IMAGE PROCESSING ON LINE

Published in Image Processing On Line on 2024–01–18.
Submitted on 2023–06–23, accepted on 2023–11–22.
ISSN 2105–1232
This article is available online with supplementary materials, software, datasets and online demo at
https://doi.org/10.5201/ipol.2024.494

Arm-CODA: A Data Set of Upper-limb Human Movement During Routine Examination

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Communicated by Jean-Michel Morel and Miguel Colom   *Demo edited by* Sylvain Combettes and Paul Boniol

Abstract

This article thoroughly describes a data set of 240 multivariate time series collected using 34 Cartesian Optoelectronic Dynamic Anthropometer (CODA) markers placed on the upper limb of 16 healthy subjects each undergoing 15 predefined movements such as raising their arms or combing their hair. Each sensor records its position in the 3D space. In total, 2.5 hours of time series are collected. A remarkable aspect of this data set is the extensive availability of metadata: subjects' characteristics (age, height, etc.) as well as movements' annotations. Indeed, for each subject and each movement, the start and end time stamps of at least two iterations of the same movement are provided. In addition to the study of human motion, this data set can be used to evaluate generic time series analytical tasks such as multivariate time series segmentation, clustering or classification.

Source Code

The data set is available from the web page of this article[1]. The web page also provides an online demo for the visualization of the data set. Python code snippets to explore the data are also provided. Usage instructions are included in the `README.md` file of the archive.

Keywords: physiological signals; biomedical data set; multivariate time series; graph signal processing

[1]https://doi.org/10.5201/ipol.2024.494

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1 Introduction

The quantification of human motion is a central problem in medical research with far-reaching consequences for public health and neurological research. In particular, designing proper and robust acquisition protocols is the first step toward an intelligent quantification of more general movement characteristics (e.g., smoothness or symmetry), which can be powerful tools for longitudinal follow-up of patients and early pathology detection.

Our paper introduces a new data set of multivariate time series measuring limbs' positions in space to study human motion. In order to develop protocols for the acquisition of massive data and their use in the clinical field, our choice was to measure the movement parameters of healthy subjects during a classical shoulder examination. These movements lend themselves to an efficient evaluation of the subject's mobility.

In previous studies, 3D position sensors have been extensively used in the clinical setting to evaluate simple kinematic parameters [7, 2, 1] and validate lighter sensors [3, 9]. As for multimodality (i.e., the inclusion of an increasing number of sensors from different sources), the number of protocols has increased in recent years. The Berkeley Multimodal Human Action Database [6] includes motion capture, IMUs, Kinect, and regular cameras that record 11 daily life actions performed by 12 subjects. A recent study presents an upper body motion acquisition protocol that includes IMUs (Xsens), 3D position sensors, Emphasis Telematics sensorized gloves, and two cameras [5]. Thirteen subjects were recorded while performing movements associated with an industrial job. Other protocols used Kinect cameras for their simplicity and the absence of sensors in the context of daily or work-related movements [4, 8].

Contributions. This paper describes a data set of 240 multivariate time series and contextual metadata for each. In detail, we distribute around 2.5 hours of continuous time series collected from 16 healthy subjects performing 15 pre-defined simple movements. More precisely, the subjects were asked to perform several types of movements, including elevation movements of the right arm, the left arm, and both arms simultaneously. To track the movements, 34 Cartesian Optoelectronic Dynamic Anthropometer (CODA) motion system 3D position markers are placed on the upper limb of the participants, each marker recording its position over time in the 3D space. The metadata consists of the participants' characteristics (age, height, weight, etc.) as well as annotations of the movements. Indeed, a remarkable feature of this data set is the extensive amount of annotations provided. For each subject and each movement, at least two iterations of the same movement are manually annotated, meaning that the start and end time stamps are given. By its time series size, metadata quantity, and annotation quality, this data set constitutes an important contribution to the study of human motion. In addition, this data set can be used to evaluate multivariate time series segmentation, clustering, or classification. Moreover, as each sensor can be seen as a node on the human body, this data set can be used for Graph Signal Processing tasks. In addition to the data files and this article, code snippets to access, visualize, and perform basic analysis are available online[2] for the standard Python programming language.

Finally, This data set can be used in many studies in several ways. Firstly, the protocol can serve as a reference for other studies that might include pathological subjects. In particular, the inclusion of "free-living" movements is consistent with movements that are often performed during clinical examinations. In addition, knowing the standard values of position, velocity, and accelerations (or other characteristics) on a healthy subjects data set will enable comparisons. Although the data set is limited regarding the number of subjects, certain normative values are often required in the medical field, and this data set could be useful in this context.

[2] https://doi.org/10.5201/ipol.2024.494

2 Acquisition

This section describes the participating population, the movements performed, and the placement of the sensors.

2.1 Participants

The measurements were conducted at the Sensorimotricité platform of Université Paris Cité, between March 2021 and December 2021, by Danping Wang, Diego Vaquero-Ramos, and Antoine Mazarguil. A total of 16 healthy subjects were recorded. The participants belonged to the professional or personal circle of the examiners, and they were asked to join the study by personal communication. All subjects provided written informed consent. Healthy subjects had no known medical impairment. Among these participants, 11 were males, and 5 were females. We know that 7 subjects were right-handed and one was left-handed, but this information is unfortunately unknown for the remaining 8 subjects. Participants' characteristics are summarized in Table 1.

	Age	Height (cm)	Weight (kg)	BMI (kg/m^2)
mean ($\pm$ std)	44.2 ($\pm$ 14.1)	173.7 ($\pm$ 8.4)	73.7 ($\pm$ 11.8)	24.4 ($\pm$ 3.1)
min	23.0	156.0	51.0	19.1
max	65.0	188.0	95.0	29.0

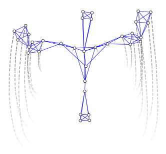
Table 1: Summary of the participants' characteristics.

2.2 Movements and Experimental Setup

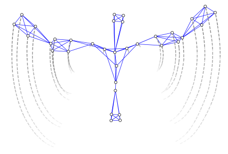
Each subject underwent 15 fixed simple movements, such as arm elevation or hair combing, that were monitored by sensors. The complete list of movements is presented in Table 2, and a visual representation of each movement is displayed in Figure 1. Overall, the subject performed two types of movements, Analytic and Functional, described as follows.

Analytic movements (arm elevation and lateral elbow rotation) are classically used in rehabilitation services to assess the patient's motricity because they involve most upper-limb muscles and joints. Regarding muscular activities, arm elevation in the different planes is achieved through the active use of the trapezius, the deltoid, the pectoralis major, the serratus anterior, the rhomboid major, and the muscles of the shoulder rotator cuff, along with the main bone structures (namely the Clavicle, the Scapula, the Humerus and the Vertebral column and the Ribs). The selected movements also scan the entire post-frontal area, thus making it possible to verify the patient's ability to reach objects in this area. A classical examination usually does not include the whole set of analytic movements proposed in the protocols but can focus on a subset. As analytic movements are associated with constraints and relate to circular arm trajectories, their analysis is simplified (one can well define, for instance, the maximum of elevation or represent the movement kinematic by the elevation angle through time).

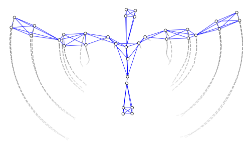
Functional movements are frequently used in everyday life and contribute to autonomy. They involve combined movements at the glenohumeral joint: scapular plane arm elevation and lateral rotation for hair combing, extension, and medial rotation for low backwashing. In particular, the trajectories taken by the body joints during these movements are less constrained than the analytic ones. Still, they are more representative of the movements in an ecological setup. As a result, these movements are more difficult to analyze and depend more on the subjects' preferential coordination process. Thus, including these movements paves the way to movement modeling methods in a more extensive setup.



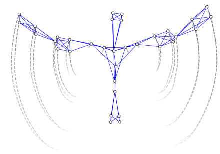
Mvt 0: Sagittal plane elevation (Seated)



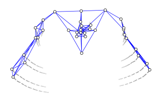
Mvt 1: Scapular plane elevation (Seated)



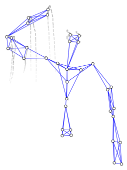
Mvt 2: Frontal plane elevation (Seated)



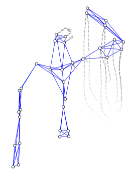
Mvt 3: Scapular plane elevation with lateral wrist orientation (Seated)



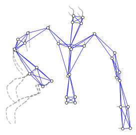
Mvt 4: Lateral elbow rotation (Seated and seen from above)



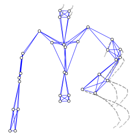
Mvt 5: Hair combing, right arm (Seated)



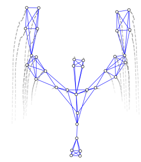
Mvt 6: Hair combing, left arm (Seated)



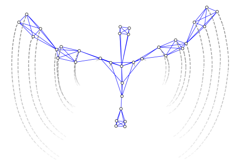
Mvt 7: Low back washing, right arm (Seated)



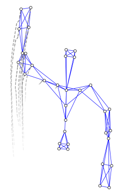
Mvt 8: Low back washing, left arm (Seated)



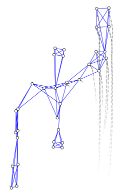
Mvt 9: Sagittal plane elevation (Standing)



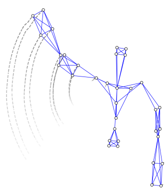
Mvt 10: Scapular plane elevation (Standing)



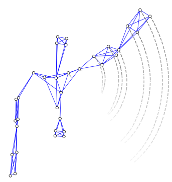
Mvt 11: Sagittal right arm elevation (Standing)



Mvt 12: Sagittal left arm elevation (Standing)



Mvt 13: Scapular right arm elevation (Standing)



Mvt 14: Scapular left arm elevation (Standing)

Figure 1: All 15 movements performed during a recording session. The gray lines represent the marker trajectories through time. The markers from the acromion clusters and the hips have been removed to improve readability.

The functional movements were performed while sitting, and the analytic movements were performed while sitting and standing. Participants were asked to face a large height-adjustable target on the wall in front of them at eye level during each arm movement to standardize the position of the head among participants. The visual target was adjusted to eye level between the sitting and standing phases. The examiner was not in the subject's visual field during the movements' execution. Each movement started in a resting position, arms alongside the body, straight back, feet flat on the floor (see Figure 2). The resting position was the same for the lateral rotations (movement 4), with the elbows bent at 90 degrees.

Each movement was performed 3 times during the same recording, with a rest time of approx. 3 seconds between each iteration. Between each different movement, the subject had a pause of approx. 30 sec. The timeline of a complete recording session of a single subject is displayed in Figure 3. On

Mvt ID	Arm movement	Functional or Analytic	Position	Bilateral or Unilateral
0	Sagittal plane elevation	Analytic	Seated	Bilateral
1	Scapular plane elevation	Analytic	Seated	Bilateral
2	Frontal plane elevation	Analytic	Seated	Bilateral
3	Scapular plane elevation with lateral wrist orientation	Analytic	Seated	Bilateral
4	Lateral elbow rotation	Analytic	Seated	Bilateral
5	Hair combing	Functional	Seated	Unilateral right
6	Hair combing	Functional	Seated	Unilateral left
7	Low back washing	Functional	Seated	Unilateral right
8	Low back washing	Functional	Seated	Unilateral left
9	Sagittal plane elevation	Analytic	Standing	Bilateral
10	Scapular plane elevation	Analytic	Standing	Bilateral
11	Sagittal plane elevation	Analytic	Standing	Unilateral right
12	Sagittal plane elevation	Analytic	Standing	Unilateral left
13	Scapular plane elevation	Analytic	Standing	Unilateral right
14	Scapular plane elevation	Analytic	Standing	Unilateral left

Table 2: List of the movements performed during a recording session, presented in execution order. The movement ID (mvt ID), from 0 to 14, corresponds to the execution order.

(a) Side view

(b) Back view

Figure 2: Resting seating position. The visual target appears in green (b).

the one hand, no duration constraint was imposed for functional movements. On the other hand, the subjects were instructed to complete the analytic arm movements within 10 seconds. For the sake of normalization, the observer counted out loud to guide the execution of analytic movements. The subjects repeated the movements that were considered invalid or non-regular by the examiner until they were performed sufficiently well. The whole recording session was performed in three phases:

- A seated phase of analytic bilateral movements. For elevation movements, the instruction was to reach maximal natural elevation and pause for approx. 1 sec, then lower the arm back to the rest position. For the lateral rotation, the instruction was to perform the elbow rotation up to the maximal natural angle. For elevation movements, the examiner counted out loud to guide the movement execution. Apart from movement 4, no indication of wrist orientation was given for the arm elevations.

  The examiner indicated the elevation planes by demonstration of the movement.

- A seated phase of functional movements. These movements are simulations of two activities of

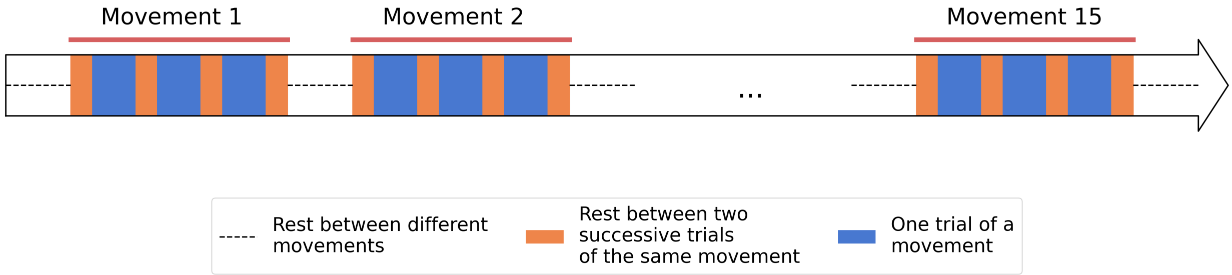


Figure 3: Timeline of a complete recording session. The overall measurement (excluding sensor installation and uninstallation) was approx. 20 minutes long.

(a) Low back washing

(b) Hair combing

Figure 4: Functional movements included in the protocols. Each movement was performed with both hands alternatively.

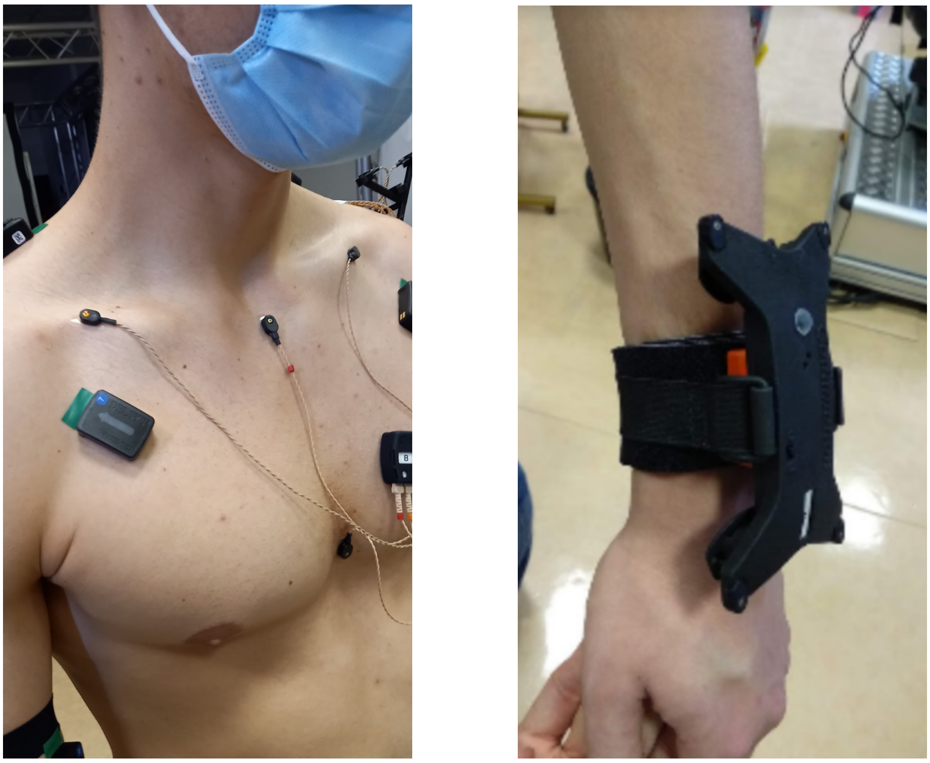
daily living (ADL): low back washing (see Figure 4) and hair combing (see Figure 4). For hair combing, the instruction was to raise the hand in front of the face, pass it above the head, and finally go down to the nape of the neck. For low back washing, the instruction was to touch the lower back (above the sensor) with the back of the hand. The participants were instructed to avoid touching the lower back sensor. Functional movements were performed with both arms alternately, right arm first.

- A standing phase of analytic movements. For the arm elevations, the instructions were the same as in the first phase. Participants performed each arm elevation with both arms alternately, right arm first.

2.3 3D Sensors Description and Placement

2.3.1 Sensor Description and Output

The subjects were equipped with 34 Cartesian Optoelectronic Dynamic Anthropometer (CODA) motion system 3D position markers (powered by a battery with an autonomy range of approximately 2 hours). These active sensors emit an optical signal received by six depth cameras. Then, a sensor fusion algorithm merges the measurements of the different cameras to obtain a reasonable estimate of the position of each sensor. All sensors were installed on the subjects by a trained physiotherapist. The data position of the 34 sensors is measured at 100 Hz. In total, we had two types of sensors:



(a) CODA simple marker placed on the front side of the subject

(b) CODA cluster placed on the subject's forearm

Figure 5: Examples of CODA markers (powered up by an attached battery through a wire)

- Simple markers (see Figure 5(a)), attached to the subject's skin by an adhesive strip, powered by a battery placed on the subject's body (each battery powers up to 4 markers).
- Markers associated with a rectangular cluster (see Figure 5(b)), including a battery, attached to the subject with a strap. Each cluster was shaped like a rectangle with 4 markers positioned in its corners, allowing it to locate the fixed structure in space and orientation.

2.3.2 Sensor Placement

As mentioned above, we have a total of 34 markers. More precisely, we have 10 simple markers and 6 clusters. These six clusters are positioned on each arm, each forearm, the forehead, and the back. The detail of the numbering and the position of the CODA markers is presented in Table 3 and Figure 6.

3 Data Description

This section presents in detail the collected data, which are composed of time series associated with metadata. The file format is also described.

3.1 Time Series

The resulting data set is composed of 240 multivariate time series (727.8 MB in .npy format and 1.7 GB in .csv format) and includes 2.5 hours of continuous measurements. Each time series corresponds to the recording of one of the 16 subjects performing one of the 15 movements. The measurements

Marker index	Marker type	Position
0-3	Cluster	Top of the forehead
4	Simple marker	Middle of the right clavicle
5	Simple marker	Sternal manubrium, just below the jugular incisure
6	Simple marker	Middle of the left clavicle
7	Simple marker	2 cm above the xiphoid process
8	Simple marker	Middle of the right scapular spine
9	Simple marker	Apophysis of T7
10	Simple marker	Middle of the left scapular spine
11	Simple marker	Apophysis of L3
12-15	Cluster	Below posterior superior iliac spine
16	Simple marker	Right elbow, lateral epicondyle of the humerus
17	Simple marker	Left elbow, lateral epicondyle of the humerus
18-21	Cluster	Right forearm
22-25	Cluster	Lateral face of the right arm, close to the elbow
26-29	Cluster	Left forearm
30-33	Cluster	Lateral face of the left arm, close to the elbow

Table 3: List of the 34 CODA markers (enumerated from 0 to 33) and their positions on the upper-limb of the subjects. Figure 6 complements this table.

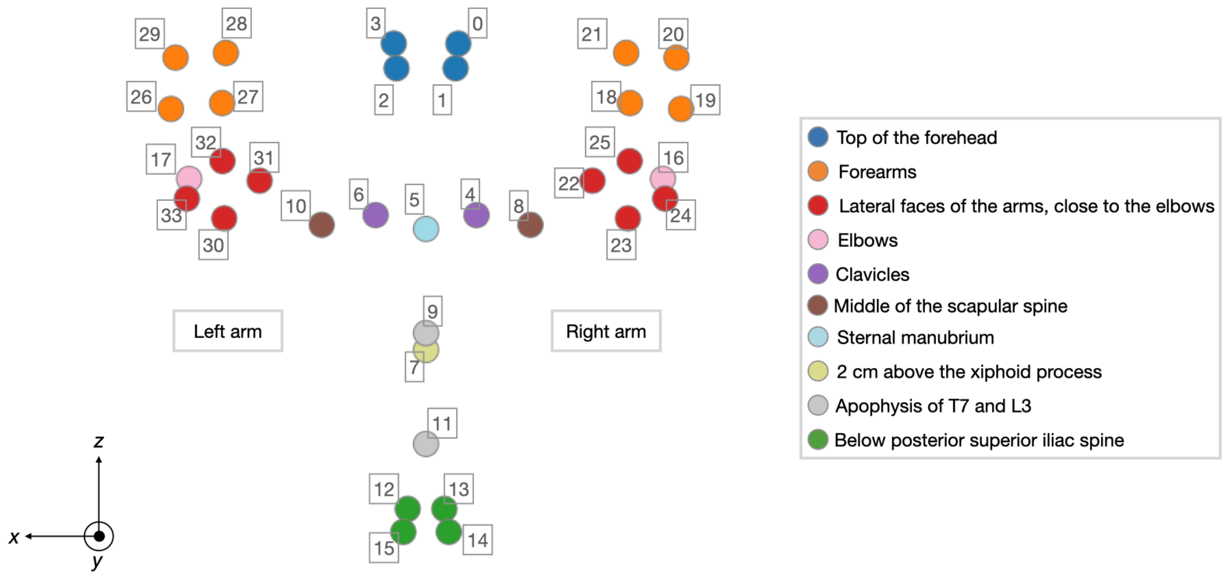


Figure 6: Locations of the 34 CODA markers (enumerated from 0 to 33) on the upper-limb of a subject. View in the sagittal plane, looking at the back of the subject. This figure complements Table 3.

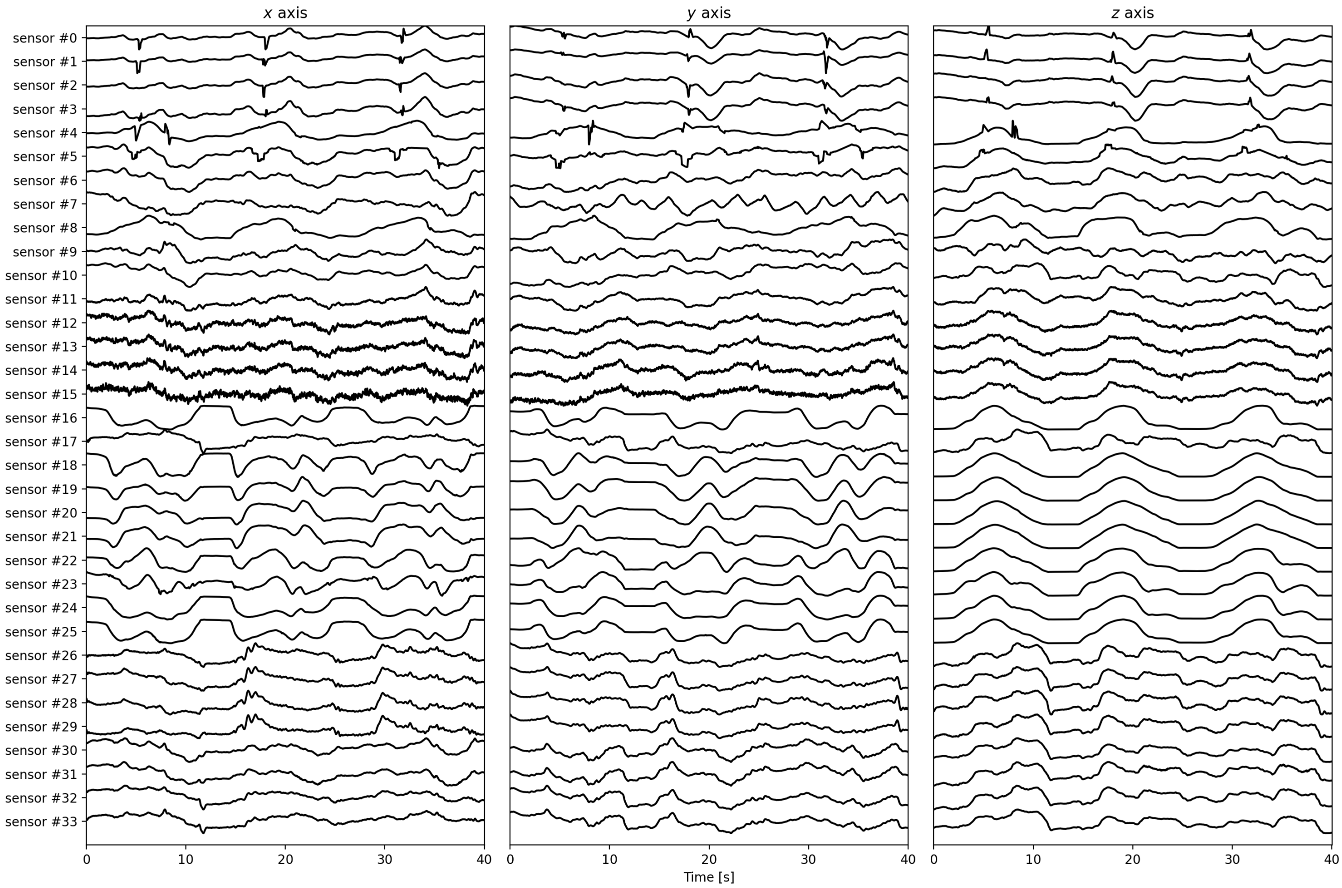


Figure 7: Examples of 3D position time series for the `armcoda_subject1_movement5.csv` time series. The time series is composed of approx. 4 000 timesteps. Each CODA marker is tracked through time in the laboratory frame.

of the sensors provide a data tensor $X \in \mathbb{R}^{N\times T\times 3}$, with N the number of markers ($N = 34$) and T the number of frames of the measurement ($T = 3\ 716$ on average). The third axis of the tensor corresponds to the spatial dimensions (x, y, or z). The positions of the markers are expressed in millimeters and relative to a fixed laboratory frame.

As illustrated in Figure 6, the position and orientation of the subject imposed by the foot position and the visual target were such that the x (resp. y) axis of the global frame corresponded to the sagittal (resp. frontal) axis of the subject. The z-axis was aligned with the local gravity, oriented upward. The 3D position time series recorder for one single movement is presented in Figure 7, and visualization of all recorded 3D time series during a single recording session is presented in Figure 1. To store a multivariate time series as a Comma-separated values (CSV) file, we convert it into a 2D array with 4 000 timestamps and 34×3, thus 102, dimensions. The columns of the resulting CSV files are the dimensions and each row corresponds to a timestamp. The dimensions are ordered as follows: position x of sensor 0, position y of sensor 0, position z of sensor 0, position x of sensor 1, position y of sensor 1, and so on. Note that the 34 sensors are indexed from 0 to 33. All 3D positions time series have been inspected, and the resulting data are in line with the experiment. In particular, we have checked the following points: (i) All the time series are well labeled with the right movement, (ii) each sensor was correctly positioned (in particular, there is no sensor permutation or misorientation), and (iii) all time series include at least two complete iterations of the same movement.

```
marker_0_x,marker_0_y,marker_0_z,marker_1_x,marker_1_y,marker_1_z, ...
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474.78,171.69,1268.43,469.89,162.07,1231.85, ...
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474.83,171.64,1268.44,469.89,162.05,1231.83, ...
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474.83,171.54,1268.21,469.97,161.94,1231.66, ...
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(a) Excerpt of a time series file


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        "Gender": "M",
        "Age": 30,
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        "BMI (kg/m^2)": 25.1,
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        "Position": "Seat",
        "Movement": {
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            "Laterality": "Bilateral",
            "Action": "Elevation"},
        "Plan": "Sagittal",
        "Hand": {
            "Laterality": null,
            "Position": null}
    },
    "Movement_label": {
        "Iteration_1": [211,1357],
        "Iteration_2": [1502,2892],
        "Iteration_3": [2912.0,NaN]
    }
}
```


(b) Metadata file

Figure 8: Excerpts from a time series file (ending in .csv) and a metadata file (ending in .json).

3.2 Metadata

Each of the 240 multivariate time series comes with some metadata. These metadata consist of the recording's identification (subject ID and movement ID), the subject's characteristics, and the annotations of at least two iterations of the movement. These variables are numerical or categorical.

1. **Subject ID** (from 0 to 15). The Number ID of the subject.
2. **Movement ID** (from 0 to 14). The movement IDs as described in Table 2.
3. **Gender**. Male ("M") or female ("F").
4. **Laterality**. Right ("R") or left "L").
5. **Age** (in years).
6. **Height** (in meters).
7. **Weight** (in kilograms).
8. **BMI** (in kg/m^2). Body mass index.
9. **MovementIteration**. Dictionary of lists $\{Iteration\_1 : [s_1, e_1], Iteration\_2 : [s_2, e_2], Iteration\_3 : [s_3, e_3]\}$ of starts and ends timestamps of the three successive iterations of a subject for the same movement.

It is important to note that any of the described variables can take the value "NaN", "null", or "None" which all stand for missing data. Moreover, for the **MovementIteration**, the annotations are made by specialists. An example of annotation of the iterations of a movement is given in Figure 9.

3.3 Data Format

Data are distributed in universal data structures which are supported by all modern programming languages, namely Comma-Separated Values (CSV), and JavaScript Object Notation (JSON). We also provide the time series in the NumPy format (.npy). In detail, each trial is associated with three files. The first two have a .csv and .npy extensions and contain the time series. The third one has a .json extension and contains the metadata

Overall, the files of our data set are identified by the subject ID and the movement ID. For instance, movement ID #3 of subject ID #2 is associated with "armcoda_subject2_movement3.csv", "armcoda_subject2_movement3.npy" and "armcoda_subject2_movement3.json". As a result, the complete data set has 720 files, equally distributed in .csv, .npy, and .json files.

Moreover, a time series file ending in .csv corresponds to a recording and a multivariate time series: it has $T + 1$ rows, where T is the number of timestamps, and $D = 34 \times 3$ columns. The additional row, located at the beginning of the file, is a header and contains the column names, separated by commas ("sensor_0_x,sensor_0_y,sensor_0_z,sensor_1_x", see Section 3.1). The columns are organized according to the marker ID and the spatial location. All positions are given in millimeters.

Then, a time series file ending in .npy corresponds to the same multivariate time series as the one in the .csv format. However, it is organized as a data tensor $X \in \mathbb{R}^{N \times T \times 3}$, with N the number of sensors ($N = 34$) and T the number of timestamps.

Finally, a metadata file contains the names and values of the metadata described in Section 3.2 and follows the JSON format (json.org[3]). In a nutshell, each JSON file is an unordered set, enclosed by braces, of name/value pairs. Pairs are separated by commas and are arranged as follows: "name: value" (for instance, "Age: 30"). Excerpts of such files are displayed in Figure 8.

3.4 Interactive Visualization

In addition to the data set and metadata homogeneously formatted, we provide an interactive tool to visualize and explore them. The latter is accessible online at the demo page associated to this article[4] and Figure 9 depicts a screenshot of it. With our tool, the user can select a subject, a movement, and a sensor of interest. After pressing the "run" button, an interactive visualization will appear. The latter is composed of three main frames synchronized over time. The first (left) corresponds to a 3-D visualization of all the sensor placements. The second (top right) depicts the 3-D trajectory of the selected sensor. The third (bottom right) shows the corresponding time series of the chosen sensor along the x, y, and z axis. Each iteration of the selected movement is highlighted in yellow, green, or purple if it is the first, second, or third iteration, respectively. Finally, the user can either press the "Play" or "Pause" buttons to spectate the evolution over time or select the timestamps of interest with a slider.

3.5 Data Availability

This data set is distributed under a Creative Commons CC-BY-NC-SA license (creativecommons.org[5]).

[3] `www.json.org`
[4] `https://doi.org/10.5201/ipol.2024.494`
[5] `https://creativecommons.org/licenses/by-nc-sa/3.0/`

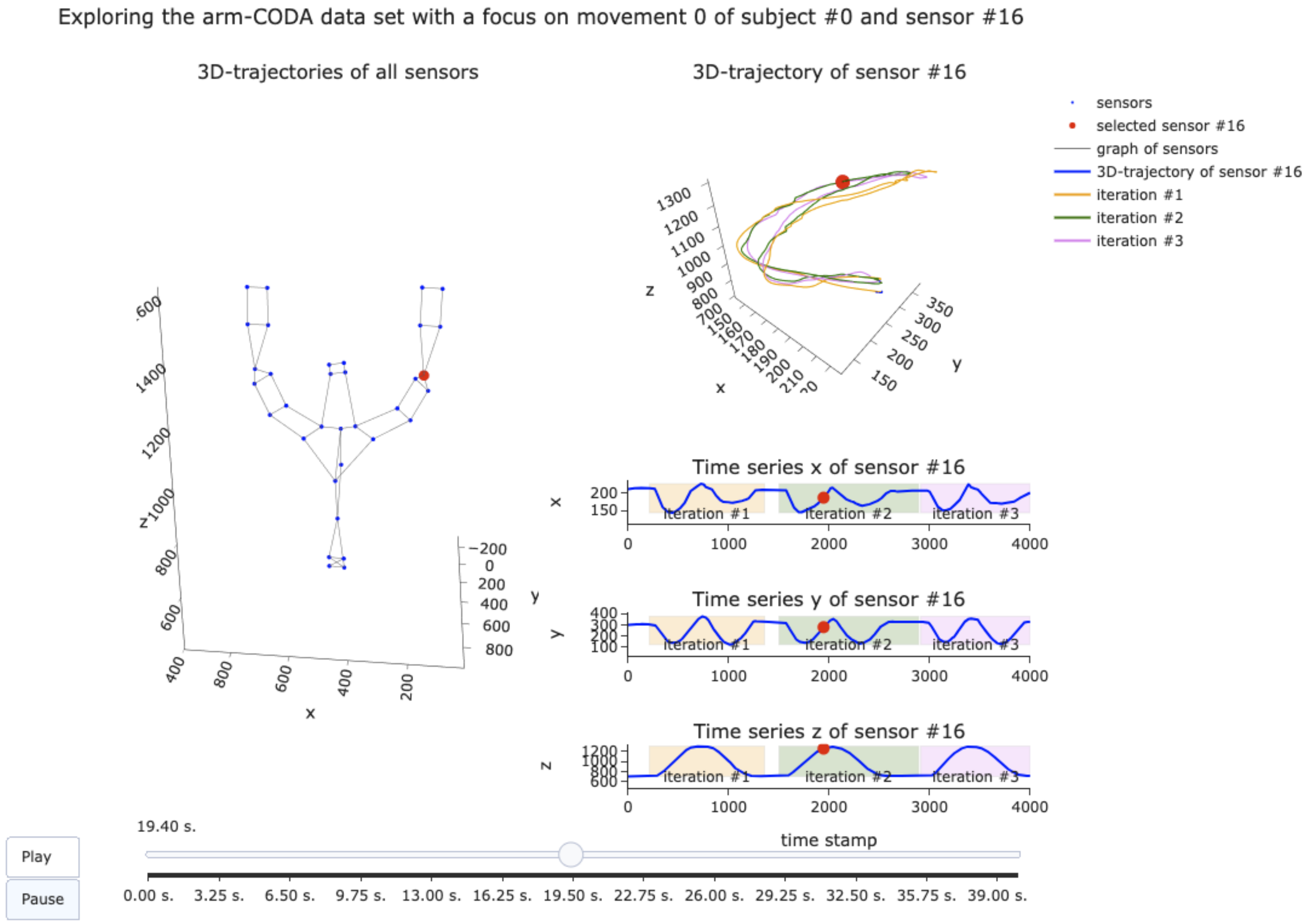

Figure 9: Example of our proposed interactive demo for visualizing the time series (here subject 0 and movement 0 with a special focus on sensor 16).

4 Conclusion

In this article, we have described a set of 240 multivariate time series, each associated with contextual metadata. Overall, 2.5 hours of time series, collected from 16 healthy subjects following a fixed protocol, are provided. The measured population is composed of healthy subjects. In addition, the metadata contains the start and end time stamps of at least two iterations of the same movement. The data are made available under a CC-BY-NC-SA license, in universal file formats (JSON and CSV). Code snippets to access, visualize and perform basic analysis are available online at the web page of the article[6] for several standard programming languages.

Acknowledgment

This work is supported by a public grant overseen by the French National Research Agency (ANR) through the program UDOPIA, a project funded by the ANR-20-THIA-0013-01. Moreover, we acknowledge the Sensorimotricity core facility of BioMedTech Facilities INSERM US36 | CNRS UMS2009 | Université Paris Cité for assistance with the generation of data.

[6] https://doi.org/10.5201/ipol.2024.494

Image Credits

The pictures in Figures 2, 4 and 5 were taken by the authors (license CC-BY-NC-SA).

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