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Data Article

UMAHand: A dataset of inertial signals of typical hand activities

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A B S T R A C T

Given the popularity of wrist-worn devices, particularly smartwatches, the identification of manual movement patterns has become of utmost interest within the research field of Human Activity Recognition (HAR) systems. In this context, by leveraging the numerous sensors natively embedded in smartwatches, the HAR functionalities that can be implemented in a watch via software and in a very cost-efficient way cover a wide variety of applications, ranging from fitness trackers to gesture detectors aimed at disabled individuals (e.g., for sending alarms), promoting behavioral activation or healthy lifestyle habits. In this regard, for the development of artificial intelligence algorithms capable of effectively discriminating these activities, it is of great importance to have repositories of movements that allow the scientific community to train, evaluate, and benchmark new proposals of movement detectors. The UMAHand dataset offers a collection of files containing the signals captured by a Shimmer 3 sensor node, which includes an accelerometer, a gyroscope, a magnetometer and a barometer, during the execution of different typical hand movements. For that purpose, the measurements from these four sensors, gathered at a sampling rate of 100 Hz, were taken from a group of 25 volunteers (16 females and 9 males), aged between 18 and

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56, during the performance of 29 daily life activities involving hand mobility. Participants wore the sensor node on their dominant hand throughout the experiments.

Specifications Table

Subject	Biomedical Engineering
Specific subject area	Human Activity Recognition based on inertial signals, identification of Activities of Daily Living (ADLs) and subject-characteristics (gender, age, dominant hand) through wearables.
Type of data	Table Raw text files (in CSV format) Video clips (in MPEG4 format)
Data collection	25 experimental users were monitored with a wrist-worn device located in the dominant hand during the execution of 29 predetermined activities that require specific manual movements. For each activity trial, the device (a Shimmer 3 unit) collected the inertial signals (accelerometer, gyroscope, magnetometer) as well as the measurements of a barometer at a sampling rate of 100 Hz.
Data source location	In order to employ a more realistic application scenario, the samples were captured in 16 domestic environments located in the city of Málaga (Spain, mean elevation above mean sea level: 19 m (62 feet).
Data accessibility	All the raw data are available in a public Figshare repository: Repository name: Figshare -UMAHand: Hand Activity Dataset (Universidad de Málaga)- Data identification number: 10.6084/m9.figshare.25638246 Direct URL to data: https://figshare.com/articles/dataset/UMAHand_Hand_Activity_Dataset_Universidad_de_M_laga_/25638246 Traces can be anonymously and directly downloaded from the previous link as a zip file. A subfolder named TRACES includes a CSV file with all the measurements for every recorded execution of any activity. Two supplementary plain text files describe the activities and the personal characteristics of the participants, respectively. An image depicts the location of the sensor on the wrist as well as the orientation of the axes of the triaxial sensors within the sensing unit. Another subfolder (named VIDEOS) contain a set of video clips with an example of the recording of each activity.

1. Value of the Data

- The UMAHand dataset provides measurements captured by four wearable sensors during the execution by 25 participants of 29 daily life activities that require specific hand movements.
- The dataset can be used both to characterize the dynamics of the most common manual movements and as a benchmarking database to train, validate, and test AI-based HAR (Human Activity Recognition) systems.
- The dataset offers a greater variety and number of activities than most existing similar repositories.
- The number of participants and sensors used also exceeds that considered by most available related datasets, providing information not only from inertial sensors but also from a barometer (which allows inferring changes in the height of the hand position).
- The dataset reports the personal characteristics (gender, weight, height, age, handedness) of the user who generated each sample, which facilitates population studies based on these characteristics.
- The dataset is accompanied by a set of videos that allow viewing examples o the considered activities and the testbed in which they were captured.

2. Background

Human Activity Recognition (HAR) based on smartwatches and other wrist wearables is gaining an increasing interest due to the variety of sensors integrate into these devices, their widespread popularity and plummeting costs. Apart from being massively employed for fitness monitoring and sport performance analysis, wrist-worn activity trackers have been also proposed for a vast number of different applications, including medical supervision and rehabilitation, workplace safety monitoring, behavioral studies, fall detection, biometric authentication, handwriting identification or gesture recognition for remote control in gaming or human-computer interaction (see a recent systematic review of this topic in [1]).

In this context, having access to the multisensory data gathered by these devices is of paramount importance for properly characterizing hand movements and training the artificial intelligence models upon which most HAR system proposals rely. In fact, over the last decade, different research groups have released for research purposes a not negligible number of repositories. These repositories include measurements collected at the wrist when a set of experimental subjects perform a series of predefined tasks (see [1–4] or [5] for diverse reviews on this topic). However, it is worth noting that many of these datasets were generated with multi-node sensing systems simultaneously located in different body locations. Thus, most of the activities performed by the participants were basic activities (walking, standing up, lying down, etc.) or actions, such as climbing stairs, that do not usually require complex or very specific hand mobility patterns. In other cases, the datasets were conceived with a specific application in mind (for example, fall detection) or for very particular application environments, such as distinguishing the movements of a worker on a packaging line. Hence, there are fewer datasets (such as PAAL [3], SAMoSA [6], or the one published by the University of Texas [7]) that offer a variety of typical manual activities captured from a broad set of participants. Nevertheless, these datasets do not include the measurements of two sensors (already included in most current off-the-shelf smartwatches) that can assist the activity of HAR systems: the magnetometer and the barometer. In order to complement the existing benchmarking tools for wrist-worn wearable-based HAR systems, the database presented here, UMAHand, includes measurements from four sensors gathered during the execution of a wide range (29) of typical manual activities by 25 subjects.

3. Data Description

The database (UMAHand Dataset [8]) consists of a main directory and three subdirectories: TRACES (with the measurements), VIDEOS (with a series of video sequences) and SCRIPTS (with two scripts that facilitate the downloading, unzipping and processing of the dataset).

The main directory also includes three descriptive plain text files and an image:

- *Readme.txt*: this file is a brief guide of the dataset which describes the basic characteristics of the database, the testbed or experimental framework used to generate it and the organization of the data files.
- "user_characteristics.txt": which contains a line of six numerical (comma-separated) values for each participant describing their personal characteristics in the following order: 1) an abstract user identifier (a number from 1 to 25), 2) a binary value indicating whether the participant is left-handed (0) or right-handed (1), 3) a numerical value indicating gender: male (0), female (1), undefined or undisclosed (2), 4) the weight in kg, 5) the height in cm and 6) the age in years.
- "activity_description.txt": for each activity, this text file incorporates a line with the activity identifier (numbered from 1 to 29) and an alphanumeric string that briefly describes the performed action.
- "sensor_orientation.jpg": a JPEG-type image file illustrating the way the sensor is carried by the participants and the orientation of the measurement axes with respect to the hand.

The TRACE subfolder with the data is, in turn, organized into 25 secondary subfolders, one for each participant, named with the word 'output' followed by underscore symbol (_) and the corresponding participant identifier (a number from 01 to 25). Each subdirectory contains one CSV (Comma Separated Values) file for each trial (each repetition of any activity) performed by the corresponding volunteer.

The filenames with the monitored data adhere to the following format: *user_XX_activity_YY_trial_ZZ.csv* where *XX*, *YY*, and *ZZ* represent the identifiers of the participant (*XX*), the activity (*YY*) and the number of the trial or repetition (*ZZ*), respectively.

In the files, which do not include any header, each line corresponds to a sample taken by the sensing node. Thus, each line of the CSV files presents a set of the simultaneous measurements captured by the sensors of the Shimmer mote at a certain instant. The values in each line are arranged as follows:

- ***Timestamp, Ax, Ay, Az, Gx, Gy, Gz, Mx, My, Mz, P***

where:

Timestamp is the time indication of the moment when the following measurements were taken. Time is measured in milliseconds elapsed since the start of the recording. Therefore, the first sample, in the first line of the file, has a zero value, while the rest of the timestamps in the file are relative to this first sample.
Ax, Ay, Az are the measurements of the three axes of the triaxial accelerometer (in g units).
Gx, Gy, Gz indicate the components of the angular velocity measured by the triaxial gyroscope (in degrees per second or dps).
Mx, My, Mz represent the 3-axis magnetometer data in microteslas (μT).
P is the measurement of pressure in millibars.

Besides, the VIDEOS directory includes 29 anonymized video clips that illustrate with the corresponding examples the 29 manual activities carried out by the participants. The video files are encoded in MPEG4 format and named according to the format *Example_Activity_XX.mp4*, where *XX* indicates the identifier (as described in the *activity_description.txt* file) of the filmed movement.

Finally, the SCRIPTS subfolder comprises two scripts written in Python and Matlab. These two programs (named *Load_traces*), which perform the same function, are designed to automate the downloading and processing of the data. Specifically, these scripts perform the following tasks:

1. Download the database from the public repository as a single compressed zip file.
2. Unzip the aforementioned file and create the subfolder structure of the dataset in a specific directory named *UMAHand_Dataset*. As previously commented, in the subfolder named TRACES, one CSV trace file per each experiment (i.e. per each movement, user, and trial) is created.
3. Read all the CSV files and store their information in a list of dictionaries (Python) or a matrix of structures (Matlab) named `datasetTraces`. Each element in that list/matrix has two fields: the filename (which identifies the user, the type of performed activity, and the trial number) and a numerical array of 11 columns containing the timestamps and the measurements of the sensors for that experiment (arranged as mentioned above).

4. Experimental Design, Materials and Methods

4.1. Sensing device: Shimmer 3 unit

Shimmer [9] is an open, off-the-shelf programmable platform intended for research in the field of wearable sensor applications. Shimmer offers a wide range of wearable sensing units and development kits that allow monitoring (through one or several synchronized nodes) not only

Table 1
Characteristics of the employed sensors (embedded in the Shimmer 3 mote).

Sensor type	Sensor model	Selected Range	Numeric Resolution	Sensitivity
Accelerometer[1]	TDK InvenSense ICM-20948 IMU	±16 g	16 bits	1/2048 g/LSB
Gyroscope	TDK InvenSense ICM-20948 IMU	±2000 dps	16 bits	1/16.37 dps/LSB
Magnetometer	TDK InvenSense ICM-20948 IMU	±4900 μT	16 bits	0.15 μT/LSB
Barometer	Bosch BMP280	300-1100 mbar	n.i.	0.0016 mbar

[1] Shimmer 3 nodes incorporates a wide range accelerometer and a low-noise small range accelerometer. For the generation of the dataset, we only employed the wide range sensor.
n.i. not indicated by the vendor,

Fig. 1. Shimmer 3 node, dock station to charge the battery and retrieve the readings, snap clips and adjustable straps used to attach the sensor to the wrist.

the user mobility but also diverse biosignals, such as electrocardiography and electromyography. For the creation of our database, we selected the Shimmer IMU unit 3 model [10], which is very popular in the field of HAR and has been frequently used to create datasets with a similar purpose (see, for example, the repositories described in [11,12] or [13]). This low consumption, light-weight (23.6 grams) and compact (51×34×14 mm) node embed 9DoF inertial sensing with selectable range (including two accelerometers) together with a pressure sensor, whose main characteristics are presented in Table 1. Although the unit is Bluetooth-enabled, it supports local storage via a microSD card. Thus, during the experiments, the measurements can be directly saved in the local memory and then retrieved in an offline way through a specific dock station [14]. Fig. 1 shows a snapshot of the node, the dock station and straps used to adjust the unit to the users' wrist.

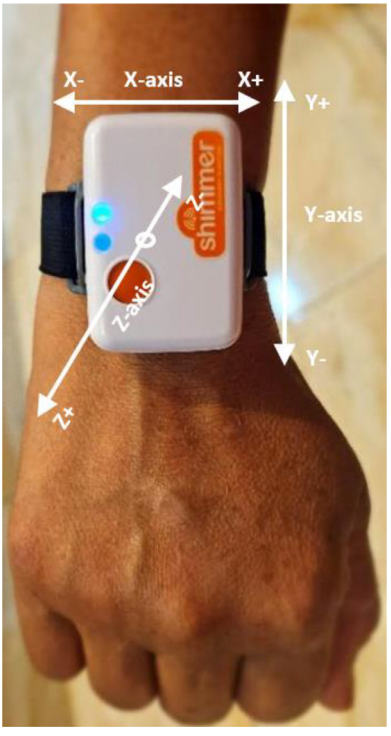

Fig. 2. Illustration of the adjustment of the sensor to the hand and orientation of the axes of the triaxial sensors.

Table 2
Characteristics of the experimental group of volunteers.

Characteristic	Range	Mean ± standard deviation
Number of subjects	25 (16 females, 9 males)	-
Age (years)	[18-56]	30.24 ± 14.04
Weight (Kg)	[50-118]	64.44 ± 15.33
Height (cm)	[150-184]	164.84 ± 10.63
Handedness	23 right-handed & 2 left-handed participants	

The files obtained from the sensing node through the dock station were post-processed using Matlab programming language [15] to generate the data in the final format utilized by the dataset (which is described in the previous section).

4.2. Protocol to collect the measurements

This study was aimed at developing an anonymized and publicly accessible database that records the variables captured by a wearable device during the execution of a series of predefined movements or activities by a set of experimental subjects. For this purpose, we recruited 25 participants, whose personal characteristics are summarized in Table 2.

Each subject was asked to sequentially perform a set of predefined activities that involve the mobility of the dominant hand. Apart from a basic description of the activity, participants were not given any explicit instruction on how the activity should be executed or how they should

Table 3
Numerical identifier (ID) and description of the performed activities.

Activity ID	Description of the activity
1	Brushing teeth with a manual toothbrush
2	Brushing teeth with an electric toothbrush
3	Washing hands
4	Eating soup with a spoon from a plate
5	Cutting food with a knife and fork
6	Peeling a fruit (an apple)
7	Clapping hands
8	Combing hair
9	Wiping a cloth energetically over a surface
10	Sweeping
11	Writing on a sheet of paper with a pen
12	Typing on the computer keyboard
13	Sending a text message via cellphone
14	Dialing a phone number on the mobile phone and bringing the phone to the ear
15	Folding a piece of paper several times
16	Picking up an object from the floor starting from an upright position and bringing it to chest height
17	Opening a screw-top plastic bottle of water
18	Drinking water from a glass
19	Pouring water into a glass from a pitcher
20	Putting on glasses
21	Putting on a jacket/sweatshirt
22	Taking off a jacket/sweatshirt
23	Putting on a shoe and tying the laces
24	Waving goodbye
25	Blowing the nose
26	Opening and closing a door (using a doorknob)
27	Buttoning a shirt
28	Zipping up and down a zipper
29	Screwing in a screw

interact with the objects (e.g. the broom, the cloth or the toothbrush) required to accomplish certain tasks. The description and numerical identifier of each activity are listed in Table 3. No participant reported any pathology or motor difficulty that prevented them from completing any of these movements. As a result, all the activities were carried out by all the volunteers at least once.

During the execution of each activity, each experimental subject wore a Shimmer unit adjusted to the wrist of the dominant hand (right in the case of right-handed participants and left for left-handed volunteers). The device was secured by using an elastic strap provided by the Shimmer vendor and following a predetermined orientation of the sensor's axes, as represented in Fig. 2. The sampling rate in the Shimmer node (which is programmable via the dock station) was set to 100 Hz for all recordings. The power of the spectrogram of human movements is concentrated in frequencies below 10 Hz [16–18]. Thus, a sampling rate of 100 Hz is clearly sufficient to fully characterize the hand dynamics.

All experiments and data acquisition were conducted in private home environments. Participants were asked to perform those activities involving sustained or continuous hand movements (e.g., clapping hands) for at least 10 s. For brief movements lasting less than 10 s (e.g., picking up an object from the floor), volunteers were simply asked to complete the action. Thus, a total of 752 samples were collected, with durations ranging from 1.98 to 119.98 s.

Limitations

Not applicable.

Ethics Statement

The experimental procedure followed adhered to the ethical protocols of authors' institutions and was specifically approved by the Ethics Experimentation Committee of the University of Malaga (CEUMA) at its meeting on February 29, 2024, in response to the request and project proposal with registration number 193-2023-H. Prior to participating in the experiments, a written informed consent was obtained from all the volunteers in accordance with European Regulation 2016/679, commonly known as the General Data Protection Regulation (GDPR). Besides, participants were provided with an additional document containing a comprehensive description of the project, informing about the goals and procedure of the study and about the nature and types of data being collected. Additionally, participants were informed that they had complete freedom to withdraw from the experiments at any point during the sample collection process, without facing any questioning. Similarly, before starting the recordings, participants were asked if they had any motor impairment that would prevent them from executing any of the scheduled activities. Based on their conditions or time availability, volunteers were free to refrain from performing any of these movements and only accomplish those activities they deemed appropriate.

Data Availability

UMAHand: Hand Activity Dataset (Universidad de Málaga) (Original data) (Figshare).

CRediT Author Statement

Eduardo Casilari: Conceptualization, Software, Formal analysis, Investigation, Methodology, Writing – original draft, Visualization, Supervision, Project administration, Funding acquisition; **Jennifer Barbosa-Galeano:** Software, Data curation, Resources, Visualization; **Francisco J. González-Cañete:** Conceptualization, Methodology, Supervision, Writing – review & editing.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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