Scholar Publishing Group
International Journal of Multimedia Computing
https://doi.org/10.38007/IJMC.2022.030205
ISSN 2789-7168 Vol. 3, Issue 2: 29-41

5G Virtual Reality Internet of Things - Research on Human Fall Behavior Recognition and Prediction Based on Wearable Inertial Sensors

Xianmin Ma*
Department of Information Engineering, Heilongjiang International University, Heilongjiang, China
maxianmin@hiu.net.cn
**corresponding author*

Keywords: Wearable, Inertial Sensors, Simple Behavior Recognition

Abstract: In order to improve the accuracy and automation of daily activity recognition and reduce manual intervention, a deep neural network based on wearable sensor signals was proposed for human activity recognition. This paper aims to identify and predict human fall behavior based on wearable inertial sensors. Selecting different device locations can have a significant impact on the efficiency of data collection. In this study, the data obtained by using sensors connected to the lower extremities should be much more effective than data obtained through the arms or other parts of the body when collecting exercise data related to the running behavior of the elderly. In addition to considering the validity of the data, we also need to consider how the data is related to the real situation and how comfortable the user can wear it in real life. Experimental data show that in order to obtain data sets that are easy to calculate, accurate and effective, two aspects need to be considered: the location of data collection equipment and the frequency of data collection. The experimental results show that the recognition accuracy is up to 93.7% after using the training decision tree algorithm with 562 features selected specifically for activity recognition. Then, the extracted features are trained by decision tree algorithm, and the recognition accuracy is only 82.8%. Finally, lSTM-RNN was used to directly train the original sensor data, and the accuracy of behavioral activity recognition in the elderly could reach 92.28%. In the aspect of behavior recognition, the traditional work mainly focuses on the identification of simple behaviors performed by a single person successively. But in real life, human behavior is complex, and applications often require high real-time recognition results.

1. Introduction

Human behavior recognition plays a rich and powerful role in many fields. Behavior recognition can be used for health detection, fall detection and medical help, and can play a big role in the field of human health. In recent decades, for example, there has been a surge in demand for sensor-based devices to monitor activity in the personal fitness industry. In addition to providing traditional pedometer functionality, these devices can use accelerometers and position sensors to record the intensity and duration of a person's movement to help people perform health management tests smoothly. In the field of medical assistance, the typical application is fall detection. Falls can cause serious injuries to older people, and using smartphones or wearable smart devices can help detect falls in time and automatically send alerts. In sports science, data can be recorded to track the athlete's physical condition in time for optimal performance and training. It can also be used to measure posture, improve the accuracy of various movements, and help improve performance. So the research and development of behavior recognition technology can not only help People's Daily life, can make People's Daily life more convenient, but also can improve the intelligence of the whole society.

Although perception methods and computing resources are widely supported by people, there are still great problems to realize the recognition of human behavior [1]. First, in behavioral recognition, the most commonly used to reflect behavioral characteristics and the most critical data types for subsequent identification are problems that have not been fully resolved. Secondly, how to ensure the data through cognitive methods can effectively use the perception data based on behavior recognition, so as to minimize the interference to People's Daily life, protect people's privacy and security and improve the wearing experience, but this is also a very difficult problem. Thirdly, from the perspective of people, People's Daily behaviors are complex, their behaviors are random, and there are complex interactions between them [2-3]. So being able to model and accurately identify complex behavior is a very difficult problem. Finally, in some application scenarios, the performance requirements of the recognition system can be expressed in real time, and the accuracy of recognition can also be considered. In terms of performance, further research is needed. Therefore, how to realize complex behaviors and implement real-time human behavior recognition technology based on wearable sensor network is a key issue for people to study in the future [4-5].

Tamura et al. suggested recording a series of falls in the elderly through the dynamic monitor triggered by the photoelectric circuit breaker. Although its accuracy is poor, it can still be the basis of the study on the detection of falls in the elderly based on the video [6]. Noury et al. developed an autonomous sensor to detect the speed threshold and detect the accelerated movement of human body through triggers. If the speed exceeds the rated limit, another system is used to determine whether a person is standing or falling [7]. The device achieved nearly 85% accuracy in each of the six test subjects' 18 drop scenarios.

The results showed that 562 features of the elderly were selected specifically for activity recognition. After training the decision tree algorithm, the recognition accuracy is up to 93.7%, and then training the extracted features with the decision tree algorithm, the recognition accuracy is only 82.8%. After direct training of the original sensor data by LSTM-RNN, the accuracy of activity recognition can reach 92.28%. In order to test whether the function group based on azimuth information can improve the performance of human behavior recognition system, we need to obtain the precise azimuth of various behaviors. At the same time, the inertial sensor has accumulated error and measurement error, which can debug algorithm parameters to extract the appropriate algorithm to improve the overall recognition rate of the system.

2. Wearable Human Activity Recognition Research

2.1. Research on 5G Virtual Reality

Virtual reality (VR) USES modern high-tech means centered on computer technology to simulate realistic visual, auditory, tactile and other integrated closed 3D virtual Spaces. From the perspective of creating and allowing users to experience their own experiences, they naturally interact with the characters in the virtual world through special input/output devices [8]. Facebook bought Oculus six years ago for a whopping $2.4 billion, propelling the VR industry into an era of rapid growth. VR has 3I functions, which can provide business experience and bring different and new experience to users.

(1) Immersive feeling: The closed helmet and computer-generated 3D stereo images enable users to be completely in the virtual environment, just like in the real objective world, giving people a sense of being in this environment [9].

(2) Interaction performance: In the virtual environment, users can interact with the system through sensors and peripheral devices (gyroscope, magnetometer, handle, touchpad, etc.), and make people feel that they are interacting in the real environment [10].

(3) Imagination performance: when users enter the virtual world, they can enhance their perceptual and rational understanding, enhance their imagination and stimulate their creative thinking by acquiring new knowledge [11]. After years of development, VR technology enjoys a high reputation among users, but it also has many defects, such as less content, poor performance of mobile terminals, low cost performance, inconsistent technical standards and imperfect measurement methods. Among them, the lack of performance of mobile terminals (built-in mobile VR terminals, all-in-one VR terminals, etc.) is one of the important factors limiting the development of VR [12].

2.2. Research Status of Behavior Recognition

Human motion recognition system is actually a data mining system based on sensor input data to judge and classify various motions. The research direction of human behavior recognition system can be divided into three main processes: different behavioral data collection, initial data processing, and behavioral classification and recognition [13]. It is mainly through the collection and processing of the original data sequence to capture the information related to the action and present it in an appropriate way. Finally, through the analysis and understanding of this information, we will understand and learn the human body behavior. At this stage, the main research issues of behavior recognition include the following categories :(1) location and type selection of wearable sensors; (2) Function selection and analysis for classification and recognition; (3) Data processing algorithm research. Since different parts of the human body are not equally sensitive to different movements, some wearable human motion recognition tasks will have inconsistent performance effects when selecting the corresponding sensors and sensor positions [14]. Today, the body parts used for position sensors are divided into head, upper limbs, chest, back, buttocks, buttocks, lower limbs and feet. In the case of the triaxial accelerometer, it is useful to measure information from the movement of the foot or leg, such as running or jumping when placed on the ankle. Another example is to place the sensor on the chest so that it does not collect data from arm movements. According to the location of sensors, wearable human activity recognition can be divided into four categories. The most basic approach is to place a single sensor on a single part of the body. The second is to place a single sensor on another body to capture a composite signal. Third, multiple categories of sensors are placed in the same location in the human body to obtain different types of data. The final approach is multibody, with multiple types of sensors (many-to-many) placed in one place, so you can combine the advantages of the first three approaches.

2.3. Design of Wearable Human Activity Recognition System

The wearable human activity recognition system is mainly divided into three parts: data acquisition part, data transmission part and data processing part. Data collection is mainly performed by various sensors connected to the human body, and collects inertial information (such as human acceleration and angular velocity) and physiological information (such as heart rate and respiration) at a certain frequency [15]. The collected sensor data is transmitted to a portable smartphone via a network module such as Zigbee or Bluetooth. Smartphones can perform data processing and recognition tasks. People can also perform basic noise reduction, shielding and compression functions on the phone. It then forwards other operations and those operations to the remote cloud platform [16]. Due to the powerful computing performance of cloud platform, it can effectively analyze, process and visualize big data.

After acquiring various types of data related to human behavior based on various sensing methods included in the wearable sensor network, a series of processing is conducted on these data to analyze the human behavior information contained therein [17]. Although the specific processing required depends on the type of perception data, and each type corresponds to a different approach, the basic system framework is essentially the same as considering the entire human behavior recognition system at the macro level. Behavior recognition problem is usually considered as a special classification problem, and behavior recognition system conforms to the architecture of general pattern recognition system [18].

Existing solutions:

(1) Data perception and acquisition technology

In addition to the use of active sensors for activity identification, a group of RFID technologies has emerged in recent years, along with the development of related technologies at gusher speed, which can use passive induction technology to perform tasks related to human tracking and activity identification. Therefore, such passive equipment usually has excellent characteristics such as small size, light weight and maintenance free, and is a perception technology with the potential to develop motion recognition technology [19].

(2) Data segmentation technology

Push-pull window technology has the advantage of being easy to use. At the same time, using sliding window for data segmentation can effectively control the time of data collection. It is well suited for time-sensitive behavior recognition systems. However, considering the requirements of cognitive delay and accuracy, it is still a difficult problem to select the optimal sliding window size to achieve accurate segmentation of behavioral data [20].

(3) Feature extraction method

For the task of motion recognition using signal strength, wireless signal function of wearable active sensor is used to realize motion recognition. Various features of sensor data, such as acceleration, environment and physiology, have been widely used in behavior recognition tasks [21].

(4) Motion recognition algorithm

1) Related technologies of a person's complex motion recognition: the algorithm can be roughly divided into static recognition algorithm and time series recognition algorithm. In the static recognition algorithm, the following algorithms are usually used for behavior recognition: naive Bayes, decision tree, support vector machine, etc. Sequential recognition algorithm: dynamic Bayesian network, conditional random airport, dynamic time normalization. Like this.

2) Multi-person interaction technology related to behavior recognition: The key to identifying multi-person behaviors is to model the interaction between multiple people. Figure 1 shows a flow chart of the existing solution technology.

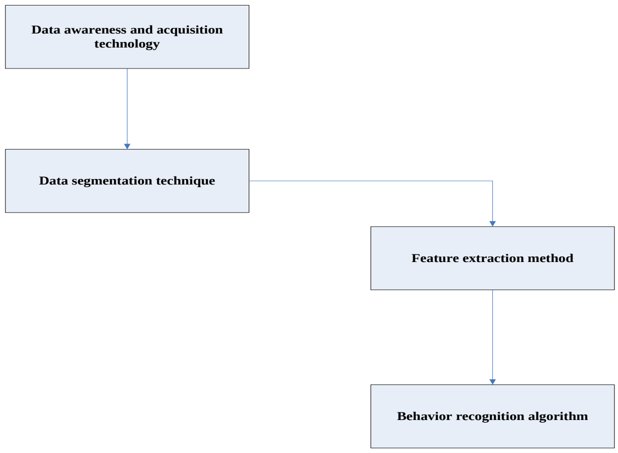

Figure 1. Flow chart of existing solutions

Wrestling testing is an interesting scientific problem because it is an ambiguous process that can be tested in different ways. Different from the method of remote monitoring of patients' motion state, the fall detection system based on image analysis performs dynamic real-time data processing on human body and provides accurate and stable sensing information to determine the motion posture of human body. However, this system has obvious limitations, so this paper does not study the technology based on image analysis. Many falls in the elderly occurred outdoors, and the fixed camera position could not effectively track the outdoor human movement information. In other words, if the user leaves the scope of the monitor, the fall motion will not be correctly judged. Not only that, the system also has the risk of personal privacy disclosure. Optical tracking systems (camera-based systems) are by far the most widely used and mature systems. However, due to the lack of space, optical tracking systems are often expensive and often not available in clinical or laboratory Settings. For daily use, a non-visual tracking system is preferred, especially considering that the patient is not in a small space at home.

2.4. Data Fusion Algorithm Analysis

(1) Human activity identification

Human activity recognition is a supervised classification problem. The main link is the design and implementation of classifier.

Existing research on human activity identification requires heuristic extraction of various characteristics representing activities in the time domain, frequency domain and time-frequency domain from the original data to effectively distinguish activities [22]. It is difficult to find attributes that completely describe different types of activities. Greater reliance on specialized knowledge and different types of data requires a priori knowledge in different areas (e.g. inertial properties differ from physiological properties). Moreover, human activities are a continuous process, which, in addition to short-term internal patterns, also depend on various types of sensory data for a long time, especially physiological signals such as human heart rate [23].

In recent years, the rapid development of deep learning technology has always emphasized the direct end-to-end learning from the original data, instead of manually designing features as in the past, thus effectively solving the problem of feature extraction. Therefore, in order to achieve the goal of information retention and transmission, researchers added a recursive module to the traditional neural network to form the fusion of recursive neural network sensors [24]. LSTM is a special form of RNN network. The hidden layer consists of a series of recursively connected blocks of storage. Each storage block contains a storage unit with three gates: input, record, and output.

The "lost slope" problem of conventional RNN can be effectively solved by reading, writing, and resetting storage cells and transferring control information between different storage cells [25].

The structure of an LSTM memory unit is shown in the following formula, and the state of the memory unit is updated by the following formula:

$$i_t = \sigma(W^i \bullet [h_{t-1}, x_t] + b^i) \tag{1}$$

$$f_t = \sigma(W^f \bullet [h_{t-1}, x_t] + b^f) \tag{2}$$

$$o_t = \sigma(W^o \bullet [h_{t-1}, x_t] + b^o) \tag{3}$$

$$c_t = f_t * c_{t-1} + i_t * \tanh(W^c \bullet [h_{t-1}, x_t] + b^c) \tag{4}$$

$$h_t = o_t * \tanh(c_t) \tag{5}$$

Where: respectively represents the output of input gate, forgetting gate, output gate, control unit and memory unit at time T. Are the corresponding bias vectors, and are the weight matrix.

(2) Distance measurement

The basic idea of distance measurement is to use distance to evaluate the similarity between samples. Distance algorithm is a classical feature weight iterative algorithm based on distance measurement. It is widely used because it performs very efficiently and has a linear relationship with sample size and eigenset size. The basic idea is to update feature weights according to equation (6). The higher the weight, the stronger the feature classification ability. If an element has a weight greater than a given threshold, it is added to the element subset. However, the distance algorithm does not consider the relationship between elements, so the algorithm cannot delete redundant elements.

$$W(i) = W(i) - diff(i, R, H) + diff(i, R, M) \tag{6}$$

Where: is the weight value of characteristic I, is the nearest distance from the sample in the same category H, and is the nearest distance from the sample in different category M.

(2) Information measurement

Feature selection methods based on information selection usually use information gain or mutual information to measure the effect of features. The basic idea is to select the characteristic with minimum training classification uncertainty. MRMR algorithm is a typical feature selection method based on mutual information. It considers the relationship between features as well as the ability to distinguish features, so redundant features can be removed. The basic idea of mRMR algorithm is to use mutual information as a metric to calculate the correlation between feature subsets and categories and the redundancy between features, as shown in Formula (7). However, this algorithm does not consider the weight of features and cannot reflect the importance of different features.

$$I(x, y) = \iint p(x, y) lb \frac{p(x, y)}{p(x)p(y)} dxdy \tag{7}$$

The larger I (x, y) is, the higher the correlation between x and y is. Using this feature, the mRMR algorithm USES maximum correlation D and minimum redundancy R measures to select the subset of features that cause d-R to reach its maximum value as the final selected feature set.

3. Behavioral Recognition Experiments for the Elderly

3.1. Collect Experimental Sensor Data

In this paper, we chose six mobile phones as the experimental data collection platform. Three types of MEMS sensors were used in the data collection process, such as gyroscope, accelerometer and electronic compass. In gathering data for this experiment, we considered some basic human behaviors: four dynamic behaviors: walking, running, climbing stairs, and two static behaviors: standing and sitting. Behavior. The data collection process must consider two aspects in order to obtain data sets that are easy to calculate, accurate, and valid. Two issues to note are: where to wear the data collection device and how often the data is collected.

3.2. Select the Installation Location of the Experimental Equipment

Choosing different device locations can seriously affect the efficiency of data collection. When collecting sports data on running behaviour, for example, wearing sensors on the lower limbs should have a far greater impact on the data than the arm. Or data obtained from other parts. In addition to the validity of the data, we also need to consider how the data is connected to reality and how comfortable the user is wearing in real life. According to an earlier survey of how mobile phone users carry themselves, 36 per cent carry their phone in their trousers pocket and 34 per cent carry it in their shoulder bag. Keep your smartphone in your backpack or jacket pocket. Based on the above factors and experimental conditions, this study chooses the location where smart phones are limited to wear. Upper pocket, trouser pocket and hand hold.

4. Discussion on Behavioral Characteristics Recognition of the Elderly

4.1. Analysis of Behavioral Characteristics of the Elderly

(1) The activity recognition model of the elderly based on LSTM-RNN is obtained by TensorFlow framework through hardware acceleration training of NVIDIA GTX 1060 graphics card on Ubuntu 16.04 platform. The super parameters in the training process, such as learning rate, batch size, loss coefficient and training iteration times, were obtained by multiple assignment tests and screening. 0.0025, 1,024, 0.0015 and 300 were selected here respectively. First, the influence of feature engineering on activity recognition accuracy was considered, and the open UCI HAR data set was used for experiments. This data set recorded the triaxial acceleration and triaxial gyroscope data through a mobile phone fixed at the waist, so as to identify 6 activities including walking, going upstairs, going downstairs, sitting, standing and lying down. For this data set, the decision tree algorithm is used to directly extract 561 features of the elderly for activity recognition. The experimental results are shown in Table 1 and Figure 2.

Table 1. Recognition effect of feature extraction based on expert knowledge

	Precision	Recall	Fl-Score	Support
1	0.95	0.93	0.93	346
2	0.92	0.95	0.95	292
3	0.94	0.98	0.96	284
4	0.96	0.98	0.94	373
5	0.97	0.99	0.91	387
6	0.99	0.92	0.99	382
Avg / Total	0.98	0.94	0.93	2062

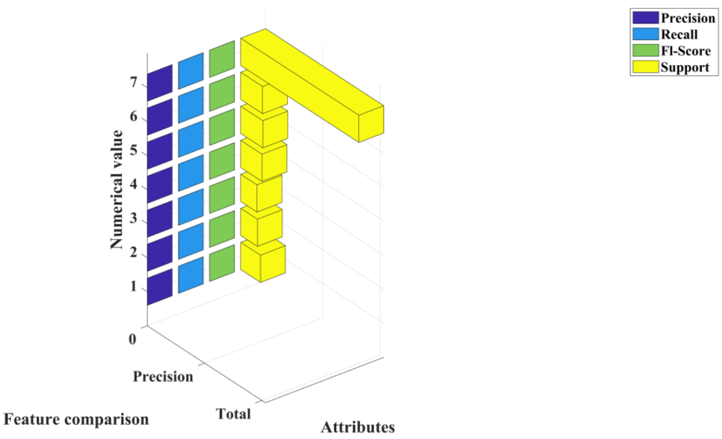

Figure 2. Recognition effect of feature extraction based on expert knowledge

(2) Scheme 2 extracted 276 time-domain or frequency-domain features from each window of each channel of the original data through a universal timing feature extraction tool, and input decision tree for activity identification. The classification effect is shown in Table 2. It can be seen from the experimental results that feature extraction has a great impact on the accuracy of activity recognition. Using 562 features specially designed for activity recognition and optimization, the recognition accuracy rate is up to 93.7% after decision tree algorithm training. Then, after the same training of decision tree algorithm, the recognition accuracy of the extracted features is only 82.8%. Finally, lSTM-RNN is used to directly train the original sensor data, and the accuracy of activity recognition can reach 92.28%. It avoids the low accuracy caused by the imperfect feature extraction method (such as plan 2) and reduces the dependence on expert knowledge. Specific data are shown in Table 2 and Figure 3:

Table 2. Recognition effects based on general time series features

	Precision	Recall	F1-Score	Support
1	0.92	0.96	0.96	352
2	0.91	0.94	0.93	317
3	0.95	0.88	0.93	274
4	0.68	0.72	0.68	337
5	0.73	0.71	0.75	355
6	0.78	0.79	0.77	423
Avg / Total	0.82	0.84	0.84	2060

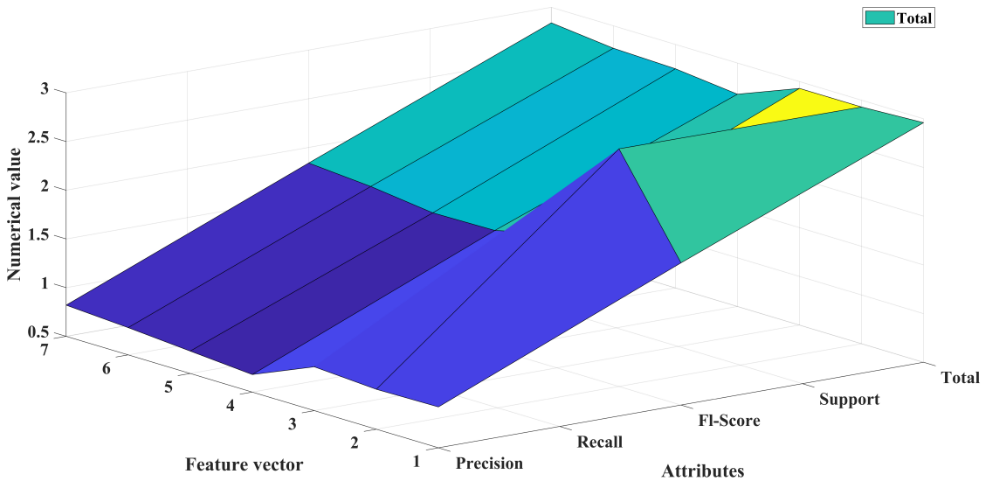

Figure 3. Recognition effects based on general time series features

4.2. Sensor Accuracy Analysis

(1) When the sensor module is installed on the shoulder of human body, the accuracy rate of the elderly in the interference group of suddenly crouching down to pick up things and lurching forward is only 40%; When the sensor modules were attached to the feet, the participants in the interference group were only 0 percent correct in walking a few steps or running to a sudden stop. When analyzing the result of miscarriage of justice, it is agreed that the case of a fall without alarm is a serious miscarriage of justice, while the case of a fall without alarm is a general miscarriage of justice. No matter which of the three parts of the human body the sensor module is placed in during the experiment, the incidence of serious misjudgment is 0, which proves that the fall detection system has good robustness. When the sensor module is placed on the human shoulder and the foot, general misjudgment occurs respectively. According to the rate of general misjudgment, the following conclusion can be drawn: Other conditions being the same, the sensor module is placed on the waist to obtain the most accurate data, followed by the shoulder and finally the foot. Figure 4 shows the accuracy data of fall detection results of the mounted shoulder.

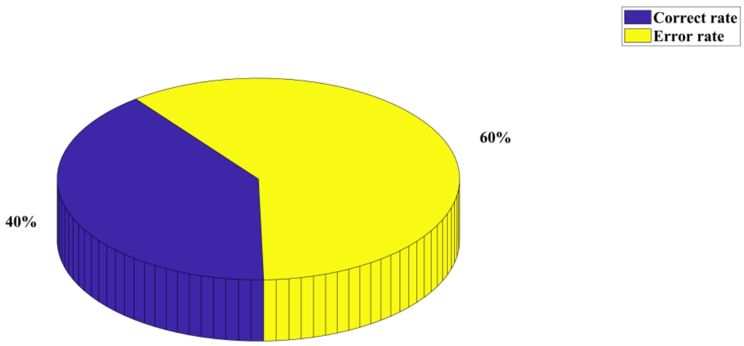

Figure 4. Accuracy data of the fall detection result of the installed shoulder

(2)During the experiment, it was found that the upper limb was impacted greatly after the elbow brace after the fall, so it was determined that the upper limb was the injured part when the elbow brace after the fall; Similarly, the injured part of the backward fall (including lying for two seconds before getting up and immediately getting up) is the head, because many old people's heads hit the wall, the corner of the table, or directly on the ground when they fall backward. The injured part corresponding to the kneeling movement of forward fall is the lower extremity (knee injury); The injured part corresponding to the forward fall on the stomach is the trunk (chest and abdomen and other parts suffered more serious impact); Side falls (including left side falls and right side falls) are associated with multiple injuries (shoulder, waist, abdomen, leg may be injured to varying degrees). The specific corresponding relationship is shown in Table 3:

Table 3. Percentage of parts corresponding to falling posture

Part	Corresponding to the fall position	Percentage
Head	Lying down	24.42
Upper limb	Back elbow	18.35
Lower limb	Kneeling down	29.30
Trunk	Fall forward	20.02
Multi-site	Fall	6.33

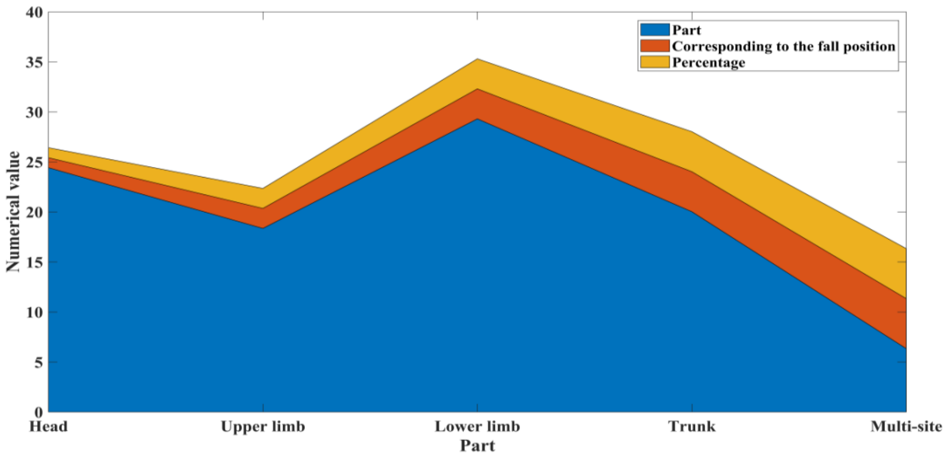

Figure 5. Percentage of parts corresponding to falling posture

5. Conclusion

(1) At the level of behavioral perception, the user experience should be perceived in the most effective and optimal way based on certain goals. Through the network level of the wearable sensor network, a more detailed study will be conducted based on the needs of human behavior identification related applications. Through the data processing level of the wearable sensor network, we will search for more optimized data processing methods based on application requirements, including data processing in the network, system energy consumption, time and computing overhead, and identification methods. Search for more efficient and scalable recognition algorithms to solve complex cognitive problems, such as complex behavior and multi-person

behavior; In addition, identify techniques to explore human behavior, physical and mental states. Generally speaking, people's future work will be closer to the practical application and human needs, and more detailed and in-depth research will be conducted in all aspects such as perception, network, algorithm and software.

(2) In this paper, we propose a wearable human activity recognition system, iWear RT, which combines multi-mode sensor data such as inertial signals and physiological signals. First, the overall system framework of iWear RT was designed, the configuration and partition of system modules were planned, and the research focus was wearable device sensor type, installation location and data collection framework, and then various types of wearable devices. The multi-peak data such as inertial data and physiological data obtained by the sensor are preprocessed by noise reduction and windowing, and lSTM-RNN deep neural network is designed to identify human activities. Finally, the simulation experiment is carried out. The experimental results show that this method does not require manual feature extraction, reduces the dependence on professional knowledge, can automatically fuse heterogeneous sensor data, and has high accuracy and good classification effect.

(3) The experimental results of this paper show that 562 features of the elderly specifically used for activity identification were used. After training the decision tree algorithm, the recognition accuracy is as high as 93.7%, and the extracted features have a recognition accuracy of only 82.8%. Lstm-rnn directly trains the original sensor data for activity recognition. The accuracy reached 92.28 percent. The content of the investigation is human behavior recognition system based on wearable sensor. At this stage, the accelerometer is the primary source of data for most human behavior recognition systems. Based on the azimuth information of inertial navigation system, this paper studies the azimuth information in detail.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Shen Y, Phan N H, Xiao X, et al. Dynamic socialized Gaussian process models for human behavior prediction in a health social network. Knowledge and Information Systems. (2016) 49(2): 455-479. https://doi.org/10.1007/s10115-015-0910-z

[2] Xu M, Guo H, Hou C, et al. Corrigendum: Olfactory perception and behavioral effects of sex pheromone gland components in Helicoverpa armigera and Helicoverpa assulta. Scientific Reports. (2016) 6(1): 22998. https://doi.org/10.1038/srep22998

[3] Xu M, Guo H, Hou C, et al. Corrigendum: Olfactory perception and behavioral effects of sex pheromone gland components in Helicoverpa armigera and Helicoverpa assulta. Scientific Reports. (2016) 6(1): 22998. https://doi.org/10.1038/srep22998

[4] Dong X, Zhang L, Milholland B, et al. Accurate identification of single-nucleotide variants in whole-genome-amplified single cells. Nature Methods. (2017) 14(5): 491-493. https://doi.org/10.1038/nmeth.4227
[5] Li G, Liu T, Yi J, et al. The Lower Limbs Kinematics Analysis by Wearable Sensor Shoes. IEEE Sensors Journal. (2016) 16(8): 2627-2638. https://doi.org/10.1109/JSEN.2016.2515101
[6] Hayashi T, Tamura Y, Hasegawa T, et al. Record-Low Spatial Mode Dispersion and Ultra-Low Loss Coupled Multi-Core Fiber for Ultra-Long-Haul Transmission. Journal of Lightwave Technology. (2017) 35(3): 450-457. https://doi.org/10.1109/JLT.2016.2614000
[7] Souri Yaser, Noury Erfan, AdeliMosabbeb Ehsan. Deep Relative Attributes. IEEE transactions on multimedia. (2016) 18(9): 1832-1842. https://doi.org/10.1109/TMM.2016.2582379
[8] Bastug E, Bennis M, Medard M, et al. Toward Interconnected Virtual Reality: Opportunities, Challenges, and Enablers. IEEE Communications Magazine. (2017) 55(6): 110-117. https://doi.org/10.1109/MCOM.2017.1601089
[9] Elbamby M S, Perfecto C, Bennis M, et al. Towards Low-Latency and Ultra-Reliable Virtual Reality. IEEE Network. (2018) 32(2): 78-84. https://doi.org/10.1109/MNET.2018.1700268
[10] Boy J, Eveillard L, Detienne F, et al. Suggested Interactivity: Seeking Perceived Affordances for Information Visualization. IEEE transactions on visualization & computer graphics. (2016) 22(1): 639. https://doi.org/10.1109/TVCG.2015.2467201
[11] Berg L P, Vance J M. Industry use of virtual reality in product design and manufacturing: a survey. Virtual Reality. (2017) 21(1): 1-17. https://doi.org/10.1007/s10055-016-0293-9
[12] Chen X, Jiao L, Li W, et al. Efficient Multi-User Computation Offloading for Mobile-Edge Cloud Computing. IEEE/ACM Transactions on Networking. (2016) 24(5): 2795-2808. https://doi.org/10.1109/TNET.2015.2487344
[13] Batchuluun G, Kim J H, Hong H G, et al. Fuzzy system based human behavior recognition by combining behavior prediction and recognition. Expert Systems with Applications. (2017) 81(SEP.): 108-133. https://doi.org/10.1016/j.eswa.2017.03.052
[14] Guo B, Chen Y J, Lane N, et al. Behavior Recognition Based on Wi-Fi CSI: Part 1. IEEE Communications Magazine. (2017) 55(10): 90-90. https://doi.org/10.1109/MCOM.2017.8067691
[15] Olszewski K, Lim J J, Saito S, et al. High-fidelity facial and speech animation for VR HMDs. Acm Transactions on Graphics. (2016) 35(6cd): 221. https://doi.org/10.1145/2980179.2980252
[16] Browne G J, Cheung C M K, Heinzl A, et al. Human Information Behavior. Wirtschaftsinformatik. (2017) 59(1): 1-2. https://doi.org/10.1007/s12599-016-0458-9
[17] Yang L, Liu J, Zhang Y. An Intelligent Security Defensive Model of SCADA Based on Multi-Agent in Oil and Gas Fields. International Journal of Pattern Recognition and Artificial Intelligence. (2020) 34(01): 269-282. https://doi.org/10.1142/S021800142059003X
[18] Bhowmik T K, Parui S K, Roy U, et al. Bangla Handwritten Character Segmentation Using Structural Features: A Supervised and Bootstrapping Approach. Acm Transactions on Asian Language Information Processing. (2016) 15(4): 29.1-29.26. https://doi.org/10.1145/2890497
[19] Okuno T, Hardison D M. Perception-production link in L2 Japanese vowel duration: Training with technology. Language Learning & Technology. (2016) 20(2): 61-80.
[20] Wang X, Zhang W, Zhang Y, et al. Top-kspatial-keyword publish/subscribe over sliding window. Vldb Journal. (2017) 26(3): 301-326. https://doi.org/10.1007/s00778-016-0453-2
[21] Huimin Z, Meng S, Wu D, et al. A New Feature Extraction Method Based on EEMD and Multi-Scale Fuzzy Entropy for Motor Bearing. Entropy. (2016) 19(1): 14. https://doi.org/10.3390/e19010014

[22] *Tao D, Jin L, Yuan Y, et al. Ensemble Manifold Rank Preserving for Acceleration-Based Human Activity Recognition. IEEE Transactions on Neural Networks and Learning Systems. (2016) 27(6): 1392-1404. https://doi.org/10.1109/TNNLS.2014.2357794*

[23] *Yasuhara M, Doi H, Wei C, et al. Biodiversity-ecosystem functioning relationships in long-term time series and palaeoecological records: deep sea as a test bed. Philos Trans R Soc Lond B Biol Sci. (2016) 371(1694): 20150282. https://doi.org/10.1098/rstb.2015.0282*

[24] *Kanarachos S, Mathew J, Fitzpatrick M E. Instantaneous vehicle fuel consumption estimation using smartphones and recurrent neural networks. Expert Systems with Application. (2019) 120(APR.): 436-447. https://doi.org/10.1016/j.eswa.2018.12.006*

[25] *Bieschewski S, Parcerisa J M, Antonio González. An Energy-Efficient Memory Unit for Clustered Microarchitectures. IEEE Transactions on Computers. (2016) 65(8): 2631-2637. https://doi.org/10.1109/TC.2015.2493518*