# A Naturalistic 3D Acceleration-based Activity Dataset & Benchmark Evaluations

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## Abstract

*In this paper, a naturalistic 3D acceleration-based activity dataset, the SCUT-NAA dataset, is created to assist researchers in the field of acceleration-based activity recognition and to provide a standard dataset for comparing and evaluating the performance of different algorithms. The SCUT-NAA dataset is the first publicly available 3D acceleration-based activity dataset and contains 1278 samples from 44 subjects (34 males and 10 females) collected in naturalistic settings with only one tri-axial accelerometer located alternatively on the waist belt, in the trousers pocket, and in the shirt pocket. Each subject was asked to perform ten activities. Benchmark evaluations of the dataset are provided based on FFT coefficients, DCT coefficients, time-domain features, and AR coefficients for the different accelerometer locations.*

## 1. Introduction

In recent years, accelerometer-based human activity recognition (AHAR) has become one of the most active research areas in pattern recognition, wearable computing, and ubiquitous computing. This is mostly due to the extensive public expectation of the potential wide reaching applications thereof in health monitoring, context-awareness, new forms of human-computer interaction, etc [1-4]. Consequently, a naturalistic 3D acceleration-based activity dataset is gaining increasing importance. Reasons for the creation of the SCUT-NAA[1] dataset are (1) to provide researchers worldwide in the field of acceleration-based activity recognition with a naturalistic activity dataset for training and testing samples, and (2) to provide a standard dataset for comparing and evaluating the performance of different algorithms.

Many previous studies on accelerometer-based activity recognition have been published in the literature [1-7]. Some of the datasets used in these works are summarized in Table 1. The "No. Act." column specifies the number of activities recognized, while the "No. Subj." column specifies the number of subjects who participated in each study. The "Data Type" column specifies whether data was collected under laboratory (L) or naturalistic (N) settings, while the "No. Sensors" column specifies the number of accelerometers used per subject.

**Table 1.** Summary of some representative datasets on activity recognition using acceleration

| Ref. | No. Act. | No. Subj. | Data Type | No. Sensors | Accuracy |
|---|---|---|---|---|---|
| [1] | 20 | 20 | N | 5 | 46.75% to 84.26% |
| [2] | 9 | 12 | N | 2 | 60% to 89% |
| [3] | 9 | 24 | L | 4 | 95.8% |
| [3] | 9 | 24 | N | 4 | 66.7% |
| [6] | 6 | 10 | L | 2 | 85% to 95% |
| [5] | 5 | 1 | L | Up to 36 | 65% to 95% |
| [4] | 4 | 6 | L | 6 | 83% to 90% |
| [7] | 3 | 8 | L | 2 | 92.85% to 95.91% |

According to Table 1, most prior work on activity recognition using acceleration relies on data collected in controlled laboratory settings. Typically, the researcher collected data from a very small number of subjects. Interestingly, Foerster reported 95.8% recognition rates for data collected in the laboratory, whereas recognition rates dropped to 66.7% for data collected outside the laboratory in naturalistic settings [3]. These results show that the performance of the

[1] SCUT is an abbreviation for the South China University of Technology, while NAA stands for Naturalistic 3D Acceleration-based Activity.

978-1-4244-6588-0/10/$25.00 ©2010 IEEE

recognition algorithms relies heavily on the dataset. None of the above-mentioned datasets, however, are publicly available. To the best of our knowledge, no public 3D acceleration-based activity dataset exists at present.

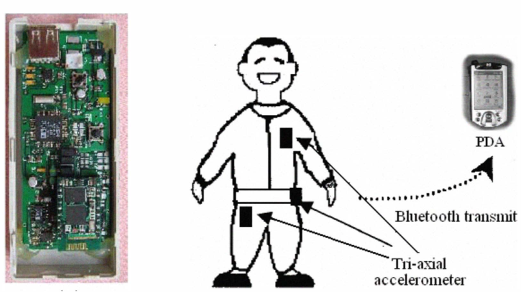
Compared with the datasets referenced above, our SCUT-NAA dataset is the first publicly available 3D acceleration-based activity dataset. It includes data for ten activities, contributed independently by 44 different individuals in naturalistic settings using only one tri-axial accelerometer.

The rest of this paper is arranged as follows. The next section introduces the data collection, while the SCUT-NAA dataset is described in Section 3. Section 4 gives benchmark evaluations of the dataset. Finally, our conclusions are presented in Section 5.

## 2. Data collection

As we clearly understand, building a naturalistic 3D acceleration-based activity dataset requires a great deal of work. Consequently, every stage in the creation of the SCUT-NAA dataset, from the selection of sampling activities, sensor positions, and subjects, to the design and development of the sampling device, was deliberately considered.

To collect activity data, we developed a sampling device comprising an accelerometer ADXL330, microprocessor ADuC7026, Bluetooth transceiver module, FLASH data storage module and keyboard module. The ADXL330 is a tri-axial accelerometer capable of sensing acceleration between -3.0g and +3.0g with tolerance within 10%. The output signal of the accelerometer is sampled at 100 Hz. The sampling device can be powered for roughly 24 hours, which is more than sufficient for the 120 minute sessions used in this study. The data collection apparatus is shown in Fig. 1(a).




(a) (b)

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

Because the sensor location is important [1], we selected three positions for locating the accelerometer including the shirt pocket, waist belt, and trousers pocket. The placement of the accelerometer is illustrated in Fig. 1(b). As the sensor is not fixed to the body, it may move randomly in the pocket (e.g., rotate) which can produce more variations among the different collectors. 44 different persons placed the accelerometer alternatively on their waist belt, or in their trousers pocket or shirt pocket as they performed each activity. The data generated by the tri-axial accelerometer was transmitted to a PDA wirelessly over Bluetooth. A diagram of our experimental setup is shown in Fig. 1(b). We used wireless communication between the accelerometer and PDA instead of wired communication for the following reasons. First, wires can restrict the subjects' movements, especially during whole body activities such as running and jumping. Second, a previous study [1] has shown that people wearing wires feel self-conscious when outside the laboratory and therefore restrict their behavior.

There is always a specific strategy for sampling objects in an activity dataset. We also have our own principles for choosing activities for the SCUT-NAA. The ten activities listed in Table 2 were selected so as to include a range of common everyday activities involving different parts of the body and a range of levels of intensity. Whole body activities such as walking, predominantly leg-based activities such as cycling, light intensity activities such as sitting, moderate intensity activities such as step walking, and vigorous activities such as jumping were included. Activities listed in the table were also selected to include more detailed classified activities, such as walking, walking quickly, walking backward, and step walking.

**Table 2.** Description of the ten activities

| Activities | Description |
|---|---|
| Sitting & relaxing (re) | Sitting & doing nothing |
| Walking (w) | Walking 50 m at normal speed |
| Walking quickly (wq) | Walking 50 m faster than normal speed |
| Walking backwards (wb) | Walking backwards for 50 m |
| Running (r) | Jogging 100 meters |
| Step walking (s) | Moving the feet alternately in the rhythm of a marching step without advancing |
| Jumping (j) | Jumping for 45s without advancing |
| Upstairs (u) | Ascending stairs |
| Downstairs (d) | Descending stairs |
| Cycling (c) | Cycling with a real bike |

44 subjects (34 males and 10 females) were selected from students at our school (South China University of Technology). Because college students are enrolled from all over the country, the activity

samples can be considered as samples performed by users from the different regions of the country.

## 3. SCUT-NAA dataset

The SCUT-NAA dataset contains 1278 samples from 44 individuals collected in naturalistic settings. Only one tri-axial accelerometer is placed on the subject's body, alternating between the waist belt, trousers pocket, and shirt pocket. Each subject was asked to perform ten activities.

Data from the accelerometer has the following attributes: time and acceleration along the x- axis, the y- axis, and the z- axis. Fig. 2 shows examples of the raw data and the corresponding colors for the axes (X- blue, Y- red, Z- green).

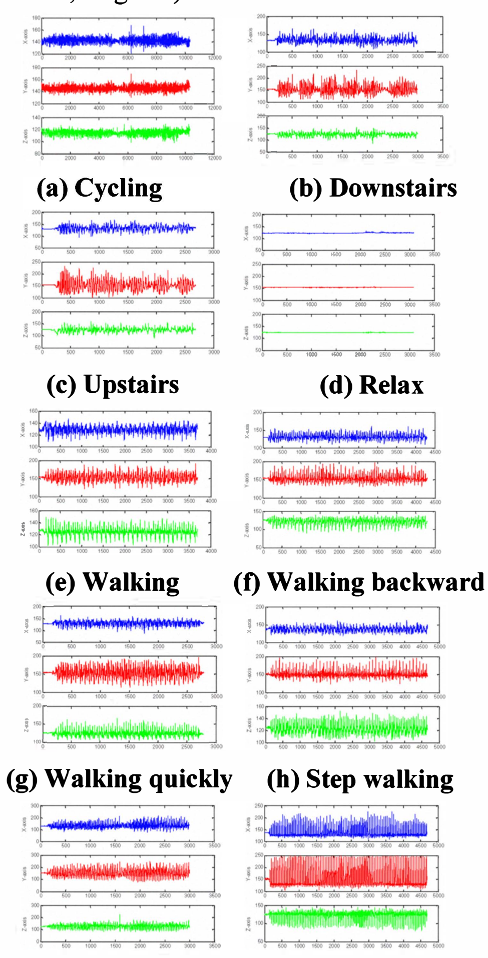



**Figure2.** Examples of raw signals for different activities

The data stream is in plain text format. Each row contains the X, Y, and Z values of a data point, with commas "," separating the values. Fig. 3 shows examples of the data stream. The first line contains the X , Y, and Z values of the first data point separated by commas. The second line contains the X, Y, and Z values of the second data point, and so on.

```
129,154,125
129,154,125
130,154,126
129,154,126
130,154,126
 ⋮   ⋮   ⋮
```

**Figure 3.** Examples of the data stream

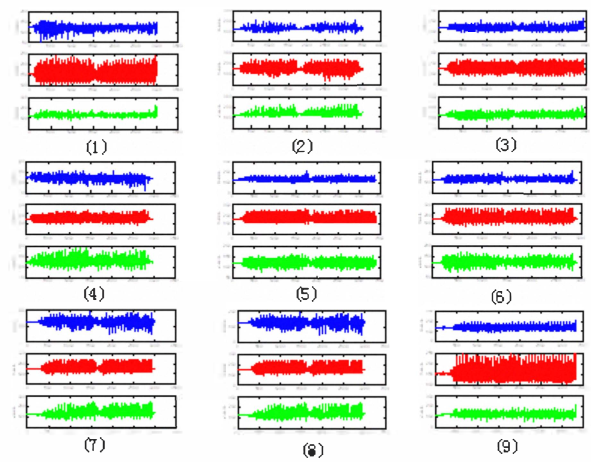


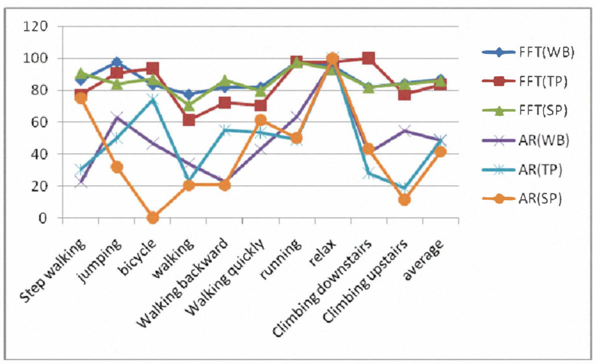

**Figure 4.** Signals for running contributed by nine subjects

The subjects were asked to perform the activities in their most comfortable and familiar manner. No restrictions were imposed on the quality of the sampling activities. Fig. 4 shows the signals of represented by the corresponding color (X- blue, Y- red, Z- green) for running contributed by nine subjects with the accelerometer attached to their waist belt. From the figure it is obvious that there is a big difference among them. This difference will create difficulties for activity recognition.

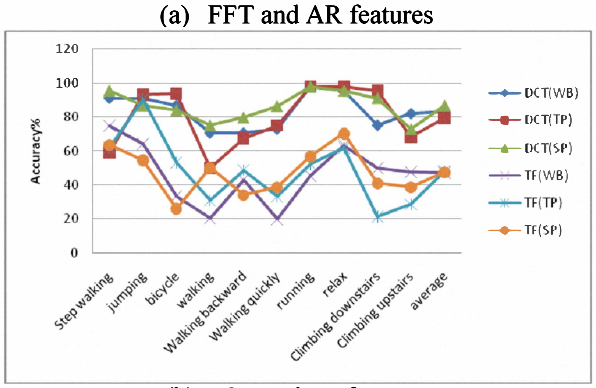
## 4. Benchmark evaluation

In this paper, benchmark evaluations were conducted by comparing several commonly used features in accelerometer-based activity recognition, namely FFT coefficients [1], DCT coefficients, time-domain features (TF) [1, 2, 7], and autoregressive (AR) coefficients [10]. Time domain features include: mean, standard deviation, FFT energy, and correlation between axes. For all experiments, we used a Support Vector Machine (SVM) [8] classifier with leave-one-subject-out validation.

Features were extracted from the raw acceleration data using a window size of 512 with 256 samples overlapping between consecutive windows. Feature extraction on sliding windows with 50% overlap has been shown to be successful in previous research [1, 9]. For each window, the first 64 FFT coefficients were extracted from each axis of acceleration data as FFT features, and the first 48 DCT coefficients were extracted from each axis of acceleration data as DCT features. The first FFT coefficient and DCT coefficient were, however, discarded respectively, as they are direct current components and represent the gravity component of the accelerometer. For each window, the 4-order AR coefficients were computed as AR features, while time domain features were computed as TF. Fig. 5 shows the recognition results based on four features for the different sensor locations, i.e. located on the subject's waist belt (WB), in the trousers pocket (TP), or in the shirt pocket (SP).




(a) FFT and AR features




(b) DCT and TF features

**Figure 5.** Accuracy based on four features for the three settings

It can be seen that the recognition rate is relatively high for the sensor located on the waist belt, but the recognition rate fluctuates for the sensor placed in the trousers pocket. Intuitively, the sensor placed in the trousers pocket should be the most powerful, since the majority of activities involve heavy use of the legs. Thus, the sensor placed in the trousers pocket should be more sensitive. However, as the sensor is not fixed to the body, it may move randomly in the pocket (e.g. rotate), thereby producing more variations during the data collection process. These variations will create difficulties for activity recognition.

Table 3 shows the recognition results based on four features for the sensor located at the waist.

**Table 3.** Accuracy based on different features

| Activities | Accuracy based on four features | | | |
|---|---|---|---|---|
| | FFT | DCT | TF | AR |
| Step walking | 86.36 | 90.91 | 75 | 22.73 |
| Jumping | 97.67 | 90.70 | 64.29 | 62.79 |
| Cycling | 83.33 | 86.67 | 33.33 | 46.67 |
| Walking | 77.27 | 70.45 | 20.45 | 34.09 |
| Walking backward | 81.82 | 70.45 | 43.18 | 22.73 |
| Walking quickly | 81.82 | 72.73 | 20 | 43.18 |
| Running | 97.73 | 97.73 | 45.45 | 63.64 |
| Relaxing | 95.45 | 95.45 | 63.64 | 97.73 |
| Downstairs | 81.82 | 75 | 50 | 40.91 |
| Upstairs | 84.09 | 81.82 | 47.73 | 54.55 |
| Total | 86.82 | 83.06 | 47.17 | 48.94 |

Table 3 shows that the accuracy using frequency-domain features is much higher than using time-domain features. Relaxing and jumping are more easily recognized than the other activities based on the four features, while jumping, running, and relaxing have a much higher accuracy than the other activities based on FFT features. Compared with other activities, the accuracy of walking is much lower.

**Table 4.** Confusion matrix based on FFT features

| | Recognized as | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **s** | **j** | **b** | **w** | **wb** | **wq** | **r** | **re** | **d** | **u** |
| **s** | 38 | | 2 | | 2 | 1 | | 1 | | |
| **j** | | 42 | | | | 1 | | | | |
| **b** | 2 | | 25 | | | | | 3 | | |
| **w** | | 1 | | 34 | 1 | 6 | 1 | | | 1 |
| **wb** | | | | 5 | 36 | 3 | | | | |
| **wq** | | | | 6 | 1 | 36 | 1 | | | |
| **r** | | | | 1 | | | 43 | | | |
| **re** | 1 | 1 | | | | | | 42 | | |
| **d** | | | 3 | 1 | 1 | | | | 36 | 3 |
| **u** | | | | 1 | 1 | | 1 | | 4 | 37 |

To ascertain which activities are relatively harder to recognize, we analyzed the confusion matrix. Table 4 shows the aggregate confusion matrix based on FFT features for the waist position. It can be seen that walking is often confused with walking quickly and walking backward, and generally harder to recognize. Downstairs is often confused with upstairs. These results are reasonable, because the raw signals for walking are similar to walking quickly and walking backward and the signals for downstairs are similar to those for upstairs. See Figs. 2 (b), (c), (e), (f), and (g).

# 5. Conclusion

This paper presents the creation of a naturalistic 3D acceleration-based activity dataset, the SCUT-NAA dataset, which is the first publicly available 3D acceleration-based activity dataset. It includes data from 44 individuals collected in naturalistic settings using only one tri-axial accelerometer located alternatively on the waist belt, in the trousers pocket, or in the shirt pocket. Each person was asked to perform ten activities. We also presented the design of the sampling device and selection of sampling activities, sensor positions, and subjects. Furthermore, descriptions of the SCUT-NAA dataset, including the contents, data structure, and sample difference of the dataset were provided. We presented a benchmark evaluation based on FFT coefficients, DCT coefficients, time-domain features and AR coefficients for the different sensor locations i.e., on the waist belt, in the trousers pocket, or in the shirt pocket.

The SCUT-NAA dataset is available at http://www.hcii-lab.net/data/SCUT-NAA/. More information can also be obtained by contacting lianwen.jin@gmail.com.

## Acknowledgments

We would like to thank all our warmly cooperative volunteers. This work is supported in part by the National Science Foundation of China (NSFC) (grants no. U0735004), Microsoft Research Asia Fundation (grant no. *FY10-RES-OPP-006)* and the GDSTP (grant no. 07118074, *2007B010200048, 2008A050200004*).

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