

Supplementary materials

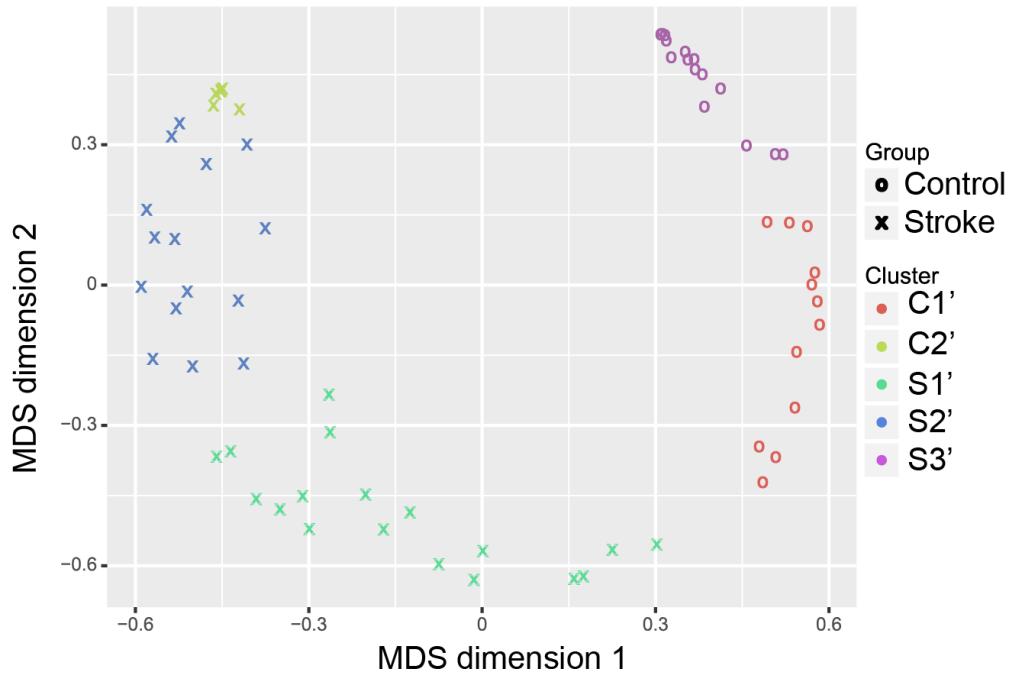
Identification of subtypes of post-stroke and neurotypical gait behaviors using neural network analysis of gait cycle kinematics

A. Kuch, N. Schweighofer, J. M. Finley, A. McKenzie, Y. Wen and N. Sánchez

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1 Supplement 1: Clusters with neurotypical self-selected walking speed

We evaluated cluster output following the same process as described in the methods, but using kinematic data at self-selected speed for neurotypical individuals. We obtained identical structure of 2 controls and 3 stroke clusters ($C1'$, $C2'$, $S1'$, $S2'$, $S3'$), suggesting that walking speed did not dictate clustering outcomes.



Clustering outcome with both control and stroke participants at their self-selected speed. Projection of the dissimilarity matrix in a 2D multidimensional scaling latent space (MDS). We see the same structure as with control at self-selected speed, suggesting that walking speed has little effect on clustering

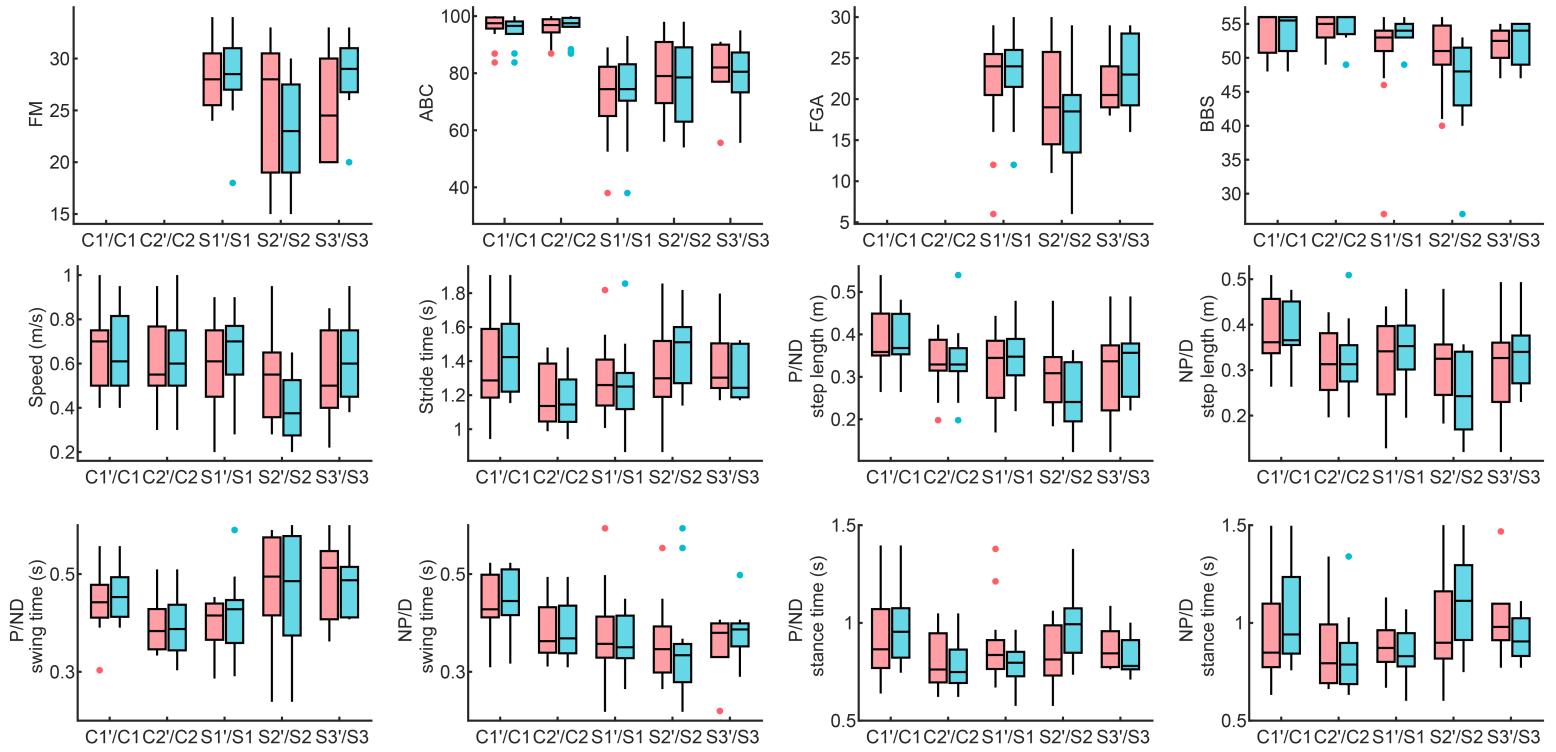
Supplement 1: Clusters with neurotypical self-selected walking speed

We provide next a contingency table comparing clusters using matched speed for neurotypical individuals and self-selected for post-stroke individuals, compared to clusters using self-selected speed for everyone. χ^2 test showed significant association ($p < 0.001$), confirming that walking speed did not dictate clustering outcomes at a cluster level. However, we can observe that for stroke clusters, the assignment to clusters $S1'$, $S2'$ and $S3'$ is less stable, which suggest

Table 1: Contingency table clusters obtained for matched speed (C1, C2, S1,S2, S3) vs self-selected speed (C1, C2, S1', S2', S3'). C1 C2: control clusters using matched speed, S1 S2 S3: stroke clusters using matched speed. C1' C2': control clusters using self-selected speed, S1 S2 S3: control clusters using self-selected speed. The clusters were paired by matching whichever self-selected speed clusters contains the most mutual information to the matched-speed clusters.

		Self-selected				
		C1'	C2'	S1'	S2'	S3'
Matched	C1	11	1	0	0	0
	C2	4	12	0	0	0
	S1	0	0	12	5	0
	S2	0	0	4	6	2
	S3	0	0	2	4	4

Next, we compared the discrete clinical and spatio-temporal characteristics: Fugl Meyer (FM), Activities Balance Confidence (ABC), Functional Gait Assessment (FGA), Berg Balance Scale (BBS), Self-selected Walking Speed, stride time and bilateral step lengths, swing times, stance times, between matched speed (C1, C2, S1,S2, S3) vs self-selected speed (C1, C2, S1', S2', S3'). We used a paired t-test with Bonferroni correction. we did not observe any significant differences. This suggest that our results are robust regarding neurotypical control walking speed.

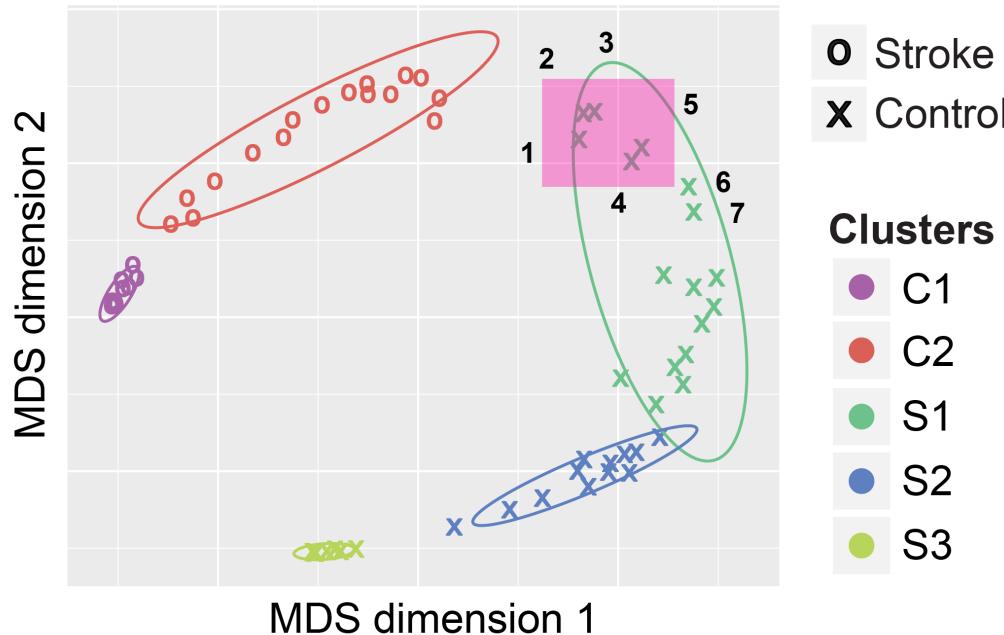


Clusters using neurotypical controls and stroke individuals walking at their self-selected speed (C1',C2', S1', S2', S3', in red), compared to clusters using neurotypical controls at matched slowed-speed to a stroke participants, and stroke participants at their self selected speed (C1, C2, S1, S2, S3, in blue). We did not observe any significant differences.

Supplement 1': Clinical and spatio-temporal characteristics comparisons between matched speed clusters vs self-selected speed clusters.

2 Supplement 2: Mislabeling stroke participant as control

We iteratively mislabeled stroke participants as control, and retrained our CNN-TCN pipeline to evaluate eventual bias in the supervised stage with the added knowledge of class to extract features. We observed a handful of stroke participants, when labeled as control, were projected with neurotypical control individuals. This suggest that these individuals might not have been detected as having having a stroke, since they have neurotypical kinematic features. These 5 participants were among the highest for Fugl-Meyer (30.0 ± 2.1), and had high Functional Gait Assessment for 4 or them (24.2 ± 4.8 , 1 individual had 16).

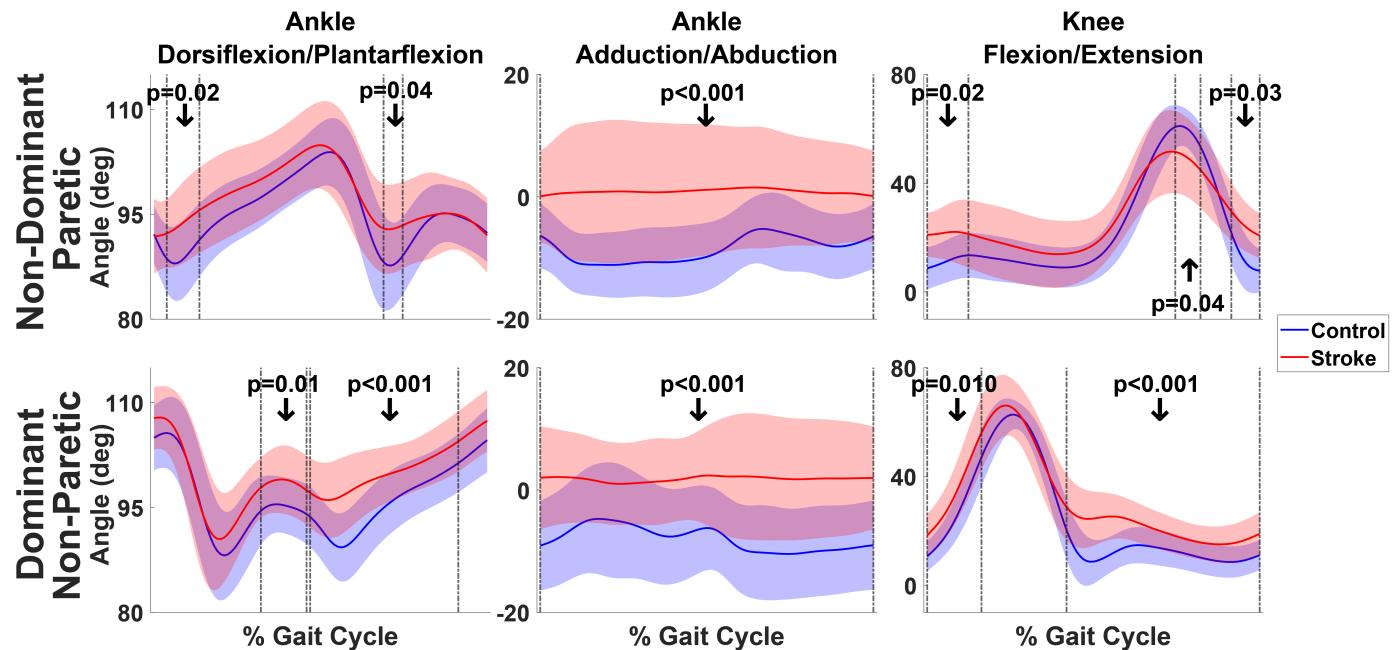


We mislabeled S1 stroke participants as control group in the multidimensional latent space (MDS). Then we looked at the new projection of the mislabeled participant in the MDS space after training CNN-TCN again. We started from participants that were closer to C2, indicated by the numbers on the figure. We continued until mislabeled stroke participants were still projected within true stroke clusters in the MDS space (6 and 7). We estimate than 5 stroke participants (1 to 5) have kinematic features that are similar to neurotypical gait.

Supplement 2: Mislabeling stroke participant as control

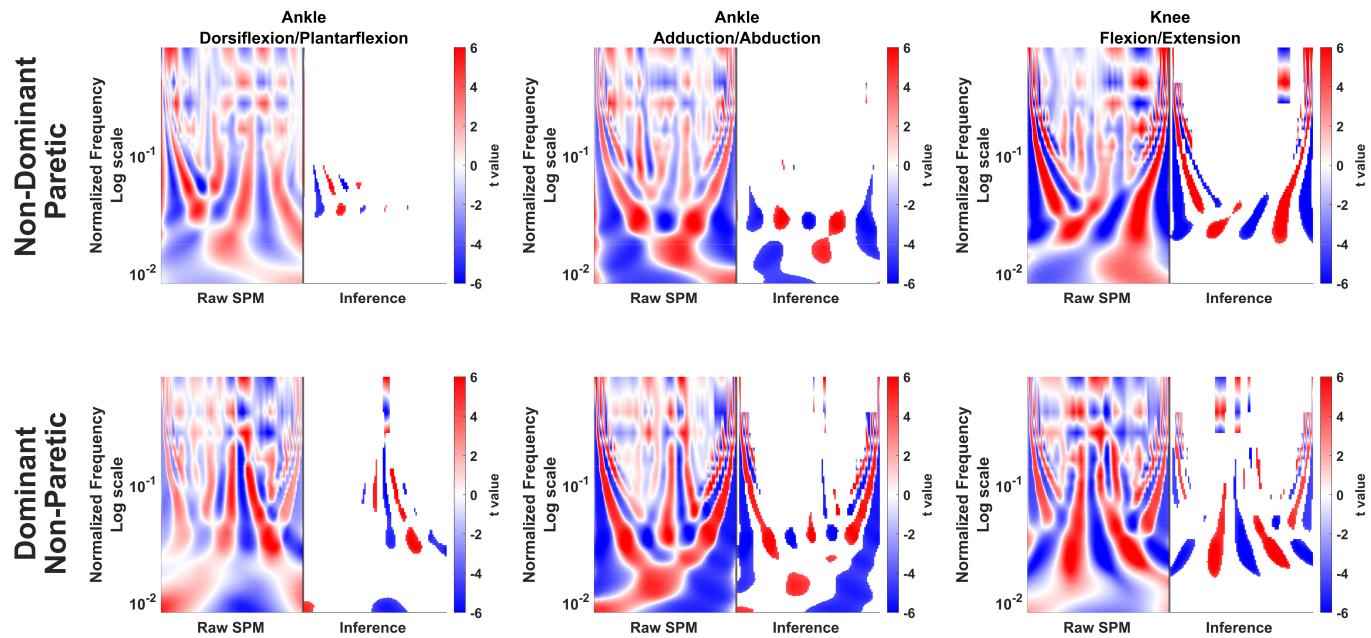
3 Supplement 3: Kinematic comparison of stroke versus control

We used statistical parametric mapping t-tests to compare all stroke participants to all neurotypical controls, in 1D using gait cycles that are fed into TCN, and in 2D using the coefficient matrix of the continuous wavelet transform that are fed to CNN. These differences distinguish stroke and control individuals.



Post-hoc 1D-Statistical Parametric Mapping t-test of joint kinematics for the median gait cycle between control participants (blue) and post-stroke individuals (red). The non-dominant side for control individuals is compared to the paretic side of post-stroke individuals, and dominant to non-paretic.

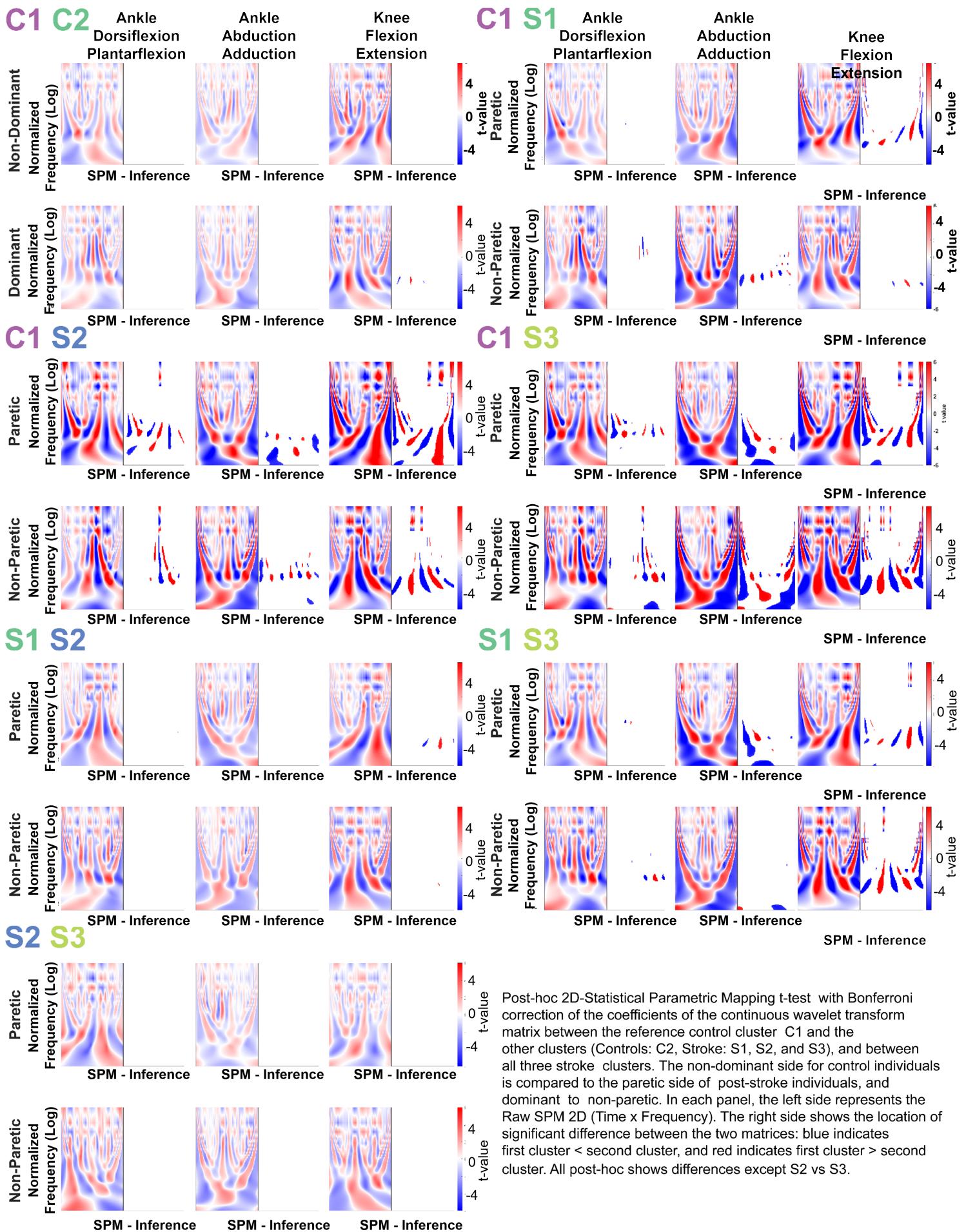
Comparing paretic to non-dominant extremities, we observed increased plantarflexion during loading response ($p=0.02$) and swing ($p=0.04$), increased ankle adduction during the whole gait cycle ($p<0.001$), increased knee flexion during loading response ($p=0.02$) and terminal swing ($p=0.03$), and lower knee flexion during swing ($p=0.04$). For non-paretic versus dominant extremities, we observed increased plantarflexion during terminal swing ($p=0.01$), loading response and stance ($p<0.001$), increased ankle adduction during the whole gait cycle ($p<0.001$) and increased knee flexion during loading response and stance ($p<0.001$ and $p=0.01$)



Post-hoc 2D-Statistical Parametric Mapping t-test of the coefficients of the continuous wavelet transform matrix between controls. The non-dominant side for control individuals is compared to the paretic side of post-stroke individuals, and dominant to non-paretic. In each panel, the left side represents the Raw SPM 2D (Time x Frequency). The right side shows the location of significant difference between the two matrices: blue indicates control < stroke, and red indicates control > stroke. Differences were identified in the time-frequency domain throughout the whole gait cycle.

4 Supplement 4: Coefficients of CWT matrix SPM2D

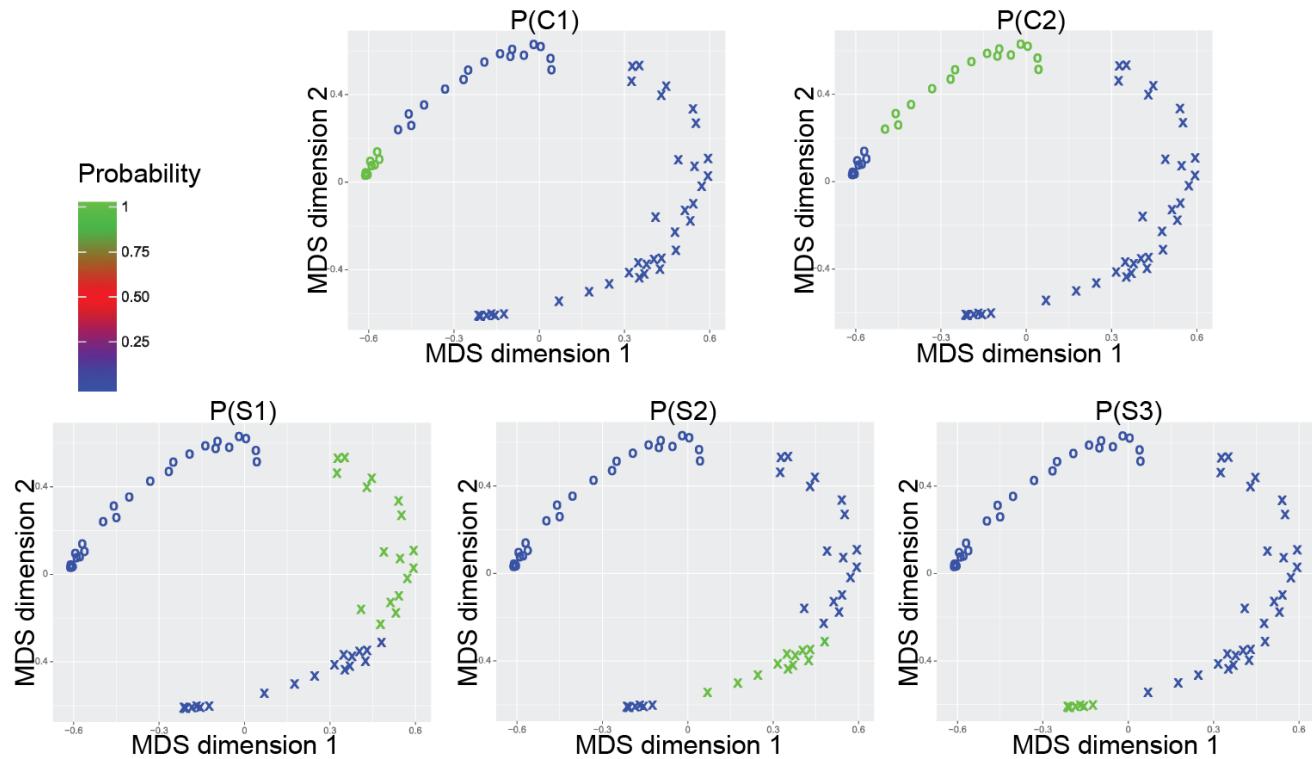
We used Statistical Parametric Mapping in 2 Dimensions (SPM2D) to compare the coefficient of the continuous wavelet transform between clusters, following the method described in https://spm1d.org/doc/Stats2D/ex2d_matlab.html. The matrices are represented on a normalized frequency log scale X Gait cycle. The left side of each plot indicates Raw SPM, i.e. differences after a t-test with Bonferroni correction, between the clusters indicated on the top left corner of each panel. Here we also corrected for 7 multiple comparisons. The right side indicates indicates the location in the matrix of significant differences. Every pairwise showed significant differences, except for S2 vs S3.



Supplement 4: Coefficients of CWT matrix SPM2D

5 Supplement 5: Gaussian mixture model probabilities

In the Multidimensional scaling latent space (MDS), we fitted a Gaussian Mixture Model with 5 components, representing the 5 clusters. Each data point has a cluster membership probability.



Projection of the dissimilarity matrix in a 2D multidimensional scaling latent space (MDS) and mixing proportions of the 5 components Gaussian Mixture Model. Green equals high probability of membership in a cluster while blue means low probability of belonging to a cluster. The lower value was 93% for a participant in S2, who also had 7% in S1. Every other participants were above 99% in their respective clusters.

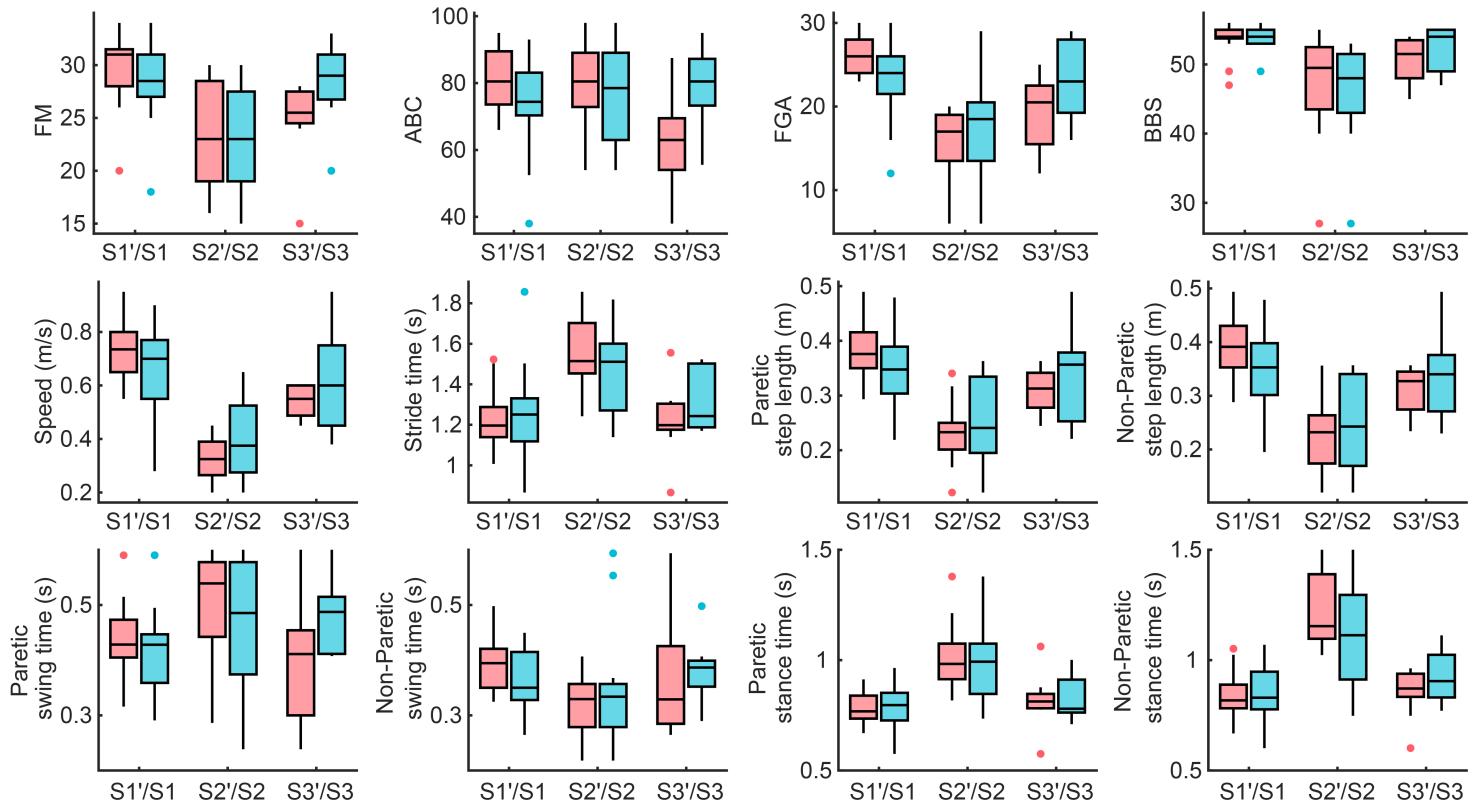
Supplement 5: Gaussian mixture model probabilities

6 Supplement 6: Clusters walking video

To see the video: https://github.com/GaitBehaviorLab/TCN-CNN_Clustering/blob/main/video_gait_clusters.mp4

7 Supplement 7: Discrete clusters characteristics

We performed a k-means discrete clustering on the following clinical and spatio-temporal characteristics: Fugl Meyer (FM), Activities Balance Confidence (ABC), Functional Gait Assessment (FGA), Berg Balance Scale (BBS), Self-selected Walking Speed, stride time and bilateral step lengths, swing times, stance times. S1 S2 S3 are the 3 stroke clusters that were obtained from the kinematic data and our machine learning pipeline described in the main text. Thus, we set the number of clusters to 3 as well for the discrete data clustering ($S1'$, $S2'$, $S3'$). We matched the clusters $S1'$ $S2'$ and $S3'$ to $S1$ $S2$ and $S3$ by counting how many participants were mutually assigned in the same groups. We performed t tests for each clinical and spatio-temporal characteristics between paired clusters ($S1$ with $S1'$, $S2$ with $S2'$ and $S3$ with $S3'$). we applied a Bonferroni correction with 3 tests within each characteristics. No significant differences were found.

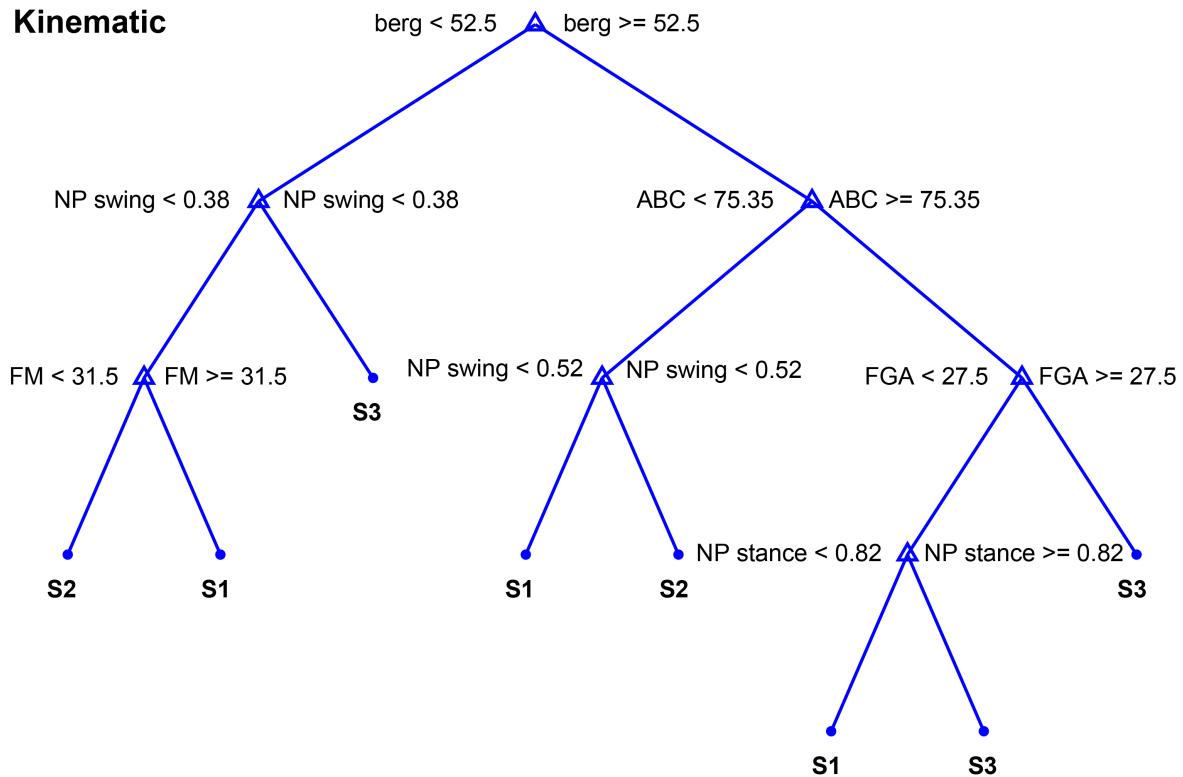


Clusters using k-means on discrete clinical and spatio-temporal characteristics ($S1'$, $S2'$, $S3'$, in red) compared to clusters using CNN-TCN on kinematic data ($S1$, $S2$, $S3$, in blue). No significant difference were found between clinical characteristics for discrete clusters vs kinematic clusters.

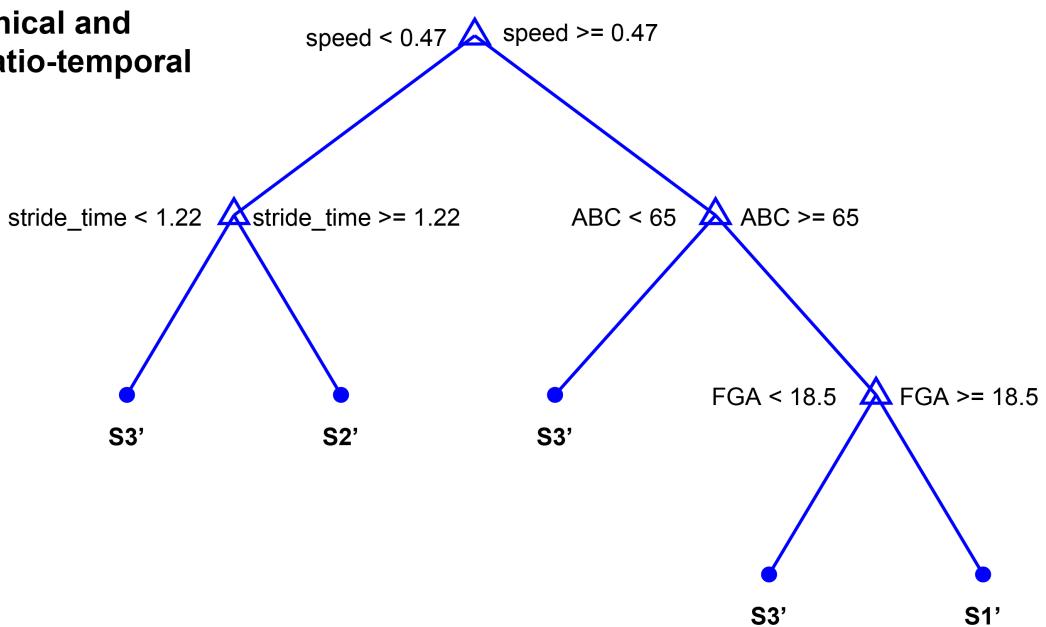
Supplement 7: Discrete clusters characteristics

To further interpret the clustering results, we fitted two separate decision tree classifiers using MATLAB's *fitctree* function with standard classification and regression trees algorithm and the Gini Diversity Index as the splitting criterion. We fitted the decision tree classifier with the labels derived from 1) the CNN-TCN-based kinematic clustering ($S1$ $S2$ $S3$) and 2) the discrete clinical and spatio-temporal clustering ($S1'$ $S2'$ $S3'$) as targets. The goal was to identify which clinical and spatio-temporal features most strongly contributed to defining each cluster in both models, which are represented in the tree leaves.

Kinematic



Clinical and spatio-temporal



Decision trees fitted on the two different clusterings for stroke participants. S1 S2 S3 are the clusters obtained using kinematics from CNN-TCN, S1' S2' S3' are the clusters using discrete clinical and spatio-temporal characteristics.

Here we trained the trees on only the clinical and spatio-temporal characteristics, with the respective clusters as classification targets. We observed that different features and boundaries characterize each cluster.