USC-HAD: a daily activity dataset for ubiquitous activity recognition using wearable sensors

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USC-HAD: A Daily Activity Dataset for Ubiquitous Activity Recognition Using Wearable Sensors

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ABSTRACT
Many ubiquitous computing applications involve human activity recognition based on wearable sensors. Although this problem has been studied for a decade, there are a limited number of publicly available datasets to use as standard benchmarks to compare the performance of activity models and recognition algorithms. In this paper, we describe the freely available USC human activity dataset (USC-HAD), consisting of well-defined low-level daily activities intended as a benchmark for algorithm comparison particularly for healthcare scenarios. We briefly review some existing publicly available datasets and compare them with USC-HAD. We describe the wearable sensors used and details of dataset construction. We use high-precision well-calibrated sensing hardware such that the collected data is accurate, reliable, and easy to interpret. The goal is to make the dataset and research based on it repeatable and extendible by others.

Author Keywords
Ubiquitous computing, Pervasive healthcare, Human activity recognition, Wearable sensor, Human activity dataset

ACM Classification Keywords
I.5.4 Pattern Recognition: Applications

General Terms
Design, Measurement

INTRODUCTION
Human activity recognition is regarded as one of the most important problems in ubiquitous computing since it has a wide range of applications including healthcare, security, surveillance, human-machine interaction, sport science, etc. Camera-based computer vision systems and inertial sensor-based systems are among several techniques used to collect basic sensor data for human activity recognition. In computer vision, human activities are captured by cameras and the task is to recognize automatically the activity based on a sequence of images [22]. However, in some scenarios which require continuously monitoring a person's activities, the camera-based method may not work due to the lack of complete camera coverage. In addition, cameras are intrusive and many people do not feel comfortable being watched by cameras continuously.

With the advancement of semiconductor and MEMS technologies, inertial sensors such as accelerometers and gyroscopes are miniaturized such that they can be attached or worn on the human body in an unobtrusive way. The data from these wearable sensors can be used in systems that understand and recognize human activities using machine learning and pattern recognition techniques. Compared to cameras, an advantage of wearable sensors is that they generally monitor activity on a nearly-continuous or continuous basis, and are not confined to a limited observation space. Furthermore, wearable sensors are unobtrusive if they are integrated into items people wear or hold in their normal lives. Examples of such items are watches, shoes, mobile phones, and clothing [17] [5] [10].

Since wearable sensors are suitable for continuous monitoring, they open the door to a world of novel healthcare applications. Specific applications include physical fitness monitoring, elder care support, sleep quality monitoring, long-term preventive and chronic care, and intelligent assistance to people with cognitive disorders [7] [24]. As an example, a sleep quality monitoring application could use activity information (body position and movement) to infer and calculate the amount of restorative sleep (deep sleep) and disruptive sleep (time and duration spent awake) that one gets throughout the night. This information helps users recognize sleeping disorders as early as possible for diagnosis and prompt treatment of the condition [11].

The applications mentioned above promotes the research of human activity recognition using wearable sensors. Over the past decade, researchers in embedded systems, signal processing, biomedical engineering, and human-computer interaction have begun to work on prototyping wearable sensor systems, building human activity datasets, and developing machine learning techniques to model and recognize various types of human activities. In this work, we focus on developing a dataset for human activity recognition research. It has been widely accepted that datasets play a significant role in facilitating research in any scientific domain. In ap-

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plication areas including human speech recognition, natural language processing, computer vision, and computational biology, there are many publicly available datasets that act as standardized benchmarks for algorithm comparison (e.g. UC Irvine machine learning repository [3], Caltech 101/256 dataset [1], and Wall Street Journal CSR corpus [18]). Although wearable sensor-based human activity recognition has been studied for a decade, most researchers develop and examine the performance of their activity models and recognition algorithms based on their own datasets. In general, these datasets are relatively small and limited by the constrained settings within which they are constructed. Specifically, they either only contain a small number of subjects (e.g. 2, 3, or even 1) or focus on some specific category of activities (e.g. cooking activities). Furthermore, most of these datasets are not available for public usage. This prohibits researchers in ubiquitous computing community to compare their algorithms on a common basis.

The lack of large, general purpose, and publicly available human activity datasets motivates us to build our own dataset. In this paper, we describe how we constructed a dataset useful for ubiquitous computing community for conducting human activity recognition research and compare it to a selection of similar existing datasets. We term our dataset University of Southern California Human Activity Dataset (USC-HAD). As a brief overview, USC-HAD is specifically designed to include the most basic and common human activities in daily life from a large and diverse group of human subjects. Our own focus is on healthcare related applications such as physical fitness monitoring and elder care, but the activities in the dataset are applicable to many scenarios. The activity data is captured by a high-performance inertial sensing device instead of low-cost, low-precision sensors. Figure 1 shows an example of the activity data sampled by the sensing device. As of the time of writing (June 2012), we have included 12 activities and collected data from 14 subjects. The entire dataset and the basic code for visualizing the data is publicly available on the web at: `http://sipi.usc.edu/HAD/` [4]. We intend to expand the number of activities and number of subjects in future, and we will provide updates on this website.

EXISTING DATASETS

The number of publicly available human activity datasets is limited. In this section, we review some of them. Although each dataset has its own strengths, none of them meets our goals, thus motivating us to build our own dataset. A full comparison of these datasets and USC-HAD is in Table 1.

MIT PlaceLab Dataset

One of the first publicly available datasets is the MIT PlaceLab dataset [20]. A single subject wearing five accelerometers (one on each limb and one on the hip) and a wireless heart rate monitor was asked to perform a set of common household activities during a four-hour period. The household activities include: preparing a recipe, doing a load of dishes, cleaning the kitchen, doing laundry, making a bed, and light cleaning around an apartment. In addition to the activities above, the subject also searches for items, uses appliances, talks on the phone, answers email, and performs other everyday tasks. The major issue with this dataset is that it only contains data from a single subject. A potential problem with it is that the small number of subjects may poorly represent the activity characteristics of a large population. In addition, the definitions of the considered activities are vague which makes the evaluation of recognition performance difficult.

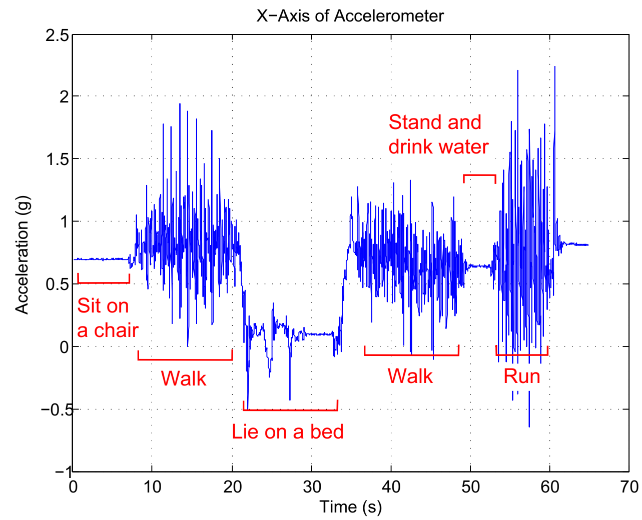


Figure 1. An example of activity data from the x-axis of the 3-axis accelerometer

UC Berkeley WARD Dataset

The WARD (wearable action recognition database) dataset developed by the University of California, Berkeley (UC Berkeley) consists of continuous sequences of human activities measured by a network of wearable sensors [23]. These wireless sensors are placed at five body locations: two wrists, the waist, and two ankles. Each custom-built multimodal sensor carries a 3-axis accelerometer and a 2-axis gyroscope. WARD includes 20 human subjects (13 male and 7 female) and a rich set of 13 activities that covers some of the most common activities in people's daily lives such as standing, walking, and jumping. Although the WARD dataset covers a large population and focuses on the most common human activities, part of the sensed data is missed due to battery failure and wireless network packet loss. In addition, the data sampled from the sensors is raw digital data and not calibrated. This makes the data hard to interpret. Moreover, the dataset does not include sensor locations where people typically carry their mobile devices (e.g. mobile phone, iPod) such as pant pockets and front hips. We feel that this makes this dataset less useful.

CMU Multi-Modal Activity Database (CMU-MMAC)

The Carnegie Mellon University Multi-Modal Activity Database (CMU-MMAC) is different from the datasets mentioned above in the sense that it contains many other modalities besides accelerometers and gyroscopes to sense and measure human activities [21]. These modalities include video, audio, RFID tags, motion capture system based on on-body markers, and physiological sensors such as galvanic skin response (GSR) and skin temperature. These sensors are located all over the human body, including both forearms and upper arms, left and right calves and thighs, abdomen, and both wrists. 43 subjects were enrolled to perform food preparation and cook five different recipes: brownies, pizza, sandwich, salad and scrambled eggs in a kitchen environment. Although this dataset contains a much bigger population and richer modalities and locations than any dataset mentioned above, it only focuses on a specific category of activities (cooking).

OPPORTUNITY Dataset

The OPPORTUNITY dataset is collected from an European research project called OPPORTUNITY [19]. The OPPORTUNITY dataset focuses on daily home activities in a breakfast scenario. Specifically, 12 subjects are asked to perform a sequence of daily morning activities including grooming room, preparing and drinking coffee, preparing and eating sandwich, and cleaning table in a room simulating a studio flat with kitchen, deckchair, and outdoor access. Like CMU-MMAC, the OPPORTUNITY dataset is recorded from many different sensing modalities including accelerometers, gyroscopes, magnetometers, microphones, and video cameras integrated in the environment, in objects, and on the human bodies. Similar to CMU-MMAC, although OPPORTUNITY dataset contains a wide range of sensing modalities, it only covers daily morning activities in a home environment.

Design Goals

The goal of our USC-HAD dataset is to overcome the limitations of the existing datasets such that it can serve as a standard benchmark for researchers in ubiquitous computing community to compare performance of their human activity recognition algorithms. In order to achieve this, our dataset has been carefully constructed with the following goals:

- The dataset should enroll a large number of human subjects with divergence in gender, age, height, and weight.
- The activities included should correspond to the most basic and common human activities in people's daily lives such that the dataset is useful for a wide range of potential applications such as elder care, and personal fitness monitoring.
- The wearable sensors should be calibrated and capable of capturing human activity signals accurately and robustly.
- We envision that in near future the wearable sensors will become a part of the mobile devices (e.g. mobile phone) people carry in their daily lives. Therefore, the locations of the wearable sensors should be selected to be consistent with where people carry their mobile devices.

In the following sections we will describe in more detail the wearable sensors we use for data collection, the activities we have chosen, and finally the data format and organization of our USC-HAD dataset. We conclude this paper with a brief summary and future work.

SENSORS AND HARDWARE PLATFORM

The majority of wearable systems for ubiquitous computing and activity recognition concentrates on placing a single type of sensor, typically accelerometers, in multiple locations on the human body (*single-modality multi-location*). However, the use of single sensor type has been proved to restrict the range of activities it can recognize [7]. An alternative is to use multiple sensor types, that is, a multi-modal sensor to collect data from a single body location (*multi-modality single-location*). The rationale behind this idea is to select sensors that are complementary such that a wider range of activities can be recognized. For example, using an accelerometer and a gyroscope together can differentiate whether the person is walking forward or walking left/right while classification fails if accelerometers are used alone. Furthermore, the reason to place the sensors on a single location is to remove the obtrusiveness incurred by placing sensors on multiple body locations. In terms of practicality, this *multi-modality single-location* design is a promising line of investigation since it is much more comfortable for users to wear a single device at only one location. Moreover, this multi-modal sensor could be incorporated into existing mobile devices such as mobile phones. Integrating sensors into devices people already carry is likely to be more appealing to users and achieve greater user acceptance. In terms of performance, the study carried out in [14] has shown that the information gained from multi-modal sensors can offset the information lost when activity data is collected from a single location. Therefore, we adopt the *multi-modality single-location* design to build our sensing platform.

The Choice of Sensors

There are many types of wearable sensors used in the literature for human gesture and activity recognition. These sensors include audio sensor (microphone), motion sensors such as accelerometer and gyroscope; geographical sensors such as magnetometer (digital compass) and GPS; physiological sensors such as galvanic skin response (GSR) sensor, pulse oximeter, and Electrocardiogram sensor (ECG); and environmental sensors such as barometric pressure sensor, ambient light sensor, humidity and temperature sensor. Intuitively, it would be optimal to include all these sensors since each provides some useful information. However, in the perspective of activity recognition performance, it is not necessary or even undesirable if we incorporate all the sensing modalities. For example, heart rate information extracted from ECG sensor has a high correlation with the accelerometer signals. Only modest gain is achieved when these two sensors are combined together [15]. Light sensor can be misleading since its readings are more dependent on how users carry devices than what activities they are performing. In the perspective of system complexity and practicality, the total number of sensors should be as small as possible such that the size of the wearable device is small. Therefore, only the most important sensors which provide complementary information should be incorporated. In [16], the rotation angle produced by gyroscope is identified to be the key performance booster for fall detection. In [13], accelerometer and microphone are identified as the two most important sensors to recognize activities including sitting, walking, walking up/down stairs, riding elevator up/down, and brushing teeth. However, for privacy considerations, we argue that sensors such as microphone should not be selected.

MotionNode

Based on the above considerations, we use an off-the-shelf sensing platform called MotionNode to capture human activity signals and build our dataset. MotionNode is a 6-DOF inertial measurement unit (IMU) specifically designed for human motion sensing applications (see Figure 2) [2]. Each MotionNode itself is a multi-modal sensor that integrates a 3-axis accelerometer, 3-axis gyroscope, and a 3-axis magnetometer. The measurement range is $\pm 6g$ and $\pm 500dps$ for each axis of accelerometer and gyroscope respectively. Although body limbs and extremities can exhibit up to $\pm 12g$

Figure 2. MotionNode sensing platform

in acceleration, points near the torso and hip experience no more than $\pm 6g$ range in acceleration [6]. Therefore, MotionNode is capable of capturing all the details of normal human activities. In addition, MotionNode is a wired device and transmits sampled sensor data to a laptop computer via a USB interface. In such case, no sensor data is missed and the fidelity of the sensor data is well preserved. A possible concern is that the wire is cumbersome and may distort the sampled data. However, we have proved by experiments that as long as the wire is soft and long, it has little impact on the quality of the collected data[1].

Compared to other commercially available inertial sensing platforms, MotionNode has several advantages:

- MotionNode is extremely small in size $(35mm \times 35mm \times 15mm)$ and lightweight enough $(14g)$ to wear comfortably for long period of time. This feature makes MotionNode unobtrusive and thus perfect as a wearable device.

- Compared to the accelerometer and gyroscope embedded in the smartphones (e.g. iPhone 4G), the integrated sensors have higher resolution ($0.001g \pm 10\%$ for accelerometer, $0.5°/second$ for gyroscope) and wider sensing ranges. In addition, MotionNode is gyro-stablized and well calibrated such that the readings are accurate and reliable.

- The highest sampling rate can reach $100Hz$. This sampling frequency is much higher than the one used in some of the existing datasets [23] [21].

[1]The experiments were performed by placing the MotionNode on a rotation table with a soft and relatively long wire connected to a PC. The rotation table was preset to rotate at a constant rate (30dps, 60dps, 120dps). The readings from MotionNode were almost the same as the preset values.

USC HUMAN ACTIVITY DATASET (USC-HAD)

In this section, we describe the details of our human activity dataset USC-HAD. We first explain our criteria for selecting the subjects and activities, then we describe the data collection procedure and how we annotate the data. Finally we present the organization of our dataset.

Human Subjects

Variation across users is an important practical issue for any pattern recognition problem. In order to build a powerful recognition system, the system needs to be trained on a large diverse group of individuals. In the context of human activities, we assume that the diversity of the subjects enrolled includes the following four factors: (1) Gender; (2) Age; (3) Height; and (4) Weight. Based on these guidelines, we have selected 14 subjects (7 male, 7 female) to participate in the data collection. The statistics of age, height, and weight are listed in Table 2. We hope the diversity in each of these four factors ca cover a wider range of population.

	Age	Height (cm)	Weight (kg)
range	21 - 49	160 - 185	43 - 80
mean	30.1	170	64.6
std	7.2	6.8	12.1

Table 2. Statistics of the participating human subjects

Activities

There are many categorization methods to classify human activities. One method categorizes activities into activities that an individual does by themselves (e.g., cooking), and activities that involve more than one person (e.g. shaking hands) [8]. Another popular categorization is based on timescale. It breaks activities into: (1) short-term activities (low-level activities), where activities are characterized by a sequence of body motions, posture or object use (e.g., walking, going upstairs). These activities typically last between seconds and several minutes; and (2) long-term activities (high-level activities), which are complex and usually composed of a collection of low-level activities. These activities typically last more than several minutes and can last as long as a few hours (e.g., cleaning the house, going shopping) [12]. In this work, we focus on building a dataset of low-level activities. We list two reasons here: (1) Low-level activities such as walking and running have a clear definition and description. This makes modeling at this granularity level much easier. As a comparison, high-level activities are typically complex. Up to now, there is still no consensus on how to define these activities in the ubiquitous computing community. (2) Normally, high-level activities consist of a sequence of low-level activities. For example, going shopping can be regarded as walking to the garage, driving a car to the shopping mall, and then shopping in the mall. Therefore, it is reasonable to assume low-level activity recognition is the basis of the high-level activity recognition. Once we reliably recognize low-level activities, we can then construct a temporal and location model on top of these low-level activities to characterize the corresponding high-level activities.

Based on the considerations mentioned above, we have selected 12 activities (see Table 3). These activities are among the most basic and common human activities in people's daily lives. Note that the description for each activity in Table 3 is generic such that each subject could perform these activities based on one's own style. We hope this diversity in performance style could cover a wider range of population.

	Activity	Description
1	walking forward	The subject walks forward in a straight line
2	walking left	The subject walks counter-clockwise in a full circle
3	walking right	The subject walks clockwise in a full circle
4	walking upstairs	The subject goes up multiple flights
5	walking downstairs	The subject goes down multiple flights
6	running forward	The subject runs forward in a straight line
7	jumping	The subject stays at the same position and continuously jumps up and down
8	sitting	The subject sits on a chair either working or resting. Fidgeting is also considered to belong to this class.
9	standing	The subject stands and talks to someone
10	sleeping	The subject sleeps or lies down on a bed
11	elevator up	The subject rides in an ascending elevator
12	elevator down	The subject rides in a descending elevator

Table 3. Activities and their brief descriptions

Data Collection Procedure
To collect data, we pack a single MotionNode firmly into a standard-sized mobile phone pouch (see Figure 3). Since MotionNode is a wired device, the MotionNode is connected to a miniature laptop via a long and soft cable to record sampled data. During data collection, the subject wears the pouch at one's front right hip (with the MotionNode oriented so the x axis points to the ground and is perpendicular to the plane formed by y and z axes), holds the miniature laptop in one hand, and is asked to perform a trial of specific activity naturally based on one's own style (see Figure 4). We choose front right hip as the location to wear the sensor because it is one of the top 5 locations where people carry their mobile phones when they are out and about in public spaces based on the survey carried out by [9]. In order to capture the day-to-day activity variations, each subject was asked to perform 5 trials for each activity on different days at various indoor and outdoor locations. Although the duration of each trial varies across different activities, it is long enough to capture all the information of each performed activity. On average, it took 6 hours for each subject to complete the whole data collection procedure.

Ground Truth Annotation
Ground truth was annotated while the experiments were being carried out. When the subject was asked to perform a trial of one specific activity, an observer standing nearby marked the starting and ending points of the period of the

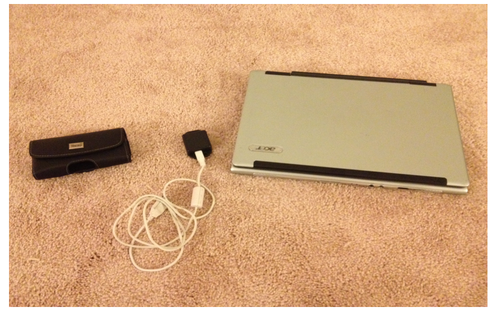


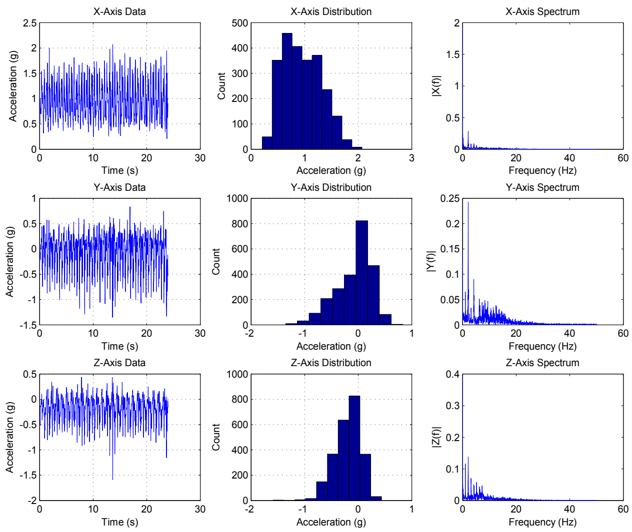
Figure 3. MotionNode, the mobile phone pouch, and the miniature laptop

activity performed. In addition, the observer was also responsible for recording the details of how subjects perform activities. Examples include how many strides the subject made during one trial of "walking forward"; how the subject climbed the stairs (one stair at a time, or two stairs at a time) during one trial of "walking up stairs", etc. This online ground truth annotation strategy eliminates the need for the subjects to annotate their data by themselves and helps to reduce annotation errors.

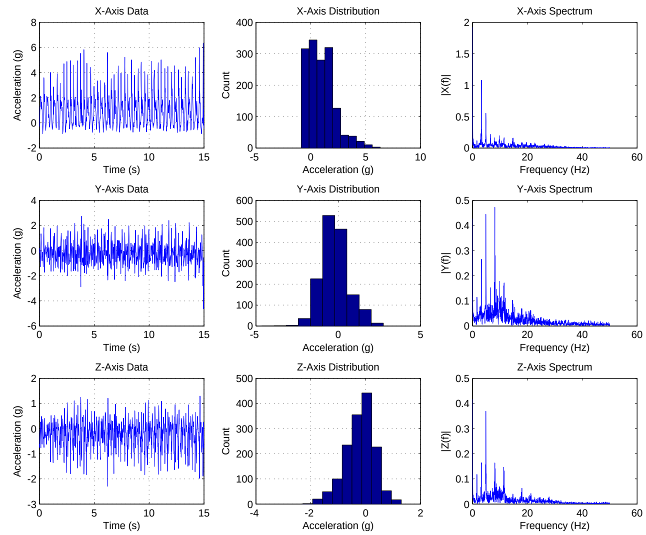
Figure 4. During data collection, a single MotionNode is packed firmly into a mobile phone pouch and attached to the subject's front right hip

Dataset Organization
After the sessions were recorded, the activity data of each trial was manually segmented based on the starting and ending points annotated by the observer. These segmented data was then stored and organized using the MATLAB computing environment. Each segmented activity trial of one subject is stored in a separate $.mat$ file. The naming convention of each $.mat$ file is defined as $a"m"t"n".mat$, where a stands for activity, m stands for activity number (see Table 3 for the activity numbers), t stands for trial, and n stands for trial number. For example, the first trial of activity "walking forward" is stored in the $.mat$ file with the name $a1t1.mat$ ("walking forward" has an activity number 1). The stored information of each $.mat$ file is listed and described briefly in Table 4.

Dataset Visualization
In addition to the collected activity data, we also provide sample MATLAB scripts for visualizing the data. An example of the plot is shown in Figure 5. In this example, we show the raw sensor data, the histogram, and the spectral



(a) An example of data plot for Walking Forward



(b) An example of data plot for Running Forward

Figure 5. The plot of the raw sensor data, the histogram, and the spectral analysis of each axis of the 3-axis accelerometer for activity Walking Forward and activity Running Forward.

Field	Description
title	USC Human Activity Database
version	The version of the dataset
date	A string indicating the date of the recording session with the format: yyyy-mm-dd
subject number	An integer representing the unique ID number of the subject
age	An integer representing the age of the subject
height	An integer representing the height of the subject in unit of centimeter
weight	An integer representing the weight of the subject in unit of kilogram
activity name	A string indicating the name of the activity
activity number	An integer representing the ID number of the activity
trial number	An integer representing the number of the trial
sensor location	The location of the sensor worn on the human body
sensor orientation	The orientations of the embedded 3-axis accelerometer and 3-axis gyroscope
sensor readings	The sampled data from the 3-axis accelerometer and 3-axis gyroscope
comments	Details of how subjects perform activities.

Table 4. Dataset fields and their brief descriptions

analysis of each axis of the 3-axis accelerometer for activity Walking Forward (Figure 5(a)) and activity Running Forward (Figure 5(b)). As illustrated in the figures, although the raw sensor data of the three axes in time domain look similar, the histograms and the spectral plots show different patterns between the two types of activities. Based on these observations, researchers can extract features and develop various pattern recognition algorithms to characterize the activity data.

DISCUSSION

The intention of the development of the USC-HAD dataset is not to replace the other existing datasets. Instead, USC-HAD is carefully designed to satisfy the key design goals presented in the beginning of this paper. Compared to other existing datasets, USC-HAD includes a representative number of human subjects, both male and female. The activities considered are well-defined basic daily activities. Finally, the activity data is collected from a high-precision well-calibrated sensing hardware such that the data is accurate, reliable, and easy to interpret. All these features make the research work using this dataset repeatable and extendible by other researchers. We have developed several activity models and activity recognition techniques based on part of this dataset, with the goal of better understanding human activity signals and developing state-of-the-art human activity recognition systems. For more information about these models and recognition techniques, please refer to [25] [27] [26].

CONCLUSION AND FUTURE WORK

This paper introduces the USC Human Activity Dataset (USC-HAD) as a resource for human activity research by the ubiquitous computing community. We have described the wearable sensors and the details of how we collect the data and construct the dataset. As a brief summary, the USC-HAD dataset currently includes 14 subjects and 12 daily activities with the sensing hardware attached to the subjects' front right hip. The full dataset is located at [4]. We encourage ubiquitous computing researchers to use it and provide feedback about it. In the future, we will consider other sensor locations such as trousers pockets, shirt pockets, shoulder bags, backpacks, and we will continue to add more subjects and more activities to our dataset.

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Dataset	Number of Subjects	Activities	Sensor Locations	Sensors	Comments
MIT PlaceLab	1	Prepare a recipe Do a load of dishes Clean the kitchen Do laundry Make a bed Light cleaning Search for items Use appliances Talk on the phone Answer emails	Left arm Right arm Left leg Right leg Hip	3-axis accelerometer $(\pm 2g)$ Heart rate monitor	The number of subjects is small. The definitions of the activities considered are vague.
UC Berkeley WARD	20 (13 male, 7 female)	Rest at standing Rest at sitting Rest at lying Walk forward Walk left Walk right Turn left Turn right Go upstairs Go downstairs Jog Jump Push wheelchair	Left wrist Right wrist Front center of the waist Left ankle Right ankle	3-axis accelerometer $(\pm 2g)$ 2-axis gyroscope $(\pm 500dps)$	Part of the sensed data is missing. Sensor data is not calibrated.
CMU MMAC	43	Food preparation Cook five recipes: Brownies Pizza Sandwich Salad Scrambled eggs	Left forearm Right forearm Left upper arm Right upper arm Left thigh Right thigh Left calf Right calf Abdomen Left wrist Right wrist Forehead	Camera Microphone RFID 3-axis accelerometer $(\pm 6g)$ 3-axis gyroscope $(\pm 500dps)$ 3-axis magnetometer Ambient light Heat flux sensor Galvanic skin response Temperature Motion capture	The dataset focuses on cooking activity.
OPPORTUNITY	12	Groom room Prepare coffee Drink coffee Prepare sandwich Eat sandwich Cleanup	Wrist Chest Limb Shoulder Foot Table Chair	3-axis accelerometer 3-axis gyroscope 3-axis magnetometer Microphone Camera Pressure sensor Power sensor	The dataset focuses on daily morning activities.
USC HAD	14 (7 male, 7 female)	Walk forward Walk left Walk right Walk up stairs Walk down stairs Run forward Jump Sit on a chair Stand Sleep Elevator up Elevator down	Front right hip	3-axis accelerometer $(\pm 6g)$ 3-axis gyroscope $(\pm 500dps)$	Data taken from one sensor location.

Table 1. A full comparison between some of the existing datasets and USC-HAD dataset