turning, and hunchback. Therefore, it is related to four daily behaviors such as walking, sitting, lying, and standing that are usually continuous. Realizing the perception of user behavior is the key prerequisite for evaluating the status of motion. Thus, we mainly select four daily behaviors including standing, sitting, lying down, and walking from the two data sets for experiments, as shown in Table 2. In Table 2, the behavior recognition model based on multiclass modeling is used to identify four effective behaviors. The status monitoring model based on the binary classifier modeling is used to determine whether the user's behavior has changed. It is worth noting that in order to verify our behavior model, we use experimental results to determine the number of classifiers. When training multiclassifiers, k selects $\{5, 10, 20, 30\}$,

TABLE 2: Classifier category.

Symbol	Behavior status	Types	Purpose
Multi	Four behaviors	Multiclass classifier	Behavior recognition
U	Upright		
S	Sit	Binary classifier	Status monitoring
L	Lie down		
W	Walk		

$\{40, 50, 60\}$, and the result of the constructed classifier on the validation set S_v is shown in Figure 4.

The abscissa of all subgraphs in Figure 4 represents the number of multiclassifiers, and the ordinate represents the recognition rate of behavior. It can be seen from Figure 4 that the recognition results of each classifier for walking, going upstairs, going downstairs, and stationary are roughly the same, and the interpolation of the recognition rate is within 1%. It can be seen from Figure 4(e) that when the number of classifiers is 30, the recognition result of the classifier for running has a small improvement. Combing the recognition rate of various behaviors, when the number of classifiers is 30, the classifier in the method designed in this paper has the best recognition effect on the verification set.

Data preprocessing: this paper uses a sliding window mechanism to frame the original data and uses the window as the smallest unit for feature extraction and behavior recognition. To ensure the accuracy of user behavior perception, the window size is set to 1 second; the overlap between windows is 50%; and the minimal time interval for sensing user behavior is 0.5 second. Aiming at the problem of data imbalance in the process of data collection, the down-sampling method is adopted in the experimental preprocessing process to ensure that the effective behavior and the quantity of other data are balanced during the model training process.

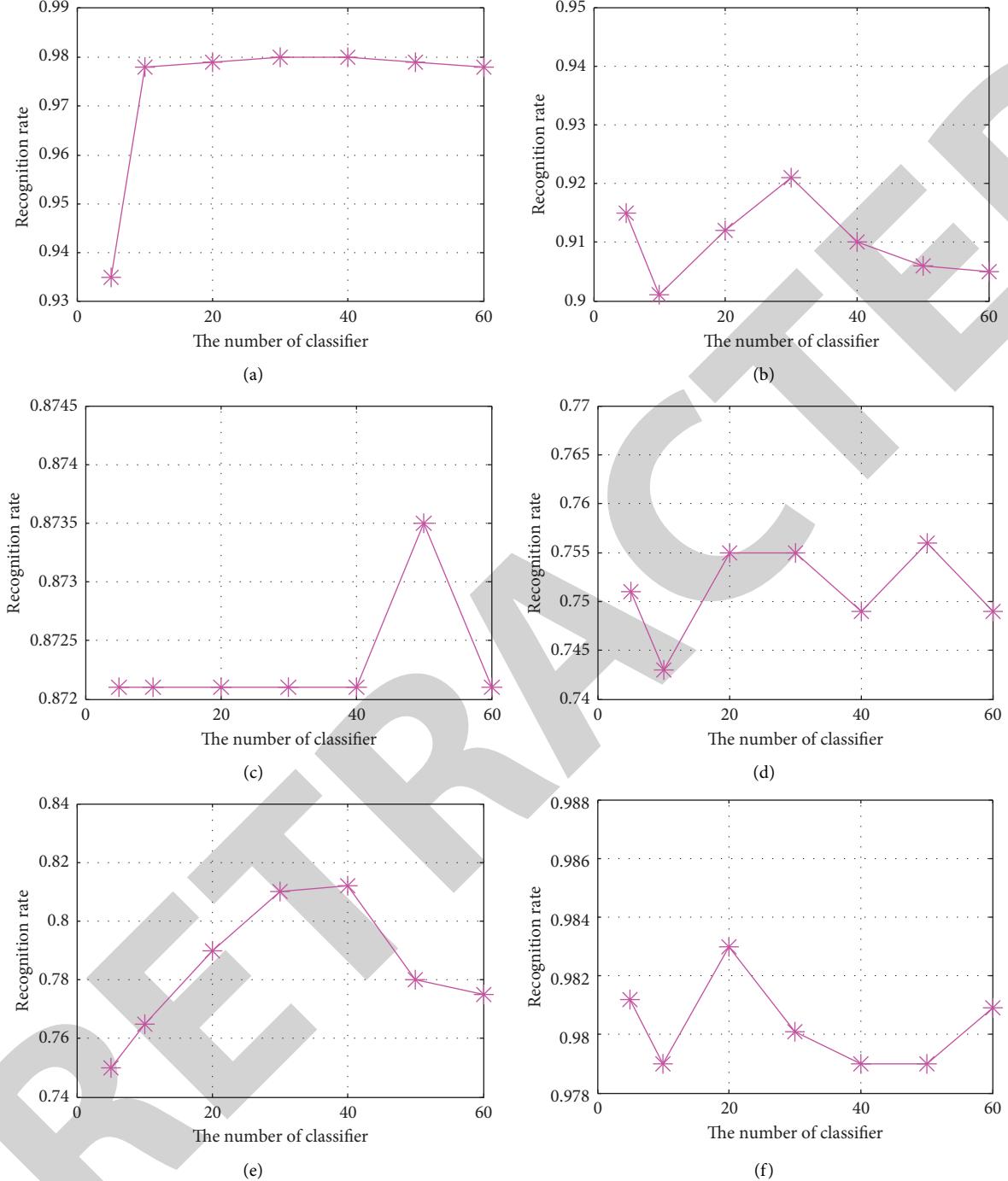


FIGURE 4: Experimental results: accuracy test of the classifier on the validation set. (a) Walk recognition rate. (b) Upstairs recognition rate. (c) Downstairs recognition rate. (d) Jump recognition rate. (e) Jogging recognition rate. (f) Stationary recognition rate.

Classifier selection: the multimodal collaborative perception method proposed in this paper divides behavior perception into two subtasks including behavior recognition and status monitoring, which are modeled by multiclassifiers and binary classifiers, respectively. In order to simplify the model training process, an extreme learning machine (ELM) [40] that supports multiclass classification and binary classification problems is selected as the classifier.

4.2. Effective Sensor Selection. The information gain calculation of the sensor is based on the information gain of related features, so common behavior statistical features are extracted in the sliding window, including mean, variance, standard deviation, zero-crossing rate, over-averaging rate, maximum value, and minimum value. Figure 5 shows the information gain of the multimodal sensor in the MHEALTH data set for the behavior recognition model and the status monitoring model (the results on the PAMAP2

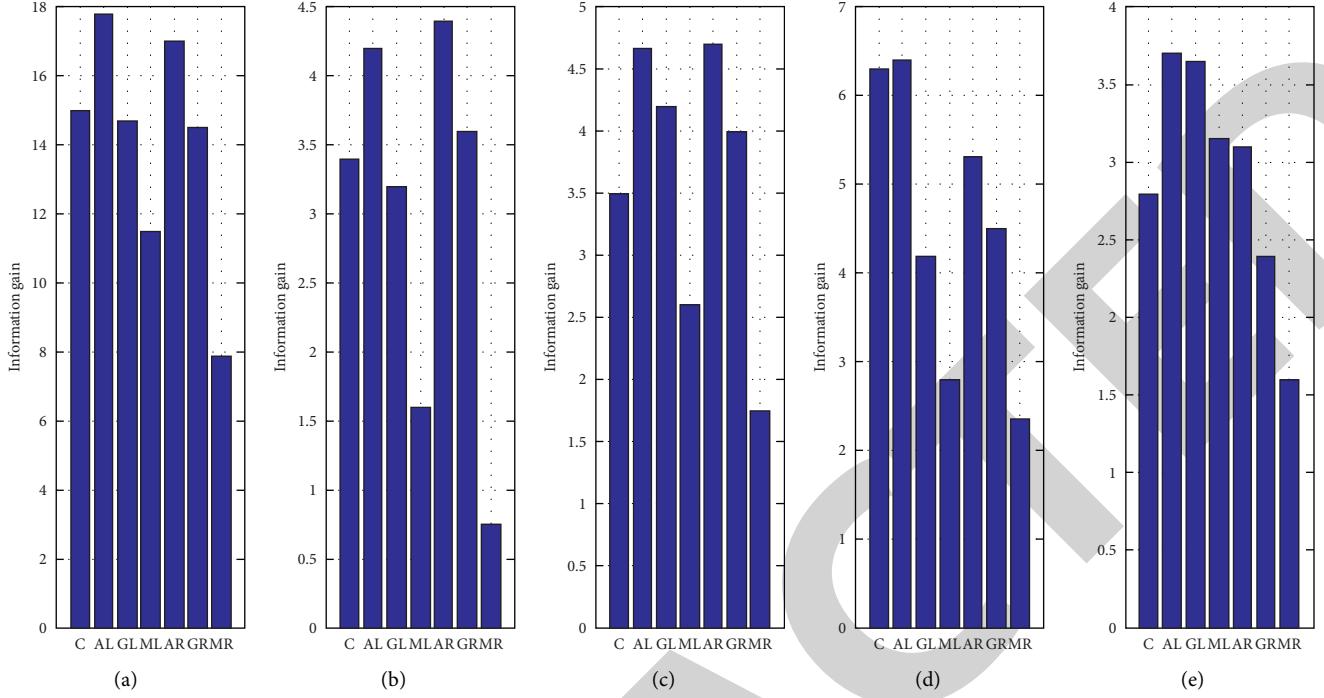


FIGURE 5: Information gain of multimodal sensors for each classification model in the MHEALTH. (a) Behavior recognition model. (b) Upright monitoring model. (c) Sitting monitoring model. (d) Lying down monitoring model. (e) Walking monitoring model.

TABLE 3: Optimal combination of multimodal sensors.

Data set	Model	Sensor combination	Number of hidden layer nodes
MHEALTH	Multi	AL, AR, C, GL	234
	Stand	AR	61
	Sit	AR, AL, GL	63
	Lie	AL, C	21
	Walk	AL, GL	112
	Multi	AAcc1, AAcc2, AMag, CAcc2, CAcc1, GMag	286
PAMAP2	Stand	AAcc1, AAcc2, AMag, CAcc1, CAcc2, CMag	21
	Sit	AAcc1, AAcc2, AMag	103
	Lie	CMag	306
	Walk	AAcc2, AAcc1, CAcc2, AGyro, CAcc1, AMag	126

data set are similar). It can be seen that the degree of contribution of the same sensor to different models is different, that is, it is scientific and necessary to select a targeted sensor combination for the behavior recognition model and the status monitoring model. In order to select the most effective sensor combination, multimodal sensors are greedily combined in descending order of information gain, and a tenfold cross-validation method is used for each combination to select the best sensor combination according to the best accuracy. According to the accuracy and time of model recognition, the optimal sensor combination is selected to achieve a balance between model performance and power consumption. The results are shown in Table 3. In the same data set, compared with the behavior recognition model, the status monitoring model needs either fewer sensors or a simpler model (with fewer hidden layer nodes), which reduces the energy consumption in terms of a number of sensor activations and computing resources consumption, respectively.

4.3. Low-Power Performance Evaluation. In the working process of WBSN, its power consumption mainly comes from data communication [41], and the energy consumption in the scheduling process comes from model calculations. On the two data sets of MHEALTH and PAMAP2, a leave-one-out cross-validation method is used to compare the method in this paper with the traditional method of multimodal sensor all working continuously. Comparing the perception accuracy, testing time, and the number of sensors, the results are shown in Figures 6 and 7. Compared with the traditional continuous working method, the method in this paper has a decrease in the accuracy of behavior perception due to the mutual scheduling between the behavior recognition model and the status when the behavior changes, but the method in this paper can be effective on the recognition of daily behavior of related users. Since only fewer sensors need to be activated in the status monitoring process and compared with the multiclass classifier consumes less resources in the

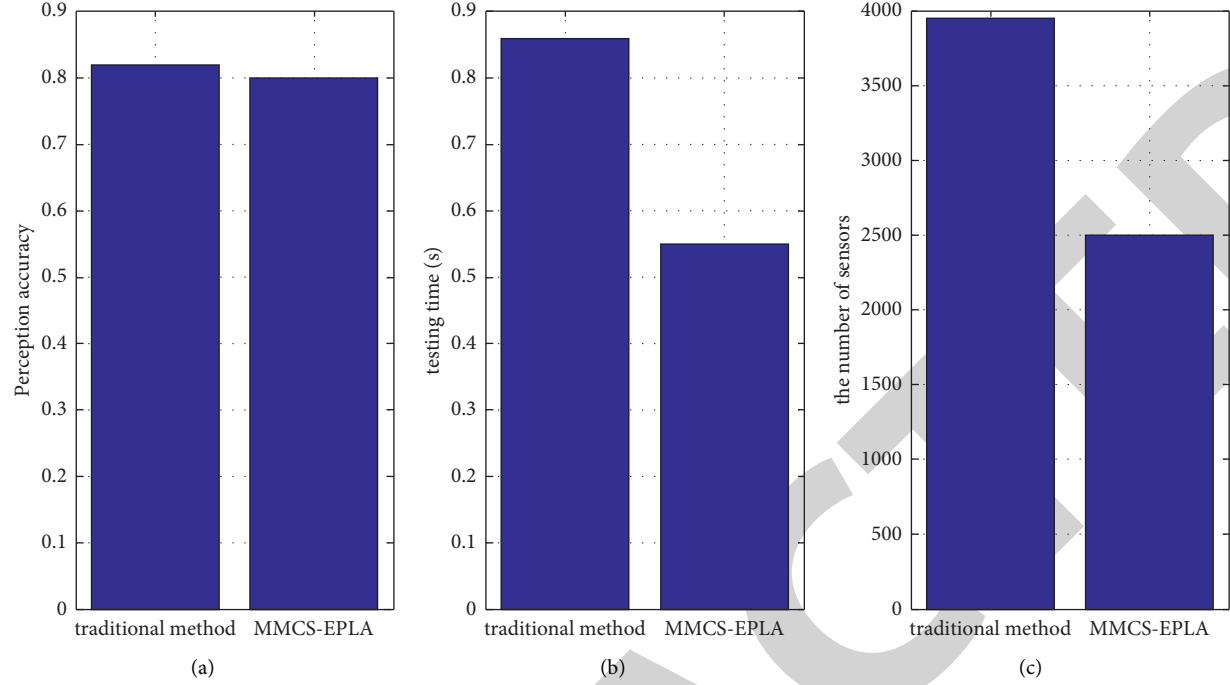


FIGURE 6: Performance comparison between MMCS-EPLA and traditional method in MHEALTH data set.

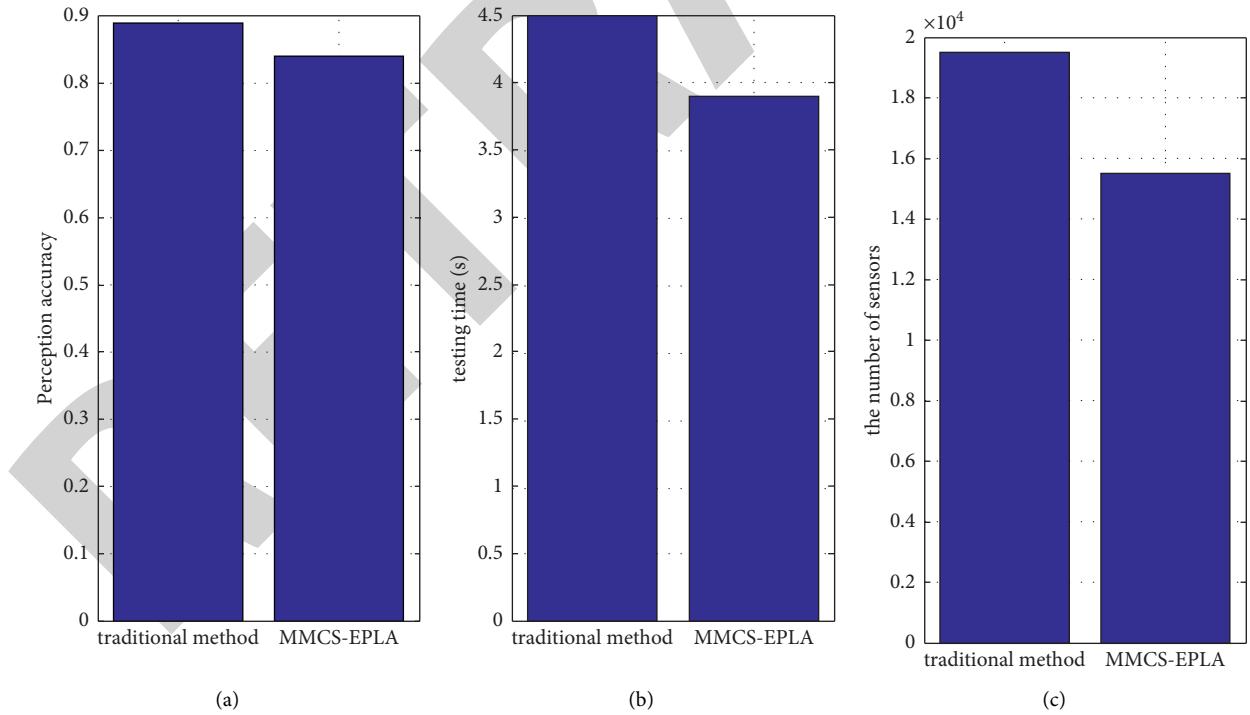


FIGURE 7: Performance comparison between MMCS-EPLA and traditional method in the PAMAP2 data set.

model calculation process, so the test time and the number of sensors showed better performance.

5. Conclusions

Based on the investigation of the research progress of WBSN perception, this paper proposes a multimodal collaborative perception method in order to reduce the energy consumption related to the daily behavior of WBSN perceiving the elderly living people. This method uses a multiclass classifier and binary classifier to perform behavior recognition and status monitoring of users' daily behaviors and perform collaborative scheduling of sensors. In addition, this paper proposes a sensor selection method based on information gain, which selects the minimum sensor combination that guarantees the sensing performance. Through experiments, the method proposed in this paper can effectively perceive the four behaviors required for the perception of PD motor symptoms. MMCS-EPLA uses the pertinence and low complexity of the binary classifier in the modeling process to reduce the power consumption of data transmission and model calculation in the behavioral perception process, thereby extending the perception lifetime of WBSN.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the present study.

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