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The Effect of Timescale Dependence on Dyadic Interactions

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Abstract

Interactions between agents are supported through a continuous process of detecting and responding to behaviors that are contingent upon the other agent's behavior. Here, we explore the temporal dependence of these mechanisms, focusing on the role of timescale compatibility in inter-agent interactions. Using continuous-time recurrent neural networks (CTRNNs) to control embodied agents in a minimal social interaction task, we demonstrate that effective interactions require agents to operate on compatible timescales. Our results indicate that time scale mismatches disrupt agents' ability to distinguish other agents from non-social entities, revealing a timescale threshold beyond which agents begin misclassifying slower agents as static objects and faster agents as non-social animate objects.

Introduction

Minimal social interaction tasks like the perceptual crossing task offer a simplified yet effective framework for studying the core mechanisms of social contingency (Malika Auvray et al., 2009; Di Paolo et al., 2008; Froese and Di Paolo, 2010; Rohde and Di Paolo, 2008; Auvray and Rohde, 2012; Lenay, 2012; Barone et al., 2020; Hermans et al., 2020; Froese et al., 2014; Lenay et al., 2011). Originally designed to observe real-time interactions between human participants, this task places agents in a virtual one-dimensional environment with another agent, a fixed object, and a "shadow" object that mimics the other agent's movements. As all objects provide identical sensory input (where the sensor simply signals contact or no contact), agents must rely solely on their sensory interactions to identify the other agent—a task requiring both agents to detect and respond to each other's presence. Recent experimental research has expanded the task to various fields, including human-computer interaction (Barone et al., 2020) and studies of social interaction across different age groups (Hermans et al., 2020; Froese et al., 2020) and populations, such as individuals with autism (Zapata-Fonseca et al., 2018). Concurrently, advances in the simulation of embodied agents has also begun to investigate the underlying circuit architecture and neuronal mechanisms using the tools of dynamical systems theory (Izquierdo et al., 2022; Merritt et al., 2024; Severino et al., 2023).

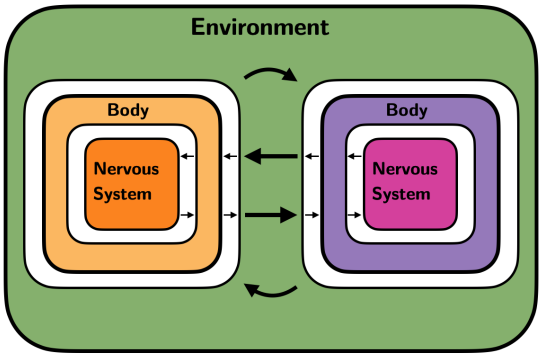


Figure 1: The mechanisms of behavior are influenced not only by it's nervous system, but also the biomechanics and function of it's body, structure of it's environment, and the subsequent interactions between brain-body-environment systems waithin said environment.

The current study investigates the role of timescale compatibility in inter-agent interactions. Specifically, we sought to understand how variations in an agent's temporal responsiveness influence its capacity to sustain social engagement. By evolving a diverse ensemble of circuits that successfully complete the perceptual crossing task, we analyzed when and why timescale mismatches lead to breakdowns in interaction. Through a dynamical systems analysis, we examined the neural mechanisms underlying these dynamics across different timescale conditions. By adjusting the operational timescales of these agents, we sought to delineate the limits within which agents recognize and sustain social interactions, and beyond which such recognition fails, potentially offering insight into why some forms of intelligence are more easily afforded social attributes than others. Following, we go over the methods used, briefly highlight some results, and outline future work.

Methods

Neural Controller and Task

Each agent is controlled by a given number of continuous-time recurrent neural networks

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(CTRNNs) (Beer, 1995):

$$\tau_i \dot{y}_i = -y_i + \sum_{j=1}^{N} w_{ji}\sigma(y_j + \theta_j) + g_i s + I_i \qquad (1)$$

where y_i is the state of each neuron, τ is the time constant, w_{ij} is the strength of the connection from the j^{th} to the i^{th} neuron, θ is a bias term, $\sigma(x) = 1/(1+e^{-x})$ is the standard logistic activation function, g_i is the sensory weight from the sensor s to neuron i, and I_i represents an external input to each neuron. The output of a neuron is $o_i = \sigma(y_i + \theta_i)$.

Each agent contains a continuous sensor, defined by the following equation:

$$s(d) = \frac{1}{1+e^{8(d-1)}} \qquad (2)$$

where d is the absolute distance between the midpoint of the agent and the midpoint of the other object. The neural network is fully interconnected, including self-connections, and the sensor, s, is fully connected to all neurons in the circuit via a set of weights. Two neurons are selected to control the left and right motors. The velocity of an agent is proportional to the difference between the outputs of the two motor neurons: $v = \gamma(o_1 - o_2)$, where o_1 and o_2 represent the outputs of the neuron controlling the left and right motors and γ is a constant that determines the agent's maximum possible velocity. The maximum velocity was set to $\gamma = 2$.

The perceptual crossing task takes places within a one-dimensional environment with periodic boundaries (refer to Fig. 2). In other words, the environment can be thought of as a ring, such that if an agent crosses the edge of the environment they appear on the other side. Two agents coexist in this environment and can encounter three types of objects (Fig. 2): the other agent's avatar, the shadow of the other agent, and a static object. Each agent is able to move around the environment with a maximum velocity (2 units of space per unit of time) in either direction. The shadow of the other agent, sometimes also called a "lure," is a mimic of the other agent's movements at a fixed distance (48 units) away from the agent it is attached to. Each object occupies a total of 2 units of space. The ring is 600 units in circumference, and the static objects are placed across from each other at units 150 and 450. Agents can move past each other and their respective static objects unimpeded. The neural controller that governs movement is rotated from one agent to the other, so that left and right movement aligns with the orientation of the agent. The shadows of the agents are reflected about the ring, so that one agent's shadow is to its left and the other agent's shadow is to its right.

Evolutionary Algorithm and Fitness Evaluation

In order to evolve the neural parameters of the controllers for our agents, we used a real-valued genetic algorithm. The corresponding ranges for the neural parameters were as follows: time-constants $\tau \in [1,10]$, biases $\theta \in [-8,8]$, and all connection weights between neurons $w \in [-8,8]$ and from sensors to neurons $g \in [-8,8]$. A generational algorithm with rank-based selection and a population size of 96 genotypes was used. We created successive generations by first applying random Gaussian mutations to each parent genome with a mutation variance of 0.05 (Beer, 1996). Uniform crossover was applied with a 50% probability with replacement occurring when the performance of the child was greater than or equal to the parent.

Fitness was evaluated by testing the ability of agents to find and stay close to each other in a ring environment (Fig. 2). The performance of pairs of agents is assessed through 78 trials with varying starting locations. In order to prevent solutions that depend on either the presence of the fixed object or the shadow, agents are additionally tested on conditions with or without fixed objects and shadows. Each trial lasts 800-time units, with the first 400 units considered transient. Once this transient is over, the score for a given pair of agents is:

$$f = 1 - \frac{\bar{d} - 2}{298} \qquad (3)$$

During a trial, $\bar{d}$ represents the average separation between the two agents, while 298 is the maximum spatial distance between them as the agents are unable to detect proximity beyond approximately 2 units due to their 2-unit width and sigmoidal sensors. The final fitness is the average fitness across all trials and is normalized based on the minimum distance at which the agents can sense each other.

Results

Evolution

In order to ensure evolution of a large and diverse ensemble of solutions to the perceptual crossing task, we ran 1,000 evolutionary runs on 3-neuron circuits. Each search yielded us a single best performing agent in the population, 183 of them achieving a fitness score greater that 0.99. In order to evaluate the generalizability and validity of the fitness score, each of these high performing agents were further subjected to additional robustness testing. This involved significantly increasing the number of initial conditions from 78 to 36,000 and doubling the trial duration to 1,600 time units. Out of the initial 183 high performing circuits, a subset of 111 of these agents demonstrated highly robust performance, maintaining a fit-

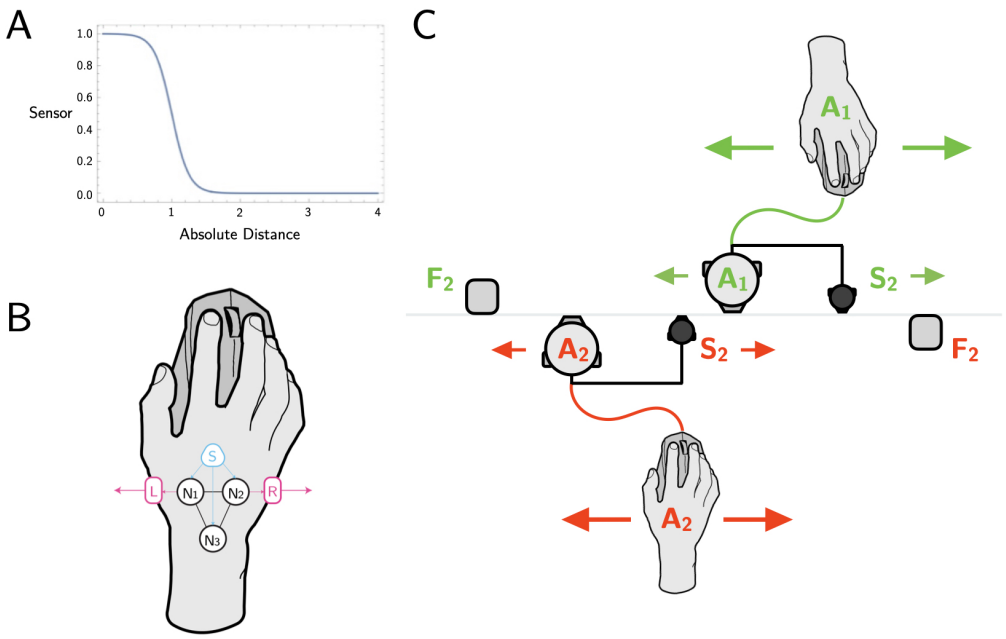


Figure 2: Agent and Task Design: **(A)** Sensor reading, calculated based on the absolute distance between the midpoint of the agent and nearest object. **(B)** Each agent has a sensor (cyan) that can send information to all N neurons (black). The neurons in the circuit are fully interconnected, including self-connections (not depicted). The output from one neuron drives the left motor, and another neuron drives the right motor (magenta). **(C)** The task takes place in a one-dimensional environment containing the agents avatars (A), shadows (S) and fixed objects (F).

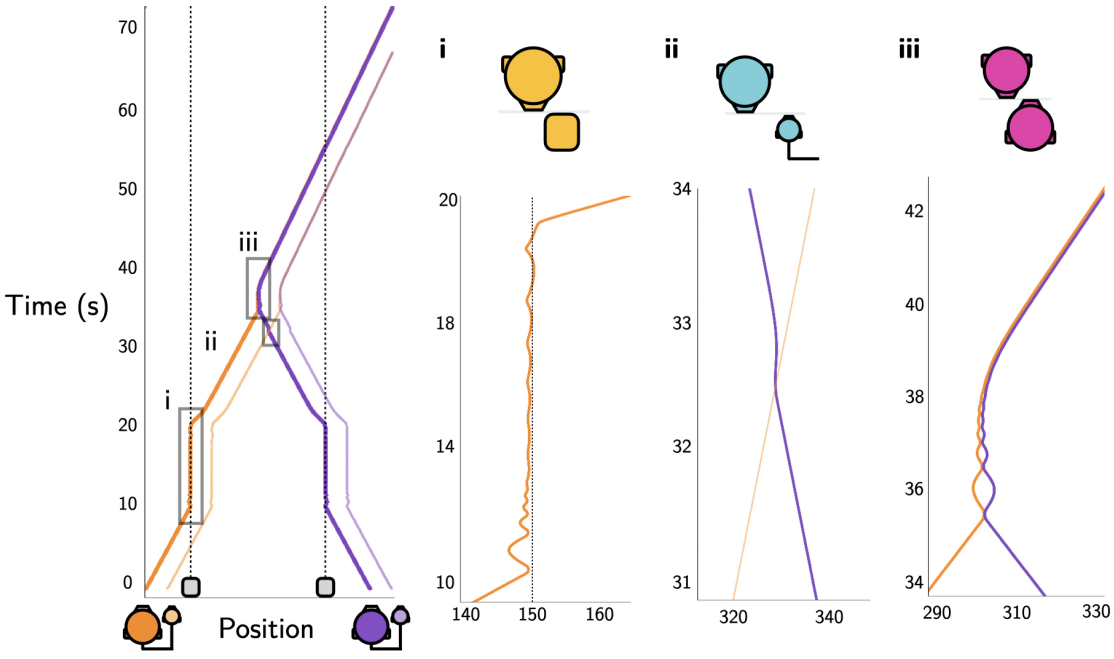


Figure 3: Example behavior of a successful circuit. In order to look closer at a typical trial, we zoom into each relevant interaction, namely between the **(i)** agent and fixed object, **(ii)** the agent and the shadow object, **(iii)** and the agent with the other agent.

ness score above 0.99 throughout the more rigorous evaluation. These 111 robust agents additionally succeeded across a variety of previously unseen conditions, including changes in the positioning of fixed objects and changes to the length of distance between an agent and its shadow. Notably, this smaller subset of highly robust agents represents the most reliable solutions capable of generalizing their performance beyond the initial training conditions, and thus present the best candidates for analysis.

Dynamical Analysis of Timescale Dependence

We investigated how timescale differences influence perceived social interactions in a simulated environment by examining an agent's sensitivity to another agent's response speed. In animal behavior studies, social interactions are generally defined as behaviors that impact the fitness of both the initiator and the responder. To test this concept, we fixed the primary agent's timescale to the rate it was evolved on and systematically varied the timescale of the other agent in it's environment across a range of integration step sizes, from 0.00001 to 0.5. This variation affected not only the other agent's movement speed but also the speed at which it's nervous system functions. We then quantified whether the agent identified the other as social by calculating the fitness function (average distance) between the two after a transient period, not unlike what the agent's experienced during evolution. Figure 5 (A) shows an example of the results of this experiment using the same candidate agent we show in Fig. 3. In this agent, we can see that there is a clear limit in how faster or slower the timescale of the other agent can be until interaction begins to break down. Furthermore, while the exact location of these upper and lower bounds can vary slightly from individual to individual, all appear to contain a similar bounded region of timescales that they are capable of sustaining a social interaction with.

In order to understand what shapes these boundaries and why these dips in fitness are occurring, we have to examine the underlying neural dynamics of these circuits in detail. In order to perform a dynamical systems analysis, it is often helpful to isolate the CTRNN and study the autonomous dynamics as a function of the different values detected by it's sensor. In doing so, one can treat the value of the sensor as a parameter and examine the dynamics of the system as the sensor is turned on and off. The perceptual crossing task can be understood as an 8-dimensional dynamical system that can be decomposed into two 4-dimensional individual circuits (each composed of 3 neurons and one sensor). As visualizing an 8-dimensional state space is not feasible, we isolated the CTRNN constituting one of the agent's nervous systems and examined its autonomous (time-invariant) dynamics by treating the sensor input, $S(x)$, as a fixed parameter (Beer, 1995; Beer and Williams, 2015). Doing so allows us to then examine how changes in the sensor affect the state space of the agent's nervous system. With this we can ask deterministic questions about the nature and function of the circuit at different sensor values, for example, the presence specific types of limit sets (e.g., equilibrium points, limit cycles) the stability of those limit sets (attractive, repulsive, or saddle) and whether or not the system undergoes any bifurcations (Strogatz, 2018). Lastly, as we are specifically interested in the relationship between the dynamics of the agents nervous system and their behavior, we can transform the embedding space to collapse the output of the two motor neurons to a single motor signal corresponding to the magnitude and direction of movement in the environment ($v = \gamma(o_1 - o_2)$).

As we are specifically interested here in temporal effects, it's crucial that we also include the non-autonomous (time-varying) neural trajectories into the analysis. Rather than treating sensor values as fixed parameters, we examined how real-time variations in sensory input, $S(t)$, influenced the neural circuits during interactions (Agmon and Beer, 2014; Beer, 1995; Severino and Barwich, 2024; Forbes and Beer, 2024). Specifically, this can be achieved by projecting real-time trajectories recorded from an agents nervous system onto it's autonomous bifurcation diagram.

In order to build some intuition, let's first walk through what this analysis reveals to us about the nervous system - environment interactions without modulating either agents time scale. In Figure 4 we can see that when the sensor is off, the system's stable point is associated with rightward movement at a moderate speed. Regardless of the source of stimulation, as the sensor turns on (S = 1) the nervous system undergoes two Fold bifurcations (also referred to as saddle-node bifurcations) that split the state space into two basins of attraction corresponding to movement in either direction. So how does the agent's nervous system react when it encounters something in its environment? When interacting with the shadow object, the shadow, not containing any way to perceive or react to the agent, passes by the agent at a relatively faster speed. As it quickly disappears, the sensor briefly turns on, but the trajectory through the agent's nervous system never fully approaches the stable point when it is on, as the stimulus quickly disappears, returning it to its original position and causing the agent to resume moving in the original direction. Interactions with the other agent and the fixed object are more similar. In both, the sensor's activation shifts the movement in the opposite direction, which causes the sensor to turn off again, which drives the movement in the original direction

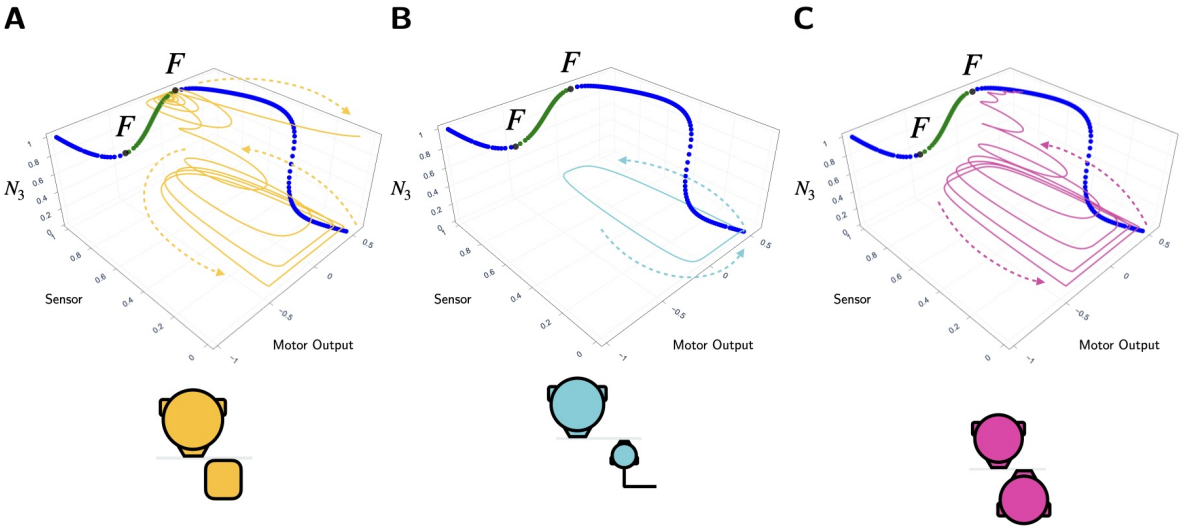


Figure 4: Example dynamical systems analysis of an agents nervous system when interacting with **(A)** the fixed object, **(B)** the other agents shadow, **(C)** and the other agent. For a range of different sensor values between $[0, 1]$, equilibrium points are colored according to their stability, with blue denoting stable points (attractors), green denoting saddle points, and black denoting bifurcation points. Non-autonomous trajectories sampled from a trial are then projected onto the agent's autonomous bifurcation diagram.

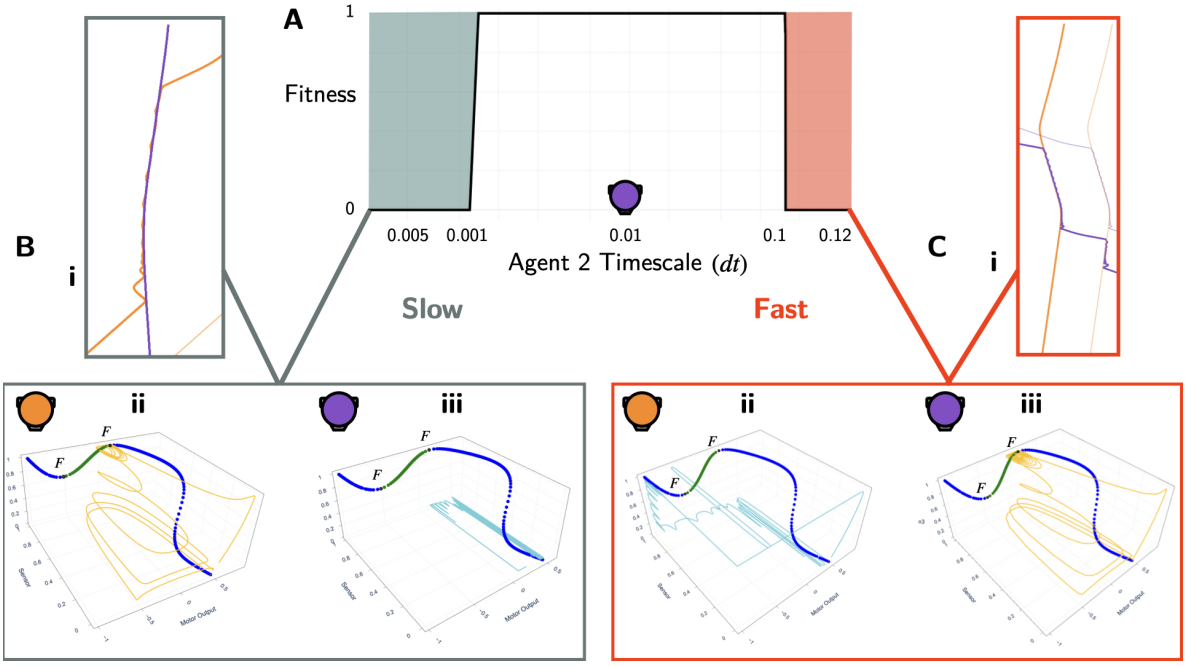


Figure 5: **(A)** Fitness measured across different timescales (integration step sizes from 0.00001 to 0.5). The primary agent (colored orange) remains at the timescale used during evolution (0.01). Where as the other agent (colored purple) has it's timescale varied. **(B)** Dynamical analysis of the breakdown in fitness when the other agent operating on the slower timescale. **(i)** Example interaction between the agents when locating one another. **(ii - iii)** When the other agent is operating on a slower time scale, trajectories in the nervous system of the primary agent (ii) reflect that of a fixed object. While for the other agent (iii) mimic that of the shadow object. **(C** The reverse is seen when breakdown occurs at the faster timescale where the trajectories in the nervous system of the other agent (iii) now reflect that of a fixed object.

and causes the sensor to turn on again, causing a brief oscillation. Importantly, this oscillation must occur long enough for the trajectory to be pulled up into the basin of attraction associated with higher inter-neuron value (N_3). This higher region is then further subdivided via the two bifurcation mentioned previously and provides the nervous system with a mechanism to distinguish between another agent and the fixed object. In the interaction with the other agent, the oscillation dampens until it settles on the stable point associated with movement to the right as a moderate speed, which we can see behaviorally as a drifting or chasing behavior (See Fig. 3). In the interaction with the fixed object, the agent is unable to converge on a direction and continues the oscillation. However, because of the stable saddle manifold generated from the fold bifurcation, the trajectory gets pulled into oscillations of a larger period until the body of the agent passes the fixed object in space, causing it to lose contact.

Can this analysis help explain the dips in fitness seen when we modulate one of the agents timescales? We examined the autonomous and non-autonomous dynamics of the same agent for each variation in it's partners timescale. We found that, for both our example agent as well as other circuits employing a similar dynamical mechanism, were robust to timescale changes that were on average 10x faster or slower than the timescale it was evolved on. When timescales exceeded this threshold, they were unable to tell the difference between the agent and the other objects in their environment. Specifically, we found that the reason for the dip in fitness occurred due to relatively slower agents being misclassified as static objects and relatively faster agents as non-social animate objects (akin to the shadow in the original task). In fact, a comparison of trajectories revealed this to be a result of the neural mechanism itself. From the perspective of the relatively faster agent, they fail to receive timely feedback from the slower agent, causing the trajectories in it's nervous system to appear almost exactly like that of a static object, causing them to identify them as such. Whereas when examining the dynamics of the slower agent, trajectories followed a path more akin to the shadow never getting a chance to reach the higher basin in state space, as by the time they begin to react, the fast moving agent had already moved on (Fig. 5).

Discussion

Overall, our results have underscored the importance of temporal alignment in dyadic interactions, highlighting how timescale differences can cause agents to misclassify each other as non-social or static objects. In particular, our simulations suggest that maintaining continuous mutual perturbation—where each agent's actions reliably affect the other's —is crucial for recognizing social contingency. Timescale mismatches thus can not only break down an interaction because of their interference with mutual perturbation, but cause a misclassification due to the heuristic nature of the mechanism.

This principle scales naturally to biological systems. Neural conduction velocity, muscle actuation, and body inertia jointly determine the temporal resolution at which an animal can close perception–action loops. Those parameters vary over orders of magnitude across taxa and even across developmental stages within a species, this may suggest genuine limitations to the degree that organisms can, in practice, "meet each other in time." A hummingbird, for example, may produce motion signatures that a snail's nervous system simply cannot sample at a rate sufficient to sustain contingent exchange without a long enough adaptation period. In the context of robotics and human–machine interaction, modern robots and virtual avatars often operate on control loops that are orders of magnitude faster than those of human partners. In turn, asynchronous processing speeds could undermine reciprocity: an autonomous system with sub-millisecond decision loop may fail to engage meaningfully with a human partner whose sensorimotor integration unfolds over hundreds of milliseconds. Embedding explicit timescale-matching mechanisms—or adaptable temporal filters—in artificial controllers may therefore be crucial for creating robots and virtual agents capable of social interactions.

Looking forward, several extensions will deepen our understanding of timescale-dependent social mechanisms. First, introducing plasticity into the agents' time constants could reveal whether—and how—controllers learn to adjust their own timescale through interaction, potentially providing insight into the adaptive processes seen in social learning. Additionally, future dynamical analyses can identify general principles about how neural processes give rise to social contingency detection through an analysis of the population of mechanisms and strategies that results in successful social interaction. These principles may include the roles of sensor-driven bifurcations in the neural controller, however, our results here have demonstrated the high degree to which performance in the task is dependent on the non-autonomous dynamics of the nervous system. By connecting such in-depth analyses to experimental work in perceptual crossing, we can develop more precise hypotheses about the forms of temporal coordination needed to sustain social interaction in both simulated and real-world settings.

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