Characterising gameplay and autism spectrum disorder development with swipe pattern networks

Ruaridh A Clark[1,2], Malcolm Macdonald[1], Szu-Ching Lu[2], and Jonathan Delafield-Butt[2]

[1] Department of Electronic & Electrical Engineering, University of Strathclyde, Glasgow, UK
[2] Laboratory for Innovation in Autism, University of Strathclyde, Glasgow, UK

1 Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental condition affecting at least 700,000 individuals in the UK [1] with an aggregate annual healthcare and support cost of at least £28 billion [2]. Early identification, proceeded by therapeutic intervention, can produce significant, lifelong health and economic benefit. An ASD diagnosis currently requires a trained clinician, but there is a long and growing waiting list for such assessments. To meet demand, and create more accessible means of assessment, bespoke touchscreen games have been developed for early autism detection and trialled for children aged 2.5–6 years. These games focus on recognising ASD through detecting disorder in intentional movements [3].

In this study, we employed a serious iPad game for young children (441 without known neurodevelopmental problems, 373 diagnosed with autism spectrum disorders, and 64 diagnosed with other neurodevelopmental disorders) [4] that allowed for different play patterns, but where the child was encouraged toward a social aspect of gameplay (sharing food) with attractive sensory feedback. Children were encouraged to drag four pieces of food from a serving area (food zone) to deliver them to a set of four children (snap-to-plate zones) to trigger feeding animations and an audible celebration (Figure 1a). By converting gameplay swipes into a graph, we can identify – for the first time – the specific pattern signatures of autistic users. We find that autistic participants employ an indirect, two-step, sharing process in contrast to the direct, single-step, approach employed by children without neurodevelopmental disorders. These insights into the serial organisation of play actions could form the basis of effective diagnosis and tailored therapeutic interventions.

2 Graph Definition

A swipe pattern graph is constructed by combining a complete graph C with a swipe transition matrix T that is based on a participant's swipe pattern. In the complete graph C, the vertices are all connected to each other with the same small edge weighting where $C_{ij} = 0.01 \ \forall \ i, j \in V$, where the main results of this study were shown to be resilient to variation in the weighting of C_{ij}.

The swipe transition matrix T consists of 16 vertices, associated with the 16 zones displayed in Figure 1b. The matrix T is created so that the weight of each edge T_{ij} is equal to the number of swipes connecting an origin vertex i and a destination vertex j. The swipe transition matrix only contains swipes that transfer between zones, i.e., $T_{ii} = 0 \ \forall \ i \in V$. For the analysis of direct food delivery, T^D is defined such that food delivery swipes must originate from the *food zone (f, vertex 2)* and end in the plate zones (ψ, vertices 4–7) or snap-to-plate (vertices 8–11) zones as shown in Figure 1. All food delivery swipes, whether they end in snap-to-plate or plate zones, are defined such that their destination vertex j is in the plate zone set ψ (i.e., $T^D_{ij} \geq 0 \ \forall \ i \in f$ where $j \in \psi$, else $T^D_{ij} = 0 \ \forall \ i \notin f$ where $j \in \psi$). Swipes ending in a snap-to-plate zone, that do not originate in the food zone, are reconnected such that the last zone the swipe was in, prior to entering a snap-to-plate zone, is taken as the swipe destination. This swipe reconnection is necessary as swipes not originating in the food zone will not be moving food items (with one exception to be discussed below).

The swipe transition graph is updated $A_T = T^D / \sum_{(i,j \in V)} T^D_{ij}$, such that the proportion of swipes transitioning between zones or remaining within a zone, with reference to the total number of swipes, are used as edge weights. The swipe pattern adjacency matrix for direct food delivery is defined as $A_D = A_T + C$.

The exception to food originating in the food zone is that food can be moved from the set of plate zones, referred to as inter-plate swipes (see Figure 1a), where multiple food items can be placed on a single plate and items then transferred between plates to achieve an even distribution. To account for both direct and indirect food delivery, T^I is defined such that food delivery swipes are allowed to originate from either food or plate zones (i.e., $T^I_{ij} \geq 0 \ \forall \ i \in \{f, \psi\}$ where $j \in \psi$, else $T^I_{ij} = 0 \ \forall \ i \notin \{f, \psi\}$ where $j \in \psi$). The swipe pattern adjacency matrix including indirect food delivery is defined as $A_I = T^I / \sum_{(i,j \in V)} T^I_{ij} + C$.

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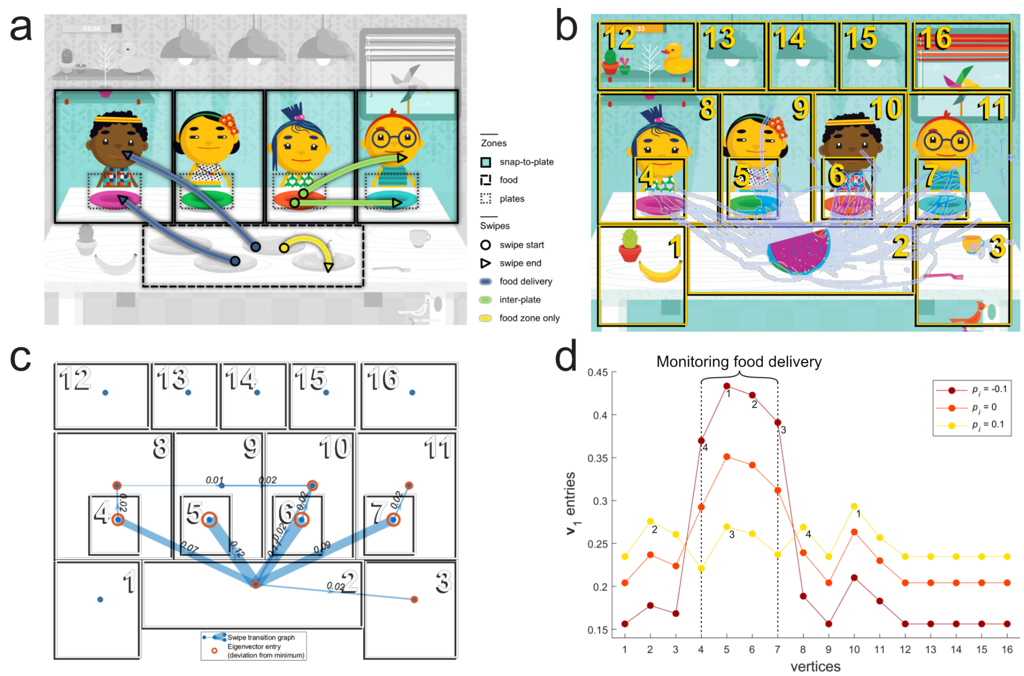

Fig. 1. **a** Game overlay of swipe types including food delivery swipes from food to snap-to-plate zones; inter-plate swipes from plate to snap-to-plate zone; food zone only swipes. **b** 16 zones defining graph vertices with user swipes shown. **c** User swipes from b converted into a swipe transition graph with eigenvector entries highlighted. **d** Eigenvector entries shown for same user, alongside influence of perturbation p_i.

3 Sharing Score

A graph metric (sharing score) was created to monitor a participant's adherence to the food sharing aspect of gameplay, considering both the proportion of swipes devoted to food delivery and the evenness with which food was placed on the four plates. The *sharing score* considers the entries of the first left eigenvector of the adjacency matrix, capturing the relative popularity of zones as destinations for swipes. The first left eigenvector v_1 of an adjacency matrix is associated with the largest eigenvalue λ_1, where $v_1 A = \lambda_1 v_1$, where the largest entries are associated with the most popular destinations.

By monitoring the eigenvector entries of the vertices 4–7, associated with the four character's plates, the relative popularity of each plate as a destination can be identified as shown in Figure 1d. These eigenvector entries are monitored after applying an artificial perturbation to the graph. This perturbation is applied to the vertices 4–7 using a vector of perturbation values p, to produce a perturbed matrix $P = A - diag(p)$ where $p_i = 0 \; \forall \; i \notin \psi$. This perturbation alters the first left eigenvector entries as shown in Figure 1d, where increasing $p_i \; \forall \; i \in \psi$ decreases the entries for vertices 4–7. The *sharing score* is the largest perturbation for which vertices 4–7 are still the largest four entries of x_1, with a sharing score of $0 < p_i > 0.1$ for Figure 1d.

By monitoring this sharing score for both A_D and A_I (without and with inter-plate swipes), we have found a reliance on inter-plate swipes and development of a two-step sharing process that is only evident in the ASD group. Children without neurodevelopmental disorders and children with other neurodevelopmental disorders show a significant increase in direct sharing score (without inter-plate swipes) from 2.5 to 6 years in age, which is not present in the autistic group due to the prominence of indirect food sharing.

References

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