# Weightlessness Feature — A Novel Feature for Single Tri-axial Accelerometer based Activity Recognition

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## Abstract

*In this paper, a novel weightlessness feature for activity recognition from a tri-axial acceleration signals have been proposed. Since the orientation between accelerometer and user's body may continuously change when user perform activities, we propose an algorithm to calibrate the actual vertical direction of accelerometer signal through estimating the gravitational direction. We combine peaks of signal and weightlessness feature to produce six dimensional weightlessness-based features for activity recognition. Classification of the activities is performed with Support Vector Machine (SVM). The average accuracy of four activities using the proposed weightlessness-based features is 97.21%, which are better than using traditional widely used time-domains features (mean, standard deviation, energy and correlation of acceleration data). Experimental results show that the new features can be used to effectively recognize different human activities and they are robust for different location of accelerometer.*

## 1. Introduction

Context awareness is a central issue in ubiquitous and wearable computing [1]. Accurate recognition and tracking of human activities is an important goal of ubiquitous computing. Activity recognition is also one technology frequently embedded in wearable systems [1~8]. For example, several activities such as ambulation, typing and talking were distinguished in [6] with five small bi-axial accelerometers. In [7] and [8], daily activities of standing, walking, climbing up/down stairs and brushing teeth, were analyzed based on the data collected from accelerometers .

Although in the literature there are already exist many approaches of using acceleration signals for physical activity recognition, little works have been done to validate the idea under real-world circumstances [6]. Most results use data collected in laboratory conditions and very few subjects (often the experimenters themselves). Interestingly, Foerster [3] demonstrated 95.8% recognition rates for data collected in the laboratory but recognition rates dropped to 66.7% for data collected outside the laboratory in naturalistic settings. In this work, we collected 43 volunteers' data from different day under realistic natural conditions.

As activity recognition can be formulated as a typical classification problem and just like many pattern recognition problem, features extraction plays a crucial role during the recognition process. Although in the literature there are already many studies on exploring the extraction of features from acceleration data, few works that make quantitative comparison of their quality are reported. In general, most of the attempts to extract features from acceleration date can be classified into two categories, say, time-domains features and frequency-domains features. Traditional widely used time-domains features are peak [4], mean [2, 6, 8], variance or standard deviation [2, 6], energy [2, 6, 8], entropy [6], correlation between axes [2, 6, 8] and so on. The most popular frequency-domains features are FFT coefficients [1]. As the time-domains features can be easily extracted in real time, they are more popular in many practical acceleration activity recognition systems.

In this paper, firstly we propose a novel weightlessness feature from vertical direction of acceleration signal. Secondly, we propose an algorithm to calibrate actual vertical direction of acceleration through estimating the gravitational direction. Finally, we combine peaks of signal and weightlessness feature to extract six dimensional weightlessness-based features. Classification results based on SVM show that the weightlessness-based features can effectively recognize different realistic human activities and it robust enough for different location of the sensor.

## 2. Data Collection

Data collection apparatus and the diagram of our experimental setup are shown in Fig.1. We use a tri-axial accelerometer ADXL330 manufactured by Analog Devices, which is capable of sensing accelerations from −3.0g to +3.0g with tolerances within 10%. The output signal of the accelerometer is sampled at 100 Hz. The data generated by the accelerometer is transmitted to a PDA wirelessly over Bluetooth. We collected four common activities: jumping, still, running and walking. In order to achieve robustness with regard to sensor position, subjects put the accelerometer in their clothes pocket, waist bell and trousers pocket respectively. Forty-three subjects were asked to perform each activity about one minute. Fig. 2 shows examples of the vertical axis raw data.
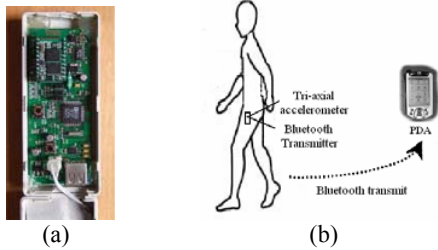


<center>(a)                                      (b)</center>

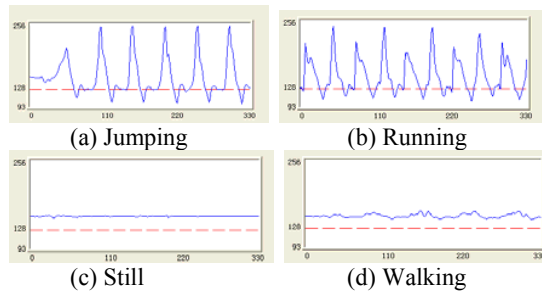**Figure 1:** Data collection apparatus (a), Diagram of experimental setup (b).



<center>(a) Jumping                        (b) Running</center>

<center>(c) Still                              (d) Walking</center>

**Figure 2:** Examples of the vertical axis (Y-axis) raw signals for different activities

## 3. Feature extraction

### 3.1. The Peak Detection

Peaks in the signals of the accelerometer can be expected to reveal a great deal more than the basic statistics, such as the minimum, maximum, average or variance/covariance over a certain intervals [4]. The peak of the acceleration signal reflects the intensity of the activity. Therefore it can roughly classify different activity. In order to detect the peaks, we first reduced the noise using 1-D Gaussian smoothing and moving

average for each axis data. The accelerometer used in our experiments provides 3-axis outputs (X, Y and Z) of data. However, instead of detect the peak form these acceleration signals separately, which might be sensitive to device's placement and orientation, we thus combination of them using Eq.1 to derive a net acceleration independent of orientation.

$$A(i) = \sqrt{a_x^2(i) + a_y^2(i) + a_z^2(i)} \quad i = 1, \cdots, n \quad (1)$$

where $A(i)$ is the net acceleration at time $i$, $a_x(i)$, $a_y(i)$, $a_z(i)$ stands for X-axis, Y-axis, and Z-axis acceleration at time $i$ respectively, and $n$ is the number of recorded data. Finally, we detect the peak from net acceleration using a dynamic threshold similar to [9].

### 3.2. The Weightlessness Detection

**3.2.1. The weightlessness feature.** We know that when people run and jump, the human body would leave the ground and stay in a weightlessness state for a short while. Since the three-axis accelerometer is attached to the human body, the weightless state can be revealed in the vertical axis signal. Fig.3 shows the weightlessness phenomenon while people jump. We observed that the vertical direction signal reveal a period of weightlessness while the human body away from the ground.
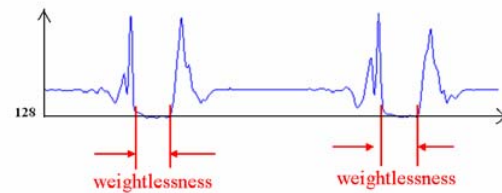


**Figure 3:** The weightlessness of jumping

**3.2.2. Calibration of the vertical directional acceleration signals.** In order to extract the weightless feature from the 3D acceleration signal, it is necessary to determine the vertical direction of the three-axis accelerometer. The most popular algorithm is attaching the accelerometers in a known position and orientation relative to the use's body. However, it is neither practical nor robust to indicate a direction as the vertical direction. Since the orientation between accelerometer and user's body may continuously change, we propose an algorithm to calibrate the actual vertical direction of accelerate signal through estimating gravitational direction. The algorithm works as follows:

As we know, when the sensor is static, the total acceleration of the sensor is due to the gravitational acceleration, which means ［2］:

$$(a_{x0}, a_{y0}, a_{z0}) = G \qquad (2)$$

Let $(a_x(i), a_y(i), a_z(i))$ be the acceleration vector of the three-axis accelerometer at time $i$, thus the dynamic component of signals is given by:

$$(a'_x(i), a'_y(i), a'_z(i)) = (a_x(i), a_y(i), a_z(i)) - (a_{x0}, a_{y0}, a_{z0}) \quad (3)$$

In order to detect the static state of raw accelerometer signal, we calculate the max, min and mean values of the acceleration signal within $N$ samples time window as following:

$$a'_{k\_max} = Max(a'_k(i)) \ (k = x, y, z, i = 0,1 \cdots N) \qquad (4)$$

$$a'_{k\_min} = Min(a'_k(i)) \ (k = x, y, z, i = 0,1 \cdots N) \qquad (5)$$

$$(a'_{x\_mean}, a'_{y\_mean}, a'_{z\_mean})$$
$$= \frac{(a'_{x\_max}, a'_{y\_max}, a'_{z\_max}) + (a'_{x\_min}, a'_{y\_min}, a'_{z\_min})}{2} \quad (6)$$

If the 3D acceleration signals satisfy the Eq.7 and Eq.8, we assume that the sensor is static.

$$\left\| a'_{k\_max} - a'_{k\_min} \right\| \le \varepsilon \quad (k = x, y, z) \qquad (7)$$

$$\left\| (a'_{x\_mean}, a'_{y\_mean}, a'_{z\_mean}) \right\| - G \le \varepsilon \qquad (8)$$

where $\varepsilon$ is a boundary parameter. Then the vertical direction is calculated as:

$$D_\perp = \frac{(a'_{x\_mean}, a'_{y\_mean}, a'_{z\_mean})}{\left\| (a'_{x\_mean}, a'_{y\_mean}, a'_{z\_mean}) \right\|} \qquad (9)$$

The actual vertical signal can be finally calibrated as:

$$a'_\perp = (a'_x(i), a'_y(i), a'_z(i)) \bullet D_\perp \qquad (10)$$

In practical application, although the position and orientation of the accelerometer are not known, our algorithm can calibrate the actual vertical direction of acceleration through estimating the gravitational direction.

### 3.3. Weightlessness-based features

Features were extracted from the raw accelerometer data using a window size of 512 with 256 samples overlapping between consecutive windows. Feature extraction on windows with 50% overlap has demonstrated success in previous work [6, 8]. At a sampling frequency of 100Hz, each window represents 5.12 seconds. For each window, the following six dimensional features were extracted:

- The mean of the peak height
- The mean of the weightlessness length
- The mean of the peak interval
- The mean of the weightlessness interval

- The ratio of the peak number to the weightlessness number
- The ratio of the weightlessness length to the window length

## 4. Classification Method

The classification algorithm we used is Support Vector Machine (SVM) [10]. We used One-versus-One Strategy (OVO), where a set of binary classifiers are constructed using corresponding data from two classes. While testing, we used the voting strategy of "Max-Wins" to produce the output.

The leave-one-subject-out validation test [2] was used to evaluate the classifiers' ability to recognize unacquainted actions. Classifiers were trained on activity data for all subjects except one. The classifiers were then tested on the data for only the subject left out of the training data set. This process was repeated for all subjects. In other words, the recognition process is subject-independent.

## 5. Experimental Results and Discussion

Since six dimensional weightlessness-based features are time-domains features, thus we compare their performance against widely used traditional features. The following four kinds of traditional time-domains features were extracted from each axes of accelerometer (result in total 12 features): mean, standard deviation, energy and correlation between axes. The effectiveness of these features has been demonstrated in many prior works [e.g. 6, 8].

Since the sensor location is important [6], we evaluate the recognition results for different sensor locations respectively, namely the locatoin in subject's clothes pocket (CP), waist bell (WB), trousers pocket (TP) and mixed data of all (MD). We carried out leave-one-subject-out validation tests for each of the above setting. Table 1 shows recognition results based on tradition time-dominions features for the four settings respectively.

**Table 1:** Accuracy of traditional time-domain features for different accelerometer location

|    | Still | Walk | Run | Jump | Average |
|----|-------|------|------|------|---------|
| CP | 99.70 | 1.16 | 72.67 | 58.43 | 57.99 |
| WB | 6.68 | 98.54 | 81.68 | 82.26 | 67.29 |
| TP | 97.67 | 92.15 | 79.94 | 64.82 | 83.64 |
| MD | 99.22 | 4.26 | 86.53 | 40.40 | 57.60 |

It can be seen that the sensor placed on the subject's trousers pocket is the most powerful while the sensor located in clothes pocket and waist bell perform badly. This may be due to the following reasons: first, as the

main parts of the activities (still, walking, running and jumping) involve with the legs, thus the sensor dose not sensitive when only using one sensor locating in clothes pocket or waist bell. This may cause the values of walking data small and they are similar to that of still (see Fig 2 (c) and (d)). Therefore, the walking and still often confuse each other. For example, we can see from table 1 that walking often recognize as still when we put the sensor in subject's clothes pocket while still often recognize as walking when the sensor locate in waist bell. For lower body activity, the best placement for acceleration sensors is around trousers pocket. Second, the characteristics of the gait signals are unique for every person while leave-one-subject-out test is subject-independent.

Table 2 shows the recognition results of our six dimensional weightlessness-based features for different sensor location. It can be seen that accuracy using our proposed new features is significantly much higher than using traditional time-domains features. Although the sensor is located in different place, our weightlessness-based features perform better in every position. In other words, our new method is robust enough for different location of sensor and is more practical for real-time acceleration activity recognition system.

**Table 2** Accuracy of weightlessness-based features for different accelerometer location

|    | Still | Walk | Run | Jump | Average |
|----|-------|------|-----|------|---------|
| CP | 99.70 | 95.63 | 94.76 | 97.96 | 97.02 |
| WB | 97.96 | 97.09 | 98.25 | 97.09 | 97.60 |
| TP | 98.25 | 98.54 | 97.38 | 95.93 | 97.52 |
| MD | 98.74 | 97.48 | 96.12 | 96.51 | **97.21** |

**Table 3** Confusion matrix based on mixed data for weightlessness-based features

|       | Still | Walk | Run | Jump |
|-------|-------|------|-----|------|
| Still | 98.74 | 1.06 | 0.09 | 0.09 |
| Walk  | 1.93  | 97.48 | 0.38 | 0.19 |
| Run   | 0.58  | 0.96 | 96.12 | **2.32** |
| Jump  | 1.20  | 1.06 | 1.16 | 96.51 |

In order to find out which activities are relatively harder to be recognized, we analyzed the confusion matrices. Table 3 shows the aggregate confusion matrix based on mixed data for our new features. It can be seen that running activity is often confused with jumping and in general hard to recognize. This result is reasonable, because the raw signals of running are similar to the jumping and both reveal a period of weightlessness (see fig. 2 (a) and (b)).

# 6. Conclusion

A novel Weightlessness feature for activity recognition from a tri-axial acceleration signals have been proposed in this paper. We propose an algorithm to calibrate actual vertical direction of acceleration through estimating the gravitational direction. And then we combine peaks of signal and weightlessness feature to extract six dimensional weightlessness-based features as the input features of the SVM classifier. Activity recognition results are based on acceleration data collect from a tri-axial acceleration placed on 43 subjects under naturalistic conditions. The average accuracy of four activities using the proposed weightlessness-based features is 97.21%, which are better than using traditional time-domains features. The experiment results show that the new features can effectively recognize different human activities and it robust enough for different location of accelerometer.

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