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Grace Qiyuan Miao[1], Rick Dale[1], Alexia Galati[2]

[1]Department of Communication, University of California, Los Angeles

[2]Department of Psychological Science, University of Carolina, Charlotte

Author Note

Grace Qiyuan Miao https://orcid.org/0000-0001-7171-0542

Rick Dale https://orcid.org/0000-0001-7865-474X

Alexia Galati https://orcid.org/0000-0001-7593-6629

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Correspondence should be addressed to Grace Qiyuan Miao, University of California, Los Angeles, Department of Communication, 2133 Rolfe Hall, Los Angeles, CA 90095, United States. Email: q.miao@ucla.edu.

Abstract

People coordinate to perform joint tasks in daily interactions, and successful outcomes often require that they perform synchronized and complementary behaviors. Using computational methods, we develop a simple linear model to describe dynamics of synchrony and complementarity and explore their task-dependence, with task context consisting of active, inactive, and inhibitory constraints on communication. Results reflect that task constraints can be a robust predictor of simulated agents' behaviors over time. We describe preliminary theoretical implications from these results, and relate them to broader proposals of synergistic self-organization in communication.

Keywords: modeling and simulation, interpersonal dynamics, synchrony, complementary, synergy, active inhibition

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People coordinate with each other to perform joint tasks in a wide variety of circumstances. Such coordination involves individuals performing synchronized and complementary behaviors to achieve successful outcomes. For example, when searching for a missing item in a room, two people could both look at the bed (i.e. synchronized joint attention), or one at the bed while the other at the table (i.e. complementary visual search). These intuitive and pervasive behaviors require both cognitive skills and social understanding. How do people balance synchronized and complementary behaviors during cooperation, and what are the underlying cognitive processes that make them possible? These questions pertain to theories of social interaction and have implications for how we optimize collaboration and task performance (Galati et al., 2021; Hasson & Frith, 2016).

One possibility is that synchrony and complementarity are supported by cognitive control processes. Consider two interlocutors engaging in friendly turn-taking, where one speaks and the other listens (i.e. complementarity). Active inhibition in this case (e.g., when one partner suppresses what they want to say until the other finishes) could be important for maintaining interpersonal harmony and keeping the conversation going. Indeed, there is evidence that, in situations involving multiple perspectives and potential ambiguity, language users need to actively inhibit their own perspective to process language appropriately (Brown-Schmidt, 2009).

One way to investigate these cognitive questions is through computational simulation (e.g., Hilbert et al., 2019; McClelland, 2009). Computational models represent a simplification of a real-world system, allowing researchers to test experimental treatments or what-if scenarios that are practically infeasible in real-life settings. Moreover, simulated data complement empirical data collected in laboratories, granting researchers greater power to draw theoretical implications (for discussions, see Álvarez-Gálvez, 2017; Hilbert et al., 2019; Smaldino, 2017).

One open question is *how* humans determine when to synchronize with or complement each other, particularly in tasks that permit both options. There is mixed evidence about the prevalence and benefits of alignment. Some studies show negative effects of excessive alignment (Fusaroli et al., 2012), others highlight its importance (Richardson & Dale, 2005), and yet others suggest that alignment is highly dynamic and complex, so its benefits are dependent on context (Riordan et al., 2014). Although computational models have been developed for joint action– especially related to motor control (Nalepka et al, 2019), few account for the emergence of partners' behavior in conversation (see Dale et al, 2014 for review). Proposals of computational models (e.g., Wilson & Wilson, 2005; Pickering & Garrod, 2013) are often schematic, and have not yet been implemented and tested (cf. Smaldino, 2017; Donnarumma et al., 2017).

In this research project, we develop a simplified linear model to describe dynamics of synchrony and complementarity and explore their task-dependence. The model is deliberately simple, using coupled linear equations (cf. Wilson & Wilson, 2005). This permits easily integrating hypotheses about cognitive and social constraints. In a preliminary version here, we show that the model offers clues about the emergence of synchrony and complementarity, through integration of parameters that characterize the context of the interpersonal task.

Method

Our initial approach is to draw from simple discrete dynamic systems models that permit clear interpretation of parameters and behaviors (Richardson et al., 2014). We model a single behavior for two interacting partners, and represent these behaviors as a two-dimensional vector that is updated iteratively over time. We take their behavior as numeric descriptions, scalars, which can abstractly capture any quantitatively described behavior (e.g., eye movements, body motion, etc.). Taking ***B*** to be this vector ($b_{\text{Person 1}}$, $b_{\text{Person 2}}$) at time *t*, we have:

$$B(t) = C \cdot I \cdot B(t-1) + U(-.5, .5) - \alpha B(t-1)$$

The behavior of two people ***B***(*t*) is a function of a given context ***C*** and power of influence ***I***. We take this ***C*** parameter to be a "context matrix," because it transforms two-person behaviors based on a prior time step (*t* – 1), with added noise (*U*). In this iteration, ***I*** is set as constant (***I***=1), which represents 100% receptivity of two people towards all signals. The final subtractive term is a decay term to ensure the model does not saturate and go to positive or negative infinity.

The task context is numerically described as a 2x2 matrix whose values can be 0, 1, or -1, representing inactive, active, or inhibitory constraints on communication. For example, during a presentation, the speaker is actively speaking, while the audience is inactive in speaking. If the audience has a question in mind but inhibits the act of asking questions immediately to maintain the presentation flow, the audience is practicing active inhibition. This ***C*** matrix specifies how much individuals influence each other, how much they are autocorrelated (influence themselves), and can vary across *specific* tasks that humans face:

C = ($\boldsymbol{S_1}$ how much *Person 1* influences self, $\boldsymbol{O_1}$ how much *Person 2* influences *Person 1*;

$\boldsymbol{O_2}$ how much *Person 1* influences *Person 2,* $\boldsymbol{S_2}$ how much *Person 2* influences self)

For example, if $\boldsymbol{C}$ is "null" with $\boldsymbol{C} = (0, 0; 0, 0)$, the model generates agent behaviors that are random with no meaningful structure or interaction. When $\boldsymbol{C} = (1, 0; 1, 0)$ or $(0, 1; 0, 1)$, there is a role asymmetry. This would be relevant to educational scenarios, such as lectures, where one partner primarily drives the interaction. We can also implement *inhibitory* cues, such as $\boldsymbol{C} = (0, -1; -1, 0)$ to represent cases where partners actively inhibit imitating one another.

Results

We show in preliminary simulations that task contexts ***C*** involving active, inactive, and inhibitory states of communication result in different patterns of interpersonal dynamics. Illustrations of the model are shown in Fig.1, and all the code can be found at https://github.com/miaoqy0729/sim-syn-sims.

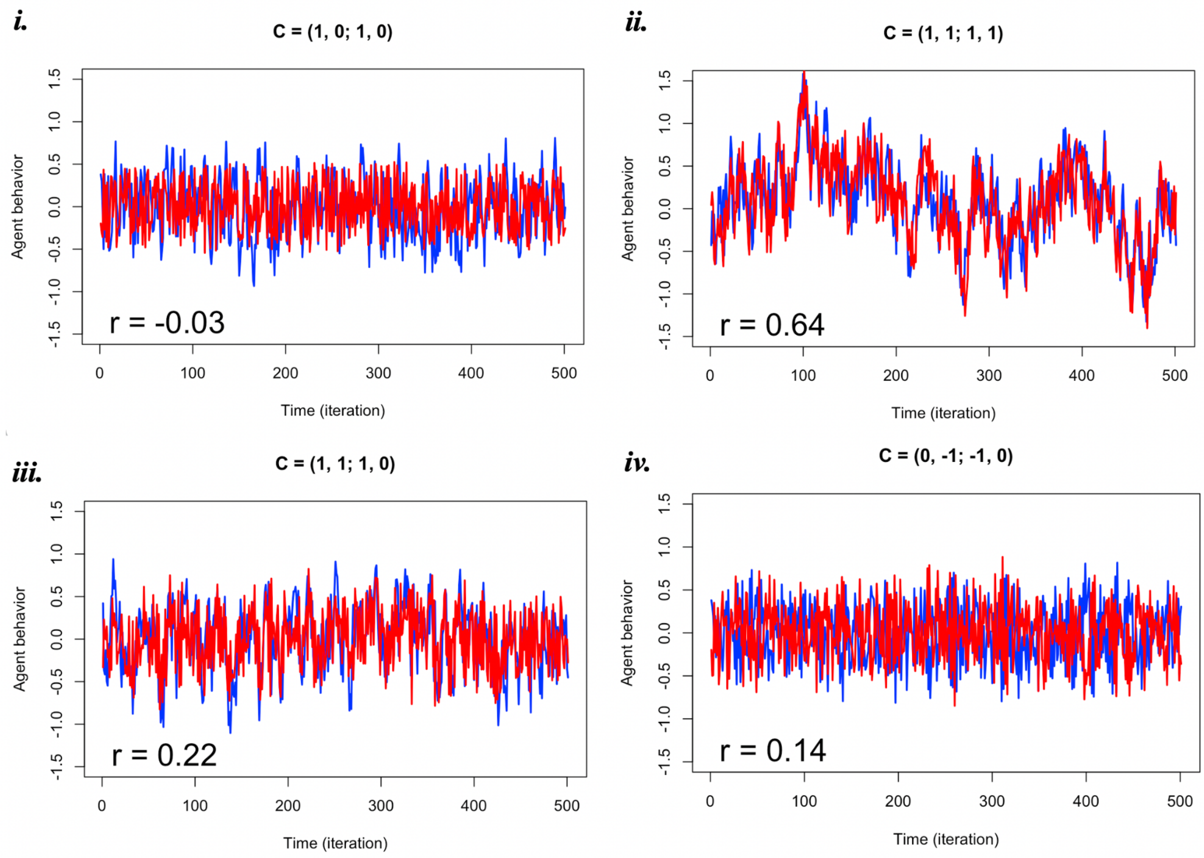

Fig.1: Time series of two dyads (blue, red are $b_{\text{Person 1}}$ and $b_{\text{Person 2}}$) under different context matrices.
i. When Person 1 is active but Person 2 is inactive, they have no interdependence.
ii. Total coordination between two agents (such as singing a song together) produces close synchrony.
iii. In a leading/following scenario (such as teaching), blue precedes red and correlates in their simulated behaviors.
iv. With inhibitory parameters, a negative correlation (calculated using 0-lag cross-correlation) is exhibited by the simulated dyad, and their behavior fluctuates between states.

With 4 digits and 3 possible values (-1, 0, 1) in each digit, there are $3^4 = 81$ combinations of the ***C*** matrix. We ran 100 simulations under random starting conditions for each of the 81 possible ***C*** matrices (examples shown in Fig.1). Across the 8,100 simulations, we find that in order for models to exhibit a strong negative correlation in agent behavior similar to turn-taking (for convenience, we define this as $r < -0.25$ here), the task constraints (***C***) contained a negative value 99.8% of the time. To test this significance, we conducted a chi-square test on uniform probability, yielding a significant result ($\chi = 1317.00$, $p < .00001$). With uniform probability being not the optimal to perform test on, we conducted an additional test using probabilities of the corresponding positive correlation ($r > 0.25$) in the simulations as baseline. These contained only 83.3% negative task parameters. This difference from the turn-taking distribution is also significant by a chi-square test ($\chi = 259.98$, $p < .00001$). This suggests that in order for there to be a robust turn-taking pattern, the combination of constraints in ***C*** must include at least one negative value almost at all time.

In order to understand how different combinations of active, inactive, and inhibitory states of communication between two people influence the behavioral dynamic between them, we performed multicategorical analysis on the simulated data. All four parameters of the ***C*** matrix (S1, O1, O2, S2) were dummy coded with value 0 as the reference group, resulting in 8 parameters (S_1p, S_1n, O_1p, O_1n, O_2p, O_2n, S_2p, S_2n) representing each C matrix ("p" and "n" stand for "positive" and "negative"). With the positive and negative values specified for each of the four parameters, regression analysis can reveal whether the valence of three different states of communication plays a role in impacting the communication flow. In addition, to better explore the components that account for correlations of dyadic behavior in the simulated data, linear interactions across all possible dummy coded parts of the model are calculated. The resulting regression model contains all possible predictors that account for the variability of dyadic correlation, including 8 dummy coded parameters in the C matrix (S_1p, S_1n, O_1p, O_1n, O_2p, O_2n, S_2p, S_2n) and all possible interactions between different parameters (8*6 = 48 interactions), consisting of 56 predictors in total.

To evaluate the amount of variability in the simulated data the regression model could explain, we considered the R^2 values of the regression model. The overall model with 56 predictors yields an R^2 value of 0.95, which represents 95% of variability in the dependent variable *r*, the synchrony between the two agents. We further examined whether an R^2 value greater than 0.9 can be obtained using subsets of the predictors, instead of all 56. We found that more than 90% of variability could be accounted for with less than half of the 56 predictors. For example, the R^2 of the model that accounts for how Person 1 influences self (s_1p, s_1n) and Person 2 (o_2p, o_2n) is 0.91. And the R^2 of the model that accounts for how Person 1 influences self (s_1p, s_1n) and is influenced by Person 2 (s_2p, s_2n) is 0.94. This means more than 90% of the variability in the dyadic system could be estimated based on one agent's influences. Though a highly simplified exploration of these effects, the model offers a foundation for understanding how behavioral dynamics between partners may be accounted for with task constraints. These regression results suggest that relatively efficient information from a task (the task matrix ***C***) can be used to predict how interlocutors in the simulation will synchronize under that task.

Discussion and Conclusion

While the current results may be expected from an intuitive interpretation of ***C***, they reflect a step towards modeling the coupling of task parameters and behavioral dynamics. Specifically, changes in the task constraints, through the context matrix, lead to different stable patterns of behavior. Results from various matrices can, in combination, simulate dyadic interaction from the onset of interaction to emergent synchrony and complementarity. Indeed, the importance of inhibitory parameters to yield clear complementary dynamics is consistent with work on the central role of executive processes (Brown-Schmidt, 2009).

Conceptually, these findings are consistent with wider theoretical proposals of synergistic self-organization, a concept used to explain the behavior of complex dynamic systems. Under this framework, cognition and behavior in a multi-agent environment exhibit distinct and partly stable patterns of coordination emerging from various constraints across people and the task environment (Richardson et al., 2016; Richardson, Dale & Marsh, 2014; Riley et al., 2011). We would argue that a perspective rooted in synergy elegantly frames our initial modeling endeavors. Model and theory may serve together as a framework for exploring key characteristics of interpersonal processes through a computational lens. Though the model we present here is highly simplified and a first step in this direction, the overall goal is to form a basis for future extensions that can both specify and directly simulate more complex tasks and multiple behaviors in human interactions.

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