

HuGaDB: Human Gait Database for Activity Recognition from Wearable Inertial Sensor Networks

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Abstract. This paper presents a human gait data collection for analysis and activity recognition consisting of continuous recordings of combined activities, such as walking, running, taking stairs up and down, sitting down, and so on; and the data recorded are segmented and annotated. Data were collected from a body sensor network consisting of six wearable inertial sensors (accelerometer and gyroscope) located on the right and left thighs, shins, and feet. Additionally, two electromyography sensors were used on the quadriceps (front thigh) to measure muscle activity. This database can be used not only for activity recognition but also for studying how activities are performed and how the parts of the legs move relative to each other. Therefore, the data can be used (a) to perform health-care-related studies, such as in walking rehabilitation or Parkinson's disease recognition, (b) in virtual reality and gaming for simulating humanoid motion, or (c) for humanoid robotics to model humanoid walking. This dataset is the first of its kind which provides data about human gait in great detail. The database is available free of charge <https://github.com/romanchereshnev/HuGaDB>.

1 Introduction

The increasing availability of wearable body sensors leads to novel scientific studies and industrial applications [1]. The main large areas include gesture recognition, human activity recognition, and human gait analysis. Several databases have been released for benchmarking; however, due to a wide variety of sensor types and the complexity of activities, these databases are rather distinct. Now, we will review these areas and the corresponding databases in a taxonomic manner.

Gesture recognition (GR) mainly focuses on recognizing hand-drawn gestures in the air. Patterns to be recognized may include numbers, circles, boxes, or Latin alphabet letters. Prediction is usually made on data obtained from smartphone sensors or some special gloves equipped with kinematic sensors, such as 3-axis accelerometers, 3-axis gyroscopes, and occasionally electromyography (EMG) sensors, to measure the electrical potential on the human skin during muscular activities [2]. A database for gesture recognition is available in [3].

Human activity recognition (HAR), on the other hand, aims at recognizing daily lifestyle activities. For instance, an interesting research topic is recognizing activities in or around the kitchen, such as cooking; loading the dishwasher or washing machine; preparing brownies or salads; scrambling eggs; light cleaning; opening or closing drawers, the fridge, or doors; and so on. Often these activities can be interrupted by, for example, answering phones. Databases on this topic include the MIT Place dataset [4,5], Darmstadt Daily Routine dataset [6], Ambient Kitchen [7], CMU Multi-Modal Activity Database (CMU-MMAC) [8], and Opportunity dataset [9,10]. In this topic, on-body inertial sensors are usually worn on the wrist, back, or ankle, however, additional sensors are used, such as temperature sensor, proximity sensor, water consumption sensor, heart rate and so on. For instance, CMU-MMAC includes videos, audios, RFID tags, motion capture system based on on-body markers, and physiological sensors such as galvanic skin response (GSR) and skin temperature, which are all located on both forearms and upper arms, left and right calves and thighs, abdomen, and wrists.

Other types of HAR usually focus on walking-related activities, such as walking, jogging, turning left or right, jumping, laying down, going up or down the stairs, and so on. Data on this topic can be found in the WARD dataset [11], PAMAP2 dataset [12,13], HASC challenge [14–16], USC-HAD [17,18], and MAREA [19]. For data collection, on-body sensors are often placed on the participant’s wrist, waist, ankles, and back.

In some databases, exceptional efforts are taken to provide a reliable benchmark. The body sensor network conference (BSNC) (<http://bsncontest.org>) [20], for instance, has carried out a contest where organizers provided three different datasets from different research groups. Databases differ in sensor types used and activities recorded. Another team, called the Evaluating Ambient Assisted Living Systems through Competitive Benchmarking – Activity Recognition (EvAAL-AR), provides a service to evaluate HAR systems live on the same activity scenarios performed by an actor [21]. In this contest, each team brings its own activity recognition system, and the evaluation criteria attempt to capture the practical usability: recognition accuracy, user acceptance, recognition delay, installation complexity, and interoperability with ambient-assisted living systems.

Gait analysis focuses not only on the recognition of activities observed but also on how activities are performed. This can be useful in health-care systems for monitoring patients recovering after surgery or fall detection or in diagnosing the state of, for example, Parkinson’s disease [22,23]. For instance, the Daphnet Gait dataset (DG) [24] consists of recordings of 10 participants affected with Parkinson’s disease instructed to carry out activities that are likely to be difficult to perform, such as walking. The objective is to detect these incidents from accelerometer data recorded from above the ankle, above the knee, and on the trunk. On the other hand, Bovi et al. provide a gait dataset collected from 40 healthy people with various ages as a reference dataset [25]. In the aforementioned BSNC, the third database (ID:IC) contains gait data before knee surgery and 1, 3, 6, 12, and 24 weeks (respectively) after it.

2 Motivation and Design Goals

The main purpose of this dataset is to provide detailed gait data to study how the parts of the legs move individually and relative to each other during activities such as walking, running, standing up, and so on. A summary of the activities can be found in Table 1. This dataset contains continuous recordings of combinations of activities, and the data are segmented and annotated with the label of the activity currently performed. Thus, this dataset is also suitable for analyzing human gait and activities between transitions.

Table 1. Characteristics of HuGaDB

ID	Activity	Time sec (min)	Percent	Samples	Description
1	Walking	11544 (192)	32.15	679073	Walking and turning at various speeds on a flat surface
2	Running	1218 (20)	3.39	71653	Running at various paces
3	Going up	2237 (37)	6.23	131604	Taking stairs up at various speeds
4	Going down	1982 (33)	5.52	116637	Taking the stairs down at various speeds and steps
5	Sitting	4111 (68)	11.45	241849	Sitting on a chair; sitting on the floor not included
6	Sitting down	409 (6)	1.14	24112	Sitting on a chair; sitting down on the floor not included
7	Standing up	380 (6)	1.06	22373	Standing up from a chair
8	Standing	5587 (93)	15.56	328655	Static standing on a solid surface
9	Bicycling	2661 (44)	7.41	156560	Typical bicycling
10	Up by elevator	1515 (25)	4.22	89144	Standing in an elevator while moving up
11	Down by elevator	1185 (19)	3.30	69729	Standing in an elevator while moving down
12	Sitting in car	3069 (51)	8.55	180573	Sitting while travelling by car as a passenger
	Total	35903	598	100.00	2111962

Mainly inertial sensors were used for data acquisition. We decided to use inertial sensors because they are inexpensive, simple to use anywhere such as indoor and outdoor area, and widely available compared with other systems. For instance, compared with video-based motion capture systems, they require expensive video cameras and special full bodysuit with special markers on it. In addition, they are restricted to being used in the installed test area and they are sensitive to lightning and suffer from lost markers phenomenon.

In total, six inertial sensors were placed on the right and left thighs, shins and feet; and data were collected from 18 healthy participants, providing total 10 h of recording. This allows one to investigate how the parts of the legs move individually and relative to each other within and in-between activities. Our dataset could be used as control data, for instance, in health-care-related studies, such as walking rehabilitation or Parkinson’s disease recognition. In virtual reality or gaming, our dataset can be used to model a virtual human movements by reproducing the leg movements from the accelerometer data by simply taking the integrals. In fact, it is not limited to virtual environment and could be used to train to walk and move humanoid robots to make them more humanlike and cope with the uncanny valley.

This dataset is unique in the sense that it is the first to provide human gait data in great detail mainly from inertial sensors and contains segmented annotations for studying the transition between different activities.

3 Data Collection and Sensor Network Topology

In data collection, we used MPU9250 inertial sensors and electromyography (EMG) sensors. Each EMG sensor has a voltage gain is about 5000 and band-pass filter with bandwidth corresponding to power spectrum of EMG (10–500 Hz). A sample rate of each EMG-channel is 1.0 kHz, ADC resolution is 8 bits, input voltages: 0–5 V. The inertial sensors consisted of a 3-axis accelerometer and a 3-axis gyroscope integrated into a single chip. Data were collected with accelerometer’s range equal to ± 2 g with sensitivity 16.384 LSB/g and gyroscope’s range equal to $\pm 2000^\circ/\text{s}$ with sensitivity 16.4 LSB $^\circ/\text{s}$. All sensors are powered from a battery, that helps to minimize electrical grid noise.

Accelerometer and gyroscope signals were stored in int16 format. EMG signals are stored in uint8. Therefore, accelerometer data can be converted to m/s^2 by dividing raw data 32768 and multiplying it by 2g. Raw gyroscope data can be converted to $^\circ/\text{s}$ by multiplying it by 2000/32768. Raw EMG data can be converted to Volts by multiplying it 0.001/255. We kept the raw data in our data collection in case one prefers other normalization techniques.

In total, three pairs of inertial sensors and one pair of EMG sensors were installed symmetrically on the right and left legs with elastic bands. A pair of inertial sensors were installed on the rectus femoris muscle 5 cm above the knee, a pair of sensors around the middle of the shinbone at the level where the calf ends, and a pair on the feet on the metatarsal bones. Two EMG sensors were placed on vastus lateralis and connected to the skin with three electrodes. The locations of the sensors are shown in Fig. 1. In total, 38 signals were collected, 36 from the inertial sensors and 2 from the EMG sensors.

The sensors were connected through wires with each other and to a microcontroller box, which contained an Arduino electronics platform with a Bluetooth module. The microcontroller collected 56.3500 samples per second in average with standard deviation (std) 3.2057 and then transmitted them to a laptop through Bluetooth connection.

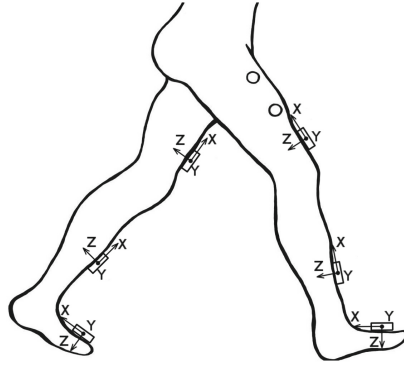


Fig. 1. Location of sensors. EMG sensor are shown as circles while boxes represent inertial sensors

The data were collected from 18 participants. These participants were healthy young adults: 4 females and 14 males, average age of 23.67 (std: 3.69) years, an average height of 179.06 (std: 9.85) cm, and an average weight of 73.44 (std: 16.67) kg.

The participants performed a combination of activities at normal speed and casual way, and there were no obstacles placed on their way. For instance, a participant was instructed to perform the following activities: starting from a sitting position, sitting - standing up - walking - going up the stairs - walking - sitting down. The experimenter recorded the data continually using a laptop and annotated the data with the activities performed. This provided us a long, continuous sequence of segmented data annotated with activities. We developed our own data collector program. In total, 2,111,962 samples were collected from all the 18 participants, and they provided a total of 10 h of data.

Data acquisition was carried out mainly inside a building. However, activities such as running, bicycling, and sitting in a car were performed outside. We collected data in a moving elevator and vehicle. In these scenarios, the activities performed were simply standing or sitting. However, a force impact on the accelerometer sensors and in certain applications, it may be important to consider these facts. Note that we did not collect data on a treadmill.

4 Data Format

Data obtained from the sensors were stored in flat text files. We decided to store the data in flat files because they have one of the most universal formats, and they can be easily preprocessed in all programming languages on every system. One data file contains one recording, which is either a single activity (e.g., walking) or a series of activities. Every file name was created according to the template **HGD_vX_ACT_PR_CNT.txt**. HGD is a prefix that means human gait data and vX means the version of the data files, currently v1. ACT is a variable, and it

denotes the activity ID that was performed. If a file contains a series of different types of activities, then it is indicated as VARIOUS. PR indicates the ID of the person who performed the activity. Data recording was repeated a few times, and CNT is a counter for this. For example, a file named HGD_v1_walking_17_02.txt contains data from participant 17 while he was walking for the second time. The file naming convention is summarized in Table 2.

Table 2. Description of the file naming convention

TAG	Description	Type	Comment
HGD	Prefix	Fixed	Data files start with this prefix
vX	Version number	Integer	Indicates the version of the data format
ACT	Activity	String	Indicates the type of activity
PR	Participant ID	Integer	Indicates the subject whose data was recorded
CNT	Counter	Integer	Counter for repeated experiments

The main body of the data files contains tab-delimited raw, unnormalized data obtained from the sensors directly. Each data file starts with a header, which contains meta-information. It summarizes the list of activities, the IDs of the activities recorded, and the time and date of the recording. This is summarized in Table 3.

Table 3. Description of the data file header

TAG	Description	Type	Comment
#Activity	List of the activities	String	Lists the activity types in this file
#ActivityID	List of the ID of activities	List of integers	Lists the activity types in this file
#Date-Time	Date and Time	YEAR-MM-DD-HR-MN	Year-Month-Day-Hour-Min format

The main data body of every file has 39 columns. Each column corresponds to a sensor, and one row corresponds to a sample. The order of the columns is fixed. The first 36 columns correspond to the inertial sensors, the next 2 columns correspond to the EMG sensors, and the last column contains the activity ID. The activities are coded as shown in Table 1. The inertial sensors are listed in the following order: right foot (RF), right shin (RS), right thigh (RT), left foot (LT), left shin (LS), and left thigh (LT), followed by right EMG (R) and left EMG (L). Each inertial sensor produces three acceleration data on x, y, z axes and three gyroscope data on x, y, z axes. For instance, the column named ‘RT_acc.z’ contains data obtained from the z-axis of accelerometer located on the right thigh.

Sample data with respect to the activities are visualized through a heat map representation in Fig. 2.

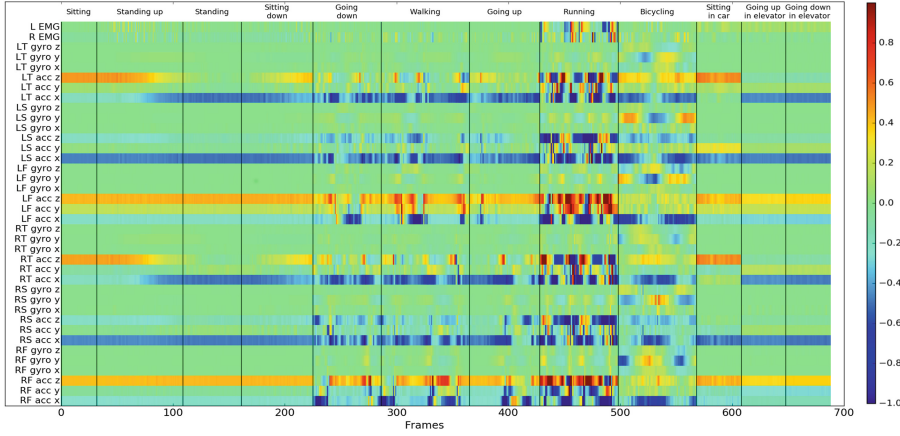


Fig. 2. Data visualization. For normalization data from initial sensors were divided by 32768 and data from EMG were subtracted by 128 and divided by 128

A screenshot of some part of data file can be seen in Fig. 3

```

#Activity: sitting standing up standing sitting_down sitting standing up standing sitting_down sitting standing up standing sitting_down sitting standing up standing sitting_down sitting
#ActivityID: 5 7 8 6 5 7 8 6 5 7 8 6 5 7 8 6 5
#Date: 10-10-17-47
#Sensor: acc_x acc_y acc_z gyro_x gyro_y gyro_z acc_x acc_y acc_z gyro_x gyro_y gyro_z acc_x acc_y acc_z gyro_x gyro_y gyro_z acc_x acc_y acc_z gyro_x gyro_y gyro_z
-7184 -1000 13000 14 11 -22 -14464 320 -7480 -4 -2 22 -6828 -1016 13264 36 -7 -4 -6912 9720 13824 36 -7 -22 -18176 400 -7168 12 -24 38 -4064 988 13840 37 -10 -21 120 1
-7172 -1140 13920 21 10 -13 -14880 400 -7776 11 5 28 -6836 -802 13044 47 -10 -7 -6962 9608 13888 40 -14 -14 -18296 344 -7040 26 -24 44 -8872 1128 13904 41 -5 -18 1
-7728 -1084 13440 28 8 -20 -14376 392 -7264 26 6 28 -6880 -832 13232 80 -8 -14 -7088 9704 14032 46 -13 -18 -18080 868 -6920 34 -21 48 -8720 904 14120 45 -14 -36 120 1
-7892 -1084 13440 20 10 -23 -14400 424 -7360 33 2 38 -6608 -832 13234 46 -4 -21 -7008 9768 13800 47 -8 -13 -18168 840 -6920 36 -28 50 -8482 1024 14168 44 -18 -38 1
-7716 -1084 13812 20 8 -20 -14404 440 -7416 39 5 38 -6728 -880 13512 41 -7 -17 -6896 9776 13792 81 -13 -17 -18112 804 -7064 20 -27 80 -8576 1096 14004 85 -14 -39 1
-7708 -1048 13496 10 11 -26 -14416 560 -7760 29 0 27 -6616 -864 13480 38 -14 -8 -7064 9840 13968 49 -8 -13 -18120 608 -7064 12 -19 47 -8482 1248 14012 62 -12 -30 1
-7696 -964 13848 2 13 -23 -14832 752 -7844 -4 -2 16 -6704 -864 13376 36 -10 7 -6880 9712 13696 46 -11 -14 -18240 892 -6960 8 -22 47 -8482 1232 14416 62 -9 -17 1
-7692 -1036 13920 -8 9 -24 -14824 712 -7868 -12 -8 13 -6760 -876 13216 29 -10 18 -6928 9752 13760 49 -7 -17 -18160 824 -6712 12 -12 47 -8440 1236 14236 64 -9 -14 1
-7668 -984 14004 -9 17 -22 -14868 824 -7968 -11 -4 -2 -6624 -936 13200 18 -16 24 -7048 9768 13672 42 -2 -19 -18176 704 -7056 18 -14 48 -8392 1382 14252 65 -8 -14 1
-7660 -1060 13920 -10 19 -21 -14876 720 -7768 0 -7 -1 -6720 -896 13232 18 -22 18 -6976 9808 13784 41 -2 -18 -18168 604 -6712 29 -9 52 -8464 1312 14096 79 -14 -12 1
-7688 -1000 13920 -14 14 -22 -14924 624 -7480 16 -10 -4 -6628 -868 13344 9 -26 21 -6992 9864 13928 39 -4 -24 -18200 724 -6840 22 -10 48 -8688 1320 14096 70 -11 -13 1
-7648 -1008 13972 -19 20 -27 -14880 640 -7776 7 -10 -13 -6888 -648 13160 6 -20 22 -7096 9832 13884 36 -12 -21 -18112 792 -7112 18 -11 48 -8488 1456 13992 60 -9 -9 1
-7724 -1072 13816 -19 22 -24 -14804 688 -7816 -7 -15 -14 -6880 -848 13472 2 -18 28 -7096 9816 13792 30 -10 -21 -18104 680 -7088 16 -11 38 -8484 1416 13728 50 -11 -11 1
-7696 -1016 13800 -21 30 -28 -14804 704 -7712 -13 -17 -21 -6720 -896 13208 8 -20 36 -7048 9808 13768 27 -8 -26 -18296 720 -7112 19 -10 29 -8472 1528 14128 44 -9 -10 1
-7732 -1028 13408 -24 28 -24 -14832 648 -7820 -19 -21 -20 -6812 -760 13176 3 -27 35 -7096 9888 13784 20 -6 -21 -18128 640 -7084 4 -6 39 -8484 1384 14032 42 -6 -4 1
-7776 -1032 13440 -26 24 -28 -14824 532 -7712 -7 -19 -26 -6856 -844 13144 -8 -28 29 -7096 9888 13472 16 -14 -22 -18104 832 -7264 3 -13 18 -8712 1744 14032 39 -12 -4 1
-7736 -1040 13496 -29 24 -31 -14824 584 -7872 1 -22 -29 -6896 -820 13096 -12 -24 34 -7168 9864 14036 9 -8 -23 -18160 856 -7064 7 -9 9 -8736 1712 14036 5 -2 8 1
-7648 -1080 13800 -29 33 -27 -14848 648 -7488 -1 -22 -43 -6768 -704 13396 -20 -24 38 -7152 9816 13824 -1 -14 -23 -18256 688 -6840 9 -6 4 -8464 1320 14104 -1 -8 14 1
-7716 -1120 13932 -29 31 -31 -14464 560 -7456 -8 -27 -38 -6688 -904 13234 -14 -29 36 -6960 9864 13728 1 -9 -22 -18192 752 -6932 4 -6 -2 -8576 1288 14248 2 3 22 1

```

Fig. 3. Screenshot of the data file

The data files can be loaded easily in most of the popular programming languages. For instance, they can be loaded in Python using the following script:

```

import numpy as np
data = np.genfromtxt(path_to_file ,
                    delimiter='\\t' ,
                    skip_header=4)

```

Please note that it requires NumPy library. It also can be loaded in Matlab with the following one-line command:

```

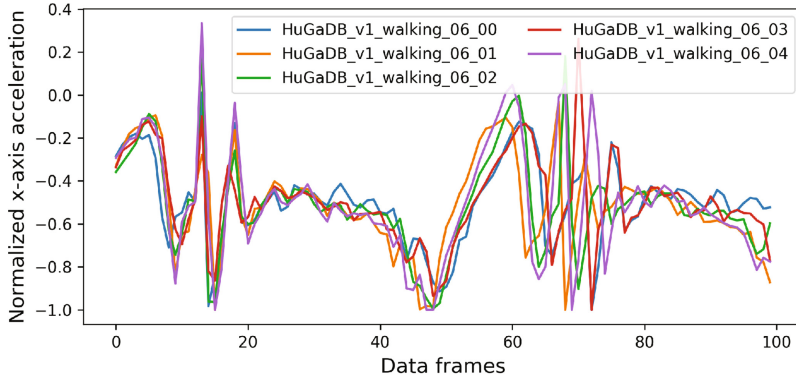
data = dlmread(path_to_file , '\\t' , 4,0);

```

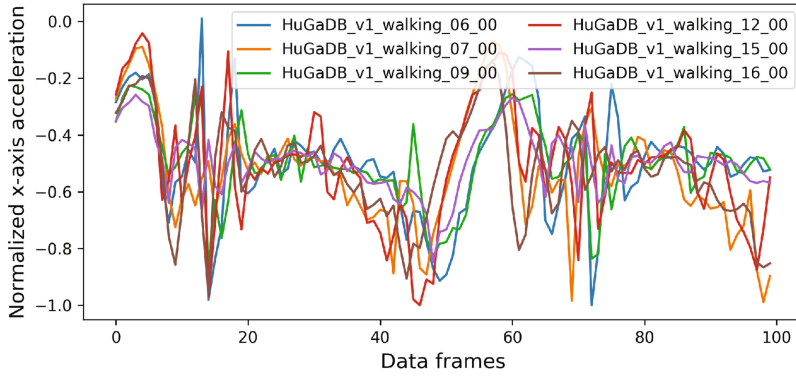
We have prepared a script to load the data into SQLite database, which is available at the database's website: https://github.com/romanchereshnev/HuGaDB/blob/master/Scripts/create_db.py.

5 Discussion on Data Variance

We were interested seeing the variance among the data collected, in particular, the data variance (A) within a single user and (B) between several users. For this reason, we plotted in Fig. 4 the x-axis acceleration data from the thigh recorded during a short two-three-step walk. Panel A shows the data from various recordings performed by the same user. It can be seen that the data variance at a single



(A) Single user



(B) Various users

Fig. 4. Data variance during walking. (A) Activity performed by the same user multiple times. (B) Activity performed by different users. Legend indicates the source of the data. Data are scaled to the range $[-1, +1]$.

frame is quite low suggesting that people perform activities very similar way. On the other hand, panel B shows data obtained from six different, randomly chosen users. Here, a much higher variance can be seen in the same frames compared to the previous case. The increased variance may arise from several facts including: difference in gait, difference in leg shape, sensors mounted in slightly different positions, etc. We obtained similar conclusions on data obtained from different sensors during different activities. We note that, even higher variance was observed in the EMG data, which resulted from the difference in the electricity conduction characteristics of the skin, skin thickness, etc.

Taking into account the high data variance between different users, we emphasize the importance of proper evaluation of machine learning methods developed for human activity recognition. Therefore, we propose using the supervised cross-validation approach for constructing training and test sets [26]. In this approach, all the data from a designated user are held out only for tests and the data from the other 17 participants are used for training. Thus, this approach provides a reliable estimation of how an activity recognition system would perform with a new user whose data was not seen before.

Variance can arise from using different brands of sensors. Unfortunately, we did not have the capacity to collect data from different brands of sensors. We hope the measurement noise is small in general and that different sensors can be calibrated to be compatible with each other.

6 Availability

The database is available free of charge at <https://github.com/romanchereshnev/HuGaDB> (455 Mb).

7 Summary

The HuGaDB dataset contains detailed kinematic data for analyzing human gait and activity recognition. This dataset differs from previously published datasets in the sense that HuGaDB provides human gait data in great detail mainly from inertial sensors and contains segmented annotations for studying the transition between different activities. Data were obtained from 18 participants, and in total, they provide around 10 h of recording. This dataset can be used in health-care-related studies, such as walking rehabilitation, or in modeling human movements in virtual reality or humanoid robotics. The dataset will be updated with new data from new participants in the future.

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