**Methods**

**Subjects & measurements**

Nine FA participants (3 males and 6 females, aged 24-63) and three controls (1 male and 2 females, aged 25-56) participated in this study. FA patients had all been diagnosed with Friedreich’s ataxia based on clinical criteria and a genetically confirmed GAA-repeat expansion on both alleles of the *FXN* gene. More information on the patient selection process is available at 1. They had all provided written informed consent before any study-related procedures were initiated. Our clinical trial was approved by the UK Medicines and Healthcare Products Regulatory Agency (MHRA; EudraCT 2011-002744-27), the Riverside Research Ethics Committee (11/LO/0998) and the Imperial College London Joint Research & Compliance Office. All measurements were done at our clinical facility (NIHR Imperial Centre for Translational and Experimental Medicine, Hammersmith Hospital).

Measurements were taken four times from the FA patients and once from the controls during the course of the study (Day-1/Baseline, after 3 weeks, 3 months and 9 months) and this enabled collection of behavioral data that can be used in monitoring the progression of the ataxic disease on a longitudinal scale. One of the FA patients dropped out of the study after 2nd visit due to personal reasons however, we still included the collected data in the further analysis where possible. Motion capture suit data was not collected during the last visit of another patient because of technical issues. Blood sample for FXN measurement was not collected for a patient. The characteristics of the participants of our study is listed in Supplementary Table 1.

The EFACTS study data comes from a longitudinal study2 of a large cohort of Friedreich's ataxia patients from 11 European study sites where the patients were seen at baseline, 1 year, and 2 years and the different clinical scales were recorded. For our analysis, we included only subjects who had 2 longitudinal visits. Also, for SCAFI, we excluded subjects who did not perform the tests for reasons other than “unable to perform”. The subset of EFACTS data used for our analysis included 425 subjects for SARA and 302 subjects for SCAFI. The characteristics of the EFACTS study participants included in our analysis is listed in Supplementary Table 2.

**Wearable full-body motion capture system (the “suit”)**

The movement from the entire body was recorded using an IGS-180 motion capture suit [Animazoo UK Ltd, Brighton, UK]. The suit consists of an elastic Lycra trouser and jacket with 17 sensors embedded into the fabric to measure the movement of various limbs. The sensors are 9-axis inertial measurement units (IMUs) and the data from all sensors can be streamed wirelessly to a laptop at 60Hz. The calibration of the motion capture suit is performed using a simple routine provided by the manufacturer as part of the control software. The suit reports the motion data fused with a skeleton structure in a BVH format, which saves each joint's position as Euler angles. In Fig. 1d, we show a FA patient performing the 8 Meter Walk clinical assessment while wearing the motion capture suit. The same figure also shows a few of the reported joint angular positions throughout the task and a reconstruction of the body posture at a single frame.

**Standard operating procedures for the suit**

The suit required the assistance of a trained nurse (not the carer) when putting it on or taking it off during the experiments, to avoid damaging the sensors in the process. First, the subjects took off their shoes and trousers and put on the suit trousers (we allowed subjects to wear tights, leggings, or other tight-fitting clothes underneath). The suit trousers were tightened by adjusting the Velcro straps around the hips, thighs and calves. The subjects then put the shoes back on and the foot sensors were attached on top of each foot using Velcro straps. Afterwards, the subjects took off any heavy clothes worn on top (jackets, jumpers, or any loose/warm clothes) and put on the suit's jacket. The trouser cables were connected to the splitters inside the jacket and the jacket was zipped and tightened using the Velcro straps on both sides of the trunk, the upper and the lower arms. The jacket was also attached to the trousers using Velcro patches. Then the cap was placed on the subjects' head with the sensor on the left-hand side. Finally, the transmitter was connected to the suit and was placed in the left front pocket along with the battery pack. Taking the suit off followed exactly the reverse process. All these steps are part of our Standard Operating Procedures (SOPs) in accordance with the Good Clinical Practice (GCP) standards and they have been approved for studies involving monitoring of patients with neurodegenerative disorders. These steps ensured patients' safety during the experiments and protected the integrity of the suit.

**Standard FA clinical assessments (SARA and SCAFI clinical scales)**

We used two clinical scales, the Scale for the Assessment and Rating of Ataxia (SARA) and the Spinocerebellar Ataxia Functional Index (SCAFI). The Scale for the Assessment and Rating of Ataxia (SARA) has been found to be one of the most appropriate ways to measure disease severity and progression in FA patients3. SARA is a discrete scale scored from 0 (no ataxia) to 40 (severe ataxia) and it is based on an aggregate score of the following eight sub-tests: gait (0-8 score), stance (0-6 score), sitting (0-4 score), speech disturbance (0-6 score), lack of coordination in finger chase (0-4 score), tremor during nose to finger test (0-4 score), fast alternating hand movements (0-4 score) and heel-shin slide (0-4 score)4. The Spinocerebellar Ataxia Functional Index (SCAFI) is a continuous scale composed of the following 3 time-based sub-tests: the 8 Meter Walk (8MW), the 9-Hole Peg Test (9HPT) and the rate of repetition of the phrase “PATA” over 10 seconds (PATA). These components are then z-scored across all subjects and expressed as a standard deviation (SD) from the baseline mean. Being further away from the baseline suggests a more severe ataxia5.

We focused on the analysis of the 8 Meter Walk (8MW) and 9-Hole Peg Test (9HPT), two simple scenarios which are closely related to activities we perform on a daily basis (i.e., walking around in the house and performing tasks while seated on a table).

The 8 Meter Walk (8MW) clinical subscale we focused is measured as the time needed to walk an 8m distance with any assistive device as quickly as possible but safely (without the help of another person). 8MW is measured from standing with feet behind the start line until one of the legs reach the 8-meter mark5. Fig. 1d presents a typical 8MW time-lapse (every frame shown is 0.5s apart) as collected by the motion capture suit. The second clinical subscale we focused on is the 9 Hole Peg Test (9HPT), which is defined as the time taken by a subject to complete the 9-hole pegboard (Rolyan 9-hole peg test apparatus, plastic one-piece model [Patterson Medical Ltd, Huthwaite, UK]) and then remove all pegs5. During our clinical trials, the 9HPT was repeated twice for each hand separately (D - Dominant, ND - Non-Dominant) with the writing hand considered to be the dominant one. The hand that was not involved in the test was rested on the subject's lap. Fig. 1e presents our setup where a subject is wearing the motion capture suit while performing the 9HPT and the blue 9-hole board is clearly shown on the table. Additionally, in Fig. 1e we present a typical 9HPT time-lapse (every frame shown is 0.5s apart) from a single subject as collected by the motion capture suit.

**Feature generation:**

The full-body suit supplied us with 51 degrees of freedom (DoF) (3DoF x 17 Joints) joint angular data and 78 degrees of freedom (3DoF x 26 segments) 3D position data of the body segments. The BVH files from all subjects and visits were imported in Matlab R2015b [The Mathworks Inc., Nattick, MA] for analysis. A simple pre-processing has been applied on the data to transform the data into biomechanically meaningful values6 . Using the joint angular and 3D body segment positions from the suit data of the 8MW and 9HPT subtasks, we extracted the features list in Table 1 (F1 - F20). A detailed description of the generation of these features is presented later in the methods. Both 8MW task and the 9HPT task (for each hand) were repeated twice as per the SCAFI protocol. For each repeat of the task, we have a suit recording. Features were generated for each of the two suit recordings separately. So, for each visit of the subject, we have two sets of features for the 8MW task and two sets of features for the 9HPT task.

**Feature selection and model evaluation:**

We applied Gaussian Process (GP) Regression algorithm to combine the extracted behavioral features and find a mapping against the clinical scales. We used a nested cross-validation procedure for feature selection and model evaluation (to avoid leakage of the test data during the feature selection process). The inner cross-validation loop was used for the feature selection and the outer cross-validation loop was used to evaluate the performance of the model. We used a leave-one-subject-out (leave the rows corresponding to all visits of a subject) for both the inner feature selection cross-validation loop and the outer model evaluation cross-validation loop. We used an exhaustive feature selection approach to select the most optimal subset of features.

For s number of subjects with each v visits, the data consists of s x v rows and the outer cross-validation splits the data into s folds (ensuring all the visits of a subject are in a single fold and each fold contains only the rows corresponding to the visits of a single subject). So, we have s training and test folds. Forward feature selection of features was done for each of the s training folds using the leave-one-subject-out cross-validation error of the inner cross-validation loop as the objective function and s subsets of features were generated. The most frequent subset among the s subsets was selected as the optimal subset as the frequency of the subset of features is a measure of the robustness of the subset of selected features to changes in the training data. Finally, the overall performance of the GP regression was evaluated for the selected optimal subset of features using the outer cross-validation for the s test sets. This method ensured that an optimum subset of features is selected without any data leakage of the test set into the training set. This nested cross-validation approach ensured that the test data in each fold of the outer cross-validation loop was never used during feature selection in the inner cross-validation loop and therefore provides a reliable estimate of the model performance. The hyperparameters of the Gaussian process were chosen based on the cross-validation error on the inner nested loop. The predicted values from all the test folds of the outer fold were aggregated and the aggregate root mean squared error (RMSE) and the coefficient of determination (R2) was calculated and reported in the results section.

The cross-sectional predictions of the SARA and SCAFI scores were done for the FA patients and healthy controls. For the longitudinal results (Fig. 4c and 4f), which show the performance of the predictions as a function of the number of subjects used to build the machine learning models, nCk (up to a maximum of 100) combinations (where *n* is the total number of subjects in the dataset and *k* is the number of subjects used for building the machine learning model) of the models were built for each *k* and the mean and standard deviation of the aggregate performance of the nCk models was reported.

**FXN measurement : RNA extraction and Quantitative Real-time polymerase chain reaction (qRT-PCR)**

Human blood samples were obtained from FA patients in accordance with UK Human Tissue Authority ethical guidelines. Peripheral blood mononuclear cells (PBMC) were isolated from the blood samples using a Ficoll-Hypaque TM gradient (Sigma) kit by following the manufacturer’s protocol. Total RNA was isolated from the pelleted PBMC using Trizol (Invitrogen) and reverse transcribed using the ThermoScript TM Reverse Transcription system (Invitrogen) by following the manufacturer’s instructions. Multiplexed qRT-PCR using TaqMan probes targeting FXN and TATA-box binding protein (TBP) were performed in TaqMan Fast Advanced Master Mix (Applied Biosystems). The measured FXN mRNA levels were expressed relative to TBP as the endogenous control mRNA levels. The data presented are the normalized Ct values and therefore the higher the value the lower the level of FXN mRNA.

**Suit features**

This section gives a description of the behavioral features that we extracted from the data of the 8MW test and the 9HPT. Features F1 – F10 were extracted from the suit data of the 8MW task and the features F11 – F20 were extracted from the suit data of the 9HPT task.

**F1 - Coefficient of variation in the walk cycle duration**

We were first interested to examine how repeatable the FA patients’ walking pattern was, therefore we estimated the coefficient of variation of the walk cycle, a feature that is widely used in the analysis of walk patterns in patients with Parkinson’s Disease7. Using the hip and knee angular data from both legs we developed a simple algorithm that can extract the start and stop frame for each step. Then we used these frames to calculate the duration of each walk-cycle. To evaluate how irregular the subjects’ walking cycle was, we evaluated the average Coefficient of Variation (CoV) for each subject’s walking sequence using: CoV = σ/μ, where σ is the standard deviation and μ is the mean of the walking cycle speed. We found that variability in FA patients’ walking cycle, as characterized by their CoV (0.12 ± 0.04) was statistically higher (p < 0.05, Kruskal-Wallis one-way ANOVA) than controls (0.08 ± 0.01), thus FA patients’ walking is more irregular than the controls.

**F2 - Workspace probability density volume & entropy**

We measured the Workspace Volume (WV), a concept that is extensively applied in biomechanics and rehabilitation applications for measuring the rigidity of body parts8,9. Workspace volume can be described as the volume generated by the movements of the limbs in space.  The idea of workspace volume is illustrated in Supplementary Fig. 1a. Since the subjects were not stationary in the 8MW test, we adapted the concept of the workspace volume to make the computation more robust.  We set the subject’s trunk to a fixed reference point and adjusted the position of the other joints relative to the trunk. We then computed the occupancy density of the joints by separating the joint’s 3D locations in space in a grid of 2 x 2 x 2cm voxels. An example is shown in Supplementary Fig. 1a, where the color of each voxel represents the occupancy frequency on a log10 scale. Using the generated occupancy density of the joints, we computed the workspace volume by counting the non-empty voxels and multiplying the result by the volume of a single voxel (i.e., 8 cm3). Applying this analysis across all subjects, we observed that FA patients needed significantly more space (almost double) than the controls to perform the 8MW task (Supplementary Fig. 1b, p<0.001, Kruskal-Wallis one-way ANOVA).

To obtain a measure that is sensitive to the variability of workspace used, we defined the workspace entropy (WE) as negative Log(probability) averaged over all non-empty voxels. Zero entropy implies no variability in the system: the body part occupies only a single voxel, while maximum entropy is achieved when a body part occupies all reachable voxels with equal probability, thus higher entropy implies more disorder/variability. We found that patients applied a wider range of joint configurations which correlated with an increased entropy of the workspace density as shown in Supplementary Fig. 1c, demonstrating a higher entropy in FA patients than controls (p<0.001, Kruskal-Wallis one-way ANOVA). This suggested that not only was the FA patients’ workspace volume larger than controls, but their movements were also more variable, within their workspace volume. Thus, the walking patterns of FA patients were more disordered and less predictable, probably caused by the presence of compensatory mechanisms to balance their sensorimotor dysfunction during the walk.

**F3 - Lower body joint variability**

We examined the variability of hip and knee velocities during the walk in the same way as standard gait analysis methods had been previously applied to Parkinson’s patients10,11. Using step detection algorithm, we segmented the time-series data into walking cycles, afterwards we Z-scored the joint angular velocities of hip and knee joints of each leg across all angular joint movement dimensions (flexion, abduction, and rotation) to make a comparison across subjects fairer. We calculated the average variability along each joint dimension and the results for both FA patients and controls are shown in Supplementary Fig. 2. Patients exhibited a statistically higher variability across all joint dimensions (Kruskal-Wallis one-way ANOVA, where \* represents p< 0.05, \*\* is p < 0.01 and \*\*\* is p < 0.001) which supports our initial hypothesis that FA patients’ walk is more disordered.

**F4 - Walk autocorrelation & decay**

While our measures up to this point focused on spatial features, as defined by the posture of the body, we next wanted to investigate the temporal structure. Autocorrelation is defined as the cross-correlation of a signal with itself at different points in time. We calculated the autocorrelation of the joint angular velocities of each one of the 51 DoF as collected by the suit and the result is shown in Supplementary Fig. 3a. While the 51 individual degrees of freedom exhibit some clear periodical patterns and some fewer periodical patterns, we wanted to analyze if there were underlying commonalities that were conserved. Because the autocorrelation was in a periodic setting, we converted the individual joint’s autocorrelations across time into vectors: We discretized at 50-time points the autocorrelation function using bins of a width corresponding to 4% of a walk cycle. This produces a 50-dimensional vector covering 2 walk cycles (200%). We then performed Principal Component Analysis (PCA) on the collection of these 51 autocorrelation vectors and found that just 3 Principal Components (PCs) can explain 80% of the variability in the autocorrelation signals across the 51 joints (see Supplementary Fig. 3b). The 1st, 2nd and 3rd PCs are plotted in Supplementary Fig. 3c. These data-driven features of the walk-cycle correspond to the various swings of legs, arms and body during walking. Comparing the PCs value at the 1st walk cycle (see Supplementary Fig. 3d), there is a significant difference between patients and controls on the 1st (p < 0.001) and 2nd (p < 0.05) PCs but not on the 3rd (p = 0.93, Kruskal-Wallis one-way ANOVA). This means that both leg and arm swing are more variable in duration than in controls. This suggests that the repeatability of body postures while walking is significantly reduced in FA patients in the temporal domain -- they effectively accelerate and decelerate their swings more randomly than healthy controls.

Since there is a significant decrease in the FA patients’ autocorrelation over time, we were interested in modelling this decrease over multiple walk cycles. We used only the first PC of the autocorrelation signal and re-sampled the data so that the walk cycles of all subjects were aligned (Supplementary Fig. 4a). Then using the projected 1st PC points at each walk cycle (i.e., the peaks of the autocorrelation signal), we found that an exponential fit (y=e-λx) explains the data very well (see Supplementary Fig. 4b), i.e., providing a high Goodness of Fit (average GoF =0.94). Consequently, we applied an exponential fit across all subjects and computed the exponential decay of the autocorrelation functions (i.e., the parameter λ). Supplementary Fig. 4c shows that the value for FA patients is statistically higher than the controls (p < 0.01, Kruskal-Wallis one-way ANOVA), meaning that their autocorrelation is decaying faster and thus their walking cycles increase in variability twice as fast as healthy controls.

**F5 - Channel delay cross-correlation**

While the measures so far focused on spatial or temporal measures, we wanted to capture the correlation structure of the data across space and time. Therefore, we used the channel delay cross-correlation measure, which has been applied for extracting abnormalities in high dimensional neurological and motion capture data12,13. We applied the channel delay cross correlation on our 8MW dataset to capture the spatiotemporal correlation changes between all 51 joints of FA patients and controls. The main step for applying channel delay cross-correlation method is the construction of a 51 x 51 block matrix based on the joint angular velocities we get from the motion capture suit (51 DoF). The blocks along the main diagonal contain the within-channel autocorrelations and the off-diagonal blocks contain the cross-channel correlations. Within each block, the correlations are calculated for 10 different lags (10 linearly spaced lags from zero up to the average walk cycle of the subject). Therefore, the channel delay cross-correlation matrix captures both spatial and temporal correlations of the joints during the walk. The matrix for one subject is shown in Supplementary Fig. 5a.

The next step is to calculate the matrix eigen spectrum, i.e. the array of eigenvalues, sorted from largest to smallest. The eigen spectrum encodes the magnitude of covariance in each (de-correlated) dimension and it is invariant to the ordering of the channel delay cross-correlation matrix columns and thus to relationships among particular time-delayed joints of the body. The eigen spectrums are reported in Supplementary Fig. 5b where the averaged eigen spectrum for patients and controls is shown in red and blue respectively. The decreased power in the patient's first few eigen values (i.e., eigen values with indices 1-20) and the equivalent increase in power for the patient’s remaining eigenvalues (i.e., eigenvalues with indices 20-200) reflect the increased dynamical complexity in their walk when compared with controls. We speculate that this is a reflection of what clinicians subjectively characterize as the more ataxic gait of FA patients.

**F6 - Extremities velocity**

The next feature we were interested to explore was the difference in the velocity profiles of subjects’ extremities as performed in standard gait analysis practices14. Using the extremities’ 3D locations in space (wrists, ankles and head), as provided by the suits’ biomechanical model, we estimated the velocity on each body plane (sagittal, frontal and transverse) and then calculated the magnitude of the velocity by applying root-mean-square (RMS) operation. Using our step detection algorithm, we segmented the velocity signal at each walking step and then averaged the peak velocities observed at extremities across all voxels. The results for each extremity (separated in dominant (D) and non-dominant (ND) side) are presented in Supplementary Fig. 6a where there is a statistical difference between FA patients and controls on the D & ND ankles and the ND wrist (p <0.05, Kruskal-Wallis one-way ANOVA).

**F7 - Walk complexity**

We have quantified the complexity of human walking using a dimensionality reduction algorithm PCA where we observed the number of principal components required to successfully explain the variability in walking motion (higher number of PCs implies a more complex movement)15,16.We have applied the same analysis on our subjects’ joint angular velocities and the results are presented in Supplementary Fig. 6b. It seems like the patients’ kinematics are a lot more complex since they require more PCs to explain the variability present (i.e. to explain 80% of the motion variability in FA patients it requires at least 5 PCs but only 2 PCs are needed for the controls). This observation is supported by the fact that ataxia patients are known to develop compensatory mechanisms to balance out the effects of the disease17.

To achieve quantification of the human movement complexity, we developed a metric based on the previous observations. For each subject, we calculated the area developed under the arc of the variability curve, divided that by the whole area of the upper left triangle and expressed the results as a percentage. We applied this analysis to all subjects and the results are shown in Supplementary Fig. 6c highlighting the statistically increased walk complexity of FA patients when compared to controls (p <0.001, Kruskal-Wallis one-way ANOVA).

**F8 - Legs movement root mean square power spectrum**

Our next feature is based on the analysis of the walking signature on the frequency domain. Spectral analysis of kinematic signals has been efficiently used for detecting abnormal gait patterns18. We low-pass filtered the angular velocities of hip flexion, hip abduction and knee flexion with a 10 Hz cut-off and then extracted a Short-Time Fourier Transform (STFT) based on a 200 ms window with 100 ms overlap. An example is shown in Supplementary Fig. 7a, where we calculated the STFT on the angular velocities from a subjects’ dominant (D) knee flexion and used different colors in the spectrogram (Supplementary Fig. 7b) to represent the power carried by a specific frequency of the signal at a specific moment in time. Afterwards, we computed root-mean-square (RMS) on each window, which summarizes the information content of the power spectrum at each time point (see Supplementary Fig. 7c). Finally, for each walk cycle, we calculated the area under the curve which combines the total energy used by that joint. We applied the same analysis on the lower-body joints of each leg and then averaged the energy presented across all walk cycles. The results are shown in Supplementary Fig. 7d where the FA patients present a significantly lower energy in their D hip flexion, D knee flexion and ND knee flexion (Kruskal-Wallis one-way ANOVA) than controls. This finding is consistent with the muscle weakness in the arms and legs clinically reported to frequently occur in FA19.

**F9 - Joint velocities correlation coefficient**

We additionally investigated the correlations between the movement of the joints of the lower body during the walk by estimating the Pearson’s product-moment correlation coefficients (ρ)20. Since FA patients exhibit a less standardized walking pattern, we would expect the correlations between various joints to be lower. Therefore, we used the angular velocities from the hip flexion & abduction and knee flexion joints and evaluated the correlation coefficients both across joints but also between D and ND leg. The results are shown in Supplementary Fig. 8 which compares the correlation coefficients of FA patients (blue) and controls (red) with most presenting a statistical difference between the two groups (Kruskal-Wallis one-way ANOVA, where \* represents p< 0.05, \*\* is p < 0.01 and \*\*\* is p < 0.001).

**F10 - Head-spine movement plane area**

The last feature we extracted from the 8MW data is based on clinical observations that subjectively characterize FA patients as ‘wobbling’ or sideways ‘swaying’ during the 8m walk. The degree of sway has been suggested to be an early indication of the disease stage in ataxia4. To objectively quantify the “wobbling” walking effect, we used the following approach: we tracked the location of the head in a coordinate system that is stationary with respect to the axes of the hips. Thus, all motion in this coordinate system is seen relative to the hips and is hence always centered on the hips even during locomotion. Then, we calculated the location of the head marker with respect to the hip as shown in Supplementary Fig. 9a. The distance between the head and hips is relatively constant and so the head movements with respect to the hips are localized mainly in a 2-dimensional surface that is orthogonal to the line connecting the hip’s center of mass with the head maker. During walking the head markers move through this plane and hence we calculated the area covered by the head movements generated during the walk of all subjects. Our results show a statistically higher area covered by the FA patients than the controls (see Supplementary Fig. 9b, p < 0.001, Kruskal-Wallis one-way ANOVA), which confirms the qualitative observations “by eye” during the clinical trial. Analyzing the variability of head movements independently for the frontal and sideways axis shows that there is no statistical difference between FA patients and controls on the forward plane (Supplementary Fig. 9c, p = 0.27, Kruskal-Wallis one-way ANOVA), however, this is not true for the sideways movement as FA patients have a statistically higher variability (see Supplementary Fig. 9d, p < 0.001, Kruskal-Wallis one-way ANOVA).

**F11 - Average joint velocity**

The first feature we extracted from the 9HPT data is based on the average angular velocities of the shoulder and elbow joints. The FA disease causes progressive neuro degeneration, and this should result in slower joint velocities during the 9HPT task. The results in Supplementary Fig. 10a supports our hypothesis as the joint velocities of the FA Patients are statistically lower than Controls (p < 0.001, Kruskal-Wallis one-way ANOVA).

**F12 - Upper body complexity**

Our next feature was also used in the 8MW analysis, and it is based on a Principal Component Analysis (PCA) of the joint angular velocities during the 9HPT. In this case, though we only applied the analysis to the upper-body joints, and we also excluded the joints of the hand not performing the task. Supplementary Fig. 10b shows the variability explained by using different numbers of principal components (PCs). Observing the plot, we can see that FA patients require slightly more PCs to explain the variability in their movements than the Controls. This result is consistent with our findings in the 8MW task. We have additionally calculated our complexity metric in the same way as described in the 8MW section and found that FA Patients have statistically more complexity in their movements than Controls (see Supplementary Fig. 10c, p = 0.03, Kruskal-Wallis one-way ANOVA).

**F13 - Workspace probability density volume & entropy**

Similar to the workspace density analysis done for 8MW, we first calculated the density plot for each subject (an example is shown in Supplementary Fig. 11a ), which was then used to estimate the overall workspace volume. Since the task was performed twice per hand, we averaged the volume of each trial based on hand dominance. The results are shown in Supplementary Fig. 11b where the FA Patients seem to have a significant difference between the volume generated by each hand (p = 0.003, paired t-test) something that is not true for Controls as they occupy roughly the same space when performing the task with either hand (p = 0.08, paired t-test). Furthermore, comparing the performance between the two subject groups, the FA Patients use a much larger workspace than Controls when they perform the task with the D hand (p = 0.009, Kruskal-Wallis one-way ANOVA), something that is not true for the ND one (p = 0.16, Kruskal-Wallis one-way ANOVA). We additionally extracted the entropy of the subjects' density plot as a measure of how ordered the space occupancy was. Based on the results in Supplementary Fig. 11c, FA Patients have a lot more disorder across both hands than the Controls during the 9HPT.

**F14 - Upper body autocorrelation full-width at half-maximum**

The next feature we explored for the 9HPT analysis was the joints' autocorrelation full-width at half-maximum (FWHM), which is used as an indication of how rapidly the joint kinematics change6. We first calculated the autocorrelation up to a 10 seconds lag. Since the 9HPT task is not a cyclic task, the output was a single bell-shaped curve centered around the 0 seconds lag. The FWHM is defined as the width of the bell-shaped curve at the point when it reaches a 0.5 autocorrelation value (half-maximum). We calculated the FWHM of all the joints of the arm performing the 9HPT and the results are shown in Supplementary Fig. 12a. The FA Patients have a significantly higher autocorrelation FWHM than Controls in all joints' dimensions except the shoulder elevation (Kruskal-Wallis one-way ANOVA), which indicates that patients’ movements are changing more slowly.

**F15 - Channel delay cross-correlation**

Another feature that has been previously used in the 8MW analysis and it could potentially capture the differences between FA Patients and Controls in the 9HPT is the channel delay cross-correlation. We estimated a 31 x 31 channel delay cross-correlation matrix based on the cross-correlations between the angular velocities of the upper body joints (31 DoF) within a window of 10s with steps of 100ms. We then calculated the eigen spectrum for each subject and the results averaged per subject group are shown in Supplementary Fig. 12b. In a similar fashion as the 8MW, we observe a decreased power in the patients' lower eigenvalues and an equivalent increase in power of the higher eigenvalues. This reflects an increased complexity in their FA Patients' upper body movements with respect to Controls.

**F16 - Arm root mean square power spectrum**

We additionally extracted the average power from the upper body joints during the 9HPT. This was achieved using the root mean square power spectrum analysis explained earlier. However, since the task cannot be separated in cycles (like the 8MW) we simply averaged the power intensity throughout the whole task. The results shown in Supplementary Fig. 12c reveal a significantly reduced power in the FA Patients' joints except for the shoulder pronation (Kruskal-Wallis one-way ANOVA).

**F17 - Wrist average velocity**

We also looked into the average velocity of the subjects’ wrist during the 9HPT. Using the suit biomechanical model, we calculated the 3D position of the wrist in space (only for the hand performing the task), we estimated the velocity on each plane (sagittal, frontal and transverse) and then estimated the velocity magnitude by applying a root-mean-squared (rms) operation. The subjects’ average velocity separated by hand dominance is shown in Supplementary Fig. 12d, where FA Patients have a significantly reduced speed in both hands compared to Controls (Kruskal-Wallis one-way ANOVA) but they also have a slower speed in the ND hand than the D (p = 0.02, paired t-test), something that is not true for Controls as both hands can perform the task with the same average speed (p = 0.41, paired t-test).

**F18 - Upper body joints' correlations**

The next feature we explored in the 9HPT analysis is the correlation between the shoulder and the elbow joints of both the dominant (D) and non-dominant (ND) arm. The Pearson's product-moment correlation coefficient (ρ) was evaluated on the angular velocities of each joint for FA Patients and Controls. The results in Supplementary Fig. 13 show a significant reduction in FA Patient's correlations between the Elbow Flexion - Shoulder Direction and the Shoulder Axial Rotation - Shoulder Elevation for the D arm. Additionally, there is a significant decrease in the Shoulder Direction - Shoulder Elevation, Shoulder Direction - Elbow Flexion and Shoulder Elevation - Elbow Flexion correlation coefficients for the FA Patients ND arm (Kruskal-Wallis one-way ANOVA).

**F19 - Logistic fit on joints' angular velocity**

An additional feature we extracted that can successfully capture the differences between the FA Patients and Controls is the variability of joints' angular velocities during the 9HPT. We first compared the distributions of the joint velocities between FA Patients and Controls. We observed that the Controls consistently have a much wider distribution across joints (see Supplementary Fig. 14a. for an example), meaning they were applying much faster movements. To examine these differences in a more principled manner, we fitted multiple parametric probability distributions (see Supplementary Fig. 14b) on the velocities' probability density function of each joint and examined the parameters of the distribution that best fits the data i.e., the one that minimizes the Akaike Information Criterion (AIC). From our analysis, we have consistently found that the subjects' joint velocities are best described by a logistic probability distribution. So, we fitted a logistic distribution on all joints’ velocities and compared the scale parameter (σ) of the logistic distribution between FA Patients and Controls. The FA Patients exhibit a significantly lower σ than the Controls (Supplementary Fig. 14c) for most joints indicating that they apply a smaller range of velocities during the 9HPT.

**F20 - Head-spine movement**

Finally, as performed with the 8MW analysis, we have explored the head movements as an indication of how well subjects can balance their body. Comparing the area generated by the FA Patients' heads during the 9HPT we have found that it is significantly increased when compared to the Controls (p = 0.004, Kruskal-Wallis one-way ANOVA).

**Data availability statement:**

The data used in the study are not publicly available due to them containing information that could compromise research participant privacy/consent. Anonymized data can be made available upon request for academic purposes.

**Code availability statement:**

The machine learning code that supports the findings of this study is available on request.

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