scientific data

Check for updates

OPEN

DATA DESCRIPTOR

A Multimodal Dataset Addressing Motor Function in Autism

João Ruivo Paulo[1]✉, Teresa Sousa[2,3,4], João Perdiz[1], Lara Pereira[5], Mariette Vasen[6,7], Susana Mouga[2], Gabriel Pires[1,8] & Miguel Castelo-Branco[2,3,4]

Autism has primarily been characterized at a social-cognitive level, with evidence suggesting impairments in action-perception and motor function. However, there is a lack of publicly available datasets that specifically address the neural and behavioral mechanisms linking these functions in autism. The Move4AS dataset aims to fill this gap, having been designed to facilitate the study of the underlying mechanisms of motor function in the autism spectrum. It combines multiple data modalities, including electroencephalography (EEG) and 3D motion data, collected during motor imitation tasks - dancing and walking - designed to recruit motor function in emotional and social contexts. It comprises a control group of 20 participants and a clinical group of 14 participants. EEG was recorded through a 16-channel wireless EEG cap, and 3D motion was captured using marker-based motion capture suits tracked by a 10-camera setup. Additionally, the dataset includes neuropsychological characterization of the participants (IQ and autism score).

Background & Summary

Although autism is primarily recognized as a condition characterized by social and emotional difficulties, substantial research highlights significant difficulties in action perception and motor abilities in individuals throughout the autism spectrum (AS), affecting both children and adults. Autistic individuals frequently display difficulties with motor coordination, posture, repetitive behaviors, and learning by imitation. These difficulties often appear as early as infancy[1], prompting the hypothesis that they could lead to unconventional perceptions of movement and reduced social engagement, potentially influencing the onset of the core symptoms of autism[2]. Hence, studying complex motor function in autism is vital to uncover the pathophysiology of autism and to support practical efforts such as early diagnosis and therapy.

There is considerable behavioral evidence indicating that autistic individuals struggle with imitation, though experts debate whether these difficulties are specific to imitation or part of a larger problem. Certain researchers suggest that these imitation challenges in AS do not stem from flawed action observation or mirror neuron circuitry, but rather from trouble executing precise gestures or developmental dyspraxia[3]. Nevertheless, it is uncertain whether these issues arise from delayed development, impaired perception of social actions, or a deeper problem in complex neural moor dynamics[3].

Accordingly, there is growing enthusiasm for integrating diverse data modalities to enhance the evaluation and understanding of motor function in autism, with the goal of identifying neuronal markers of these differences[4]. Yet, there remains a shortage of datasets that combine behavioral and neurophysiological observations for analyzing motor function in AS[5]. Many studies rely on functional MRI to explore brain activity, but this approach is incompatible with the recording of naturalistic motor tasks since participants cannot move freely. Beyond MRI, common sensor modalities include EEG, eye tracking, and facial tracking systems, as reviewed in[6]. Due to these constraints in data collection, discovering clear neuronal markers of motor function in autism continues to be an open research question[4].

[1]Institute of Systems and Robotics, University of Coimbra, Coimbra, Portugal. [2]Coimbra Institute for Biomedical Imaging and Translational Research (CIBIT), Institute of Nuclear Sciences Applied to Health (ICNAS), University of Coimbra, Coimbra, Portugal. [3]Intelligent Systems Associate Laboratory (LASI), Guimarães, Portugal. [4]Institute of Physiology, Faculty of Medicine, University of Coimbra, Coimbra, Portugal. [5]Physics Department, NOVA School of Science and Technology, NOVA University of Lisbon, Lisbon, Portugal. [6]Faculty of Mathematics and Computer Science, Friedrich-Schiller-University Jena, Jena, Germany. [7]Department of Informatics, Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany. [8]Engineering Department, Polytechnic Institute of Tomar, Tomar, Portugal. ✉e-mail: jpaulo@isr.uc.pt

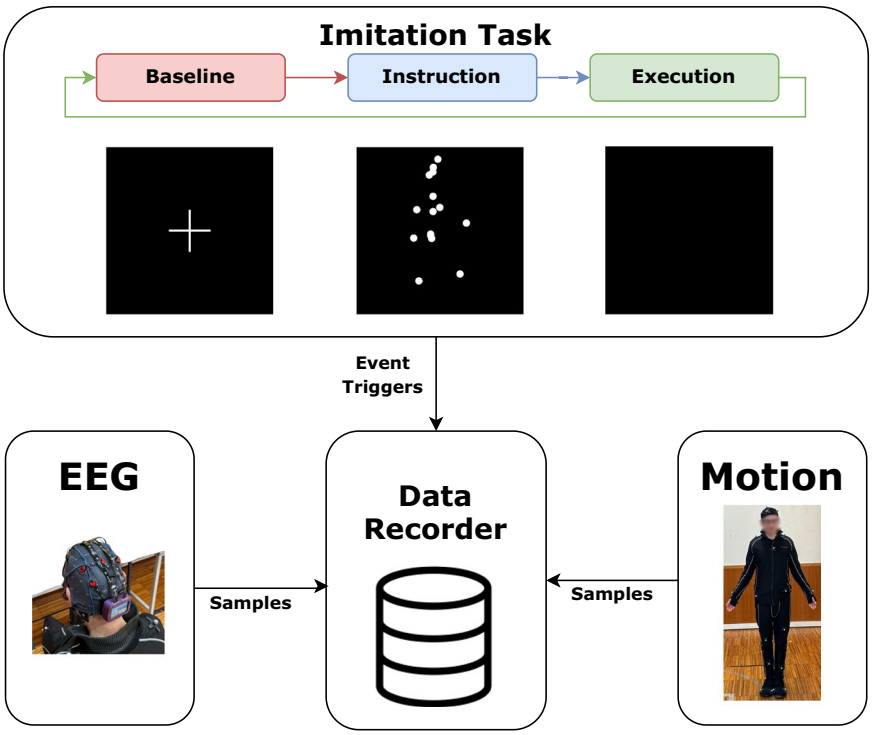


Fig. 1 Overview of the experimental protocol. The visual paradigm (upper block) is divided into distinct time periods: fixation cross, visual instruction, and execution. During the visual instruction period, a moving point-light figure was displayed, which participants were instructed to imitate. These movements represented different social and emotional contexts, like pair dancing and sad walking. The data modalities, EEG and 3D motion capture, were collected simultaneously. Time event triggers were integrated into the data, to mark the distinct periods of the trial, including baseline, instruction and execution phases.

In this paper, we introduce the Move4AS dataset, which combines wireless electroencephalography (EEG) and 3D motion capture modalities, as shown in Fig. 1. Data were collected during two distinct imitation tasks, designed to elicit motion recognition and execution under different emotional and social contexts.

This dataset was created to primarily enable the characterization of motor function in autism through objective analyses, aiming to understand underlying neural mechanisms. Additionally, it supports the development of potential innovative screening approaches for early diagnosis and intervention. The dataset uniquely combines sensor modalities (EEG and 3D motion), while also offering the flexibility to be used on a single modality basis, either EEG or 3D motion. The Move4AS dataset potentially represents a significant contribution to neuroscience research, providing a valuable resource for understanding motor function in autism. It also facilitates interdisciplinary research in fields such as biomedical applications, engineering and machine learning, serving neuronal marker discovery and the benchmarking of classification models in screening applications.

Methods

Setup and Data Collection. The setup for data acquisition incorporates a marker-based motion capture system, a wireless EEG system, and a processing and display system. The equipment used for EEG data collection was the g.Nautilus[7] wearable EEG headset (gTec, Austria) with 16 g.LADYbird active gel-based EEG electrodes (sampling rate of 250 *Hz*). For 3D motion capture, it was used the OptiTrack Flex 3 in a 10 camera configuration setup, overlooking a 5×5 meter area (data acquisition at 120 *Hz*). 37 body markers were used for automatic skeleton reconstruction. The screen used for presenting visual stimuli to the participants, was a 49" LCD TV screen with 60 *Hz* refresh rate and a pixel resolution of 1920×1080. A wide-angle view of the scene and setup can be observed in Fig. 2.

The EEG and 3D motion information were collected using a processing station, consisting of a desktop computer, using home-made Mathworks' Matlab® scripts using the Data Acquisition Toolbox and Simulink gTec models for EEG data recording, and OptiTrack's Motive software for motion capture recording. Alignment between data streams was ensured through event triggers embedded in the data streams. The screen was used to provide instructions and timing cues to participants, as detailed in Fig. 3.

Participants. The Move4AS dataset includes data from two groups: one with non-autistic adults and another with autistic adults. The non-autistic group comprises 20 neurotypical individuals, 13 males and 7 females, with an average and standard deviation age of 25.9 ± 3.8 years. The autistic group includes 14 autistic individuals, 12 males and 2 females, with an average and standard deviation age of 27 ± 6.8 years. The diagnosis of autism was previously confirmed by qualified professionals in the field. Gold standard instruments were also performed,

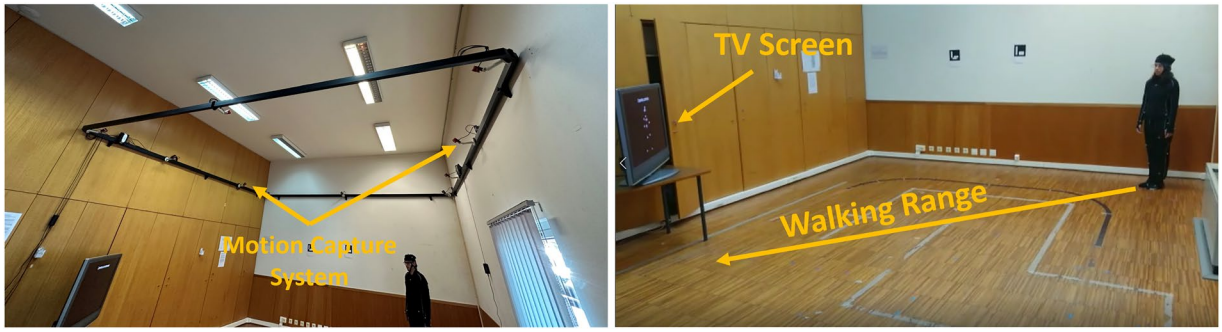


Fig. 2 Views of the experimental setup and the participant's position. left: motion capture system. Right: the walking range showing the participant facing the screen where task instructions were displayed.

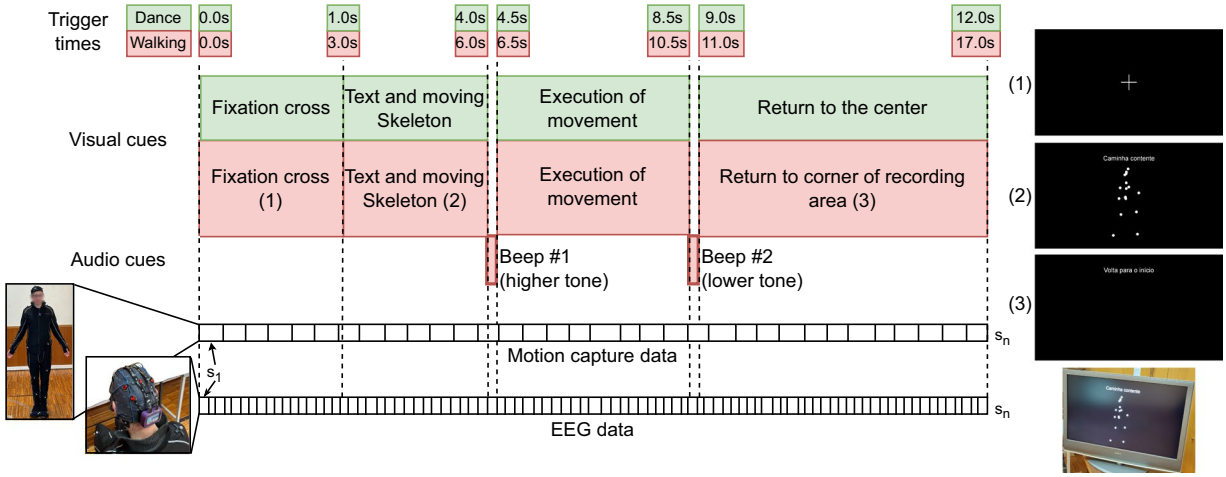


Fig. 3 Visual representation of the paradigms. Top: the paradigm's chronological flow, showing the dancing (green) and walking (red) tasks. Middle: the instructions provided to participants for each task. Bottom: EEG and 3D motion data recorded at their respective frame rates, and the introduction of the event triggers to allow data alignment at specific moments, for both tasks. Right: the point-light animations displayed on the screen to relay instructions to participants.

Group	Age	FSIQ	AQ	ADOS Total
Control	25.9 ± 3.8	118 ± 12.4	19 ± 7.54	NA
Clinical	27 ± 6.8	88.5 ± 19.7	NA	9 ± 2.06

Table 1. Average and standard deviation of demographic and neuropsychological data for the participants included in each group.

when possible, such as parental or caregiver interview with the Autism Diagnostic Interview-Revised, ADI-R[8], direct structured subject assessment with the Autism Diagnostic Observation Schedule, ADOS[9], and the current diagnostic criteria for AS according to the Diagnostic and Statistical Manual of Mental Disorders 5, DSM-5[10]. Moreover, both groups underwent a neuropsychological evaluation that included the assessment of the intelligence quotient (IQ) with a short version of the Wechsler Adult Intelligence Scale (WAIS-III)[11] and the measurement of autistic symptomology through the Autism-Spectrum Quotient (AQ)[12]. These parameters are summarized in Table 1, being the individual participant characterization provided in the dataset's repository.

Data collection and studies were approved by the Ethical Committee of The Faculty of Medicine of the University of Coimbra (Ref. CE-084/2022), and fully respect the safety guidelines for human research and the content of Regulation (EU) 2016/679: General Data Protection Regulation. All participants signed an informed consent form in accordance with the Declaration of Helsinki prior to participation, which also includes the consent to share the dataset. The dataset does not contain any personal information from the participants, pertaining to their identity or residency. All participants' data are organized using alphanumerical identifiers. The control group ranges from S1 to S20 and the clinical group from P1 to P14.

Imitation Paradigms. The tasks performed by the participants involved the imitation of specific movement patterns designed to target different emotional and social contexts: (i) walking (confident *vs*. sad), and

(ii) dancing (solo *vs*. duo). The paradigms aimed to encourage participants' engagement thereby triggering the recruitment of the mirror neuron system. The walking and dancing tasks were chosen given their social relevance. Walking allows to study motion-related patterns in a daily activity, which may reflect different emotional states. The dancing task, a more complex motion task, allows for the assessment of implicit social-related motion patterns. Participants were instructed to follow the action instructions displayed on the screen, which were based on point-light animations inspired by biological motion stimuli[13]. A representation of a single frame from the confident walk video is shown in Fig. 3.

The experimental protocols followed for both motion tasks are illustrated in Fig. 3 and are detailed below. EEG and 3D motion data were captured at the respective sampling rate. Event triggers were introduced simultaneously in each data stream providing data alignment. The paradigms were programmed in MathWorks' Matlab® taking advantage of the Psychtoolbox-3[14]. Each recording session for each participant was structured into recording blocks and breaks for rest. Participants performed the tasks in four recording blocks for the control group, and three recording blocks for the autistic group. Each block consisted of ten trials for each condition performed in random order (e.g., confident, sad, natural/control; solo, pair, and body shake/control), totaling 30 trials per block.

Walking Task. For the walking task, participants started from an initial position marked on the ground with blue tape. This location allowed a walking range of approximately 7 meters, which ensured the maximum distance possible while maintaining motion tracking and EEG recording coverage. Each trial started with a central fixation cross (visual angle of 1.8°) baseline period of 3 seconds. Then, the instruction based on a video of a walking actor labeled as confident or sad was presented for 3 seconds. There was also a neutral instruction, which served as a control condition, which was presented purely as text (no image is shown). This condition elicited the participants' natural walking pattern. As soon as the instruction disappeared, a beeping sound indicated that the participants should start the motion task. The participants had a period of 4 seconds to walk straight ahead following the patterns given in the instruction video. During this period, there was only a black background on screen. A second beep marked the end of the motion period, and the participants had 6 seconds to return to the initial position.

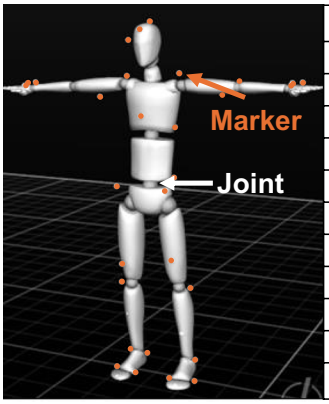
Dancing Task. For the dancing task, participants received instructions while positioned at 2 meters from the screen. This point, also marked with blue tape, was located at the center of the tracking area, to maximize participants' freedom of movement. Each trial started with a baseline period of 1 second during which a central fixation cross (visual angle of 3.6°) was displayed. Then a 3-second instruction period presented a video of a dancing actor labeled as solo or duo. Additionally, a neutral instruction, similar to the walking paradigm, was presented as text only, labeled "body shake". As soon as the instruction disappeared, a beeping sound indicated that the participant should start the motion task. The participants had 4 seconds to perform the instructed dance within a circle of 1-meter radius, following the patterns shown in the instruction video. A second beep marked the end of the motion period, and the participants had 3 seconds to return to the initial position.

Visual Stimuli. All the visual stimuli were generated using Psychtoolbox-3. The screen used for presentation had a resolution of 1920 × 1080 pixels and a diagonal dimension of 49 inches. The stimuli were displayed as white elements on a black background. The fixation cross was displayed in the center of the screen with a size of 80 × 80 pixels. The text displayed on the screen, either accompanying the point-light animations or on its own, had a font size of 48 pixels. All text is presented in Portuguese, horizontally centered and vertically placed 180 pixels above the screen's center (66.7% of the screen's height). The instructional point-light animations were displayed at a 30 *Hz* frame rate, with moving points of 28 pixels in size. These animations were generated using 3D motion captures from public databases. The extracted 3D joint coordinates were used to create 2D frames, centered horizontally and vertically using the hip point as reference. The 3D motion captures were selected as follows:

- Confident walk: From the CMU database[15] video with reference `82_09`, frames used 750-1292, no scaling, speed 4x, no rotation and 17 points used.
- Sad walk: From the CMU database[15] video with reference `91_13`, frames used 500-1300, no scaling, speed 4x, rotation $\frac{-\pi}{2}$ on the vertical axis y and 17 points used.
- Solo dancing: From the University of Cyprus database[16] video with reference `Vasso_Salsa_Shines-01`, frames used 1700-2500, scaling factor of 5, speed 3x, no rotation and 21 points used.
- Pair dancing: From the HDM5 mocap database[17] video with reference `HDM_dg_03-01_02_120`, frames used 1700-3500, scaling factor of 4.5, speed 3x, no rotation and 21 points used.

3D Motion Data Acquisition. The motion capture system recorded 3D motion from the reflective markers placed on the motion capture suit worn by the participants. The data were recorded through a polling process, where Matlab scripts requested data to the Motive software. The sampling rate varied depending on the polling cycle, resulting in a variable sampling time between samples. Across the collected 3D motion data, the average sampling rate was 50 *Hz*. Every sample has a time stamp.

The motion data are divided into two sets, 3D markers and rigid body joints, as illustrated in Fig. 4. The 37 markers placed on the suit are provided in Cartesian coordinates (x,y,z). Each rigid body joint is represented by a 7-dimensional vector containing Cartesian coordinates and a quaternion: (x, y, z, a, b, c, d), where (x, y, z) correspond to the joint's position in space and (a, b, c, d) represent its orientation. The coordinate reference system



Body Joints	
1. Hip	12. Left Forearm
2. Abdomen	13. Left Hand
3. Chest	14.Right Thigh
4. Neck	15. Right Shin
5. Head	16. Right Foot
6. Right Shoulder	17. Left Thigh
7. Right Upper Arm	18. Left Shin
8. Right Forearm	19. Left Foot
9. Right Hand	20. Right Toe
10. Left Shoulder	21. Left Toe
11. Left Upper Arm	

Fig. 4 Illustration of the positioning of markers and joints in an articulated figurine, along with the naming of the rigid body joints. 3D motion data includes 37 markers and 21 joints.

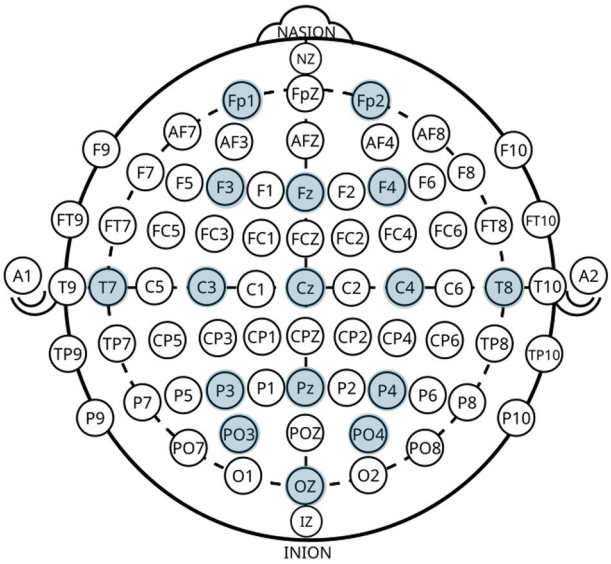


Fig. 5 EEG channel locations used for data acquisition. The 16 active channels used during the experiments are highlighted in blue, distributed over the whole head (frontal, central, parietal, and occipital regions).

is relative to the ground plane. The labels and placement of the markers and rigid body joints are provided in a separate file in the dataset.

EEG Data Acquisition. EEG data were recorded with g.Tec g.Nautilus at a sampling rate of 250 *Hz*, with a notch filter at 50 *Hz* applied to remove powerline interference. The reference channel was placed at the right ear lobe. Data were collected from a maximum of 16 EEG channels at the following positions: Fp1, Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P3, Pz, P4, PO3, PO4 and Oz, distributed across the scalp as seen in Fig. 5. In some cases, data from channel Oz (participants S1 to S20) could not be recorded. In other cases data from both channel Oz and channel PO3 were unavailable (participants P1 to P7). A list of participants with the corresponding recorded channels is provided below:

- Participants S1 - S20 (15 channels available): FP1, FP2, F3, FZ, F4, T7, C3, CZ, C4', T8, P3, PZ, P4, PO3 and PO4
- Participants P1 - P7 (14 channels available): FP1, FP2, F3, FZ, F4, T7, C3, CZ, C4, T8, P3, PZ, P4 and PO4
- Participants P8 - P14 (16 channels available): FP1, FP2, F3, FZ, F4, T7, C3, CZ, C4, T8, P3, PZ, P4, PO3, PO4 and Oz

Since g.Tec's g.Nautilus is a wireless EEG cap, a possible source of artifacts in the data stream is connection losses. However, this artifact is expected to be nonsignificant and can be addressed during EEG data preprocessing steps.

Before EEG data acquisition, the participants' scalp was prepared using a skin exfoliation gel (Weaver and Company Nuprep skin prep gel) and a conductive gel (g.Tec g.GAMMA gel). The electrode impedance was kept below 5 kΩ.

#	Stimuli	#	Cue	
			Walk	Dance
1	Fixation cross	1	Confident walk	Solo dancing
2	Instruction (text and moving point-light animation)	2	Natural walk	Body shake
3	Lower tone auditory beep	3	Sad walk	Imaginary duo
4	Execution of Movement			
5	Higher tone auditory beep			
6	Return Instruction			

Table 2. Correspondence between numerical and categorical labels for Stimuli and cues. The numerical labels correspond to the event triggers found in the data streams.

	EEG/IMU		3D Motion	
	Control	Clinical	Control	Clinical
Dancing	118 ± 8	90 ± 11	99 ± 36	77 ± 19
Walking	120 ± 7	87 ± 8	80 ± 43	63 ± 37

Table 3. Number of trials per sensor modality within each group. The presented values are averages and standard deviations of trials per participant.

Along with the EEG data, the g. Nautilus also recorded data from the inertial measurement unit (IMU), which measured acceleration data in its 3 axes (x, y, z). Acceleration data were recorded using the same sampling rate and data structure as EEG data.

Data Alignment. The three data modalities (EEG, IMU, and 3D motion) were collected at two different sampling rates. To ensure data alignment between EEG/IMU and 3D motion data, we embed time-event triggers into the data streams. These triggers identify, within each trial/epoch, the condition (confident, sad, natural/solo, pair, body shake) for the respective paradigm (walking or dancing), and the corresponding temporal segment within the epoch (fixation cross, instruction, execution, etc.). These triggers are introduced as two separate data channels (trial/epoch condition and trial/epoch time segment) in the data streams, through a numerical code. Table 2 presents the numerical code for each trigger, and their corresponding categories.

There is one folder for each participant containing one file per sensor modality and per recording block (a block consists of $3 \times 10 = 30$ trials/epochs). The number of files for each sensor modality depends on the total number of recording blocks collected during acquisition. The files corresponding to the same recording block for each sensor modality should be used for multimodal analyses. Due to technical issues, the 3D motion data does not match the exact number of recording blocks as the EEG data. Table 3 presents an overview of the difference between the sensor modalities, showing the average and standard deviation of the number of trials/epochs per participant within each group and paradigm.

The 3D motion data files contain two separate registers for the stimuli and cues stored independently. In contrast, the EEG data files embed the stimuli and cues directly within the data as two separate channels, corresponding to the two lowest rows of the data matrix. Stimuli and cues are sampled at the same sampling rate as the corresponding data modality where they are embedded in.

Data Records

The Move4AS dataset is stored in the Figshare repository[18]. The dataset is organized in folders. The root folder, starting hierarchically, contains each participant's label folder. Participants in the control group range from S1 to S20, while on the clinical group participants range from P1 to P14. Within each participant's label folder, the paradigm folder can be found, either "walk" or "dance". Within these folders, the data files are placed with a specific name for the data modality and the respective recording block for the participant. Figure 6 summarizes the structure and naming for the folders and files of the dataset. The data files found in the dataset are in `.mat` format.

Within the 3D motion data files modality the data registers of relevance and their dimensions are as follows:

- `rigidbodyData`: This cell matrix contains the 3D coordinates and quaternion samples for each of the 21 rigid body joints. Its dimensions are $1 \times N_s$ cells, where each cell is of size 7×21. N_s is the number of samples.
- `markerData`: This cell matrix contains the 3D coordinates samples for each of the 37 reflective markers. Its dimensions are $1 \times N_s$ cells, where each cell is of size 3×37.
- `cueRegister`: This register is a $1 \times N_s$ vector pertaining to the cue label for each sample.
- `stimRegister`: This register is a $1 \times N_s$ vector pertaining to the stimuli label for each sample.
- `timestamp`: This register is a $1 \times N_s$ vector pertaining to the timestamp for each sample.

The EEG data files contain a single matrix `eegDataT` of dimensions $N_{channels} \times N_s$, where $N_{channels}$ are the number of EEG channels plus 2 bottom rows, the stimuli and cue labels for each sample, respectively. N_s is the number of samples.

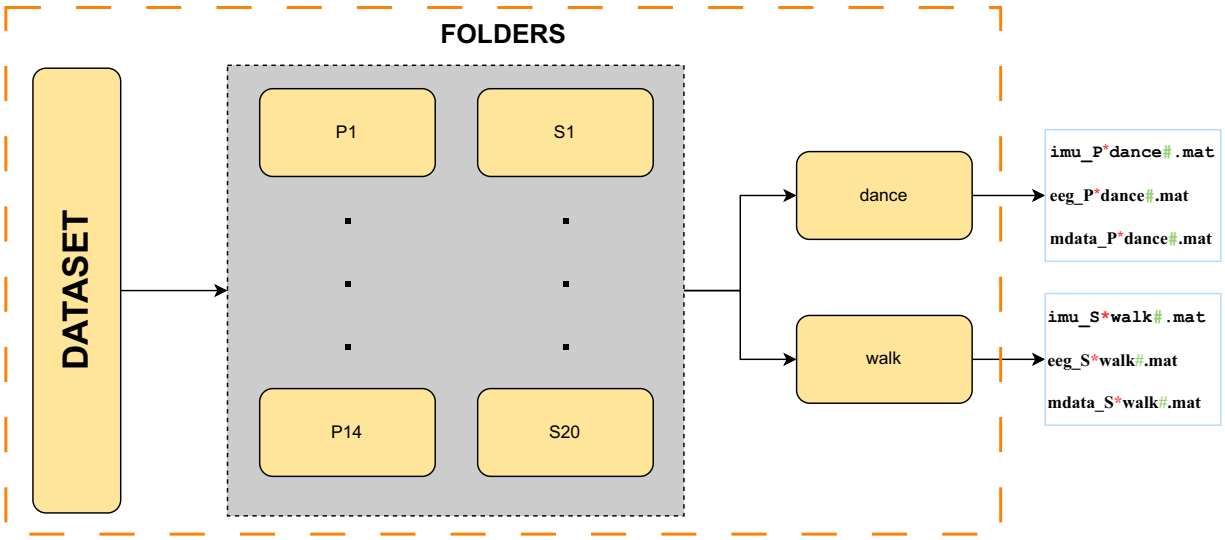


Fig. 6 Dataset's folders and files organization. At the file level the symbol ∗ represents the participants numerical identifier and # the recording block for the participant in the paradigm. A file is also named with P or an S depending on the participant's group.

File Name	Description
`Participants.xlsx`	Biological and neuropsychological information per participant.
`3DMotion_Participants_info.xlsx`	Description of limitations found during 3D motion data inspection per participant's recording block (corresponding to each data file), and list of trials/epochs used in the technical validation.
`EEG_Participants_info.xlsx`	Detailed description of limitations found per participant during EEG acquisition.
`channelslocation14to15channels.ced`	EEGlab compatible file of EEG channel locations for participants recorded with 14 or 15 usable channels.
`channelslocation16channels.ced`	EEGlab compatible file of EEG channel locations for participants recorded with 16 usable channels.
`Skeletal_info.mat`	Matlab `.mat` file with positioning and labels of the marker points and rigid body joints. For the rigid body joints, there is also the hierarchy of each joint's parent.
`Imitation_Tasks_videos.zip`	This file contains the video sequences presented to participants during each imitation task. Textual cues are given in Portuguese. Each imitation sequence consists of four sequential phases: 1. fixation cross, 2. Observation of textual and point-light animation cues 3. black screen, corresponding to the execution of motion. 4. Textual cue to return to the initial position.
`Preprocess_EEG_rawfiles.m`	Matlab `.m` script file to read and preprocess EEG raw data. Uses the EEGlab toolbox.
`Preprocess_3DMotion_rawfiles.zip`	Python code to preprocess the 3D motion raw files. It performs parsing and extraction of desired stimuli parts of each epoch, interpolates samples to have a constant sampling time, and performs skeleton normalization for equal skeleton segments' lengths across all participants. The `README.txt` file, found inside, provides usage notes.

Table 4. Brief description of the files' contents found in the dataset's root folder.

Of particular importance, is the fact that when processing participants where only 14 usable channels were recorded, the 14th row should be considered as noise. The channel location files are provided in the dataset's root directory.

Coming from the same EEG amplifier, the IMU data files contain a single matrix `imuDataT` of dimensions $5 \times N_s$, where the 3D accelerations are the first 3 rows, and the stimuli and cue labels for each sample, respectively, are the final 2 rows. N_s is the number of samples.

At the dataset's root directory, there are supporting files and code for dataset handling, parsing and preprocessing. These files also provide descriptions for each data modality and their corresponding recording blocks' particular limitations. Participants neuropsychological measurements and biological data are present in a `.xlsx` file. Table 4 describes each one of these files.

Technical Validation

In this section, each modality was analyzed separately. The goal was to confirm the presence of relevant information within the dataset, which encourages research into this topic using the dataset. We quantified motion within each group and applied a simple classification approach to discriminate between groups.

3D Motion Data Analysis. To analyze the 3D motion modality's data, we performed a participant-based and group-based motion quantification of the imitation tasks' execution period. Each participant's data were

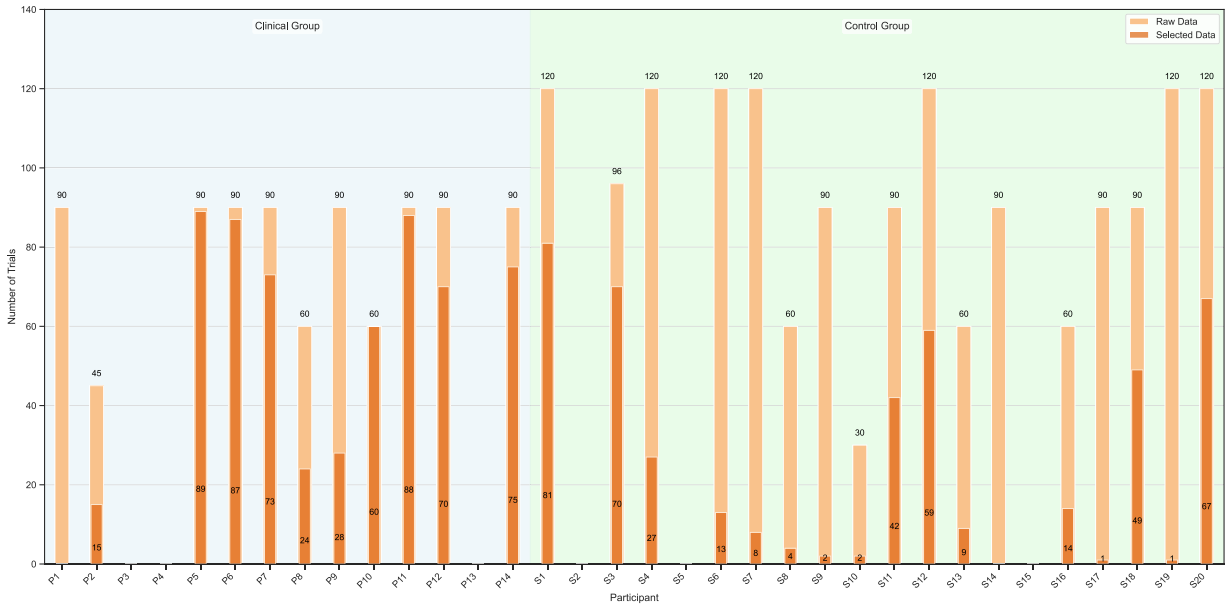


Fig. 7 Number of trials before and after inspection of the 3D motion data for the walking task.

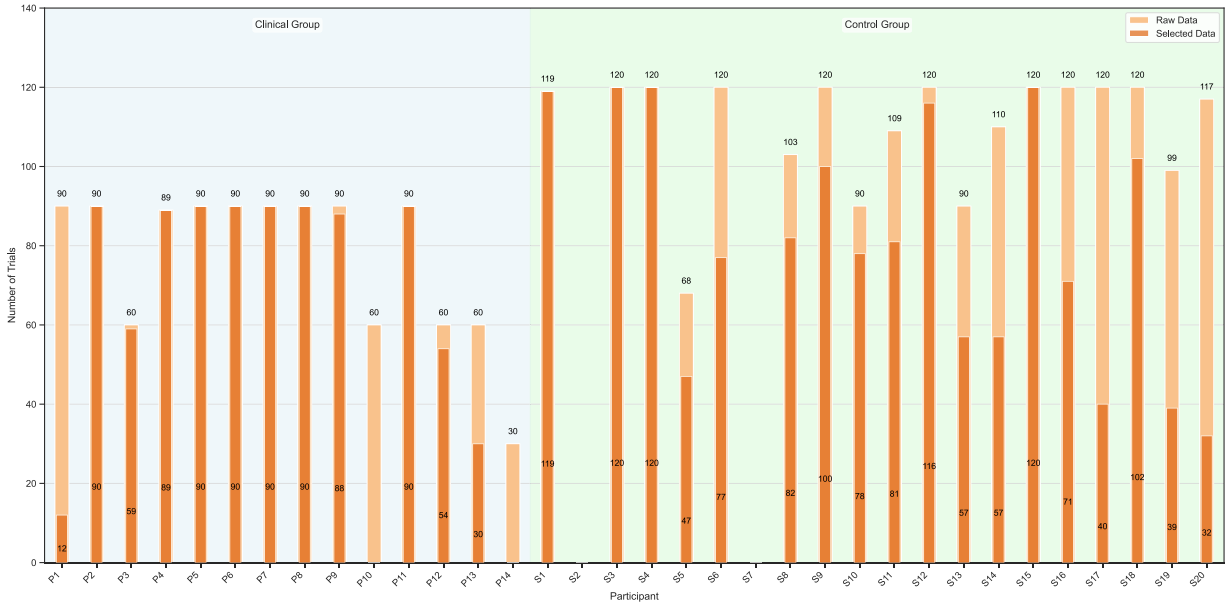


Fig. 8 Number of trials before and after inspection of the 3D motion data for the dancing task.

divided into several epochs. Each rigid body joint's motion was summed over each epoch to have a measure of how much it has moved.

Before preprocessing the data, a visual inspection was conducted to identify artifacts. A trial-based inspection was applied to each recording block, and unusable trials were excluded. We encountered issues comprising uninterpretable skeletal reconstructions, and incorrect upper limb or lower limb tracking. The file `3DMotion_Participants_info.xlsx` (included in the dataset repository) lists the selected trials and provides comments on any issues detected. Figures 7 and 8 show the number of trials before and after visual inspection for each participant. In the code used in this section, the parameter "`-blacklist`" (code in `Preprocess_3DMotion_rawfiles.zip`) lists the excluded recording blocks. The whole dataset is provided since the reported observations should be considered depending on the analyses being performed by the dataset users.

Interpolation. The first preprocessing step involved time interpolation of the execution period within each epoch. Due to the variable sampling rate, samples have variable timestamp intervals. An interpolation was

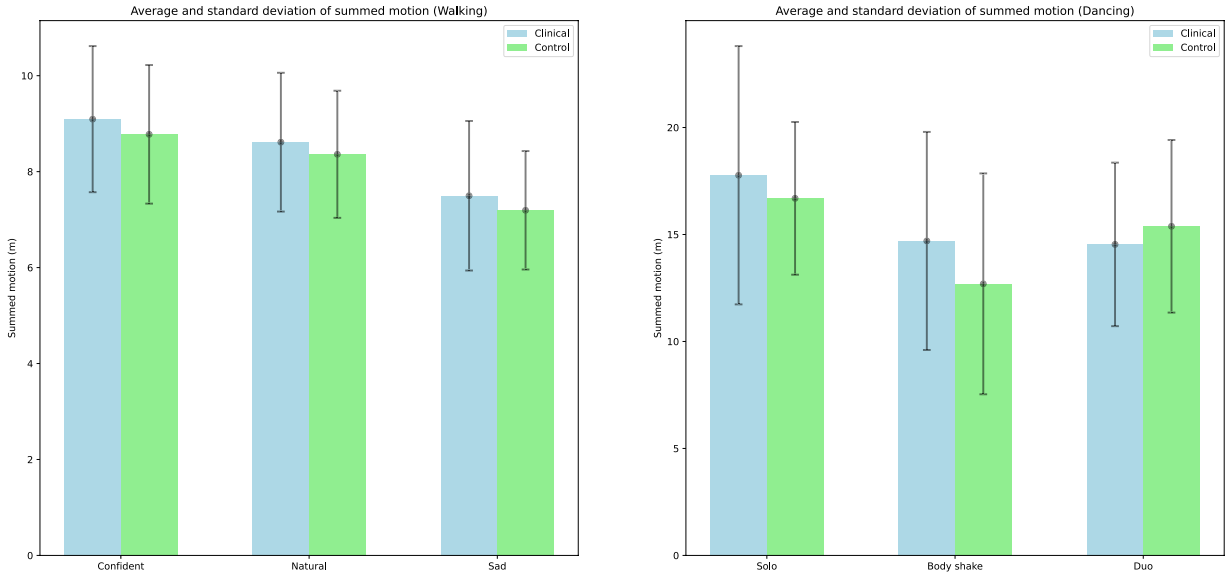


Fig. 9 Quantification of the summed up motion distance for each group. It is presented the average summed motion for each paradigm and respective cues, with the respective standard deviation. The motion values are high due to the summed motion of all the 21 joints combined.

carried out to allow to adequately quantify the motion. Let T be the set of timestamps (T is therefore different for each sample). $t_{int} \in T$ denotes the point in time that the data is interpolated to, $t_i \in T$ the previous time stamp before t_{int}, and $t_{i+1} \in T$ the next timestamp after t_{int}. The interpolation was computed by:

$$S(t_{int}) = S(t_i) + \frac{(t_{int} - t_i)}{(t_{i+1} - t_i)} \cdot (S(t_{i+1}) - S(t_i)) \tag{1}$$

Where $S(t)$ is the 3D motion sample (either marker or rigid body joint) at timestamp t, being either t_{int}, t_i or t_{i+1}. Therefore, after this step, all execution segments were equally sampled, containing N samples, N being the highest number of samples found in the dataset for the execution segments.

Normalization. To mitigate the variability of participants' body sizes, we performed a skeleton's segment-wise normalization. Meaning, that for every direct joint-to-joint segment of the body (e.g., shoulder to elbow), the segment was normalized to the size of that segment's average taken from all the participants. Therefore, the average segment size for one participant was calculated and then a normalization factor was applied. The normalization methodology follows the work in[19]. The result was a normalized skeleton for each participant. This allowed for an accurate comparison of motion between participants and groups. It should be noted that when computing the motion quantification, the motion measurements are normalized.

Motion quantification. The employed motion quantification took into account the reference system placed in the hip joint for the first sample of each epoch. It was also considered each joint's hierarchy, which allowed to remove the influence of the motion of a joint's parent on that respective joint. For instance, the influence of the elbow's motion on the hand's joint's motion. Therefore, the following transformation was first applied to each joint J and its so-called parent J_p for each sample in the interpolated and normalized dataset, before quantifying the motion, as in:

$$S(t, J) = S(t, J) - S(t, J_p) \tag{2}$$

Where the computation was performed for each dataset's sample S at timestamp t for each joint and its parent.

This motion corresponds to the displacement of a joint over a time sequence or epoch T. To quantify the motion of each joint we used:

$$M_J = \sum_{i}^{T} S(t_{i+1}) - S(t_i) \tag{3}$$

Where M_J is the summed motion of joint J across the whole time sequence. This calculation was performed for each joint of a participant's data within each epoch. Then, we computed the participant's full body motion quantification, by summing all the joints' motion, within the respective epoch. Since the skeleton's segments are normalized, the quantification is not the physical displacement of each participant, but rather a relative value that enables comparison across participants.

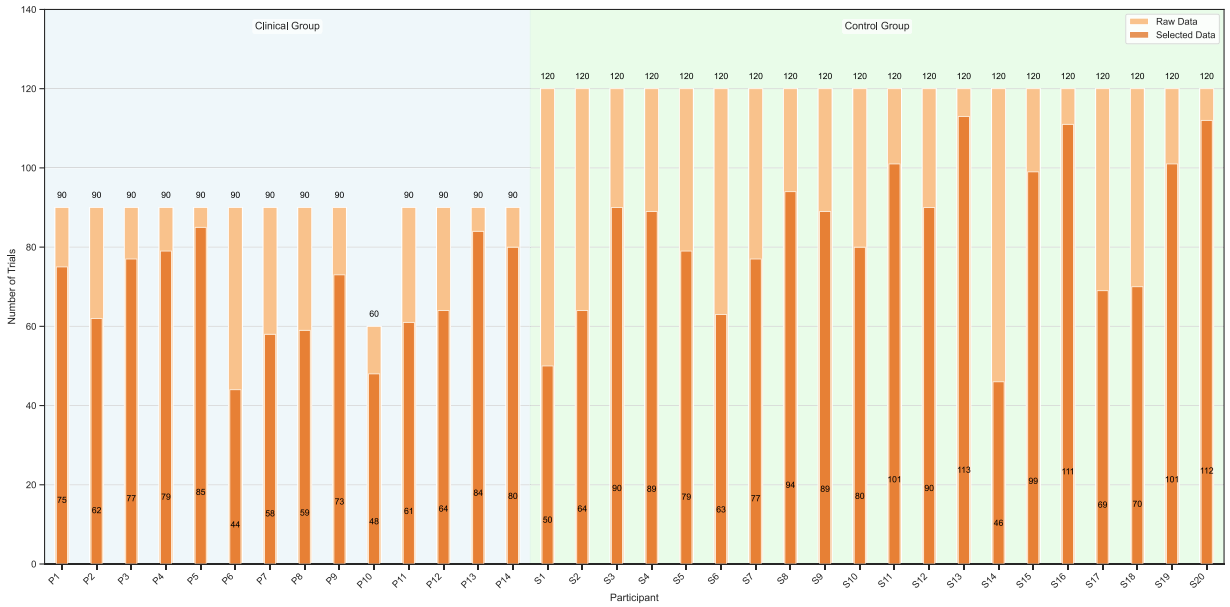


Fig. 10 Number of trials before and after inspection of the EEG data for the walking task.

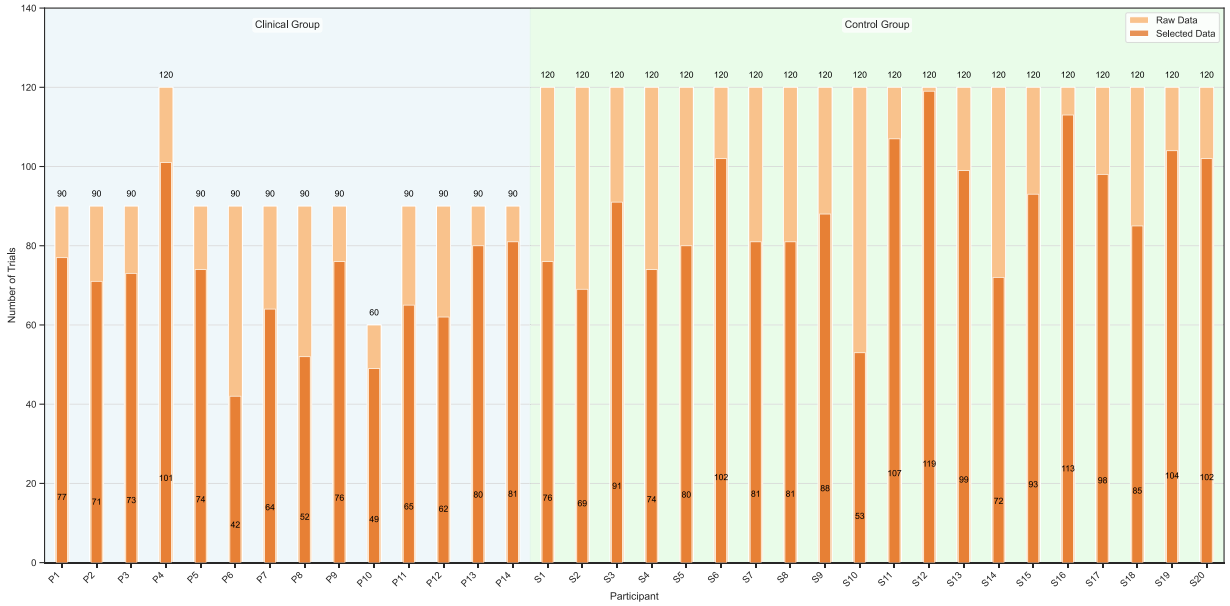


Fig. 11 Number of trials before and after inspection of the EEG data for the dancing task.

For group-level analysis, we averaged the full-body motion across all epochs for each group and imitation task (walking and dancing). The results are presented in Fig. 9 showing the average and standard deviation in meters for each motion condition. Looking at the figure, we observe distinctions between groups. This observation reinforces the study of motor function in AS, showing the relevance of the addition of the 3D motion modality into this dataset.

EEG Data Analysis. We have performed a previous preliminary validation of the collected data in[20], where we analyzed only the control group. The goal was to evaluate the hypothesis that, in the μ frequency band (8-13 *Hz*), specific oscillatory signatures would be observed during motion recognition and execution. This band is known to be related to the mirror neuron system[21,22]. That work demonstrated the correct recruitment of the brain regions related to motion, validating the paradigms, and collected data.

In this paper, we focused on discriminating between autistic and control groups to assess whether the data contain meaningful discriminative patterns. This is important to validate the relevance of this dataset, supporting its potential to uncover underlying neural mechanisms of motor function.

Paradigm	Accuracy (%)	Average summed motion (m)	
		Control	Clinical
Dancing	71.4	0.11	0.14
Walking	78	0.08	0.10

Table 5. Classification results for group discrimination. The average summed up motion distance (head's total displacement) across all the epochs of each group, in the instruction period, is also provided, confirming the residual quantity of motion during this period for both groups.

Considering the temporal sequence of each epoch, we focused on the 3 seconds of biological motion recognition (instruction). This is the period in which the participants observed the imitation tasks and were standing still. This was the time frame in which there was no considerable motion involvement.

For each imitation task (walking and dancing), we performed a classification test between groups. We considered only the epochs involving imitation, in which point-light animations and text were displayed. The neutral conditions were not considered since there is no imitation task involved. We divided the dataset into autistic (clinical) and control groups. The two condition types of epochs for all participants are compiled together in each group, and labeled according to the group. We further divided the data for each group into training and testing, being 80% of the epochs (3-second windows) for training.

The EEG data were preprocessed offline with a Hamming windowed sinc FIR bandpass filter between 1 and 45*Hz*, followed by removal of epochs that presented system disconnections. Independent component analysis (ICA) was used to remove artifacts from eye blinking, muscular interference, and channels with low signal quality. The EEG channels used are (Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4). The EEG data was preprocessed using the EEGlab[23] toolbox in Matlab. The whole number of epochs per participant in the preprocessed dataset is shown in Figs. 10 and 11.

The classification strategy was based on a Common Spatial Pattern (CSP) feature extractor[24] combined with a Linear Discriminant Analysis (LDA) model. The LDA model was fed with the first and last projections of CSP, pertaining to a two-value vector of the logarithmic variance of the power. For each imitation task (dancing and walking), a binary classification was performed to discriminate between groups.

Looking at Table 5, it is observed that this simplistic classification test points toward discriminative features present in the data. To guarantee that there was minimal influence from motion in this classification, we also present the accelerometer data recorded by the EEG amplifier. Looking at the two groups, the same average amount of motion is observed between them, during the instruction period, and at minimal motion ranges.

Usage Notes

For the purpose of reading and analyzing the provided dataset, MATLAB or Python are recommended. The data should be preprocessed, for removal of noisy or faulty epochs and filtering. We provide code scripts which are in the same root folder as the dataset, which was used for preprocessing data as in the Technical Validation section. For 3D motion data processing, we used Python version 3.12.12 with Scipy 1.13.0, Numpy 1.26.4, and Pickle 4.0 toolboxes. EEG data preprocessing was performed using custom scripts based on the EEGlab toolbox (version 2024.2.0) running in MATLAB R2021b. The use of these scripts is optional and is intended as a reference for users of the dataset.

Code availability

There is no mandatory code needed to use this dataset. The provided code scripts can be found in[18], and are based on MATLAB and Python, and are used for preprocessing. They are provided to facilitate quick data handling. They are free to use. They can be found in the root folder of this dataset.

Received: 4 February 2025; Accepted: 2 June 2025;
Published online: 07 June 2025

References

1. Kangarani-Farahani, M., Malik, M. A. & Zwicker, J. G. Motor impairments in children with autism spectrum disorder: a systematic review and meta-analysis. *Journal of Autism and Developmental Disorders* 1–21 (2023).
2. Gong, L. *et al*. Abnormal gait patterns in autism spectrum disorder and their correlations with social impairments. *Autism Research* **13**, 1215–1226 (2020).
3. Cook, J. From movement kinematics to social cognition: the case of autism. *Philosophical Transactions of the Royal Society B: Biological Sciences* **371**, 20150372 (2016).
4. Jequier Gygax, M., Maillard, A. M. & Favre, J. Could gait biomechanics become a marker of atypical neuronal circuitry in human development?—the example of autism spectrum disorder. *Frontiers in bioengineering and biotechnology* **9**, 624522 (2021).
5. de Belen, R. A. J., Bednarz, T., Sowmya, A. & Del Favero, D. Computer vision in autism spectrum disorder research: a systematic review of published studies from 2009 to 2019. *Translational psychiatry* **10**, 333 (2020).
6. Li, J. *et al*. Identification of autism spectrum disorder based on electroencephalography: A systematic review. *Computers in Biology and Medicine* 108075 (2024).
7. https://www.gtec.at/product/g-nautilus-research/.
8. Lord, C., Rutter, M. & Le Couteur, A. Autism diagnostic interview-revised: a revised version of a diagnostic interview for caregivers of individuals with possible pervasive developmental disorders. *Journal of autism and developmental disorders* **24**, 659–685 (1994).
9. Lord, C. *et al*. Austism diagnostic observation schedule: A standardized observation of communicative and social behavior. *Journal of autism and developmental disorders* **19**, 185–212 (1989).
10. Eickhoff, E. *et al*. Association, ap (2013). diagnostic and statistical manual of mental disorders. https://doi.org/10.1176/appi.books.9780890425596. buysee, dj, reynolds iii, cf, monk, t., berman, sr, & kupfer, dj (1989). The pittsburgh sleep quality index: A new instrument for psychiatric practice and research. psychiatric research, 193-213. *Health* **4**, 1–8 (2013).

11. Wechsler, D. Wechsler adult intelligence scale–. *Frontiers in Psychology* (1997).
12. Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J. & Clubley, E. The autism-spectrum quotient (aq): Evidence from asperger syndrome/high-functioning autism, malesand females, scientists and mathematicians. *Journal of autism and developmental disorders* **31**, 5–17 (2001).
13. Vanrie, J. & Verfaillie, K. Perception of biological motion: A stimulus set of human point-light actions. *Behavior Research Methods, Instruments, & Computers* **36**, 625–629 (2004).
14. Brainard, D. H. & Vision, S. The psychophysics toolbox. *Spatial vision* **10**, 433–436 (1997).
15. CMU Graphics Lab Motion Capture Database. http://mocap.cs.cmu.edu/ Accessed: 2023-02-24.
16. Senecal, S., Nijdam, N. A., Aristidou, A. & Magnenat-Thalmann, N. Salsa dance learning evaluation and motion analysis in gamified virtual reality environment. *Multimedia Tools and Applications* **79**, 24621–24643 (2020).
17. Müller, M. *et al*. Documentation mocap database hdm05. Tech. Rep. CG-2007-2, Universität Bonn (2007).
18. Paulo, J. R. *et al*. Move4AS: A Multimodal Dataset Addressing Motor Function in Autism. *figshare* https://doi.org/10.6084/m9.figshare.28296518.
19. Zanfir, M., Leordeanu, M. & Sminchisescu, C. The moving pose: An efficient 3d kinematics descriptor for low-latency action recognition and detection. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)* (2013).
20. Paulo, J. R. *et al*. A framework for motor function characterization in autism spectrum disorder. In *2023 IEEE 7th Portuguese Meeting on Bioengineering (ENBENG)*, 104–107 (IEEE, 2023).
21. Ulloa, E. R. & Pineda, J. A. Recognition of point-light biological motion: mu rhythms and mirror neuron activity. *Behavioural brain research* **183**, 188–194 (2007).
22. Oberman, L. M. *et al*. Eeg evidence for mirror neuron dysfunction in autism spectrum disorders. *Cognitive brain research* **24**, 190–198 (2005).
23. Delorme, A. & Makeig, S. Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis. *Journal of neuroscience methods* **134**, 9–21 (2004).
24. Zancanaro, A., Cisotto, G., Paulo, J. R., Pires, G. & Nunes, U. J. Cnn-based approaches for cross-subject classification in motor imagery: From the state-of-the-art to dynamicnet. In *2021 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB)*, 1–7 (IEEE, 2021).

Acknowledgements

This work is financed by national funds through FCT - Foundation for Science and Technology, I.P., under the grants 2023.07023.CEECIND/CP2863/CT0001 (https://doi.org/10.54499/2023.07023.CEECIND/CP2863/CT0001) UIDB/00048/2020 (https://doi.org/10.54499/UIDB/00048/2020), UIDP/00048/2020 (https://doi.org/10.54499/UIDP/00048/2020), UIDP&B/4950/2020, CEECINSTLA/00026/2022, and 2021.01469.CEECIND/CP1656/CT0017 (https://doi.org/10.54499/2021.01469.CEECIND/CP1656/CT0017).

Author contributions

J.R.P. collected data, analyzed and interpreted data, developed the protocol for data collection, and is the primary author of the manuscript. T.S. collected data, helped develop the protocol for data collection, and helped write and edit the manuscript. J.P. collected data, helped preprocess the dataset, and developed and wrote the code used in the experiments. G.P. helped develop the protocol for data collection and helped write and edit the manuscript. S.M. collected neuropsychological data. L.P. inspected and processed 3D motion data. M.V. helped preprocessing 3D motion data. M.C.B. helped develop the protocol for data collection and helped write and edit the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to J.R.P.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by-nc-nd/4.0/.

© The Author(s) 2025