Adaptively Learning Levels of Coordination from One's, Other's and Task Related Errors Through a Cerebellar Circuit: A Dual Cart-Pole Setup

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Abstract. Behavioral and theoretical studies have shown that during joint action in an interpersonal skilled activity, like carrying an object collaboratively, anticipation is required to further improve the precision in the realization of the task. We model this task as a dual cart pole setup, and we provide a computational basis of how this anticipation can be realized at different levels: anticipating errors originating from the agent's body control, errors related to the global task and errors derived from the anticipation of the other's actions. We model computationally the control loops of the agents as an interplay of feedback and feedforward components and we base the latter on previous research on the cerebellar circuit network. Our results confirm experimentally that anticipating the error in the task including inputs extracted from the behavior of the other, further improves precision in the realization.

Keywords: Social sensorimotor contingencies · Anticipation · Cerebellar circuit · Forward/Feedback control · Dual cart pole setup

1 Introduction

The realization of a skilled activity requires anticipation possibly realized as an interplay of feedback and feedforward components [14]. Anticipation is necessary because of the delays of the sensory feedback (up to 100 milliseconds in the case of the visual modality): to be able to guide the initial part of a movement of an action in a skilled task, sensory feedback is still not available at that moment (thus the need for feedforward control). These delays can increase even further in the case of an interpersonal coordination task [14], where the consequences of our actions can have an effect on the other. Being able to attend, anticipate and adapt to the other's actions are key factors in the coordination of joint action [5].

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Consider the example of two persons that need to carry together a table with objects on top to a target position: they need to maintain the table in an horizontal position while maintaining balance when moving and being able to anticipate the other's movements not to be uncoordinated.

In the following we contribute to the modelling of the presented task by means of two self-balancing cart pole agents that are linked by an object of variable elasticity[1] (see Fig. 1).

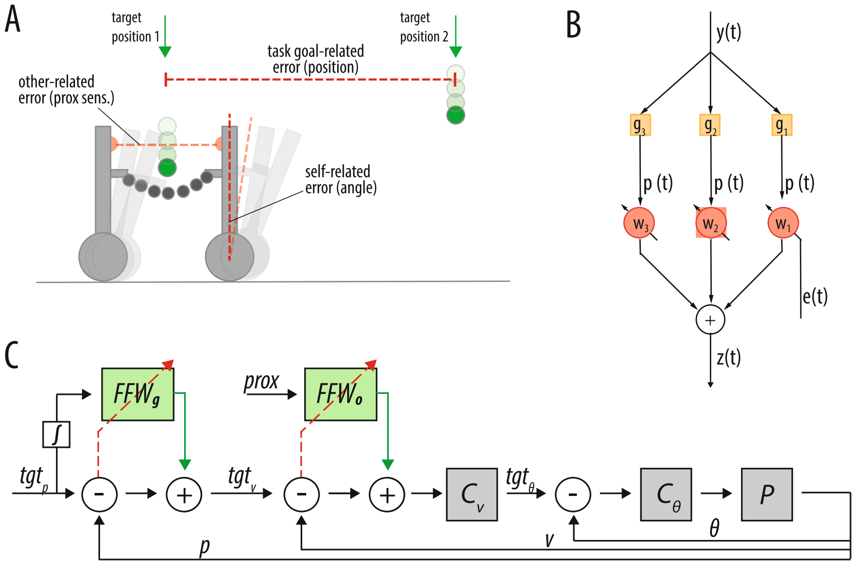

Fig. 1. Setup, control neural network and architecture. A. Dual cart pole robotic setup with two cart-pole agents facing each other and attached by an elastic chain. The agents have the goal of moving together to target positions (1 and 2) which alternate in time. B. Cerebellar circuit based on an adaptive filter neural network [4]. C. Feedfoward feedback architecture. The cascade PID feedback controller is shown as the main pipeline with the two feedforward components based on the network shown in B.

We also contribute to the computational modelling of how the task is implemented in the brain. Following [14] we model the control loops of the agents as nested feedback/feedforward loops that relate to errors originating from: the control of the agent body, from task related errors and from predicting the other. The anticipatory components are implemented based on the cerebellar circuitry presented in [4].

We propose a computational and neurobiologically plausible substrate for joint action. We provide as well experimental results of the benefits of monitoring the other agent to improve coordination, just as hypothesised in [12]

[1] The simulation has been implemented by the authors in python with pybox2d and can be download from https://github.com/santmarti/PythonRobot2DSim.

where monitoring and prediction are identified as the minimal components of an architecture supporting joint action. We address the question of what are the mechanisms supporting precise temporal coordination of actions [9], by assessing the additional precision achieved in the presented interpersonal coordination task by modelling and quantifying the contribution of the anticipatory loops related to the prediction of actions of others.

When performing a multi-agent sensorimotor coordination task (as the one just presented) different errors have to be taken into account:

1. Errors derived from the agent's own state: optimizing the posture for the realization of the joint action
2. Task related errors: e.g., if a furniture has to be carried maintaining its horizontal position (so that objects on top don't fall).
3. Resulting errors of the predictions involving other's actions: so that others intentions are anticipated or compensated as quickly as possible.

We start coupling the two agents with one feedback loop each. This first level translates task goals (target position of the agents) into a velocity and the feedback loops bring velocity and angle of the agents to zero, so that posture is controlled, and the own errors can be minimized (1). Given the parametrization of the simulation, the task can be performed using only feedback, but collisions and interactions among the agents affect performance severely. We then add an adaptive feedforward loop relating to the realization of the task which anticipates task related errors (2) as the one derived from under/overshooting the target position due to control delays. We finally show experimentally that the anticipation loop based on predicting the actions of the other (3), extracted from its own actions and the distance to the other, further improves the efficiency and precision in the realization of the task.

2 Methods

2.1 Setup

For the modelling of the task (carrying together an object to a desired location), we depart from the cart pole (inverted pendulum) setup often used as an approximation of posture and well known in the machine learning community. We implement a cart pole agent using library pybox2d (see github link in the intro for source code). The agent has one degree of freedom in its wheel, implemented as the so called revolution joint (joint of pybox2d library, basically a motor with torque). Each agent has a distance sensor in the upper part of his body which is implemented as a ray cast in the physics library (from a point and a direction vector in the body, the distance to the first colliding body is returned).

The setup is then constituted by two cart pole agents facing each other and attached by an elastic chain implemented as sequence of spheres linked by a distance joint.

2.2 Task

The task is composed of two goals: a local and a global one. Each agent has the personal goal of balancing while performing the global task. The chosen global task is an adaptation of a position reference tracking task for two agents (see Fig. 1). The target position of both agents switches from two different positions every ten seconds (see target positions in Fig. 1A). Both agents, each equipped with a different controller, have the common goal of reaching a target position, which is communicated as an additional input to the system, eliminating the problem of having to attend to it.

The agents need to collaborate if they want to perform the task efficiently and without losing balance as the chain causes indirect instabilities. The task is a collaborative motor task with multiples sources of error.

2.3 Architectures

The behavior of both agents is driven by a control scheme composed of coupled feedback and feedforward controllers (see Fig. 1). The feedback controller is in charge of adjusting the velocity and the angle of the agent according to a desired target position based on sensory feedback. On the other hand, the feedforward controllers are in charge of issuing sensory predictions (following the counterfactual predictive control, CFPC scheme [3]) with the goal to minimize a given error by acting in anticipation.

The feedback controller is implemented as a cascade PID composed by: a module setting a desired angular position (tgt_θ) that minimizes the error in velocity, and, a module generating a motor response (u) modifying the state of the plant to minimize the angular error and consequently the error in velocity (see Fig. 1C). A desired position is achieved by setting a desired velocity (tgt_v) as the difference between target (tgt_p) and current position (p).

Each feedforward controller module is implemented as a neural network consistent with cerebellar physiology and anatomy [1] (Fig. 1B), that expands an input $y(t)$ into a set of 100 gaussian bases (g). The output (z) of a single adaptive module is obtained as a weighted linear combination the bases vectors p. The weight vector (W) is updated according to a variation of the Widrow-Hoff rule such that: $w_j(t) = \beta e(t) p_j(t)$, where β (=10) is the learning rate, δ (=200 ms) accounts for the anticipatory delay and e is the error function. Importantly the two feedforward modules are identical in the implementation but differ in the nature of the error they minimize. FFW_g acquires a prediction useful to minimize a goal related error (i.e. position) associated with a change in target position. As such the input is defined as $y_{ffwg} = \int tgt_p$ and its error signal is defined as $e_{ffwg} = p_{tgt} - p$. Finally, the output (z_{ffwg}), representing a prediction of the error in position, is linearly integrated with the input to the descending reactive module C_v and processed as an anticipatory change in target velocity.

Differently, FFW_o acquires a prediction useful to minimize an error in velocity elicited by the distance to the other agent. Its input is defined as $y_{ffwo} = H(x_{prox})$, with $y = 1$ for $x_{prox} > 0.4$ and $y = 0$ otherwise, while its error signal is defined as $e_{ffwo} = v_{tgt} - v$. Finally, the output (z_{ffwo}), representing a prediction of the error in velocity, is linearly integrated with the current error in velocity and further transformed into a desired angular position by C_v.

3 Results

We run experiments where the agents have to minimize the displacement from a target goal position in two conditions: first, by learning to anticipate the target goal related error (ffGoal, ffG for short, condition in Fig. 3C legend, where only the feedforward goal component is activated) and second, by learning to anticipate simultaneously the goal related and the other related error (ffMixed, ffM for short, condition in Fig. 3C legend where both feedforward components are activated).

We start checking the performance of the agents engaged in the collaborative sensory-motor task by describing the performance of the feedback controller alone (Fig. 2A). Here, the error in position (red shaded) is due to the control latencies introduced by the physical properties of the plant, responsible for delays and overshooting, and by the interaction of the two agents introducing oscillations when colliding. A minimization of the first source of error is achieved by enabling the FFW_g module. After a number of repetitions a feedforward signal encoding a position error prediction (Fig. 2B) is issued with enough anticipation to trigger a corrective movement before the actual error is perceived (Fig. 3A, B black solid line). At the end of the experimental session the original error in position is reduced by approximately 40% (Fig. 3C, black solid and dashed lines).

Importantly, an ulterior increase in performance is achieved by enabling the FFW_o. This module learns over time to issue an anticipatory prediction of the velocity error introduced by the collision with the partner in response to its proximity (Fig. 2C). As a result, the agents progressively increase their ability

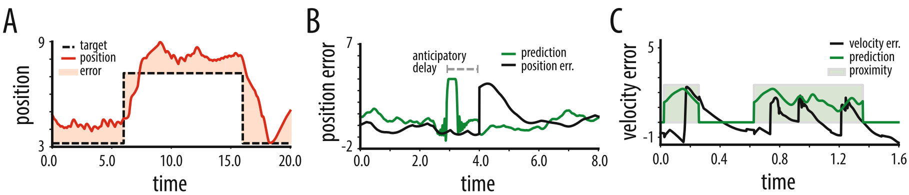

Fig. 2. Feedback and feedforward results. **A**. Results of the feedback controller alone for one of the agents. The curve shows the position of one agent with respect to the target reference which switches position every ten seconds. **B**. Predictive response signal of the first feedforward component FFW_g at the moment where the reference target changes. It can be observed that a predictive anticipatory signal is generated after 8 trials. **C**. Response signal of the second feedforward component FFW_o component that issues a response predictive signal (green solid line) every time the proximity sensor is activated (green shaded area). (Color figure online)

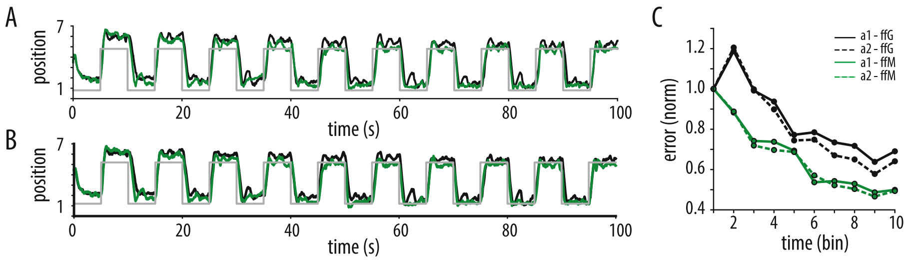

Fig. 3. Comparison between experimental conditions. **A**. Agent one results for the two conditions denoted ffG (black solid line) and ffM (green solid line), referring to the goal and mixed conditions (ffG and ffM respectively). **B**. Agent two results for the two conditions as in A. **C**. Learning curves of both agents for both conditions: ffG (only goal feedforward component activated) and ffm (both goal and proximity feedforward components activated). Legend refers to: agent one/ffG condition (a1-ffG), agent one/ffM condition (a1-ffM), and similarly for agent two. (Color figure online)

to react to the collision before it is perceived (see Fig. 3A, B green solid lines). Learning to predict the effects of the action of the other has a beneficial effect on performance by reducing the initial error by a total of 55% (15% addition to FFW_g alone, see Fig. 3C).

4 Discussion

We study the computational basis of sensorimotor contingencies (SMCs) involved in the realization of joint action during a skilled activity. We characterize social SMCs in a truly collaborative sensorimotor coordination task. The task itself (carrying something together to a target) has been proposed as a prototypical example of collaborative task with a common goal 90 years ago by Allport in his seminal book "social psychology" as credited in [9]. We have modeled the task by two cart pole agents linked by an object. We used different types of objects to be able to control levels of physical linking. Available objects in the implementation are: (1) two rigid bars linked by a spring of variable elasticity and (2) a chain made up of spheres linked by a join with variable elasticity. This feature is not exploited in the current paper and we leave the study of the effects of varying elasticity of the object to the agent coordination for future work. For the current experiments we have chosen to use option (2) as the problem of balancing while moving together becomes more challenging. We observed that when using a rigid bar the two agents became more linked and balance easily.

In the following we place our research in the context of related social cognition literature. We go beyond the approach of the "perceptual crossing" task where social sensorimotor contingencies can only be characterized by the dynamics of the interaction when the two agents cross [2] and where no joint task exists truly, only the derived goal of distinguishing the other. The "perceptual crossing tasks" is more related to the distinction of self and other.

In [13] the fact that adaptation is driven linearly or proportionally to an error is discussed, but the proposed Bayesian model that processes the relevance of the error is applied to a single source of error. Here different sources of error are taken simultaneously into account and being applied to a social collaborative task.

As discussed in [14], a social joint task that we address here deals in reality with a more complex types of anticipation. Fully predicting the consequences of actions may need to include an internal model (feedforward/anticipatory component) of the other. We don't deal with this fact in the paper as each agent only considers the subjective distance to the other and does not take into account any additional aspect as: weight estimation, strength assessment or even physiological state of the other. We leave this aspect as future work and we foresee interesting experiments that could be done: interchange partner in the task and reassess convergence of efficiency; make an agent more active than the other and look at coupling and turn taking behaviours. In fact, in this paper, we are interested in the pure perceptual anticipatory nature of a joint coordination task without considering communication aspects between agents; as we did in [6] for maximizing probability presence estimation within a group in occluded environments; or like they do in [11] for coordinating autonomous crossing vehicles in junctions.

The proposed architecture could be the basis to model and explain the neurophysiological basis of anticipatory aspects involved in social interaction, based on the cerebellar circuitry. It can also shed light into explaining experimental data of behavioral experiments like the lifting and balancing task presented in [7].

5 Conclusion

Wolpert et al. [14], investigate theoretically the role of the interplay of feedback/ feedforward components in social interaction. We propose and test experimentally a computational biologically plausible architecture for joint action supporting anticipation and monitoring of self, other and task related errors. We base the computational modeling of adaptive loops in the cerebellar circuitry [4] which has been proposed as a plausible substrate of the neurophysiological cerebellar circuit and has been identified to be crucial for anticipatory action [1], and its malfunctions and deficits have also been pointing to possible causal factors of complex disorders like autism [8,10].

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