Discovering Multicausality in the Development of Coordinated Behavior

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Abstract

Human interaction involves the organization of a collection of sensorimotor systems across space and time. The study of how coordination develops in child-parent interaction has primarily focused on understanding the development of specific coordination patterns from individual modalities. However, less work has taken a systems view and investigated the *development* of coordination among multiple interdependent behaviors. In the present work, we used Granger causality as a mathematical model to construct dyadic causal networks of multimodal data collected from a longitudinal study of child-parent interaction. At a group-level, we observed increases in the number of causal links and in the strength of such links in dyadic interaction from 9-months to 12-months. At an individual-level, we observed high variability in the types of causal links that emerged across developmental ages. We discuss these results in terms of a multicausality hypothesis for the development of human coordination.

Keywords: Interpersonal Coordination; Social Interaction; Child-Parent Interaction; Granger Causality; Multimodal Social Interaction; Multivariate Autoregressive Model

Introduction

Human interaction entails the organization of a vast array of sensorimotor systems across space and time (Kendon, 1970). We imitate, align and synchronize over a spectrum of social behaviors with our social partners during communication and studies have shown fine-grained temporal structures across modalities in interpersonal coordination (Fusaroli & Tylén, 2016; Garrod & Pickering, 2009; Louwerse, Dale, Bard, & Jeuniaux, 2012). How we are able to organize behaviors across multiple modalities and achieve seamless coordination in only fractions of a second is one of the most important questions about human cognition (Marsh, Richardson, & Schmidt, 2009).

One effective approach to answering this question is to examine how such smooth coordination evolves during development. In developmental science, past research have shown that within specific behavioral modalities, coordinated behaviors emerge early in life and develop incrementally with age (Yale, Messinger, Cobo-Lewis, & Delgado, 2003). For example, infants start to follow and coordinate the gaze direction of their social partner (Scaife & Bruner, 1975) and form vocal and facial expression feedback loops with their parents early in their first year of life (Cohn & Tronick, 1988). Such social contingencies are suggested to be indicative of later language development (Goldstein, King, & West, 2003; Mundy & Newell, 2007; Warlaumont, Richards, Gilkerson, & Oller, 2014).

Development is about change. The multicausality assumption in dynamical systems theory (Smith & Thelen, 2003) indicates that change and growth in the system emerge through the relationships between different interdependent components, without an executive pre-programmed and unified path. Certain patterns and behavioral influences emerge or diminish at different developmental ages, and through different developmental pathways. In light of this, the aim of the present study is to examine the change in the organization of coordination among multiple interdependent behaviors. More specifically, we want to investigate the connectivity and directional influences from one modality to another in the course of development.

Towards this goal, in this paper, we proposed a novel approach to modeling multimodal coordinated behaviors between children and parents as a directed graph network with Granger causality (Bressler & Seth, 2011; Granger, 1969). A longitudinal study was conducted in which we invited children at 9 months and their parents to participate in a toy play experiment, and again at 12 months. During the toy play sessions, we recorded the dyad's momentary eye gaze and manual action data with eye-trackers and multi-view video recording. With this study and our analytic approach, we can investigate the development of human coordination through directional causal relations among a network of interdependent behavioral variables.

This framework of modeling child-parent interaction as causal networks allowed us to determine changes in the amount of causal links and the strength of causal links across 9- and 12-months. We tested two specific hypotheses about the development of coordination. First, the *developmental hypothesis*: on a group level, we expected that the number and strength of causal links in the child-parent coordination network would increase from 9- to 12-

months. Second, *the multicausality hypothesis*: we expected the increased coordination to be achieved by the emergence of new causal influences in the network, among multiple different behavior variables. One key assumption of this hypothesis is that no causal link has developmental priority. If dyads show individual differences in their coordination development pattern, it would be an indication that they each follow distinct pathways to achieve increased levels of sensorimotor coordination.

Granger Causality for Point Process Data

Coordination patterns change throughout the course of an interaction and require real-time adjustment of actions and predictions in accordance with their sensorimotor input (Clark & Brennan, 1991; Yu & Smith, 2016). When we study interpersonal coordination and development from a dynamical approach, one challenge is quantifying directional influence and connectivity between two specific variables. This is due, in part, to the interconnectivity and complexity of information exchange among behavioral variables (Fusaroli, Konvalinka, & Wallot, 2014; Hidaka & Yu, 2010).

Granger causality, or G-causality, is a well-established and effective method for the investigation of directional relationships among a set of interdependent variables in many domains (Bressler & Seth, 2011). Granger (1969) formalized the basic idea of causality between signals introduced by Wiener (1956) based on multivariate autoregressive (MVAR) models: if past values of $\boldsymbol{Y}$ contain information that help predict $\boldsymbol{X}$ above and beyond the information contained in the past values of $\boldsymbol{X}$ alone, then $\boldsymbol{Y}$ is said to Granger-cause $\boldsymbol{X}$.

Kim et al. (2011) proposed a point process framework to enable G-causality to be applied to point process data with a discrete nature. A temporal point process is a stochastic time series of binary events that occurs in continuous time. It can only take on two values at any point in time, indicating whether or not an event has occurred. With a time series dataset of an ensemble of variables, the occurring likelihood of the event variable $\boldsymbol{X}$ can be modeled by the generalized linear model (GLM): a linear combination of time series $\boldsymbol{X}$'s dependency to the history of each individual element in the ensemble. Given a set of multivariate temporal streams, the causal relationships from variable $\boldsymbol{Y}$ to $\boldsymbol{X}$ is assessed by calculating the relative reduction in the likelihood of producing this particular history of time series of $\boldsymbol{X}$ when the history of $\boldsymbol{Y}$ is excluded, compared with the likelihood if all the available covariates are used in the prediction calculation. If the prediction likelihood is reduced when the history of variable $\boldsymbol{Y}$ is excluded from calculation, then there exists a Granger causal relationship from $\boldsymbol{Y}$ to $\boldsymbol{X}$. In addition, Kim et al. (2011) proposed that the sign of averaged influence of the occurring history of variable $\boldsymbol{Y}$ on $\boldsymbol{X}$ can be used to distinguish excitatory (positive estimate) and inhibitory (negative estimate) influences: whether the event history of $\boldsymbol{Y}$ is more or less likely to lead to the event occurring for variable $\boldsymbol{X}$. Finally, the point process framework also affords researchers to identify the statistical significance of a causal link based on the likelihood ratio test statistic. The goodness-of-fit statistics were applied by comparing the deviance between the estimated model with trigger variable $\boldsymbol{Y}$ excluded and the estimated full model in the GLM framework. Then, a multiple hypothesis testing error measure, FDR, proposed in (Benjamini & Hochberg, 1995; Storey, 2002) was used to control the expected proportion of false discovery rate when the number of hypothesis tests is large and the number of rejected null hypotheses is consequentially large.

Calculating G-causality with GLM model fitting makes very general assumptions about the data (Barnett, Barrett, & Seth, 2009) and with the point process framework, we are able to apply G-cause to categorical behavioral data. In the present paper, we used this framework to construct quantitative causal networks among different behavioral modalities in child-parent interaction and study child's coordination development.

Methods

Participants

21 parent-child dyads participated in this study. Dyads came into the lab when the children were 9-months-old and 12-months-old.

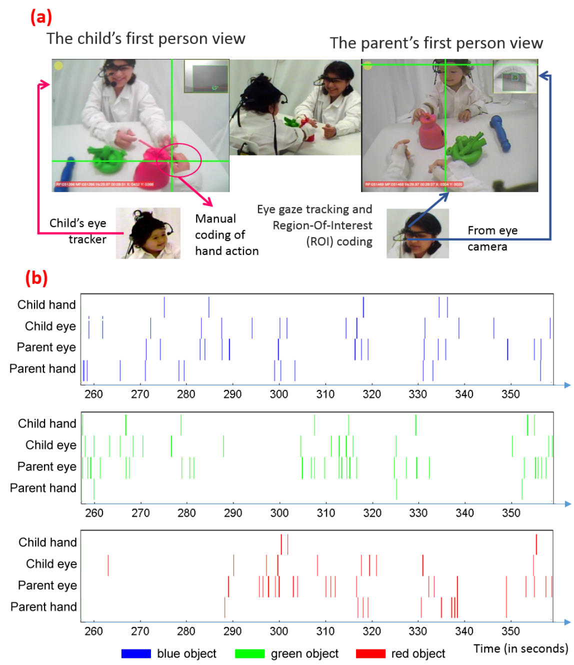

Figure 1: (a) A dual eye-tracking child-parent interaction paradigm. (b) Eye movement and object manipulation events from both the child and parent were coded into categorical data streams. The data streams were then divided into three different ROI groups, preserving only the onset of events. Finally, per subject, the three groups were concatenated as input for subsequent calculations of Granger causality.

Procedure

Figure 1(a) shows the experimental setup of our dual eye-tracking child-parent interaction experimental paradigm (Yu & Smith, 2013, 2016). Parents and their children were seated across from each other at a plain white table (61cm × 91cm × 64cm). Head-mounted Positive Science eye trackers (Franchak, Kretch, Soska, & Adolph, 2011) were put on both the child and parent to capture their gaze data in real time. Each eye-tracking system includes an infrared camera that records eye images (mounted on the head and pointed to the right eye, see Figure 1a), and a scene camera capturing the first-person view from the participant's perspective. The scene camera's visual field is 108 degrees providing a broad view. Each eye-tracking system recorded both the first-person view video and precise gaze allocation in that view, with a sampling rate of 30 frames per second. Another high-resolution camera was mounted above the table and provided a bird's-eye view at a recording rate of 30 frames per second.

For each trial of the experiment, there were two sets of toys. Each set consisted of three toy objects with three different colors (blue, green, red). The toys were of similar size and weight. Parents were told that the goal of the experiment was to study how parents and toddlers interacted with objects during free play and they were asked to engage their children with the toys as what they would naturally do in daily life. Each of the two sets of toys was played with twice for 90 seconds, resulting in approximately six minutes of play over four trials from each dyad. Toy set order (ABAB or BABA) was counterbalanced across dyads.

Data Processing

Human coders went through the videos from multiple viewpoints and manually annotated frame-by-frame about which object was gazed at and held by the child and the parent with both of their hands. In this study, we coded four Region-Of-Interest (ROI)s for the eye movement data: blue, green and red object categories (1-3) and other (0). Each value represents where the child or the parent was looking at in every frame. The participants could be looking at each other's face, but our analysis didn't include face looking events in this paper. The same object and empty ROIs (0-3) were also the coding categories for hand action data streams, indicating the target object was held by either the left or the right hand of the child and the parent. For each trial, after data processing, four coded categorical data event streams (child gaze events, child holding events, parent gaze events, and parent holding events) were obtained.

The next step was to convert our behavioral temporal data streams into multivariate point processes. All behavioral data streams were divided into three groups by different ROIs and then only the onsets of object ROI events were preserved to fit the point process framework for calculating G-causality. Figure 1(b) shows the point process data streams from one experimental trial. After point process conversion, for each dyad, three groups were concatenated as input data for calculating G-causality. In each group, all streams contained the onset of the same category of events. With this point process data transformation, we extracted Granger causality among different behavioral variables acting on the same object. For example, we estimated G-causality from the event of child looking at the red object to the occurrence of the parent looking at the same object.

Analysis

For each dyad, we constructed a dyadic causal network among four behavioral variables (child eye movement, child hand action, parent eye movement and parent hand action) at 9 months and 12 months. Figure 2 shows the G-cause network constructed with two dyads' interaction data. In each network, there are 4 behavioral variables (child eye, child hand, parent eye and parent hand) and 12 different types of directional links between every pair of variables. The different types of directional links are illustrated in Figure 2.

Significance tests based on the likelihood ratio test statistic with FDR controlling false positive causal interactions (Storey, 2002; Kim et al., 2011) was performed to determine the statistical significance of every causal link with regard to the entire network. In Figure 2, red colored links indicate the significantly positive links with number at the end of each link representing the G-cause value from one behavioral variable to the other. For example, at 12 months, Dyad#1 had a significantly positive causal link from child's gaze to child's holding behavior. This means that the child was looking at a certain object and the occurrence of this event significantly increased the likelihood of the child holding the same object. In addition, to best comprehend the magnitude of G-cause values for our

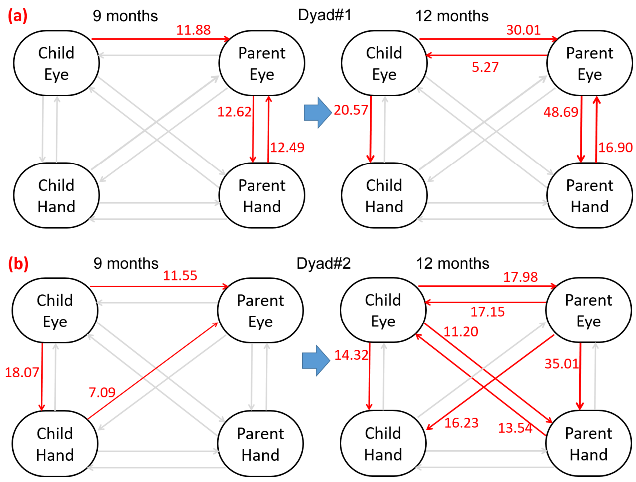

Figure 2: (a) The G-cause coordination network among child eye, child hand, parent eye and parent hand time series for Dyad#1 at 9 months (left) and 12 months (right); red links are significantly positive G-cause links and the number indicates the G-cause value of that causal relation. (b) The G-cause coordination network for Dyad#2 at 9 months (left) and 12 months (right).

multimodal coordination data, we also calculated the baseline G-cause network for every interaction. This was done by randomizing the order of event streams (with all ROIs and their event durations) for the behavioral variables. Then, the randomized onsets of object ROI events were preserved to convert the data to fit point process model for baseline G-cause network calculation.

The source code, a more detailed explanation of the Granger causality calculation process and more supplementary materials of this study are available at: https://github.com/lingerxu/Granger_causality_coordination .

Results

To examine our developmental hypothesis – increased coordination from 9-months to 12-months – we first looked at two group-level measures: the number of significantly positive G-cause links and the average G-cause value per link in each interaction network. For example, in Figure 2a, Dyad#1 had 3 significantly positive links at 9 months and 5 links at 12 months and the average G-cause value per link was 2.96 at 9 months (baseline value 0.19) and -2.27 at 12 months (baseline value -0.04). Average baseline G-cause values obtained with the randomized event streams were close to 0 for both age groups. In the present paper, we focused on examining the significantly positive G-cause links, which have much higher values than baseline and entail a strong causal link from one behavior variable to another.

As shown in Figure 3, we observed more significantly positive G-cause links at 12 months (M=3.95, SD=0.23) compared to each dyad's network at 9 months (M=2.38, SD=0.20), $t(20)$=3.27, p=.004. We also observed that the G-cause network for 12 month olds (M=5.50, SD=0.39) had significantly higher average G-cause values per link than 9 months (M=2.52, SD=0.26), $t(20)$=3.85, p<.0001. Overall, the multimodal coordination between child and parent showed increased developmental changes from 9 months to 12 months. The observation of increased positive causal links in the network and higher G-cause values on average from 9- to 12-months, suggests that the coordinative patterns of the child-parent dyadic system are becoming more dense and stronger.

Multicausality and Individual Differences

The main proposal of the multicausality hypothesis is that increased coordination is achieved by the emergence of multiple new causal influences between different pairs of behavioral variables and that no causal link has developmental priority. The results observed in the last section provided clear evidence that child-parent dyadic systems become more coordinated from 9 months to 12 months. Next, we want to look at how this increased level of coordination was achieved and whether we will observe individual differences in the developmental pattern in the dyadic causal network.

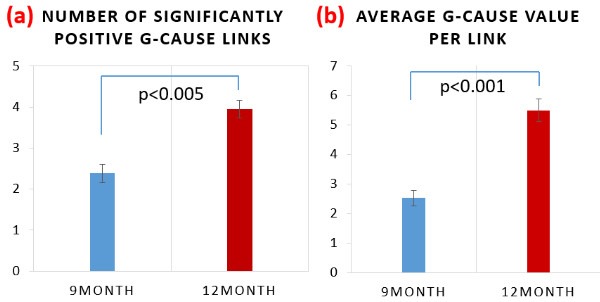

Figure 3: (a) Amount of significantly positive G-cause links and (b) average G-cause values of child-parent eye hand coordination networks at 9 months and 12 months.

When we take a closer look at the individual development between the two networks of each dyad, and how each causal link in the network changed from 9 months to 12 months, there are multiple types of change. Here we will mainly focus on examining the *emergence* of new significantly positive link, which means that this positive causal link did not exist in the 9-month coordination network, and only appeared in the 12-month network.

With 12 different types of G-cause links in total, the development of the coordination network can be described by a vector of developmental changes in each type of causal relations. The developmental coordination row vector for each dyad is visualized in Figure 4a. Three causal relation links, child hand→child eye, parent hand→child hand and child hand→parent hand, are omitted in the illustration because we did not observe any emergence of new positive links in these three link types. For example, the two dyads in Figure 2 can be mapped to the first two vector representations in Figure 4a. For Dyad#1, two new positive links emerged in their G-cause network at 12 months. This emergence is depicted in the developmental coordination vector: two red cells in parent eye→child eye and child eye →child hand categories (see Figure 4a, row 1). In another example, for Dyad#2 (see Figure 4a, row 2), five new links emerged from 9 months to 12 months. And we can see that, between the two dyads, four out of five emergent links from Dyad#2 were completely different from the G-cause relation types in which Dyad#1's emergent links belonged to.

Finally, if increased coordination from 9 months to 12 months was achieved through one type of causal link with causal priority, then the hypothesized frequency distribution of emergent links will be similar to Figure 4b. We can observe that the majority of emergent links belong to the same causal relation type. Alternatively, the multicausality hypothesis entails that increased coordination is achieved via multiple different causal relations. In an ideal situation, we would observe a uniform frequency distribution of emergent causal relations. This possibility is depicted in Figure 4c. Figure 4d shows the empirical frequency distribution of emergent links. The empirical distribution provides evidence for a diffuse collection of emergent causal relations, supporting the multicausality hypothesis

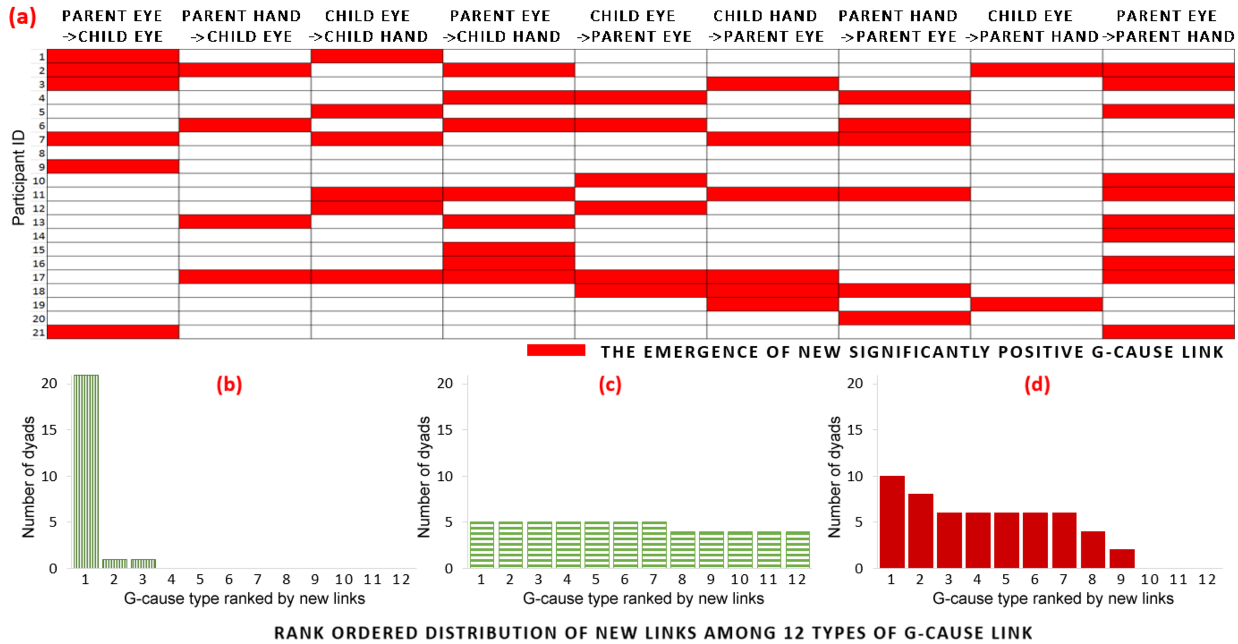

Figure 4: (a) The development coordination vector for each dyad's G-cause network. Red cells indicate the emergence of significantly positive G-cause links from 9 months to 12 months between different pairs of behavior variables. Each row represents the developmental change in coordination network for one dyad. Each column represents the developmental change for a particular type of causal relation link. Three causal relation links, child hand→child eye, parent hand→child hand and child hand→parent hand, are omitted here because we did not observe the emergence of significantly positive links. (b) The hypothesized frequency distribution of emergent causal links if increased coordination was achieved by only one link with causal priority. (c) Illustration of the frequency distribution of emergent links for the ideal uniform distribution under the multicausality hypothesis. (d) The empirical frequency distribution of emergent links in our results.

that child-parent dyads are utilizing multiple coordination patterns to achieve increased coordination.

General Discussion

The goal of the present paper was to investigate the development of multimodal organization in naturalistic child-parent interactions. We used a novel causal network modeling approach to better understand how multimodal dyadic systems change across developmental age. The observed results provide preliminary evidence for the developmental and multicausality hypotheses that we proposed at the outset of the paper.

At a group-level, we observed an increase in the amount of causal links and an increase in the strength of causal links from 9 months to 12 months. These results provided support for the *developmental* hypothesis, suggesting that the multimodal coordination patterns across the child-parent dyadic system became stronger with more components being coordinated within the dyadic system. This is an important observation because it provides novel evidence for an important property of the developing child-parent dyadic system: development includes adding redundancy to the social interaction by creating new pathways for coordination to occur (Yu & Smith, 2016). Redundancy is an important property for any complex system because it affords adaptability in the face of intrinsic and extrinsic perturbations (Kugler & Turvey, 1987; Thelen & Smith, 1998).

At an individual level, we observed that the causal relation links were distributed among all types of G-cause relations between two behavioral variables both within and between agents. Furthermore, the frequency distribution of emergent causal links was approximately uniform suggesting that there was no single behavioral link taking developmental causal priority in the network. These results add preliminary support for the *multicausality* hypothesis. These observations provide important conceptual and empirical contributions. Multicausality has been proposed to be an important property of a complex system (Smith & Thelen, 2003), however there has been little work to extend the proposal of multicausality to a dyadic model of child-parent interactions. This framework quantifies the directional causal influences between different behavioral variables to model the complex system of interpersonal coordination at sensorimotor level. Thus, it can provide heuristics towards understanding the individual differences in the establishment of joint attention and possibly the reasons underlying the correlations between joint attention and many developmental outcomes (Mundy et al., 2007; Tomasello & Farrar, 1986; Yu & Smith, 2016). Finally, to our knowledge, this is the first study to use MVAR-based Granger causality to model multimodal coordination as directed causal networks. Our results provide evidence for the promise of this analysis method as a novel dynamic modeling method for many domains, such as developmental science, behavioral science, etc.

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