Motor Differences Identify Children with Autism Engaged in iPad Gameplay

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Abstract

Autism is a developmental disorder evident from infancy.[1] Yet, its clinical identification is often not possible until after the third year of life. New evidence indicates disruption to motor timing and integration may underpin the disorder, providing a potential new marker for its early identification.[2,3] We employed smart tablet computers with touch-sensitive screens and embedded inertial movement sensors to record the movement kinematics and gesture forces made by 37 children 3-6 years old with autism and 45 age- and gender-matched children developing typically. Machine learning analysis of the children's motor patterns identified autism with 93% accuracy. Analysis revealed these patterns consisted of greater forces at contact and with a different distribution of forces within a gesture, and gesture kinematics were faster and larger, with more distal use of space. These data support the notion disruption to movement is core feature of autism,[4] and demonstrate autism can be assessed by smart device gameplay.

Method

Participants. ASD Group: 37 children 3-6 years old clinically diagnosed with Childhood Autism (ICD-10 2010), 12 female. TD Group: 45 children age- and gender-matched with no concern for developmental pathology. Inclusion criteria normal or corrected-to-normal vision, no other sensory or motor deficits.

Serious Games. Two games (www.duckiedeck.com) running on iPad mini tablets (Apple Inc.) set within a bespoke app to organised the display of the games sequentially for a 2 minute training phase followed by a single 5 minute test phase. The app included code for collecting inertial sensor and touch screen data.

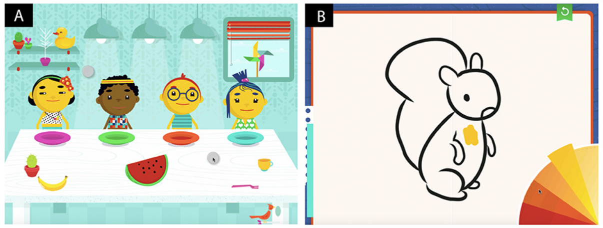

Figure 1. iPad mini screen shots of (A) Sharing and (B) Creativity.

(A) Sharing. Gameplay consisted of dividing a piece of food and distributing it evenly among four cartoon children present on the screen. When the food was distributed evenly, all children exclaimed, "Yipee!" and proceeded to munch the food in a delightful manner for 3 seconds. Then the trial repeated.

(B) Creativity. This was a colouring game with no specific rules of engagement. An object outline appeared for tracing, then a colouring wheel appeared and the child could select a colour for colouring. The toy or animal outline always remained unobstructed.

Data Acquisition. (A) **Touch Screen** and (B) **Inertial Movement Unit** sensors (tri-axial accelerometer, tri-axial gyroscope, magnetometer). Simple metrics or computations of these data were extracted to obtain two hundred forty-seven features.

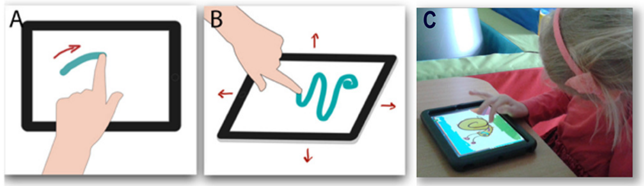

Figure 2. Data were collected on gesture (A) kinematics from the touch screen and (B) impact and and pressure from the intertial sensors during (C) children's gameplay at the table.

Results

Machine Learning Identification of Autism

Three machine learning algorithms differentiated individuals within the autism group from the control group with accuracy up to 93% (Table 1). Data from Creativity produced greater predictive accuracy. The most effective algorithm was the Regularized Greedy Forest[5] with age and gender data excluded (RGF2; Figure 3; Table 2).

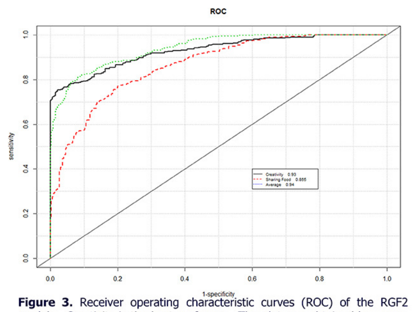

Figure 3. Receiver operating characteristic curves (ROC) of the RGF2 models. Creativity is the best performer. The plot was obtained by aggregating all predictions from 10 repetitions of 10-fold cross-validation (740 observations).

Table 1. Area Under Curve mean (and SD) obtained from three machine learning algorithms.

Algorithm	Sharing Food	Creativity	Average
ET (5000 trees)	0.785 (σ = 0.016)	0.893 (σ = 0.01)	**0.881 (σ = 0.01)**
RF (5000 trees)	0.802 (σ = 0.017)	0.892 (σ = 0.006)	**0.885 (σ = 0.006)**
RGF (500 trees, L2=sL2=1.0, square loss)	0.835 (σ = 0.017)	0.921 (σ = 0.012)	**0.927 (σ = 0.011)**
RGF2	0.848 (σ = 0.025)	0.926 (σ = 0.013)	**0.932 (σ = 0.016)**

Table 2. Sensitivity and specificity of RGF2 with thresholds selected at 0.50 and 0.55.

	Sensitivity [%]	Specificity [%]
Sharing Food (0.50)	0.81	0.67
Sharing Food (0.55)	0.76	0.73
Creativity (0.50)	0.83	0.85
Creativity (0.55)	0.80	0.88

Motor Kinematic Differences

Ten features with the greatest Kolmogorov-Smirnov (KS) distance give an approximation of those most significant to the machine-learning differentiation (Figure 4).

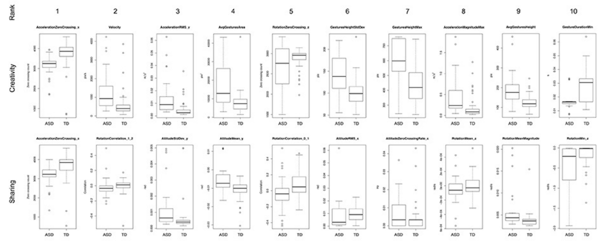

Figure 4. Boxplots of ten features ranked by greatest KS distance between Autism and Control groups.

Inertial data are the predominant identifiers (10/10 in Sharing; 4/10 in Creativity) indicate impact and gesture forces are different in ASD. Screen data indicate gesture kinematics significantly differ:

Greater Impact Force and Gesture Pressure in Autism (AccelerationRMS_y and AccelerationMagnitudeMax), **Patterns of Impact Force and Gesture Pressure Differ Between Groups** (RotationCorrelation_1_2, AttitudeStdDev_y, AttitudeMean_y, RotationCorrelation_0_1, AttitudeRMS_x, AttitudeZeroCrossRate_x, RotationMean_z, RotationMeanMagnitude, RotationMin_z), **Faster Gestures in Autism** (Velocity), **Larger, More Distal Gestures in Autism** (AvgGestArea, GesturesHeightMax, AvgGesturesHeight, GesturesHeightStdDev), **Faster Screen Taps in Autism** (GestureDurationMin).

Conclusions

- Children with autism can be identified by iPad gameplay.
- Identification based on simple computations of an autism-specific motor signature.
- Gesture force patterns appear significant contributors.
- Motor differences appear to be a core component of autism.
- Machine learning identification of autism by motor analysis of serious tablet gameplay provides a promising **new bio-behavioural marker** for early detection.

Future Work. **(1) To replicate** these findings. **(2) To commercialise** this assessment for clinical, educational, and parent use (playcareapp.com).

References

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