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Real-Time Recognition of Human Daily Motion with Smartphone Sensor

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Abstract

Aiming at problems regarding the recognition of motion states by existing smartphones, such as poor real-time performance, less movement category and complex algorithm, this paper proposes a method of using smartphone sensors to recognize six kinds of real time human movement states. Firstly, daily human movement data is acquired through smartphone acceleration sensors and gravitational acceleration sensors, and original data is handled with correction, smoothing, segmentation and direction-independent processing. Secondly, the footsteps identification algorithm is used to calculate peaks and troughs of footsteps from which the time-domain feature vectors are extracted. Finally, the movement states are classified according to feature vectors, and the Hierarchical Support Machines (H-SVMs) is used to recognize daily movement states. Experimental results show this method can effectively reduce the computational load of smartphones and improve real-time performance and accuracy of movement states recognition. This method is suitable for other similar behavior recognitions.

Keywords: real-time recognition; movement states; smartphone sensor; time-domain feature vector; H-SVMs

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1. Introduction

Smartphones have become more and more popular. In addition to basic phone communication, smartphones have been equipped with a lot of sensors, such as the gravity sensor, acceleration sensor, gyroscope sensors and distance sensors, which have made smartphones a new sensor platform. As a ubiquitous computing and data acquisition platform, smartphones have attracted great interest in many research fields, ranging from indoor pedestrian tracking [14,22] and biometric authentication [16] to human activity recognition [4,12,23]. Using smartphones to identify human motion states has many advantages. The acquisition of human activity data is not restricted by external environment and is not interfered by the user's life; the process does not require additional equipment; the user can exercise according to their own habits, as smartphones are placed in the normal position around the human body, the user does not need to worry about privacy disclosure; and so on.

Among recent studies about using smartphone sensors on human activity recognition, the analysis of acceleration data is of greatest concern. Most researchers chose the waist as the location to carry a smartphone, while a few studies considered the effect of the smartphone-places on human motion states recognition [11,24,25]. Furthermore, most of the researches used multiple feature vectors of the time-domain and the frequency-domain at the same time, which increased the computational load of smartphones and affected real-time data processing.

This present paper proposes a method for real-time identification of typical movements in people's daily life, which is based on seven lightweight feature vectors from the time-domain of smartphone sensor. The method can provide monitoring and tips for people's physical health. Motions of six kinds are chosen – stillness, walking, running, walking upstairs, walking downstairs and cycling – as recognition objects, following SM Camhi's [5] research on the relationship between the health of human cardiac metabolism and the exercise intensity. By using lightweight feature vectors from the time domain, the method can effectively reduce the computing load of the smartphone and thereby realize the real-time recognition of daily movements. The main contributions of this paper are as follows:

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- Processing original data in terms of correction, smoothing, segmentation and direction independence, which can reduce errors of the collected data, improve the quality of the data and real-time data processing, and effectively solve the independence of the motion states and the phone orientation.
- Calculating the wave peak and trough of footsteps by using footstep recognition algorithm, and extracting the seven-time domain eigenvectors from the daily exercises, which can reduce the effects of occasional jitter, improve the effectiveness of the feature vectors, avoid the phenomenon of consuming too much computing resources when calculating the frequency domain and time frequency domain, effectively reduce the load.
- Verifying the real-time performance and accuracy of the H-SVMs method by comparing with some other methods, including the naive byes method, the decision trees method and the *k*-nearest neighbor method.

The rest of the paper is arranged as follows. It describes related studies in Section 2, followed by details of data collection, data preprocessing, data analysis and feature extraction methods in Section 3. Section 4 contains the experiment setup, the accuracy of different classification methods, and the flexibility of the carrying modes of different mobile phones. Finally, Section 5 is the conclusion and possible future studies.

2. Related Studies

The purpose of human motion recognition is to discover human physical activity pattern by analyzing motion data captured by sensors. Human motion recognition has multiple potential applications, which can not only monitor human activities (such as fall detection, health care, etc.), but also help to better understand human activities (e.g., the abnormal activity detection). At present, human motion recognition methods are mainly divided into two categories: visual-based methods and sensor-based methods. As sensing and computing power have become standard setups of current smartphones, researchers have begun to use smartphones as the experiment platform for sensor-based human motion recognition.

In literature [15], 29 volunteers' motion data was collected by using acceleration sensors within smartphones. After that, 43 feature vectors were extracted to identify actions of six kinds, including walking, jogging, ascending stairs, descending stairs, sitting, and standing, the method can identify most of the activities with a 90% recognition rate. However, when the data were collecting from the volunteers, they needed to put the smartphone in the front pocket of their pants in a certain direction. Literature [1] used 17 features in time domain and frequency domain that are from the built-in acceleration sensor of the mobile phones, identified six kinds of actions (standing, sitting, laying, walking, walking upstairs and walking downstairs) with the SVM method and obtained an 89% precision. The users needed to place smartphones at the waist of human body for data collection. In literature [10], a lightweight activity model and recognition framework is proposed, which combined the accelerometer, gyroscope, proximity sensor and GPS module and can be used to identify 15 daily activities. Literature [24] used smartphone sensors (acceleration, gyroscope and magnetometer sensors) to collect 10 participants' data while they carried the mobile phones with five different kinds and then used time domain and frequency domain feature vectors to identify seven different movements, including walking, sitting, standing, jogging, biking, walking upstairs and walking downstairs. Literature [21] used wrist motion sensor and built-in sensors in mobile phones to collect the experimenters' movement data, identified two sets of a total of 13 kinds of complex movements, but as the system added additional sensors, the user costs have been largely increased. Literature [13] used the standard deviation of the linear acceleration sensor as feature vector to identify standing, walking and running. Although the accuracy is more than 98%, the recognized motion states are very few. By using time domain features, frequency domain features and time-frequency domain features of the sensors, literature [6] combined the *k*-Nearest Neighbor algorithm, random forest algorithm and support vector machine algorithm to analyze different motion states while the mobile phones are under different carrying ways.

The above studies were limited to different defects, such as the less recognized motion states, complicated calculation, the fixed positions of sensors, etc. In regard to these problems, we adopted a direction independence method [20] and used time domain feature vectors of the sensors, which can real-time identify six daily motion states with reduced computational load.

3. Methods

All kinds of sensors in mobile phones can collect data through their API, but the collected data have some defects, such as errors of the sensor itself, the influence of external environment, as well as uncertainty of the used modes. As a result, there is a lot of noise in collected data, which should be filtered to improve the accuracy of motion states identification.

3.1. Data Correction

Due to deviation of the sensor in process of manufacture and installation, the collected data should be affected [9]. Therefore, correcting the sensor data could be helpful for reducing the inherent deviation from the original data. We used a linear matrix model to calibrate the output data of smartphone sensors on the x, y and z axes, as shown in Equation (1).

$$AG' = S \cdot AG + D + N \tag{1}$$

where $AG' = \begin{bmatrix} ag_x' & ag_y' & ag_z' \end{bmatrix}^T$ represents corrected data on the x, y and z axes, $AG = \begin{bmatrix} ag_x & ag_y & ag_z \end{bmatrix}^T$ represents the three axes data before correction, $S = \begin{bmatrix} s_{xx} & s_{xy} & s_{xz} \\ s_{yx} & s_{yy} & s_{yz} \\ s_{zx} & s_{zy} & s_{zz} \end{bmatrix}$ is used to correct the calibration error and orthogonal error, $D = \begin{bmatrix} d^x & d^y & d^z \end{bmatrix}^T$ is used to correct the zero deviation of the acceleration, and $N = \begin{bmatrix} n_x & n_y & n_z \end{bmatrix}^T$ is used to correct the measurement noise.

When the phone is in a stationary state, the sum of the squares of the triaxial acceleration sensor output value should be equal to the square of the local acceleration of gravity, as shown in Equation (2), and the corresponding triaxial linear acceleration output value should be 0 m/s^2, but measured mobile linear acceleration output value is not always satisfy this condition. The output values of the acceleration sensor have been obtained, and then the Particle Swarm Optimization (PSO) algorithm is used to solve the system of nonlinear equations [8] and construct the objective function, as shown in Equation (3).

$$G_0^2 = ag_x^2 + ag_y^2 + ag_z^2 \tag{2}$$

$$L(S, D, N) = \sum_{i=1}^{n} (G_0^2 - \left| AG_i' \right|^2)^2 \tag{3}$$

where n is the number of data tested in static state, G_0 is the local gravity acceleration, AG' is the corrected data S,D,N that can be obtained by minimizing the target function. Figure 1 is a comparison diagram of the data before and after correction for the acceleration sensor under static state. It is clear that the acceleration sensor and the gravity acceleration sensor data have been improved after the correction.

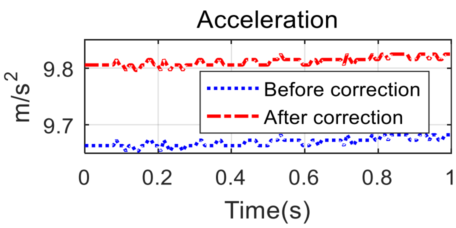

Figure 1. The data before and after correction for the acceleration sensor under static state.

3.2. Noise Processing

A variety of factors are involved in the generation of data signals from the mobile phone's built-in sensors. In this article, except for the data generated during the process of movements, all other factors that cause fluctuations of sensor are considered to be noise source, and thereby the corresponding sensor data is noise. Figure 2(a) shows the x-axis data changes of the acceleration sensor when the cell phone is used. To reduce the influence of such noise on the sensor data, we adopt the sliding mean filter to process the noise of the sensor data [26]. The sliding mean filter used the mean value of the *a* data points in a window to represent the window size, which can be used to realize data smooth processing, as shown in Equation (4):

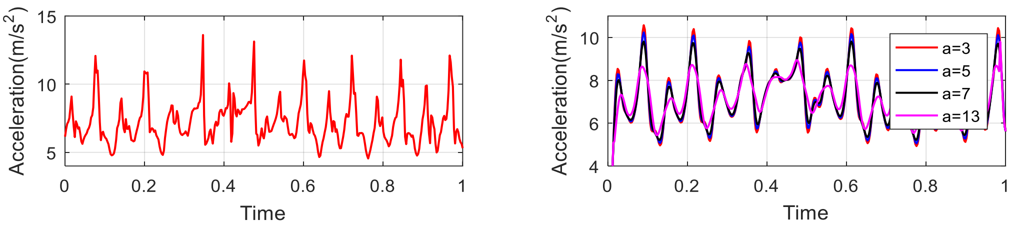

Figure 2. (a) The raw data in x-axis of the acceleration sensor (b) The *a* value of the sliding mean filter

$$\mathrm{data}[i] = \sum_{i-a/2}^{i+a/2} \mathrm{data}[i]/a \tag{4}$$

The performance of sliding mean filter is less than that of the Kalman filter, but it is simpler than the Kalman filter and can thereby effectively reduce the load of mobile phone. Generally speaking, the smoothing of the sliding mean filter is associated with the *a* value, the greater *a*, the better smoothing, but the degree of distortion is also higher at the same time. Figure 2(b) shows the effect of different *a* (3, 5, 7 and 13), and we select *a* = 7 as the filter value in this article. Comparing to Figure 2(a), the data quality has been obviously improved after the filtering.

3.3. Data Processing

Since the data collected by the sensor is continuous, it will seriously affect the real-time performance of the system if the data of each sampling point is calculated and then recognized as a state. In this paper, the sliding window mechanism is used to cut the sampled data sequence into several data sequences, and then the feature vectors calculation and motion state recognition are carried out for these cut data sequences. In order to reduce the accuracy that raise from data cut, we adopted the sliding window strategy with 50% overlap (as shown in Figure 3). The size of the sliding window *T* is set to 2 seconds [2], and then the detection and division of the motion state are carried out by using the values of the feature vectors of each sliding window.

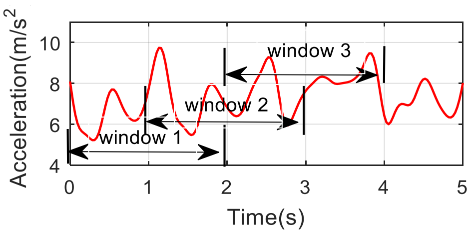

Figure 3. The schematic of sliding window mechanism

Furthermore, in order to make the sampled raw data more stable, smooth and neat, which will improve the accuracy of the system's motion state recognition, we also normalize the data.

3.4. Extraction and Analysis of Feature Variables

The extraction of feature variables is generally used to extract the most valid feature variables in the original data, and thereby obtain the essential properties of the studied objects and accurately describe them. The extraction of feature vectors directly affects the recognition performance of the system.

3.4.1. Selection of Feature Variables

According to recent research results, the most applied features include time domain features, frequency domain features and time-frequency features. Among them, the time domain features are less complex than the other two features, and it can also better reflect the essential properties of human motion. To reduce the computational load of smartphones, this article only adopts time domain features to identify the motion states of humans. We used seven lightweight features on the time domain variables, including maximum average (averageMax), the minimum average (averageMin), average, standard deviation (Std), maximum root mean square (Rms), skewness (Ske) and kurtosis (Kur).

3.4.2. Calculation of Feature Variables

The linear acceleration is the difference of acceleration and gravity acceleration at the coaxial direction, which means the acceleration after the removal of gravity. It is a three-dimensional vector, and can be calculated following Equation (5):

$$LineAcc_{t_i}^{x,y,z} = Acc_{t_i}^{x,y,z} - Gra_{t_i}^{x,y,z} \tag{5}$$

In order to obtain the overall change features of the linear acceleration, Equation (2) is used to calculate the triaxial vector sum. Meanwhile, the method is effective to solve the independence problem of identifying the motion state and the direction of cell phone placement.

In order to improve the accuracy of motion state recognition, this paper introduces two feature vectors: the maximum average and the minimum average. The maximum average refers to the average of the peaks of steps in the time window, the minimum average is the average of the troughs of steps in the time window. When calculating the maximum average and the minimum average, we need to get the number of steps in the motion. Li et al. used fixed time threshold to realize the calculation of the numbers of steps in normal state [17], but when the dynamic state occurred, it would lead to a decrease in the accuracy of steps [18,19]. This paper first searches the maximum point of the linear acceleration vector sums in time windows, and this point is considered the peak of a step in the time window. It then searches for the maximum point before and after 0.2s-0.5s from this point, and this is the peak of the previous or next step. Using the new point as a starting point, we can continue to look for the previous or next point, until the peak point of all steps in the time windows are found. The minimum average can be calculated in the same way.

The algorithm is as follows (Algorithm 1):

Algorithm 1 footsteps identification algorithm

Input: linear acceleration vector *Data[i]* and corresponding time point *time[i]*;

Output: the *stepNum* of step number, the *stepPeak[j]* of step peak value and the *stepTrough[k]* of step through value

```
set stepNum := 0,stepPeak[j] := 0 and stepTrough[k] := 0;
for i=:1 to N do begin
    find the maximum value max of Data[i] and the maximum position maxP;
    find the minimum value min of Data[i] and the minimum position minP;
end for
stepNum := stepNum + 2, stepPeak[j++] := max, stepTrough[k++] := min, lasttime := time[maxP];
for i := maxP + 1 to N do begin
    if time[i] - lasttime > 0.2 && time[i] – lasttime <= 0.5
        find the maximum value max of Data[i] and the maximum position maxP;
        lasttime := time[maxP]， stepNum := stepNum+1, stepPeak[j++] := max;
    end if
end for
lasttime := time[maxP];
for i := maxP - 1 to 1 do begin
    if lasttime - time[i] > 0.2 && lasttime - time[i] <=0.5 then
        find the maximum value max of Data[i] and the maximum position maxP;
        lasttime := time[maxP]， stepNum := stepNum+1, stepPeak[j++] := max;
    end if
end for
lasttime := time[minP];
for i := minP + 1 to N do begin
    if lasttime - time[i] > 0.2 && lasttime-time[i] <= 0.5 then
        find the minimum value min of Data[i] and the minimum position minP;
        lasttime := time[minP]， stepNum := stepNum + 1, stepTrough[k++] := min;
    end if
end for
lasttime := time[minP];
for i := minP - 1 to 1 do begin
    if lasttime - time[i] > 0.2 && lasttime - time[i] <=0.5 then
        find the minimum value min of Data[i] and the minimum position minP
        lasttime := time[minP]， stepNum := stepNum + 1, stepTrough[k++] := min;
    end if
end for
stepNum := StepNum/2;
```

When calculating the values of other feature vectors of human motion, we need to use the peaks and troughs data in the time window, as shown in Equation (6).

$$stepData = stepPeak \cup stepTrough \tag{6}$$

The calculation formula of all feature vectors is shown in Equations (7)-(13):

$$averageMax = \frac{1}{n}\sum_{j=1}^{n} stepPeak_i \tag{7}$$

$$averageMin = \frac{1}{n}\sum_{i=1}^{n} stepTrough_i \tag{8}$$

$$average = \frac{1}{n}\sum_{i=1}^{n} stepData_i \tag{9}$$

$$Std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(stepData_i - average)^2} \tag{10}$$

$$Rms = \sqrt{\frac{\sum_{i=1}^{n}(stepData_i)^2}{n}} \tag{11}$$

$$Ske = \frac{\sum_{i=1}^{n}(stepData_i - average)^3}{(n-1)Std^6} \tag{12}$$

$$Kur = \frac{\sum_{i=1}^{n}(stepData_i - average)^4}{(n-1)Std^8} \tag{13}$$

3.4.3. Analysis of Motion State

Through the preliminary data processing, we obtained seven feature vectors of six daily motion states. From the kinematic point of view, the averageMax and Std values of running are maximum. At the stationary state, except for the gravity acceleration, users are not affected by other forces, and thereby the averageMax, averageMin, average and Std remain at ~0 m/s^2. Linear acceleration changes are not very large for cycling motion state, averageMax and average are larger than those under static state but less than those under walking and stairs. This paper used naive Bayes, decision trees, KNN and H-SVMs methods to distinguish different motion states. H-SVMs has more advantages than other traditional machine learning algorithms, such as small sample size, small structural risk, nonlinearity and high-dimensional pattern recognition. The classification idea is simple and the classification effect is good. When the H-SVMs method is used, the motion state is divided into a multiple recognition model, as shown in Figure 4. After dividing, the motions in a subcategory have large similarities, while there are larger differences between different subcategories. This can therefore distinguish the different motion states as much as possible.

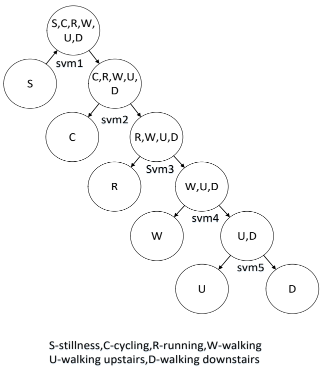

Figure 4. The division of motion states by using H-SVMs

4. Experiments

4.1. Description of Experiment

The acceleration and gravity acceleration sensors equipped in the Android platform-based smartphone are used in this paper, and both of these two sensors are triaxial sensors. A program has been written to store triaxial acceleration data of the smartphone every 30ms. Experimental data are derived from six students from a network engineering lab at Northwestern University. These students were in durative movement states of no less than two minutes under stillness, walking, walking upstairs, walking downstairs, running and cycling conditions. A durative two minutes of experiment data was taken in this study. During the test, four ways of carrying mobile phones were used: pants' pocket, shirt's pocket, waist, and backpack, and the mobile phones were carried in arbitrary directions. The experimental data were collected in residential buildings, office buildings, teaching buildings, cement roads, asphalt roads and school playground.

4.2. Experiment Results and Discussion

For each group of collected data, we first performed effective preprocessing, including data correction, noise treatment, data segmentation and independence of direction. Then, we used Algorithm 1 and the related feature vectors calculation formula to calculate six kinds of daily movement feature vectors, and the data ranges of every feature vector are shown in Table 1.

Table 1. The intervals of the seven attribute data for six studied motion states (m/s^2).

Labeled Activity	averageMax	averageMin	average	Std	Rms	Ske	Kur
stillness	[0.02,0.22]	[0.00,0.18]	[0.01,0.19]	[0.01,0.14]	[0.02,0.28]	[-1.07,3.32]	[1.56,14.01]
cycling	[0.25,0.71]	[0.09,0.35]	[0.21,0.51]	[0.09,0.31]	[0.20,0.56]	[-0.66,1.31]	[1.47,5.33]
running	[6.10,15.20]	[1.70,9.90]	[4.11,12.43]	[1.87,5.16]	[4.59,12.78]	[-1.14,1.25]	[1.10,5.00]
walking	[1.68,7.63]	[0.78,2.83]	[1.21,4.37]	[0.41,2.38]	[1.30,4.92]	[-1.00,0.86]	[1.23,4.81]
upstairs	[1.65,7.41]	[0.53,1.61]	[1.12,4.55]	[0.49,1.22]	[1.35,2.77]	[-0.33,0.99]	[1.17,3.79]
downstairs	[1.66,7.89]	[0.37,2.00]	[1.12,4.26]	[0.89,2.09]	[1.42,3.71]	[-0.69,1.53]	[1.06,4.39]

As shown in Table 1, the feature vectors of stillness, cycling and running can be obviously distinguished, while those of walking, upstairs and downstairs are not well distinguished. Therefore, by using naive Bayes, decision trees, KNN and H-SVMs methods, the feature vectors are mapped to the high-dimensional models to identify the six kinds of daily motions. The experiment was divided into five groups according to four different carrying modes of mobile phones and a mix of four different ways, and then ten-fold intersection was used for experimental verification. The resulted accuracies by different recognition methods are shown in Tables 2-6.

Table 2. The accuracy of different algorithms for mobile phones in the pants' pocket

	Naïve Byes	Decision Tress	KNN	H-SVMs
stillness	91.67	92.35	91.48	96.12
cycling	87.81	86.68	86.95	90.51
running	90.70	92.93	91.28	92.49
walking	83.23	84.39	83.49	83.16
upstairs	83.88	81.32	82.63	84.63
downstairs	81.44	83.45	81.36	82.11
average	86.46	86.85	86.20	88.17

Table 3. The accuracy of different algorithms for mobile phones in the waist

	Naïve Byes	Decision Tress	KNN	H-SVMs
stillness	98.63	98.91	97.15	98.23
cycling	96.25	97.34	97.74	97.89
running	96.49	96.37	96.42	97.38
walking	88.39	89.65	89.27	90.81
upstairs	90.92	87.08	86.84	90.67
downstairs	86.69	90.42	87.65	90.17
average	92.9	93.3	92.51	94.19

Table 4. The accuracy of different algorithms for mobile phones in the shirt's pocket

	Naïve Byes	Decision Tress	KNN	H-SVMs
stillness	93.42	92.51	93.05	96.46
cycling	92.29	93.23	93.67	95.52
running	90.89	91.26	91.12	91.34
walking	84.30	86.34	86.72	86.91
upstairs	85.98	87.39	83.17	86.45
downstairs	83.63	84.23	81.05	86.38
average	88.42	89.16	88.13	90.51

Table 5. The accuracy of different algorithms for mobile phones in the backpack

	Naïve Byes	Decision Tress	KNN	H-SVMs
stillness	93.28	94.71	92.63	97.84
cycling	92.37	93.43	93.06	97.27
running	91.67	93.38	92.02	96.51
walking	85.95	86.13	86.29	81.22
upstairs	83.65	81.89	82.16	86.41
downstairs	84.18	82.61	83.66	85.92
average	88.52	88.69	88.30	90.86

Table 6. The accuracy of different algorithms for mobile phones with mixed modes

	Naïve Byes	Decision Tress	KNN	H-SVMs
stillness	95.63	95.91	94.15	97.23
cycling	93.25	94.34	94.74	96.89
running	93.49	93.37	93.42	96.38
walking	85.39	86.65	86.27	89.81
upstairs	87.92	84.08	83.84	89.67
downstairs	83.69	87.42	84.65	89.17
average	89.90	90.30	89.51	93.19

According to the data in the Table 2 ~ 6, the recognized accuracies are different for every motion state even with the same method. The highest recognized accuracies are stillness, running and cycling, as these three states have obvious distinguished ranges of averageMax, averageMin, average and Std, while the recognized accuracies of walking, walking upstairs and walking downstairs are relatively poor. The reason for this is that the ranges of the feature variable cannot be obviously distinguished. At the same time, due to the limitation of experimental conditions, there were platforms in the middle of the corridor, which led to the result that walking upstairs or walking downstairs more closely resembled walking.

The recognized accuracies are also different for different carrying modes of mobile phones. The highest recognized accuracy is the mobile phones in the waist, while the lowest recognition rate is in the front pants' pockets. The reason is that when the mobile phone is in the waist, the acceleration data will accurately reflect the activities of the human. On the other hand, when the mobile phone is in the front pants' pockets, acceleration data not only reflect the motion states of human, but also calculate the motion states of the legs.

Among four different kinds of recognition algorithm, the recognition accuracy of H-SVMs method is the highest. When the H-SVMs method is used, the training data are classified according to Figure 4, which make the states of movement within the same category have great similarity, while they are different between the different categories. This point, in comparison to other identification methods, improved the recognition accuracy of H-SVMs.

Although the recognition accuracy of hybrid carrying modes of mobile phones is not better that the ones at the waist, it sufficiently reflects the randomness of the carrying mode of mobile phones in daily life and has a 93.19% accuracy. In comparison to several recent methods, the recognized accuracy of our method achieves or exceeds the average level of similar research (as shown in Table 7). Through the above experiments and analysis and by using the built-in accelerometer and gravity sensors in the smartphones, we collected daily human movement data and then used the time domain feature vectors of the data and the H-SVMs recognition algorithm to effectively identify the daily motion states of humans. Overall, this method has good real-time and high accuracy.

Table 7. The comparison between this paper and similar literature

Source Study	Placements	activities	Feature	Computation Complexity	Accuracy (%)
Jennifer et al [15]	Fixed position	6	T.	very low	91.7
Davide et al [1]	Fixed position	6	T.&F.	medium	89.00
Feng et all [17]	Fixed position	6	T.&F.	medium	96.10
Zhenghua et al [7]	pants' pocket, shirt's pocket and backpack	5	T.&F.	medium	79.85
Tomas et al [3]	Fixed position	6	T.	very low	90
This Work	pants' pocket , shirt's pocket , waist, and backpack	6	T.	very low	93.19

[1]For clarity, T. refers to time-domain, and F. refers to frequency-domain
[2]In [7], the average accuracy is given in the Placement-independent experiments

5. Conclusions

This paper studied users' daily movement data by using built-in acceleration and gravity acceleration sensors of mobile phones under uncertain directions and carrying ways. Then, it improved the accuracy of footsteps by using the footsteps recognition algorithm and then analyzed and processed the time domain of the data. Lastly, it was found that H-SVMs achieved the highest classification accuracy, in comparison to the naive Byes, decision trees and KNN methods. The research of this paper can be used to identify users' behavior statuses in real time and thereby keeps real-time information about users' health and exercise.

This paper only identified six daily movements. It has not identified other complex movements, such as jumping, playing basketball, playing ping pong and so on. In addition, the mobile phones' carrying mode is not perfect, such as holding the mobile phone in hands, using the mobile phone, etc. More types of human movements and carrying modes of mobile phones will be added in further studies, and the footsteps recognition algorithm will also be further optimized to improve the identification accuracy and flexibility of the system. Human behavior recognition based on acceleration sensor has considerable application space. In addition to the application of smart home, intelligent monitoring and health monitoring, it can also be applied in patient monitoring, calorie-burning exercise assessment and traffic monitoring.

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