Unravelling Neurodivergent Gaze Behaviour through Visual Attention Causal Graphs

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1. Introduction

Humans possess sophisticated mechanisms that enable reasoning about cause and effect [1]. Research has demonstrated how these mechanisms, particularly counterfactual reasoning, can be revealed by an **observer's gaze behaviour** [2].

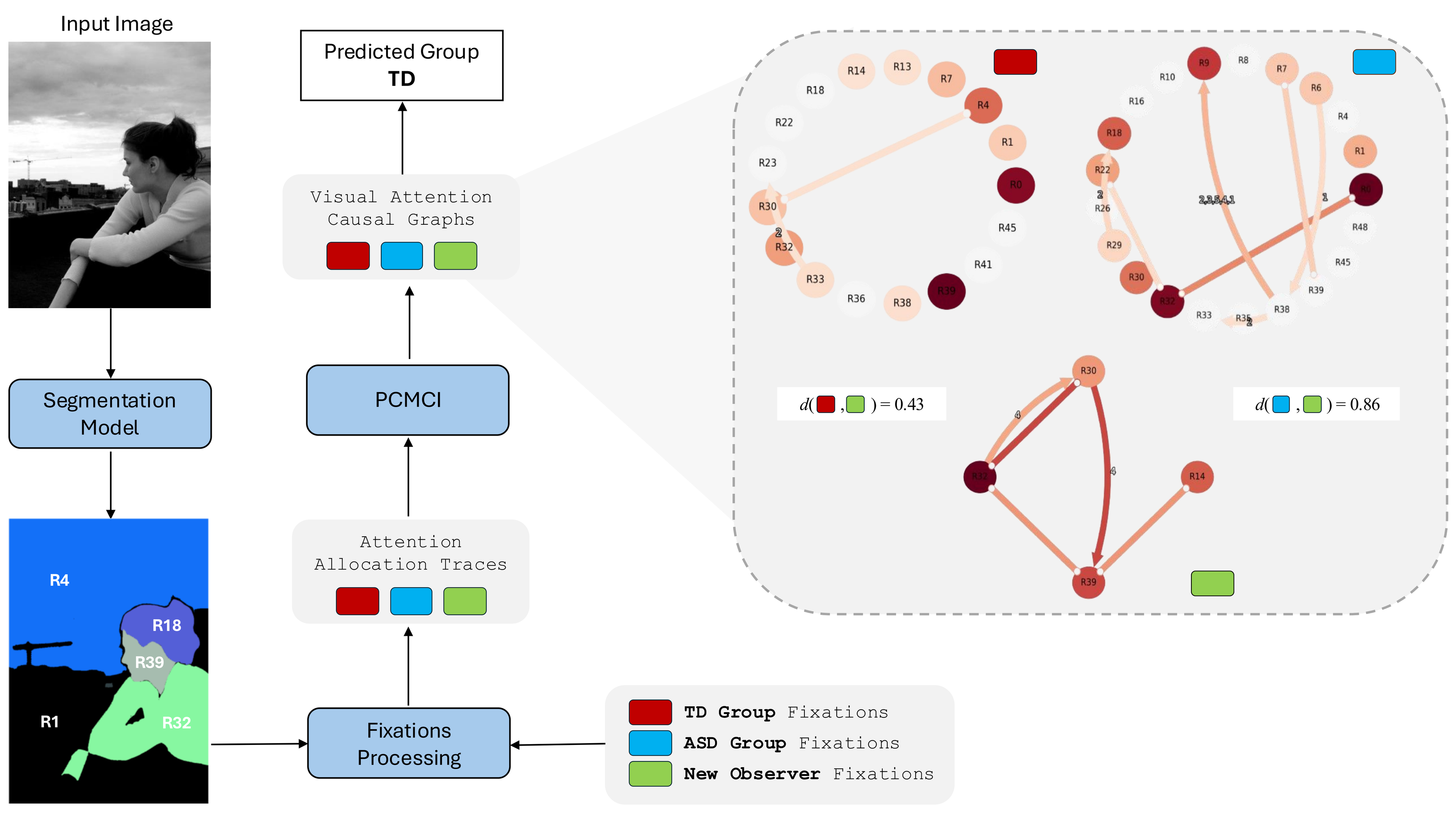
This perspective may have implications for developmental and clinical research on individuals with **Autism Spectrum Disorder (ASD)**.

🔍 **Research Question** 🔍

*Verify whether the **causal structure** governing the dynamics of attention allocation has the potential to **differentiate** subjects with Autism Spectrum Disorder (ASD) from typically developing (TD) controls.*

2. Overview of the Proposed Method

Modelling gaze as a phenomenon governed by causal relationships potentially allows for a deeper understanding of how attention is orchestrated moment-to-moment, and how this differs between groups of individuals.



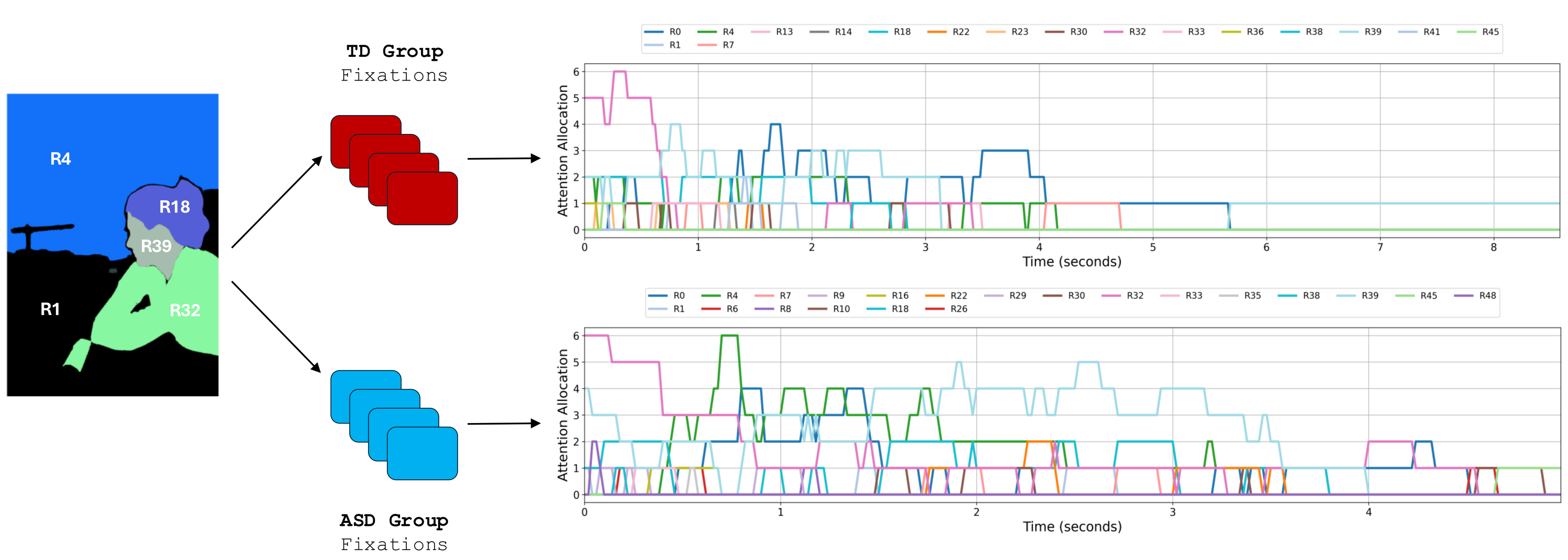
The proposed approach is divided into three phases:

- Construction of Aggregated Item-Level Attention Allocation Traces.
- Estimation of the Visual Attention Causal Graph (VA-CG).
- ASD vs. TD Classification via the Obtained VA-CG Representations.

3. Aggregated Item-Level Attention Allocation Traces

Consider a stimulus j (image), observed by a group of S subjects with their eye movements tracked in real-time.

⬛🟦🟩 A segmentation approach is adopted to define semantically relevant items within an image, where each item corresponds to a distinct region or object.



For each time instant, we quantify the visual attention allocated to each item by counting the number of fixations directed towards it.

📈 This procedure generates a **multivariate time series**, where each time series corresponds to an individual item, describing the aggregated attention allocation across multiple subjects over time.

✅ The resulting data captures the **group-level temporal dynamics of visual attention at the item level**, providing insight into how attention is distributed across different regions of the image as it is processed.

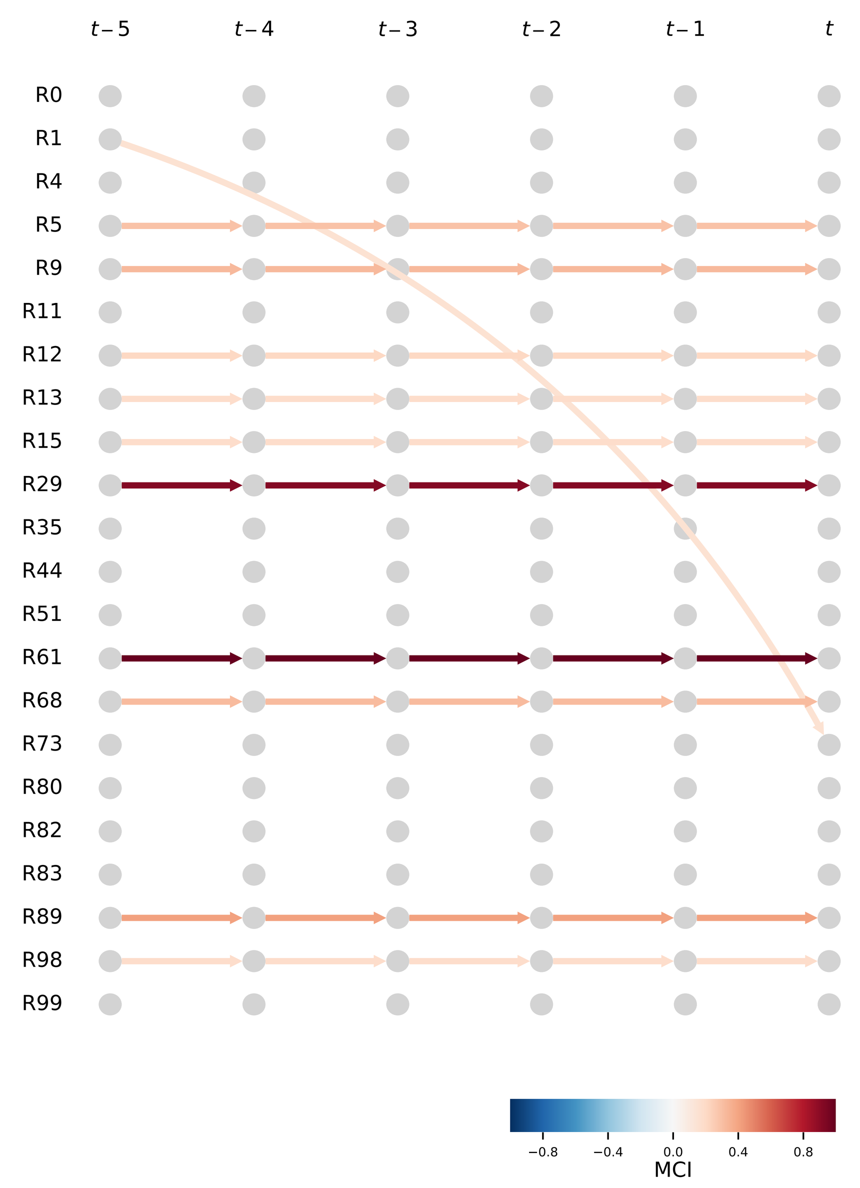
4. Estimation of the Visual Attention Causal Graphs (VA-CG)

To estimate the causal graph from the obtained aggregated attention allocation traces, we employ the **PCMCI causal discovery method** [3].

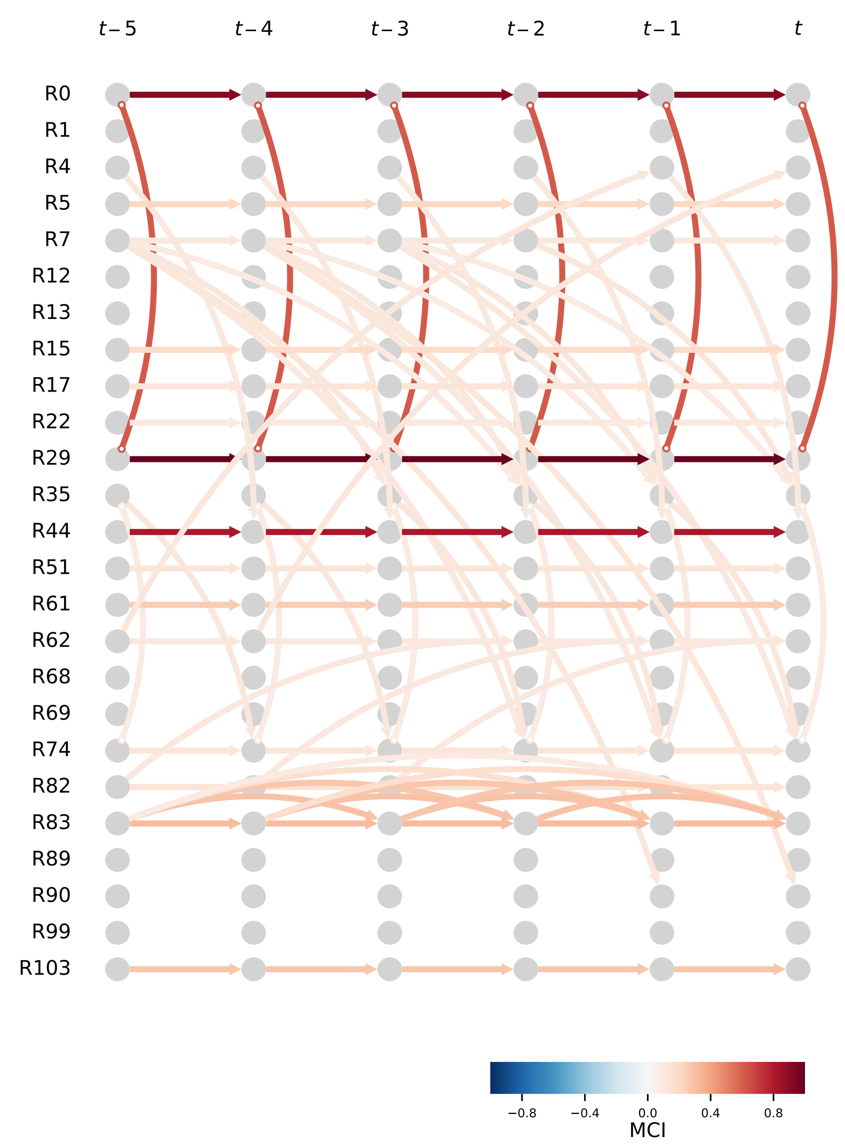
Each time series $x_i(t)$ corresponds to the amount of attention allocated to a given item i at time t. PCMCI employs Conditional Independence (CI) testing to detect causal dependencies. **Causal links** between traces $x_i(t)$ and $x_j(t)$ are determined by evaluating their conditional independence ($\perp$) with respect to a set of potentially mediating variables $\mathbf{z}(t)$:

$$x_i(t) \perp x_j(t) \,|\, \mathbf{z}(t),$$

where $\mathbf{z}(t)$ encompasses other variables that may influence the interaction between $x_i(t)$ and $x_j(t)$.



(a) TD causal graph



(b) ASD causal graph

PCMCI constructs a causal graph, named **Visual Attention Causal Graphs (VA-CG)**, that reflects the structure of attention flow across the items in a scene.

6. ASD Detection via VA-CGs

For each image j, eye-tracking data from ASD and TD groups are aggregated into Item-Level Attention Allocation Traces.

Such traces are used to construct **group-specific** Visual Attention Causal Graphs (VA-CGs), G_j^{ASD} and G_j^{TD}. To classify a new subject s, their scanpath is converted into a causal graph G_j^s, and the subject is assigned to the group whose VA-CG is closest to G_j^s according to the Jaccard distance between edge sets.

Edges are defined using a threshold β on causal strength and significance tests. The classification rule is:

$$\text{group}_j^* = \arg \min_{g \in \{\text{ASD},\text{TD}\}} d(G_j^g, G_j^s).$$

Methods	Accuracy	Precision	Recall	AUC
Chen et al. (Independent) [4]	0.89	0.86	0.93	0.92
Chen et al. (Full) [4]	**0.93**	0.93	0.93	0.98
AttentionGraph+S_{scan} [5]	**0.93**	-	-	-
AttentionGraph+S'_{scan} [5]	0.86	-	-	-
Our	**0.93**	0.93	0.93	0.93

Unlike the other baselines, our proposed solution offers a **high degree of interpretability**.

[1] J. Pearl *Causality*, Cambridge university press 2009.

[2] T. Gerstenberg et al. *Eye-tracking causality*, Psychological science 2017.

[3] J. Runge et al. *Detecting and quantifying causal associations in large nonlinear time series datasets*, Science advances 2019.

[4] S. Chen et al. *Attention-based autism spectrum disorder screening with privileged modality*, ICCV 2019.

[5] K.F. Yang et al. *Visual attention graph*, arXiv 2025.