A multi-sensor human gait dataset captured through an optical system and inertial measurement units

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ABSTRACT

Different technologies can acquire data for gait analysis, such as optical systems and inertial measurement units (IMUs). Each technology has its drawbacks and advantages, fitting best to particular applications. The presented multi-sensor human gait dataset comprises synchronized inertial and optical motion data from 25 subjects free of lower-limb injuries, aged between 18 and 47 years. A smartphone and a custom micro-controlled device with an IMU were attached to one of the subject's legs to capture accelerometer data, and 42 reflexive markers were taped over the whole body to record three-dimensional trajectories. The trajectories and accelerations were simultaneously recorded and synchronized. Participants were instructed to walk on a straight-level walkway at their normal pace. Ten trials for each participant were recorded and pre-processed in each of two sessions, performed on different days. This dataset supports the comparison of gait parameters and properties of inertial and optical capture systems, whereas allows the study of gait characteristics specific for each system.

Background & Summary

Gait analysis has been explored since the 17th century1. Advances in understanding the human motion throughout the last centuries allowed researchers apply this analysis to many applications, such as clinical assessment, monitoring of sports and athletic performances, rehabilitation support, robotics research, and biometry-based recognition2. This type of analysis can use data acquired by means of different technologies, like optical systems, inertial measurement units (IMUs), force-plate platforms, force shoes, and techniques based on computer vision. Although some of these are commonly used in most fields, as optical systems and imaging techniques, each technology has its drawbacks and fits best to particular applications3–7.

One popular technology to acquire data for gait analysis is the optical motion capture system. It has minimal impact on the natural motion of the subject, as it does not need tethering any hardware onto the individual8. This system also fosters a precise acquisition of physical movements over virtual modeling and accurate reconstruction of movement marks and subjects’ geometry9. However, optical motion capture systems are usually expensive, require high-speed processing devices and specific
installations in a controlled space for their use\textsuperscript{3}.

Recently, IMUs have been considered an appropriate option to perform gait analysis because they mitigate these drawbacks of optical motion capture systems. They are typically more cost-effective, do not need a controlled environment, and support indoor and outdoor places. However, they have other limitations as being more susceptible to drift caused by changes in motion direction, and to low-frequency noise from small vibrations during the capture. Also, the sensor attachment position significantly impacts the estimation of gait parameters\textsuperscript{3,9–11}.

Several important gait datasets comprising either optical motion capture data or inertial data have been made available\textsuperscript{12–18} in the prior literature. However, there are currently no datasets with data being simultaneous captured from both systems, which may allow a multi-modal gait analysis. This synchronized capture has proven helpful in specific applications, such as music gesture analysis\textsuperscript{19} and sports science\textsuperscript{20}. We propose, in this work, a multi-sensor gait dataset, which consists of inertial and optical motion data, and aims to provide basis for comparison and reasoning of human gait analysis using data from both systems.

The presented dataset comprises inertial and optical motion data from 25 subjects free of lower-limb injuries, aged between 18 and 47 years. A smartphone and a custom microcontroller device with an IMU were attached to one of the subject’s legs to capture accelerometer data, and 42 reflexive markers were taped over the whole body to record three-dimensional trajectories. The participants were instructed to walk on a straight-level walkway at their normal pace. The custom device uses a wireless protocol to communicate with the computer to which the optical system was connected. This setup enabled recording and synchronizing the trajectories (acquired by the optical system) and the accelerations (acquired by the dedicated device and the smartphone). Ten trials for each participant were recorded and pre-processed in each of two sessions, performed on different days. This amounts to 500 trials of three-dimensional trajectories, 500 trials of accelerations from the custom device, and 500 trials of accelerations from the smartphone.

In addition to contributing with a multi-sensor dataset which supports the comparison of gait parameters and properties of inertial and optical capture systems, the full-body marker set and the inertial sensors attached to the leg favor the study of gait characteristics specific for each system. This dataset also allows analyzing gait variations between subjects and for each one (i.e., intra and inter-subjects) by the captures in different days. This characteristic of the dataset fosters investigations about the effectiveness of gait recognition and user profiling using accelerometers.

**Methods**

**Participants**

Twenty-five subjects (12 women, 12 men, and one undeclared gender, aged between 18 and 45 years) participated in this study, which took place between December of 2019 and February of 2020. Neither of them reported injuries for both legs or medical conditions that would affect their gait or posture. The participants were either students of the School of Music at McGill University, members of CIRMMT, or authors of this work. McGill University’s Research Ethics Board Office approved this study (REB File # 198-1019), and all participants provided informed consent.
Experimental design

A proprietary optical system\textsuperscript{21}, with 18 infra-red Oqus 400 and Oqus 700 cameras and sampled at 100Hz, was adopted to track the 3D trajectories of 42 reflective markers over the participants’ body. The marker set was based on the lower-limb IORGait model proposed by Leardini et al.\textsuperscript{22}, and a simplified upper-limb and trunk Plug-in Gait models\textsuperscript{23}. This marker set is depicted in Figure 1, and each reflexive marker, as well as its anatomical landmarks, are described in Table 1. Gait analysis usually focuses on the lower limb trajectories; thus, the upper-limb and trunk simplified models are used only for skeleton reconstruction purposes. The marker placement was performed by anatomical palpation using the landmarks reported in Table 1 at the beginning of each session, and was not changed during the session trials. The proprietary motion capture software (Qualisys Track Manager - QTM)\textsuperscript{24} was employed to record and pre-process the 3D trajectories of the reflexive markers. All trajectory measurements were acquired in units of millimeters.

A Nexus 5 Android-based smartphone with an InvenSense MPU-6515 six-axis IMU was used to capture accelerometer data. An Android application was designed and developed to read accelerations at a sampling rate of 100Hz and store them into a comma-separated values (CSV) file. The accelerometer measurements yielded by the Android platform are in units of \(m/s^2\).

An InvenSense MPU-9250\textsuperscript{25} six-axis IMU mounted to an ESP8266 microcontroller (MCU) was used to capture triple-axis accelerometer data. A firmware to the ESP8266 was developed using Arduino Core libraries, to read raw accelerations by I2C protocol at a sampling rate of 100Hz. The acceleration measurements were read in \(g\) units and transformed into units of \(m/s^2\) using \(g = 9.81 m/s^2\). The MCU board was connected to the WiFi during its initialization. Then the accelerations were read from the MPU-9250, and sent using Open Sound Control (OSC) packages over UDP, following the defined rate. The smartphone and the MCU, screwed within a projected box, were attached to the leg using a band, as showed in Figure 2. Five reflexive markers were taped in the band to calibrate it as a rigid body in the motion capture system, then at least three markers were kept during the walking trials to track it as a six-degree freedom object. These markers are also described in Table 1, at the fifth first lines. In the Figure 3 is showed the motion capture software visualization of the coordinate reference calibrated for the optical motion capture system, smartphone and MCU attached to the leg being tracked as a rigid body. The MCU and smartphone were positioned to correspond to the motion capture reference in a way in which their coordinate systems are aligned.

An integration API was designed and developed to receive data from the MCU over UDP protocol and from the optical motion capture system by a real-time SDK provided by the Qualisys corporation\textsuperscript{26}. The three-axis accelerations and the 3D trajectories were acquired independently by this integration API but synchronously. The API starts to listen to the OSC packages from the MCU when the optical system begins the data acquisition. Also, the API stops listening to the OSC packages when the optical system finishes the data acquisition. Once the integration API guarantees both acquisitions initiate and finish together, and both systems have the same sampling rate, hence their data streams are synchronized.

Data acquisition

Two data acquisition sessions were performed for each participant, and each one lasted about one hour. The sessions were performed on different days. In each session, the following procedure was adopted:

1) **Calibration of the systems:** the optical motion capture system was calibrated by the Wand calibration method following
During the calibration, the coordinate system was defined as: \( x \) was the direction in which the participant walked; \( y \) was orthogonal to \( x \); and \( z \) was orthogonal to both, pointing to the participants’ head. The MCU also was turned on at this moment, and its communication to the computer was verified. As well as, the Android application was started to read and store the accelerometer readings in a CSV file.

2) **Participant preparation:** the investigator showed the laboratory to the participant, explained the recording procedure, and asked the participant to sign the consent form. Further, the participant changed their clothes to tight-fitting outfits and wore tight caps to cover their hair. The investigator attached the reflexive markers presented in Figure 1 on the participants’ skin or the tight-fitting clothes, using a proper double-sided tape. Also, the smartphone and the MCU box placed in the band were attached to the participant’s leg.

3) **Trials:** The participant was asked to stand up at the beginning of the walkway for few seconds to guarantee the proper function and communication of the systems. After these few seconds, the participant was asked to tap three times on the smartphone and MCU box (using their index finger, on which an additional marker was placed). Finally, the participant walked forth on a 5-m straight level walkway at their normal pace. At the end of the walkway, the participant stopped and tapped on the smartphone and MCU box again. The accelerations peaks generated by these taps allow a later verification of the data synchronization. Five trials of the participant walking using the band on their left leg were recorded, and five other sessions were recorded using the band placed on their right leg.

4) **Session ending:** After recording the ten trials, the band, and all the markers were removed from the participants' bodies. The Android application also was stopped. The obtained visualizations from the session recordings were shown, and the scheduling of the participant's next session was confirmed.

**Data processing**

The marker trajectories were labeled using the QTM software\(^1\), as well as their gap-filling procedure. The investigator manually selected the best fit of interpolation in the trajectory editor\(^2\) for each missing trajectory. Polynomial interpolation was applied in gaps smaller than ten frames, and relational interpolation, which is based on the movement of surrounding markers, was adopted for more complex cases (e.g., occlusions caused by the alignment of both legs during mid-stance and mid-swing phases). After that, the trajectories were smoothed, when necessary, using QTM software tool\(^2\) by selecting a range of the trajectories and employing the appropriated filter. Small ranges of noisy data were locally smoothed using a moving average filter, which is ideal to smooth spikes without affecting the movements. Larger ranges of data containing expressive high-frequency noise were smoothed using a Butterworth low pass filter with a 5 Hz cut-off frequency. After that, these filled and smoothed trajectories were exported to the c3d\(^2\) and Matlab file formats. These trajectories were then imported and processed using MoCap Toolbox\(^2\) under Matlab\(^2\). The exported trajectories were structured as *MoCap data* from MoCap Toolbox, and processed to extract the temporal section containing only walking data, i.e., removing the beginning and end of the trials. The raw accelerations recorded by the MCU and smartphone were exported into CSV files, including the full trials, i.e., the beginning, walking data,

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\(^1\)QTM version 2018.1 (build 4220), RT Protocol versions 1.0 - 1.18 supported.
\(^2\)https://www.c3d.org
and end of the trials. Additionally, the corresponding walking sections were extracted from these accelerations and exported to a CSV file. The walking sections obtained from the trajectories, MCU accelerations, and smartphone accelerations were assured to present temporal alignment.

**Data Records**

All data are available from figshare\textsuperscript{30}. They are organized in two folders: raw\_data containing the complete trials; and processed\_data storing the walking sections extracted from the raw data by removing the beginning and end of the trials. In both folders, the subjects’ trial files are organized in sub folders associated to each subject identification: userID, which IDs are from 01 to 30, not necessarily consecutive. A total of 20 trials have been recorded of each subject, 10 in day1 and 10 in day2.

**Raw data**

This folder stores the complete trials, including the beginning and end of them. These trials consists in 3D trajectories exported from the QTM software into c3d files, and MCU’s accelerometer readings stored in CSV files. The c3d files are referenced as capture\_userID\_dayD\_TT\_qtm.c3d, and CSV files as capture\_userID\_dayD\_TT\_imu.csv, in which:

- userID is the subject identification, as explained before;
- dayD refers to the first or second day of the subject trials, day1 or day2;
- TT is the trial number, i.e. 0001 to 0010, for each dayD.

The description of the c3d labels are presented in Table 1. All trajectories have the dimension $n \times 3$ ($n$ is the number of frames recorded), and the number format is real. Information about the columns of CSV files are presented in Table 2. The corresponding frames to the accelerometer measurements are indicated in the first column of CSV files. In some cases, the frame counting of the accelerations does not start in one, but they are surely synchronized to the marker trajectories’ frames.

**Processed data**

This folder stores the walking sections obtained from the complete trials, removing the beginning and end of them. The walking sections of 3D trajectories were stored in Matlab files whereas the corresponding sections of accelerometer readings from the MCU and smartphone were stored in CSV files. The Matlab files are referenced as capture\_userID\_dayD\_TT\_qtm\_walk.mat, and CSV files as capture\_userID\_dayD\_TT\_imu\_walk.csv and capture\_userID\_dayD\_TT\_nexus\_walk.csv, in which:

- userID is the subject identification, as explained before;
- dayD refers to the first or second day of the subject trials, day1 or day2;
- TT is the trial number, i.e. 0001 to 0010, for each dayD.

First, the c3d files containing the markers trajectories were read over Matlab, and their data were stored in a structure array from MoCap Toolbox named MoCap data. The scheme and fields of this structure are described in Table 4. Format and set
values of the fields are also presented. Some fields are composed by Structures, which are described on the columns to the right. Those fields kept as default values of Mocap data Structure are presented as empty or zero-valued in this table. Through the functions provided by Mocap Toolbox, walking sections were extracted by analysing the trajectories on x-axis of feet markers, medial and lateral malleolus of both sides (details in Table 1), to find the frame in which the subject displacement begins and ends. These frame numbers are stored in the field frame_init and frame_end of the Structure other of Mocap data.

Once the accelerometer readings were synchronized to the trajectories by the corresponding frame numbers, these yielded beginning and ending frames were also used to section the MCU accelerations. The columns and scheme of CSV files which store the walking sections extracted from MCU accelerations are the same of the presented in Table 2. The first value of column named frame presents the same amount of frame_init, and the last value presents the same amount of frame_end from the MoCap data Structure.

Accelerations from the smartphone were not capture synchronously to the marker trajectories, and only one CSV file stored all the accelerometer measurements of the 10 trials performed by a subject in each day. This CSV file was split into walking sections by correlation analysis between it and the walking sections of MCU accelerations, which were synchronized to the trajectories. Thus, these extracted walking sections from the smartphone accelerations do not contain the information about frame numbers although these were motion-aligned to the MCU’s accelerometer readings. The columns of the CSV files that store the walking sections of the smartphone accelerations are described in Table 3.

Technical Validation

The presented multi-sensor dataset consists of three sources: an optical motion capture system, an IMU mounted to an ESP8266 board and an Android-based smartphone. The same experienced investigator attached the markers and the smartphone and MCU within a box mounted to a band on the participant’s body for consistency purposes.

Optical motion capture system: The calibration of the optical motion capture system was performed as described in the Data acquisition of the Section Methods, right before the beginning of each data acquisition session. In all achieved calibrations, the average residuals of each camera remained below 3 mm and similar among the 18 cameras. Also, the standard deviation between the actual wand length and the length perceived by the cameras was up to 1mm in the adopted calibrations. The gaps in the 3D trajectories of the markers were filled (i.e., all the trajectories are 100% tracked), and the average residuals of 3D measured points fell below 4mm.

MCU: The firmware was implemented using Arduino Core libraries without adopting IMU libraries to avoid potentially applying of library default filters to the accelerations. Commonly, a scale range between ±2g and ±8g is adopted to the accelerometer in the gait literature. The scale range of ±2g is enough to measure the maximums instantaneous accelerations of normal walking (bellow to 1g), and can capture more gait details (a scale range of ±2g corresponds to 16384 LSB/g according to the MPU-9250 specification). Thus, the firmware reads the registers’ position of the MPU-9250 accelerometer and calculates the accelerations according to this sensors’ sensitivity.

Smartphone: The developed Android application uses the sensor routines provided by the platform and the Android Open
Source Project (AOSP). The same scale range of ±2g used to the MPU-9250 accelerometer was set to the MPU-6515 one using the Android Sensor API. This scale also corresponds to a specificity of 16384 LSB/g for the MPU-6515. The Android API reads these accelerations from the IMU and calculates them in units of m/s², including the gravity.

Usage Notes

The c3d files can be read by several free and open source tools which provide support to c3d files, such as EZC3D and Motion Kinematic & Kinetic Analyzer (MOKKA). The Matlab files store the structure MoCap data from MoCap Toolbox, and can be manipulated using the functions provided by this Toolbox. It presents several routines to visualize, perform kinematics and kinetics analysis and apply projections on the data. This Toolbox supports any kind of marker set. The CSV format files can be read using any text or spreadsheet editor, as well as by common functions over Matlab or Python.

Code availability

The developed Matlab and Python codes to process the data are freely available on the first author’s github repository. The MoCap Toolbox is freely available and extensively documented on the University of Jyväskylä website.

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3 https://www.mathworks.com/help/matlab/ref/readtimetable.html
4 https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.read_csv.html
5 https://github.com/geisekss/motion_capture_analysis
6 https://www.jyu.fi/hytk/fi/laitokset/mutku/en/research/materials/mocaptoolbox
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Author contributions statement

G.S. designed the protocol, performed the data acquisition, and processed the data. M.W. provided the technical support and resources to establish the data collection. M.W. and G.S discussed the experimental design. G.S. T.T. and A.R. contributed to the data analysis and the manuscript writing. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.
Figure 1. The adopted marker set based in the model proposed by Dumas and Wojtusch and the Plug-in Gait model.
Table 1. Description and placement of each reflexive marker attached to the participants’ body.

| Labels     | Description                                           | Landmarks for marker placement                                                                 |
|------------|-------------------------------------------------------|------------------------------------------------------------------------------------------------|
| top_right  | Marker on the top right of the band                   | Located approximately on the top right of the smartphone                                       |
| top_left   | Marker on the top left of the band                    | Located approximately on the top left of the smartphone                                         |
| top_imu    | Marker on the center of the band                      | Located approximately on the top of the MCU’s box                                              |
| head_imu   | Marker on the left half of the band                   | Located approximately on the left side of the MCU’s box                                         |
| power      | Marker on the right half of the band                  | Located approximately on top of the powerbank used as power source to the MCU                  |
| finger     | Index finger                                          | Placed on the distal phalanx of the right/left index finger according to the leg which the band was placed on |
| head_FR    | Right front head                                      | Located approximately over the right temple                                                    |
| head_FL    | Left front head                                       | Located approximately over the left temple                                                     |
| head_BR    | Right back head                                       | Placed on the back of the head, roughly in a horizontal line of the right front head marker    |
| head_BL    | Left back head                                        | Placed on the back of the head, roughly in a horizontal line of the left front head marker      |
| shoulder_R | Right shoulder                                        | Placed on the acromio-clavicular joint                                                        |
| shoulder_L | Left shoulder                                         | Placed on the acromio-clavicular joint                                                        |
| c7         | 7th Cervical Vertebrae                                | Spinous process of the 7th cervical vertebrae                                                  |
| clav       | Clavicule                                             | Jugular Notch where the clavicles meet the sternum                                             |
| elbow_R    | Right elbow                                           | Lateral epicondyle approximating elbow joint axis                                             |
| elbow_L    | Left elbow                                            | Lateral epicondyle approximating elbow joint axis                                             |
| wrist_BR   | Right wrist marker B                                 | Right wrist bar pinkie side                                                                     |
| wrist_AR   | Right wrist marker A                                 | Right wrist bar thumb side                                                                     |
| wrist_AL   | Left wrist marker A                                  | Left wrist bar thumb side                                                                      |
| wrist_BL   | Left wrist marker B                                  | Left wrist bar pinkie side                                                                     |
| finger_R   | Right finger                                          | Dorsum of the right hand just below the head of the second metacarpal                          |
| finger_L   | Left finger                                           | Dorsum of the left hand just below the head of the second metacarpal                           |
| ips_R      | Left PSIS                                             | Right posterior-superior iliac spine                                                           |
| ips_L      | Left PSIS                                             | Left posterior-superior iliac spine                                                            |
| ias_R      | Right ASIS                                            | Right anterior-superior iliac spine                                                            |
| ias_L      | Left ASIS                                             | Left anterior-superior iliac spine                                                             |
| ftc_R      | Right greater trochanter                             | Most lateral prominence of the right greater trochanter                                        |
| Column  | Description                                               | Format                      |
|---------|-----------------------------------------------------------|-----------------------------|
| ftc_L   | Most lateral prominence of the left greater trochanter    |                             |
| fme_R   | Most medial prominence of the left medial femoral epicondyle |
| fme_L   | Most medial prominence of the right medial femoral epicondyle |
| tcc_R   | Most anterior border of the right tibial tuberosity       |                             |
| ttc_L   | Most anterior border of the left tibial tuberosity         |                             |
| fax_R   | Proximal tip of the head of the right fibula               |                             |
| fax_L   | Proximal tip of the head of the left fibula                |                             |
| fle_R   | Most lateral prominence of the right lateral femoral epicondyle |
| fle_L   | Most lateral prominence of the left lateral femoral epicondyle |
| heel_R  | Right posterior calcaneus                                 |                             |
| heel_L  | Left posterior calcaneus                                  |                             |
| fal_R   | Lateral prominence of the right lateral tibial malleolus   |                             |
| fal_L   | Lateral prominence of the left lateral tibial malleolus    |                             |
| tam_R   | Most medial prominence of the right medial tibial malleolus|                             |
| tam_L   | Most medial prominence of the left medial tibial malleolus |                             |
| fm5_R   | Dorsal margin of the right fifth metatarsal head           |                             |
| fm5_L   | Dorsal margin of the left fifth metatarsal head            |                             |
| fm2_R   | Dorsal aspect of the right second metatarsal head          |                             |
| fm2_L   | Dorsal aspect of the left second metatarsal head           |                             |
| fm1_R   | Dorsal margin of the right first metatarsal head           |                             |
| fm1_L   | Dorsal margin of the left first metatarsal head            |                             |

Table 2. Description of the columns of the CSV files generated by the MCU accelerations during the subjects’ trials.

| Columns | Description                                                                 | Format                      |
|---------|-----------------------------------------------------------------------------|-----------------------------|
| Frame   | Frame number to correspond to the marker trajectories’ frames               | Integer                     |
| Acc x   | x-axis of accelerometer reading in the referenced frame number              | Real (in units of m/s²)     |
| Acc y   | y-axis of accelerometer reading in the referenced frame number              | Real (in units of m/s²)     |
| Acc z   | z-axis of accelerometer reading in the referenced frame number              | Real (in units of m/s²)     |
Table 3. Description of the columns of the CSV files generated by the smartphone accelerations during the subjects’ trials.

| Columns | Description                               | Format                        |
|---------|-------------------------------------------|-------------------------------|
| Acc x   | x-axis of the accelerometer measurement   | Real (in units of m/s²)       |
| Acc y   | y-axis of the accelerometer measurement   | Real (in units of m/s²)       |
| Acc z   | z-axis of the accelerometer measurement   | Real (in units of m/s²)       |

Figure 2. The smartphone and MCU box mounted to a band to be attached to the leg.

Figure 3. Coordinate reference of the motion capture system, and the smartphone and MCU attached to the leg being tracked as a rigid body.
Table 4. Description of the scheme, fields, their format and set values on Mocap data structure.

| Field name   | Format        | Value                     |
|--------------|---------------|---------------------------|
| type         | String        | ‘MoCap data’              |
| filename     | String        |                           |
| nFrames      | Integer       | \( f \)                   |
| nCameras     | Integer       | 18                        |
| nMarkers     | Integer       | 47                        |
| freq         | Integer       | 100                       |
| nAnalog      | Integer       | 0                         |
| anaFreq      | Integer       | 0                         |
| timerOrder   | Integer       | 0                         |
| markerName   | String        | 47 x 1 String             |
| data         | Real          | \( f \times 141 \) Real (in units of mm) |
| analogdata   | Real          |                           |

| other        | Structure     | descr String               |
|--------------|---------------|----------------------------|
|              |               | timeStamp String            |
|              |               | dataIncluded ‘3D’           |

| RigidBodies  | Structure     | Bodies 1                    |
|--------------|---------------|----------------------------|
|              |               | Name ‘imu_nexus_box’        |
|              |               | Positions \( 1 \times 3 \times f \) Real (in units of mm) |
|              |               | Rotations \( 1 \times 9 \times f \) Real (rotation matrices) |
|              |               | RPYs \( 1 \times 3 \times f \) Real (in units of degrees – roll, pitch and yaw) |
|              |               | Residual \( 1 \times 1 \times f \) Real (in units of mm) |

frame_init Integer
frame_end Integer

\( f \) is the number of frames of the walking section.

All fields’ names are in bold. The ones which format is Structure, their fields are detailed on the rightmost columns. The empty or zero-valued fields were not filled in the Mocap data structure.