Automated Detection of Stereotypical Motor Movements in Children with Autism Spectrum Disorder Using Geometric Feature Fusion

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Background

- One of the two main diagnostic criteria for autism spectrum disorder (ASD) in the DSM-5 is restricted, repetitive patterns of behavior, interests, and/or activities
- One of the ways these behaviors manifest in ASD is stereotypical motor movements (SMM).
- Traditional measures of SMM primarily include rating scales, direct behavioral observation, and video-based methods, all of which can be subjective, inaccurate, time-intensive, and difficult to compare across different individuals with ASD.
- More reliably, accurately, and efficiently detecting and monitoring SMM over time could provide important insights for understanding and intervening upon a core symptom of ASD.

Objective

- Leverage a novel set of features based on sliding windows and topological data analysis to computationally detect the onset and type of SMM using accelerometer data from children with ASD.
- Method should be **efficient/automated,** and **objective**
- Method should lead to **interpretable, parsimonious features**

Methods Prior Art: Recurrence Quantification[1]

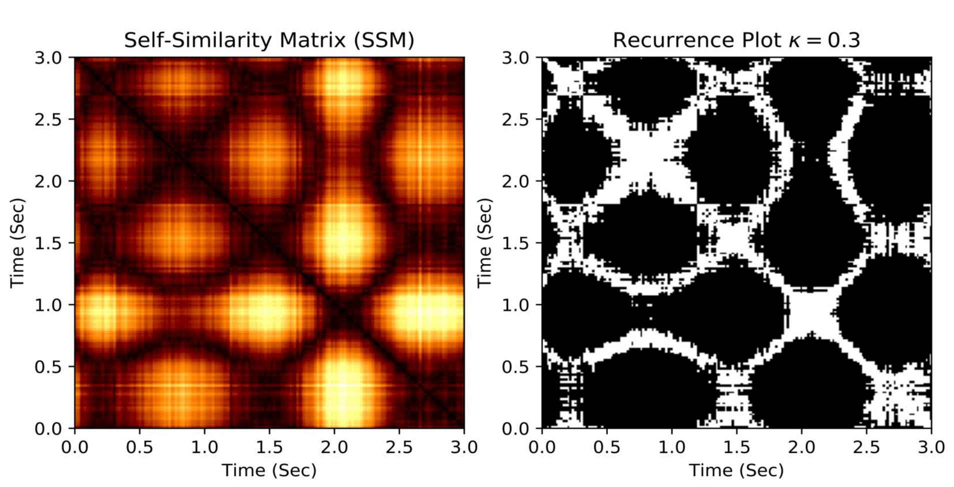
- Geometric statistics from dynamical systems[3]
- Based on self-similarity matrix (SSM) and recurrence plot (R)

$$\text{SSM}[i,j] = ||\boldsymbol{A}(t_i) - \boldsymbol{A}(t_j)||_2$$

$$\text{R}_\kappa[i,j] = \begin{cases} 1 & \text{SSM}[i,j] < \min(\epsilon_i^\kappa, \epsilon_j^\kappa) \\ 0 & \text{otherwise} \end{cases}$$

where ϵ_i^κ is the distance of the κN^{th} nearest neighbor of $\boldsymbol{A}(t_i)$

- Compute 9 statistics for each accelerometer, for **27 total features**



RQA measure name	Equation
Recurrence rate	$\text{RR} = \frac{1}{N^2}\sum_{i,j=1}^{N} R(i,j)$
Determinism	$\text{DET} = \frac{\sum_{\ell=\ell_{\min}}^{N} \ell P(\ell)}{\sum_{i,j=1}^{N} R(i,j)}$
Laminarity	$\text{LAM} = \frac{\sum_{v=v_{\min}}^{N} vP(v)}{\sum_{v=1}^{N} vP(v)}$
Ratio	$\text{RATIO} = N^2 \frac{\sum_{\ell=\ell_{\min}}^{N} \ell P(\ell)}{(\sum_{l=1}^{N} P(\ell))^2}$
Average diag. length	$\text{L} = \frac{\sum_{\ell=\ell_{\min}}^{N} \ell P(\ell)}{\sum_{\ell=\ell_{\min}}^{N} P(\ell)}$
Trapping time	$\text{TT} = \frac{\sum_{v=v_{\min}}^{N} vP(v)}{\sum_{v=v_{\min}}^{N} P(v)}$
Entropy	$\text{ENTR} = -\sum_{\ell=\ell_{\min}}^{N} p(\ell)\ln p(\ell)$
Longest diag. line	$\text{L}_{\max} = \max(\{\ell_i\}_{i=1}^{N_\ell})$
Longest vert. line	$\text{V}_{\max} = \max(\{v_i\}_{i=1}^{N_v})$

ℓ and v are the length of diagonal and vertical lines in recurrence plots, respectively, $\ell_{\min}$ and v_{min} are the minimal diagonal and vertical length that should be considered. The total number of diagonal and vertical lines of lengths ℓ and v is expressed as histograms P(ℓ) and P(v), respectively. While p(ℓ) and p(v) describe the estimated length distributions, $N_\ell = \sum_{\ell \geq \ell_{min}} P(\ell)$ is the total number of diagonal lines and, similarly, N_v the total number of vertical lines.

Methods: Data Overview

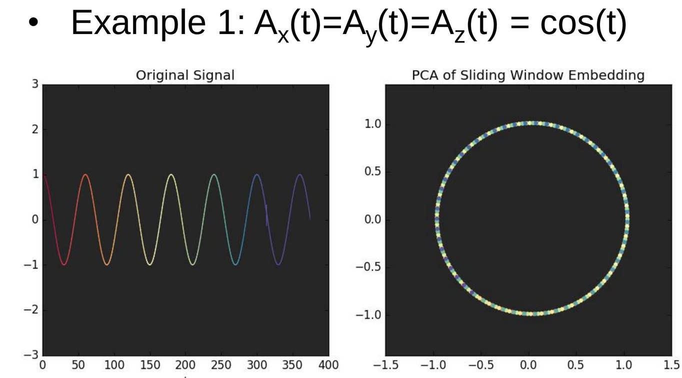
- We used publicly available data from Goodwin etal. 2014[2] to study automated classification of SMM in a subset of 6 subjects, with each session spanning approximately 20 minutes.
- Each subject had a *3-axis accelerometer* **A(t) =** ($A_x(t)$, $A_y(t)$, $A_z(t)$) on his/her left wrist, right wrist, and torso to measure stereotypical hand flapping and body-rocking.
- Each accelerometer time series was accompanied by annotated ground truth labels provided by human coders indicating time-stamped onset and offset for the following three operationally defined SMM: **flap**, **rock**, and **flap+rock**.
- We segmented all of the accelerometer data into 2-second windows that overlapped by 130 milliseconds and computed features in each window to classify the window as one of the three types of motion, or a "normal motion" (lack of SMM)

Methods New Features: Sliding Window + Topological Data Analysis

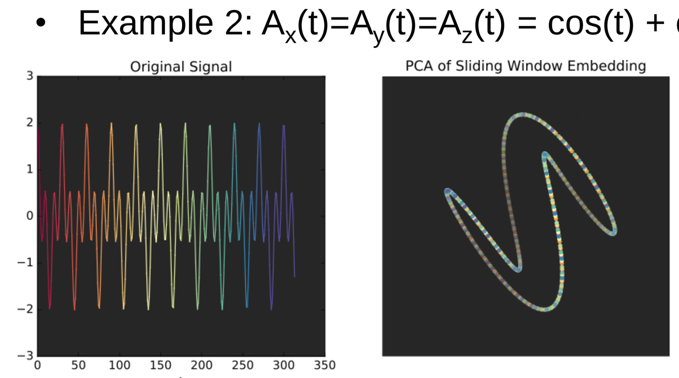
$$\boldsymbol{S}_{M,\tau}(\boldsymbol{A}(t)) = \begin{bmatrix} A_x(t) \\ A_y(t) \\ A_z(t) \\ A_x(t+\tau) \\ A_y(t+\tau) \\ A_z(t+\tau) \\ \vdots \\ A_x(t+M\tau) \\ A_y(t+M\tau) \\ A_z(t+M\tau) \end{bmatrix}$$

$$\in \mathbb{R}^{3(M+1)}$$

- Example 1: $A_x(t)=A_y(t)=A_z(t) = \cos(t)$

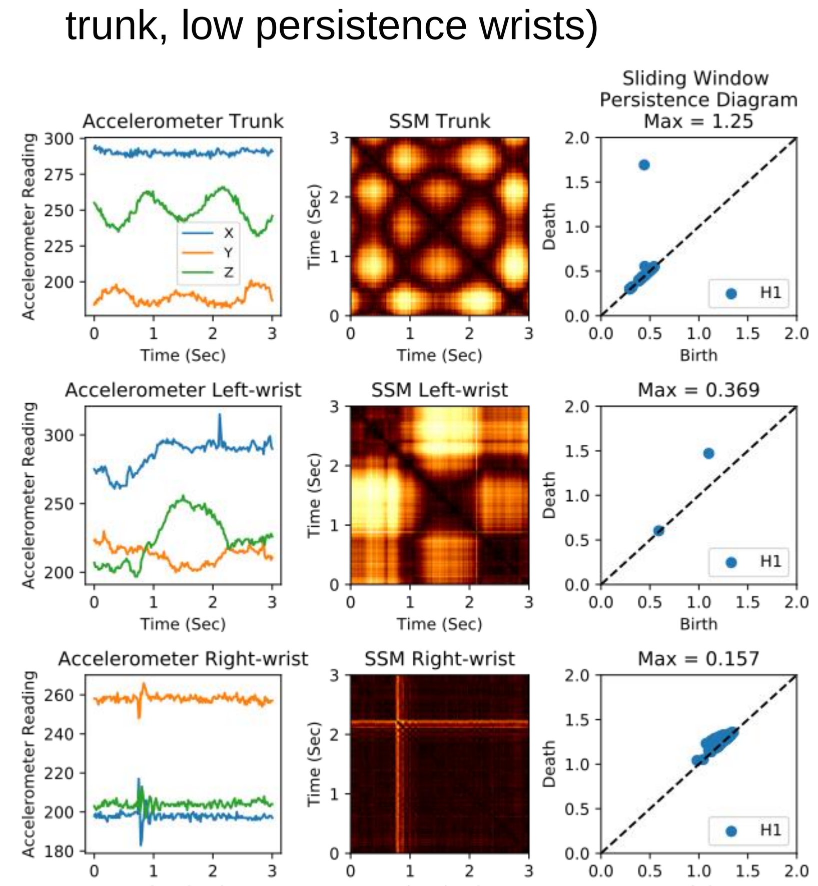


- Example 2: $A_x(t)=A_y(t)=A_z(t) = \cos(t) + \cos(3t)$

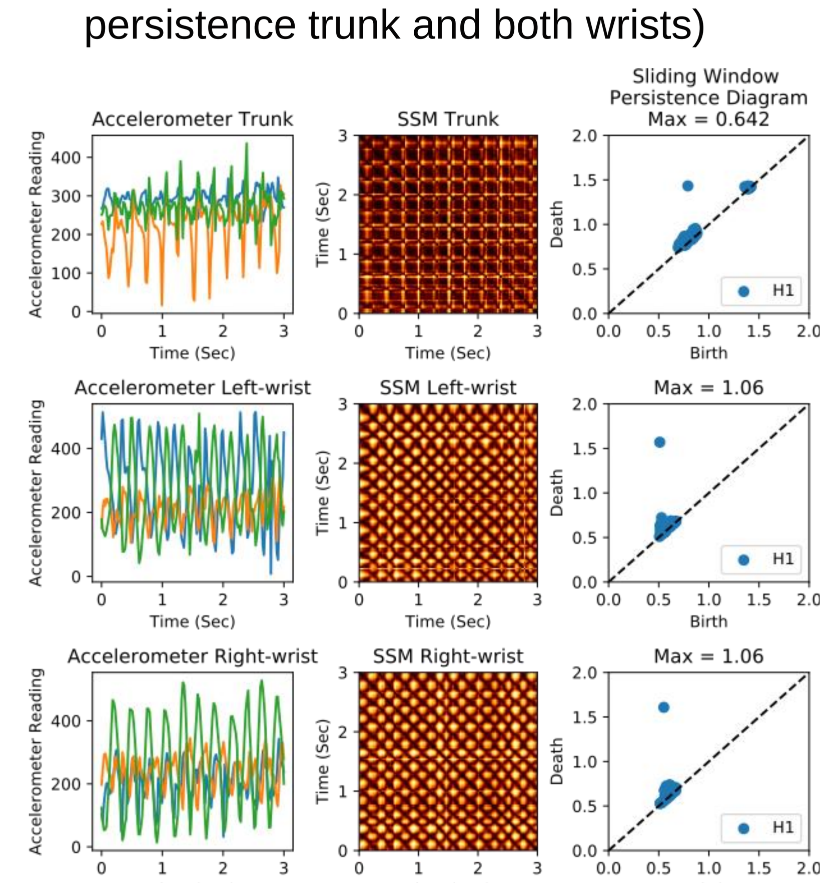


- Sliding windows $S_{M,Tau}$ turns 3D accelerometer time series into a point cloud in 3(M+1) dimensions
- All periodic signals turn into ***topological* loops** after sliding window embedding [5, 6, 7].
- Measure the roundness of these loops with topological data analysis.
  - "Birth time" $\mathbf{b_i}$ is largest distance between adjacent points on the i^{th} loop in a point cloud
  - "Death time" $\mathbf{d_i}$ is (roughly) width of the i^{th} loop in a point cloud
  - "Persistence" $\mathbf{p_i = d_i - b_i}$ is (roughly) roundness of i^{th} loop in a point cloud
  - Score of Z-normalized sliding window is **maximum persistence / sqrt(3)** (biggest loop in point cloud, normalized)[5, 6]
  - Score is **0 for not periodic**, **1 for maximum periodicity** (perfect circle sliding window)
  - 1 score for each accelerometer, for **3 total features**

- Ex) **Rock Action** (high persistence trunk, low persistence wrists)

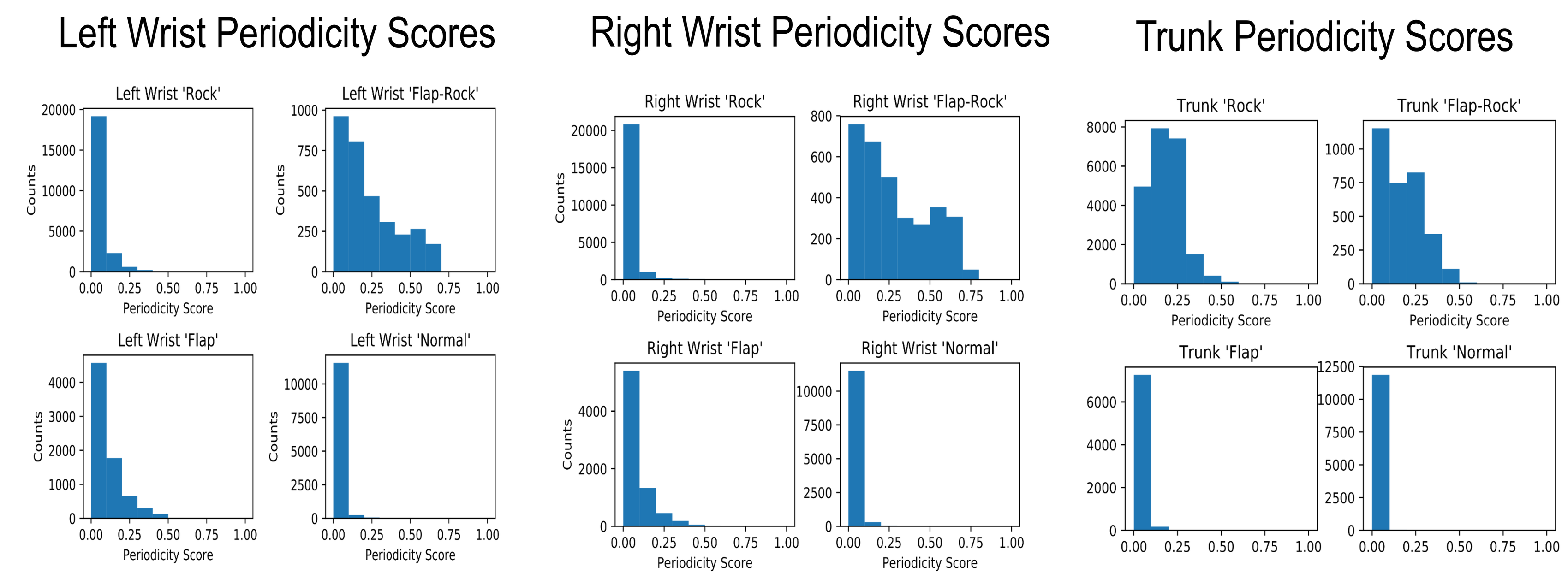


- Ex) Flap-**Rock Action** (high persistence trunk and both wrists)



Results / Conclusions

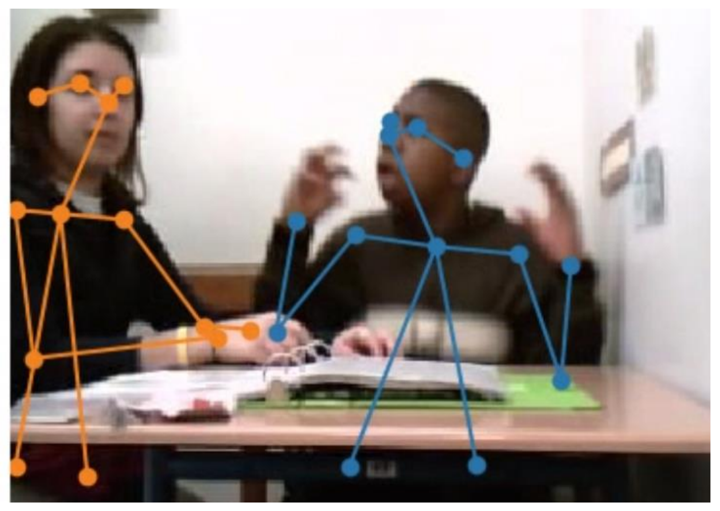
- Histogram of periodicity scores for 3 accelerometers for different actions **matches intuition**



- Classification experiment with 10-fold cross-validation using a decision tree shows our 3 features have **comparable performance** and are **complementary** to the 27 RQA features

	Persistence Periodicity Scores (3 Features)	RQA Features (27 Features)	RQA + Persistence (30 Features)
Flap-Rock	**0.903**	0.816	**0.902**
Rock	0.942	0.947	**0.955**
Flap	0.91	0.877	**0.933**
Normal	**0.936**	0.884	0.917
Overall Classification	84.75%	85.91%	**90.61%**
Periodic Or Not	90.52%	90.76%	93.45%

Future Work



- Quantifying stereotypical motor motion in videos using extracted skeletons OpenPose[8]
- Combining accelerometer and video modalities

References/Code

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Open Source Code Repository: https://github.com/ctralie/AutismPeriodicities

Acknowledgements

Christopher Tralie: NSF big data grant DKA-1447491, NSF Graduate Fellowship NSF DGF-1106401
Guillermo Sapiro: Partially supported by NSF, NIH, and DoD
Matthew Goodwin: National Institute on Deafness and Other Communication Disorders (P50 DC013027)