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Dance Movement Interference Suppression Algorithm Based on Wearable Sensors in a Smart Environment

Junpei Zhong

Nottingham Trent University, Britain

zhong@junpei.eu

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Abstract: Wearable device (Wearable device) is a hardware device that can be installed on clothes, clothing accessories or directly worn on the body for easy carrying. It can collect a large amount of user data and behavior habits in real time, and complete some by using software information technology. This paper aims to study the dance movement interference suppression algorithm based on wearable sensors in a smart environment. This paper proposes a method of human action recognition based on wearable sensors, using the original motion capture data collected by the wearable sensors to perform three-dimensional reconstruction, which shows that the basic link of constructing action words is the extraction of key gestures. In addition, this article also proposed an interference suppression algorithm, introduced wavelet noise reduction processing, calculated wavelet coefficients, noisy signals and other basic information, which proved the effectiveness of the interference suppression algorithm. The experimental results of this article show that the wearable sensor dance movement recognition in a smart environment has been greatly improved compared with the traditional dance movement recognition. Among them, the recognition rate of dance movements has increased by 25%, and the error of dance movements has become smaller and smaller. The results show that the interference suppression algorithm has obvious effects on the dance movements of the wearable sensor.

1. Introduction

With the popularization of Internet technology and the wide application of a large number of multimedia devices, a large number of multimedia video terminals have appeared. Music and dance video, as a widely distributed video, is gradually being promoted by researchers. Effective retrieval of dance video clips is helpful to dance teachers in choreography and dance teaching. Cutting-edge video dance video restoration technology will strongly promote the inheritance and development of dance. It has important theoretical significance and practical value.

With the accelerating pace of modern life, people's attention to physical health continues to increase. In order to achieve dynamic monitoring of human body information, wearable devices have become ideal products for people, especially the popularization of mobile smart devices and short-range wireless communication. With mature applications, the public’s awareness of wearable smart devices is also rapidly increasing. Its portability and functionality are gradually changing people’s lifestyles. Smart wearable devices are not only a weapon for future smart life practices, but also in the networked era., An important terminal that collects user data in addition to mobile phones.

The effective use of multimodal information is a promising method for human activity recognition (HAR) based on wearable sensors. Li G proposed a method to use the diversity of basic classifiers to build a good set of multimodal HAR, and obtain diversity indicators from labeled and unlabeled data; MARCEL uses neural networks (NN) as the basic classification to build the HAR model, and the diversity of the classifier set is embedded in the error function of the model. In iteration after iteration, the error of the model will be decomposed and propagated back to the basic classifier to ensure the overall accuracy of the model. But the complexity of this method is too high [1]. The Internet of Things (IoT) is a dynamic global information network composed of objects connected to the Internet, which have become an integral part of the Internet in the future. Perera C surveyed more than one hundred IoT smart solutions on the market and carefully checked them to identify the technologies, functions and applications used. Based on the application field, he classified these solutions into five categories: 1) Smart wearable devices; 2) Smart wearable devices. 3) Smart city; 4) Smart environment; 5) Smart enterprise. This survey is intended to serve as a guide and conceptual framework for future research on the Internet of Things to inspire and inspire further development. However, due to certain errors in the survey, the results will not be so accurate [2]. Honig M L proposed an adaptive rank reduction interference suppression algorithm based on multi-stage Wiener filter (MSWF). Check performance in the context of Direct Sequence (DS) Code Division Multiple Access (CDMA). Different from the principal component method used for rank reduction filtering, the algorithm he proposed can achieve close to full rank performance, and the rank of the filter is much smaller than the dimension of the signal subspace. But the practicality of this algorithm is not very high [3].

The innovation of this paper is (1) Analyze the significance of wireless sensor network positioning and tracking technology research, and propose various positioning algorithms in wireless sensor networks in a smart environment, which are mainly divided into ranging and non-ranging algorithms. (2) A quantification method of human motion is proposed. By extracting 8 important angle features to replace the original data of each frame in the motion sequence, the redundant information of the original motion capture data is effectively eliminated. (3) A method for obtaining basic video sequences adapted to continuous actions is proposed. In the characteristic export stage, if the posture of the human body is directly used for the posture characteristics of the human body, or the area of the human body in the image is determined by the posture information, it reflects the dependence of the knowledge of behavior on the attitude of the person, and the misunderstanding of the attitude of the person Will directly affect the results of behavioral awareness.

2. Dance Movement Interference Suppression Algorithm Based on Wearable Sensors

2.1. Human Action Recognition Method Based on Wearable Sensors

(1) Three-dimensional reconstruction

Although BVH has the advantages of wide sources, convenient storage, and high visibility, it has a fatal problem: the rotation data of each link point is created relative to the parent link point, which is not conducive to global analysis [4]. In addition, a small change in the rotation angle of the parent joint point will have a huge impact on the child joint, and it is easy to generate noise. In order to better analyze the human motion process, this paper will divide the initial traffic collection data collected by the wearable sensor into three parts to reconstruct the size [5-6].

Each connection point in the original data should have six degrees of freedom, that is, rotation data and translation data in the three directions of X, Y, and Z coordinate axes. The process of converting the local coordinates of the connection point into global coordinates should be:

1) Rotate the local joint coordinate system by corresponding angles in the three directions of Z, X, and Y [7].

2) Use the conversion table to convert the local coordinate system.

3) Multiply the local coordinates of the connection point by the local coordinate conversion table of the parent joint point until the root connection point is reached, and finally the global coordinates of the connection point are obtained [8].

The calculation of the above process is shown in formula (1).

$$U' = M \bullet U \tag{1}$$

Among them, U'represents the global coordinates of the connection point, M represents the transformation matrix in the global coordinate system, and U represents the local coordinate of the connection point.

The specific calculation method of conversion table M is shown in formula (2). Using the above method, the transformation matrix from each connection point to the global coordinate system can be obtained. $[T_x, T_y, T_x 1]^T$ is the final position of each common point in the global coordinate system [9].

$$M = \prod_{i=0}^{n} M_i = \begin{bmatrix} & & & T_x \\ & R & & T_y \\ & & & T_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

Among them, the coordinates of the global coordinate system X, Y, Z are respectively represented by T_x, T_y, T_z, where R represents the rotation matrix [10-11].

According to the above method, the total coordinates of different connection points are calculated according to the level, and the adjacent connection points are connected into a straight line to form a complete skeleton [12]. On this basis, the frame structure of each frame is calculated in the motion capture data, and the time interval between adjacent frames is reconstructed by determining the three-dimensional body motion [13].

(2) Key gesture extraction

The basic part of constructing action words is the extraction of key gestures [14]. This link is not only related to the ability of the final action words to describe the original action sequence, but also determines the number of final action words generated, which in turn determines the conversion efficiency of the action text [15].

This article completes the reconstruction of the action sequence by linear interpolation of the important postures in the action sequence [16]. Assuming that the action data of the t1 and t2 frames are f(t1) and f(t2), respectively, the action data f(t) of the t frame can be calculated by formula (3), where t1<t <t2.

$$f(t)=\frac{t_2-t}{t_2-t_1}f(t_1)+\frac{t-t_1}{t_2-t_1}f(t_2) \tag{3}$$

For an action sequence S={f 1, f 2, …, f N} of length N, the first frame and the last frame in S are defaulted as the key pose frames, and the reconstruction sequence obtained by formula (3) S ', where fi and fi' are the i-th frame in the original sequence S and the reconstructed sequence S 'respectively. Then, the reconstruction error e^r of the two sequences can be expressed as (4), where d represents the distance between the two frames of action data, which can be calculated by (5) [17]. The distance is actually calculated by first calculating the similarity of the two frames of action data, and then using 1 to subtract the similarity to get the degree of dissimilarity of the two frames of posture [18-19].

$$e^r=\max_{i=1,2,\ldots,N}\{d(f_i,f_i')\} \tag{4}$$

$$d(f_i,f_i')=1-\frac{f_i\bullet f_i}{|f_i|\bullet|f_i|} \tag{5}$$

2.2. Dance Action Recognition Method

It is assumed here that there are n dance moves $x_1,x_2,\ldots,x_n$ and category $y_1,y_2,\ldots,y_n$ in the dance data set. At the same time, the A kernel functions corresponding to the HOG feature are defined as:

$$k_a(x_i,x_j),a=1,2,\ldots,A \tag{6}$$

The B kernel *functions corresponding to the HOF feature are defined as:*

$$k_b(x_i,x_j),b=1,2,\ldots,B \tag{7}$$

The M kernel functions corresponding to the audio signature feature are:

$$k_m(x_i,x_j),m=1,2,\ldots,M \tag{8}$$

In this paper, the linear combination of the kernel function combining the above three characteristics can be expressed by the following formula:

$$k(x_i,x_j)=\sum_{a=1}^{A}\beta_a k_a(x_i,x_j)+\sum_{b=1}^{B}\beta_b k_b(x_i,x_j)+\sum_{m=1}^{M}\beta_m k_m(x_i,x_j) \tag{9}$$

Among them, β_x is the weight of the corresponding kernel function [20].

In the support vector machine based on multi-core learning, the task of the multi-core learning model training stage is to learn and solve the weights of each kernel function and the parameters a and b of the support vector machine classifier itself. Based on the SimpleMKL algorithm idea introduced in the previous section, the objective function of the algorithm in this article is defined as the following formula:

$$\min_{\beta_x, a, b} J = 1/2\sum_{a=1}^{A}\beta_a\alpha^T K_a\alpha + 1/2\sum_{b=1}^{B}\beta_b\alpha^T K_b\alpha + + 1/2\sum_{m=1}^{M}\beta_m\alpha^T K_m\alpha$$
$$+ C\sum_i \zeta_i y_i[\sum_{a=1}^{A}\beta_a K_a(x_i) + \sum_{b=1}^{B}\beta_b K_b(x_i) + \sum_{m=1}^{M}\beta_m K_m(x_i)]\alpha + y_i b \geq 1 - \zeta_i \forall i \tag{10}$$

$$y_i \geq 0\forall i, \sum_{a=1}^{A}\beta_a + \sum_{b=1}^{B}\beta_b + \sum_{m=1}^{M}\beta_m = 1 \tag{11}$$

According to the idea of SimpleMKL algorithm, the gradient descent algorithm is used to minimize the objective function to learn and solve the optimal parameters. The specific process is that in each iteration process, first calculate the classifier parameters a and b through the given kernel function weights; Then by given a and b, calculate the new kernel function weight. Therefore, the classification function based on multi-core learning support vector machine is as follows:

$$y = F(x) = [\sum_{a=1}^{A}\beta_a K_a(x_i) + \sum_{b=1}^{B}\beta_b K_b(x_i) + \sum_{m=1}^{M}\beta_m K_m(x_i)]\alpha + b \tag{12}$$

In addition, formula (12) is a two-class classification function, and the recognition problem we want to solve in this article is a multi-class classification problem [21]. So it is necessary to convert the two-class classification problem into a multi-class classification problem. Currently, SVM-based multi-class classification strategies are divided into two types: one-to-one and one-to-many [22].

(1) One versus one strategy For N types of classification problems, N (N-1)/2 classifiers are required, and each classifier is trained on any two class samples [23]. When classifying unknown samples, count the number of votes of N categories in all classifiers, and the category with the most votes is the category of location samples [24].

(2) One versus rest classification strategy for all samples, the samples of a certain class are classified into one class, and the samples of all the remaining classes are classified into another class. For N classification problems, this strategy requires training N classifiers. When training each classifier, one of the samples is assigned a positive label, and all other samples are given a negative label [25].

This article chooses the second strategy when classifying. The multi-category problem in this article is converted into multiple joint binary classification problems, that is, for each category in the data set, all dance moves belonging to this category are marked as positive, and other dance moves are marked as negative [26]. According to the introduction in the SimpleMKL algorithm, assuming that there are p-type dance moves, p two-type SVM classifiers need to be trained. Therefore, the objective function of multi-class classification also becomes as shown in equation (13):

$$J = \sum_{n=1}^{N} J_n(\beta_a, \beta_b, \beta_m, a_n, b_n) \tag{13}$$

In the above formula, J_n is the nth support vector machine class-2 classifier? The output is dance moves of n, and the negative samples are dance moves whose category is not n. Finally, the algorithm in this paper obtains the action category according to formula (14) when performing multi-class classification:

$$y = \arg\max_{y_n} F_n(x) \tag{14}$$

2.3. Interference Suppression Algorithm

Wavelet transform is a time-frequency change algorithm, which is defined as the inner product of the displacement υ based on the basic wavelet function $\partial(t)$ for the signal to be analyzed under the action of different scale a:

$$WT_x(a,\upsilon) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\partial^*(\frac{t-\upsilon}{a})dt, a > 0 \tag{15}$$

Among them, the frequency resolution of wavelet transform time t changes dynamically, the frequency width is very narrow at low frequencies, and the time range at high frequencies is very small. Suppose the noisy signal s(k), then:

$$s(k) = f(k) + e(k); k = 0,1,\dots,n-1 \tag{16}$$

Among them: s(k), f(k), e(k) respectively represent noisy signal, useful signal, and noise signal; therefore, wavelet transform can obtain two parts of wavelet coefficients, which are useful signal f(k) and noise signal e (K) Corresponding wavelet coefficients $W_{f(a,d)}$ and $W_{e(a,d)}$.

Wavelet transform analysis can analyze the noise signal in two parts, and use two additional filters for detailed analysis [27]. The approximate part represents the division of high and low frequency signals, and the detail signal represents the division frequency of low-scale and high-level signals. The approximate part can be solved in the nth layer, see formula (17):

$$S = aL_M + a\sum_{i=1}^{M} H_i \tag{17}$$

From the decomposition process, it can be found that the low-frequency or high-frequency part also contains noise signals, and the wave conversion coefficient can be adjusted accordingly. The wave transform will suppress the frequency of the noise room and convert the output signal to achieve the purpose of suppressing noise interference [28]. Since there are some disadvantages to only using hard and soft limits, this article uses a compromise between soft and hard limits to reduce noise. The compromise between soft and hard limits is defined as:

$$\begin{cases} w_{j,i} = (|w_{j,i}|) \\ sign(w_{j,i})|w_{j,i} \geq \lambda|, 0 \leq \alpha \leq 1 \\ 0, |w_{j,i} < \lambda| \end{cases} \tag{18}$$

Among them: $\lambda = (\delta\sqrt{21gN} / \log 2^{(j+1)})$. The process of selecting wavelet noise reduction processing is: (1) Analyze a certain wavelet and decompose it to the required level N; (2) Select an appropriate threshold, quantify the high-frequency coefficient thresholds under all decomposition scales, and estimate the wavelet threshold (3) Complete the wavelet reconstruction processing of the signal with the help of the low-frequency coefficients of the bottom layer and the high-frequency coefficients of each layer [29].

2.4. Human Dance Recognition Technology Based on Wearable Sensors

After obtaining different types of human behavior-related data through different detection methods included in the wearable sensor network, these data must undergo a series of processing to determine the human behavior information contained therein. Although different types of perception data require different specific processing methods, when we observe the overall system of human behavior recognition, the basic framework of the system is basically the same. The behavior recognition problem is usually regarded as a special classification problem. The behavior recognition system should conform to the framework of the standard recognition system. In this basic framework, the following basic processing steps are included:

(1) Data collection. Data collection is to remove the perception of behavior and transmission from the perspective of the behavior recognition system. Concerns about data collection include the perception and transmission of human behavior data, as well as the data required for conversion, noise filtering and performance improvement.

(2) Data division. The data received from the wearable sensor network is a continuous, potentially unlimited data stream. The problem to be solved by data fragmentation is how to reasonably monitor part of the behavior recognition of such an infinite sensor data stream.

(3) Characteristic output. The behavior existence contains raw sensor data corresponding to one or more behaviors of the relevant human user. When we recognize the existence of data, we often need to extract features from the data.

Behavior recognition. The behavior recognition algorithm recognizes the human behavior contained in the behavior existence based on the characteristic entity corresponding to the existence, which is the behavior obtained through the output characteristic. Behavior modeling is the core of behavior recognition algorithms [30].

3. Dance Movement Design Experiment of Wearable Sensor

3.1. Collection of Dance Movement Data

Human bones are the basis of life activities and provide support for the human body. However, the number of bones in the whole body has reached more than 200, and the movement structure is extremely complicated. In order to simplify the analysis of human motion, most of the current motion recording devices are focused on moving parts with basic information, and the non-essential parts are supplemented by animation technology. The sensory neuron motion capture system used in this article is one of them.

3.2. Basic Steps of Dance Movement Recognition

The human motion capture data is a time sequence composed of the rotation angle and relative displacement of the human joints at different moments. Therefore, a mechanical learning method with multiple time series classifications can effectively solve the recognition problem of human motion. The human motion recognition system is mainly composed of three parts: (1) three-dimensional reconstruction of human motion; (2) feature extraction and pattern representation, Classification and recognition of human movement. Among them, the output of characteristics and the representation of human behavior patterns are directly related to the understanding of human behavior, which is a key issue in understanding human behavior. Therefore, this article will focus on the extraction methods of human behavior characteristics, and will specifically explain how to use low-level distribution problems, demonstrate behavior patterns by comparing different replication methods and prove the benefits of the proposed method.

3.3. Wearable Sensor Design

Due to the portability and mobility of mobile wearable devices, they have inherent advantages for dynamic data collection. At the same time, they are limited by size and power consumption. They generally do not have the ability to directly access the mobile Internet, but through wireless low The power consumption protocol is networked with mobile smart terminals (such as mobile phones), and the data is bridged and forwarded and finally connected to the Internet. This solution not only takes advantage of the advantages of mobile wearable devices, but also satisfies their networking needs. However, with the advent of the era of big data, people’s thirst for all kinds of dynamic information will increase the number of mobile wearable devices. If they must be connected to smart terminals, this will bring a great deal to our smart terminals. This design proposes a solution to this contradiction. First, a piconet is formed for multiple wearable devices within a certain range, and then a mobile smart terminal is connected through a specific node, and finally data networking and sharing are realized.

According to the above network structure and equipment characteristics, under the premise of satisfying functions and performance, the key considerations in design are:

(1) Cost, low cost is more competitive in the market, which directly improves economic efficiency.

(2) Power consumption. Low power consumption means long life, good stability, and more durable operation with the same energy, which indirectly affects the portability of use.

(3) The size and smaller appearance are more conducive to wearable performance and determine the convenience of the use process.

The block diagram of the overall system architecture is shown in Figure 1.

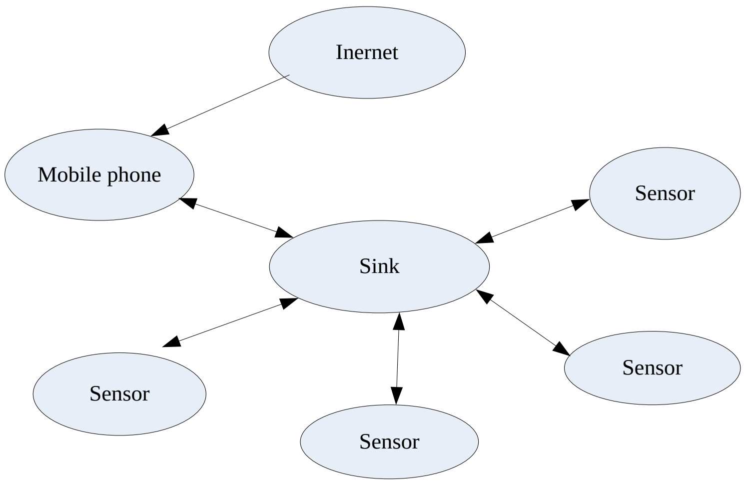

Figure 1. Frame diagram of wearable sensor system

The Sink node and the Sensor node use a custom RF2.4G protocol communication, and the mobile phone communicates with the Sink node using the low-power Bluetooth 4.0 protocol. When the sink node is not connected to the mobile phone, it can also independently communicate with the Sensor node group net, just read that the sensor data is not saved.

4. Interference Suppression Algorithms for Dance Movements Based on Wearable Sensors in a Smart Environment

4.1. Dance Movements

According to the test plan, output and analyze different AO simulation values reflected by the knee joint pressure at different positions. Table 1 shows the AO simulation data of six trials conducted at six representative locations. Figure 2 shows the trend chart of the six representative locations where the AO ratio data is changed to six tests.

Table 1. Test results of different dance poses

Knee angle(°)	1	2	3	4	5	6
0	0	0	0	0	0	0
15-25	150	224	264	348	367	243
30-45	440	340	470	390	250	340
80-90	770	725	750	770	745	760
90-100	815	880	810	855	834	812
10-180	910	915	910	950	930	945

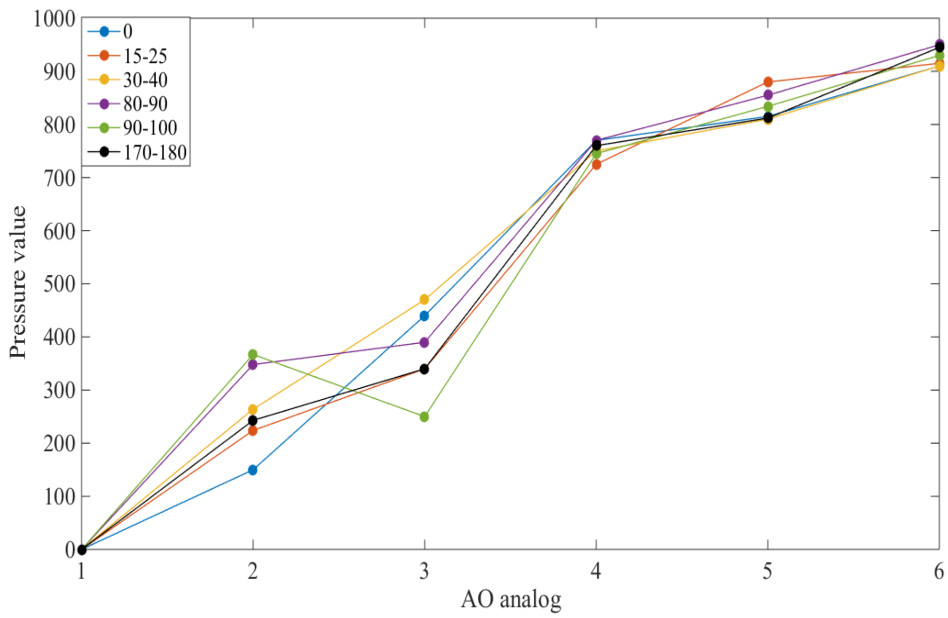

Figure 2. AO simulation trends of different dance poses

Judging from the pressure value reflected by the proportional amount of the human knee joint AO at different bending angle positions in Fig. 2, the greater the bending degree, the higher the output value of the pressure response. When standing, the proportion of AO corresponding to no pressure is 0. As the angle increases, the pressure gradually increases, and the output also increases. When the knee joint is at 90 degrees, the output value is 700-800mA, until the limit bending is close to 180 degrees, the output value is as high as 900mA or more. This result is consistent with the actual situation, indicating that the portable lower limb recognition system we designed can reflect the movement of the human knee joint in real time. These reliable data can provide references for the health assessment and analysis of the knee joint system.

4.2. Dancing Action Recognition Effect

Table 2 and Figure 3 show the recognition effects of the eight action descriptors proposed in this article on human actions under different numbers of action words. It can be found from the chart that the recognition rates of the eight topic models all increase with the increase of the number of action words, and tend to stabilize when the number of action words reaches a certain level. When the number of action words is greater than a certain number, both action descriptors achieve the best recognition results, and no significant changes occur. Therefore, generating an appropriate number of action words is extremely important for topic models. Too many action words will increase the computational complexity. In addition, from the data in the chart, it can be found that the recognition rate of fast action has a small increase compared with the recognition rate of slow action. It can be seen that the speed in the action sequence has a certain influence on the recognition of human actions. Will continue to expand as the types of movements continue to increase.

Table 2. Recognition effect of different dance moves

Number of topics	5	15	25	35	45	55	65	75
station	40	42	51	65	77	88	92	96
Stand up	90	91	92	93	94	94	94	94
straight	90	92	94	95	97	98	97	98
Row	45	54	56	76	87	90	90	95
tough	45	46	78	79	85	90	93	96
fast	56	65	67	78	84	90	93	94
slow	57	68	71	71	89	94	95	94
stable	46	54	61	72	79	96	97	96

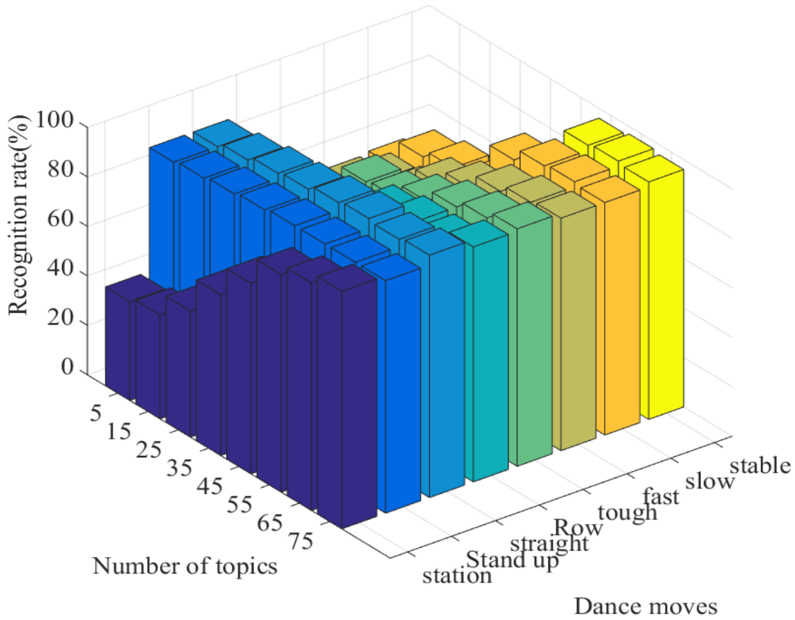

Figure 3. Comparison of recognition rates of different dance moves

4.3. Effect of Interference Suppression Algorithms

This paper compares the proposed interference suppression algorithm (ISA) with several existing latest action feature description methods, as shown in Table 3. The identification time is the time required to continuously identify all samples in the test set. TF-GDA is a feature obtained by using generalized discriminant analysis to reduce the dimensionality of the time-frequency feature of the joint angle. HOD is the histogram of directional displacement. In this paper, the number of cells is set to 8, and a three-layer space-time pyramid is used for description. The Sequence of the Most Informative Joints (SMIJ) is currently the mainstream action descriptor. According to the best effect of this feature, this article sets the number of joints to 6 and the segmentation window to 60. Through comparison, it can be found that the method proposed in this paper is superior to other methods in recognition rate and recognition time.

Table 3. Comparison of recognition rate and time of different algorithms

Algorithms	ISA	HOD	SMIJ	TF-GDA	LDA	LDA+HMM
Recognition rate（%）	99.6	93.2	2.6	91.2	98.7	99.2
Time（s）	26.2	74.5	35.2	34.6	37.2	36.4

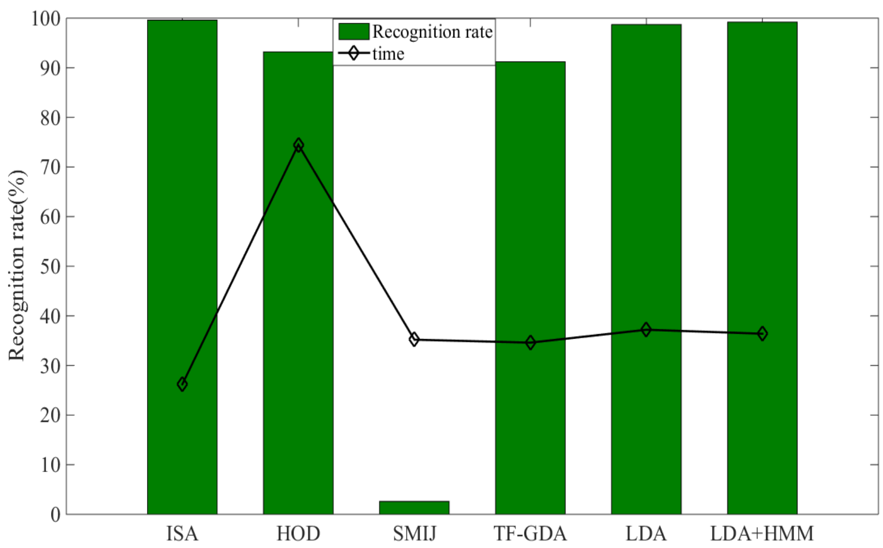

Figure 4. Recognition rate and time results of interference suppression algorithm

By comparing Figure 4, it can be seen that the ISA descriptor has the fastest recognition time. This is because the descriptor has only a few simple operations in the process of extracting time-frequency features, and the dimensionality reduction process only needs to be multiplied by the projection matrix. In addition, the descriptor applied generalized discriminant analysis to effectively extract the important information in the action features, so a better recognition result was obtained. The two descriptors proposed based on the topic model, LDA and LDA+HMM, have the best recognition accuracy, which can be explained as: the topic model-based method refines the difference of different types of actions to the difference of the posture frame. Sampling makes action words with smaller discrimination in similar types of actions have greater weight, so that action descriptors of similar action types have greater differences.

4.4. Sensor Network Positioning in a Smart Environment

Combining specific practical applications in an intelligent environment, Kalman filtering in target tracking application and simulation, assuming that the target is moving on a two-dimensional plane, the initial position is (-100m, 200m), the horizontal movement speed is 2m/s, and the vertical movement The speed is 20 m/s, the scanning period of the wireless sensor node (radar, sonar) is T=1s, the mean value of the observed noise is 0, and the variance is 100. The smaller the process noise, the closer the target is to a uniform linear motion, otherwise, it is a curved motion.

Table 4. Comparison of filtered trajectory tracking

X/m	-100	-80	-60	-40	-20	0	20	40	60	80
True trajectory	200	400	600	800	1000	1200	1400	1600	1700	1900
Observe the track	200	400	550	750	990	1120	1380	1540	1680	1770
Filtered trajectory	200	430	620	760	980	1240	1450	1560	1670	1910

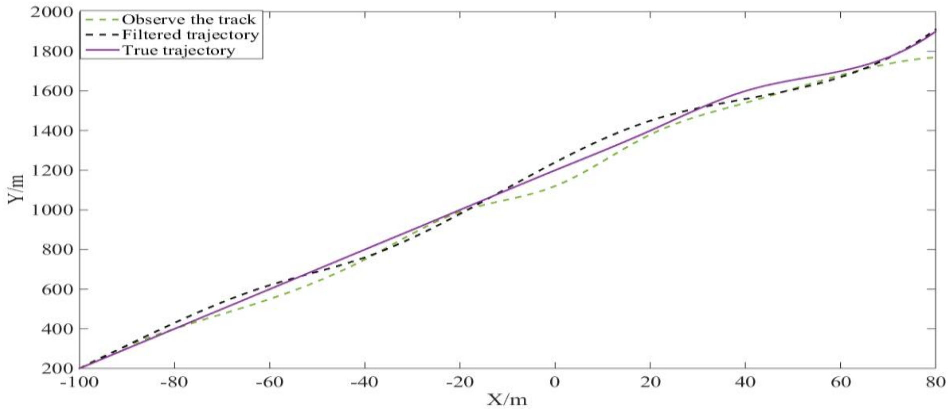

Figure 5. Filtered trajectory tracking diagram

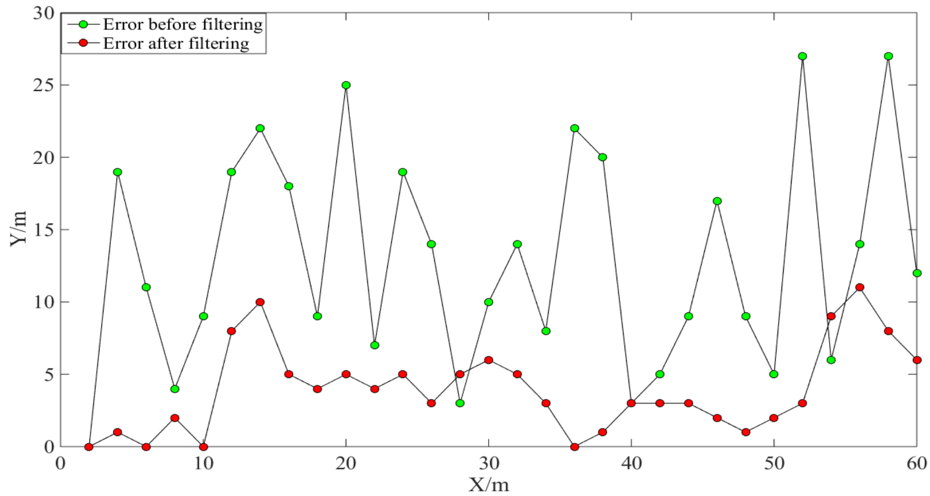

Figure 6. Tracking error comparison chart

The simulation results are shown in Table 4, Figure 5 and Figure 6. It can be seen that the trajectory after Kalman filtering is closer to the true trajectory of the object, and the error after filtering is significantly smaller than the error before filtering, indicating that the Kalman filtering algorithm is online A good tracking effect is achieved in the sexual system.

4.5. Dance Suppression Interference Algorithm

The experimental results of the algorithm and the three features in the four groups of dance combinations on the FolkDance dance data set are shown in Table 5 and Figure 7:

Table 5. Comparison of a single feature on the FolkDance dataset and the experimental results of this method

Dance group	Directional gradient feature	Optical flow direction characteristics	Audio signature features	Method characteristics of this paper
Follow-up double flower combination	43%	38%	33%	53%
Lining flower combination	40%	33%	40%	54%
Hand towel flower combination	33%	38%	42%	50%
Fragment Combination	29%	33%	38%	46%

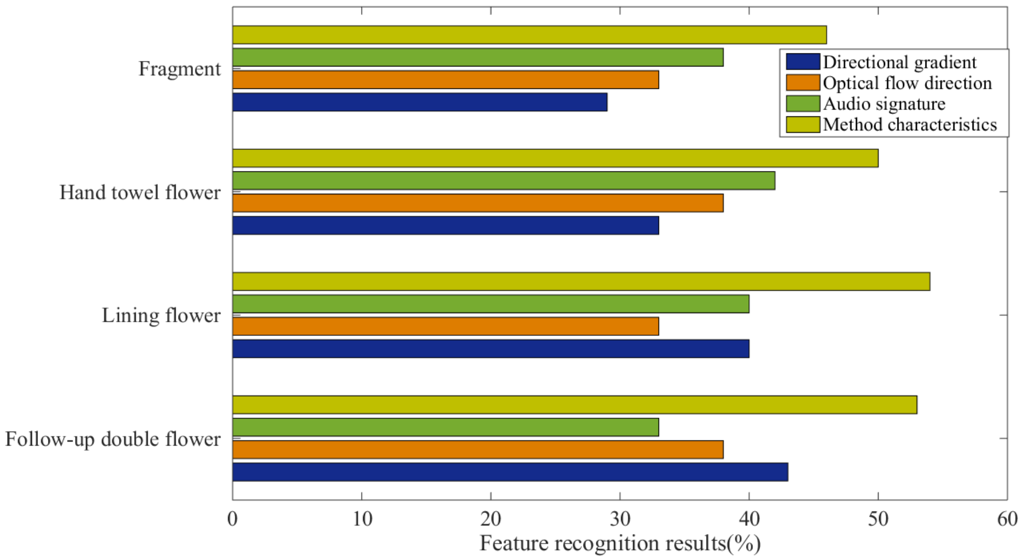

Figure 7. Comparison of the results of a single feature on the FolkDance dataset and the interference suppression algorithm

From the experimental results in the chart, it can be seen that the recognition rate of dance movements for each single feature in each group is still relatively low. The HOG feature is used to characterize the local appearance and shape of the action. When the similarity between the actions in the dance combination is too high, it will increase the difficulty of recognition and affect the recognition accuracy. It can be seen from the table that the recognition rates of the HOG feature in the follow-up double flower combination and the inner flower combination are respectively 43% and 40%, which are higher than 33% and 29% in the towel flower combination and the patch flower combination. Among the four dance combinations in the FolkDance data set, the similarity between the dance moves in the follow-step double flower combination and the inner flower combination is much smaller than the towel flower combination and the patch flower combination. Similar dances exist in both the towel flower combination and the patch flower combination. Actions, especially the combination of clips, have multiple similar actions and the same action is divided into different directions, which also increases the difficulty of dance action recognition. The recognition rate of HOG features in this group is 29%, the lowest among the four groups.

5. Conclusion

The wireless sensor network came into being with the continuous development of science. It integrates the technologies of a variety of complex disciplines and has great application value in positioning and tracking technology. The application of wireless sensor network target positioning and tracking in a smart environment can achieve functions such as grasping the location information of related targets in the environment and tracking trajectories of moving objects. This paper studies the positioning and tracking of objects in wireless sensor networks, and solves the problem of positioning and tracking of observation objects in a smart environment, and achieves good results.

Aiming at the problem of how to extract low-dimensional effective motion features from high-dimensional motion capture data, this paper proposes a quantification method of human motion. The basic motion unit of human motion is extracted to characterize human body posture, and the feature is used to reduce dimensionality and theme construction. The modular method obtains the pattern characteristics of the action sequence, and the robustness of the algorithm is verified by testing on the standard action database.

Tracking multiple targets in wireless sensor networks is a challenging and even more complex problem. Similar to the situation of tracking a single target, we can track multiple targets at the same time. This research is left to future work. The research in this article is only limited to target tracking algorithm research and simulation verification. In the future, an experimental platform can be built to carry out experimental research, which will be more practical.

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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.

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