Extended Abstract: Spontaneous Shifts of Social Alignment in Synthetic Robot-Robot Interactions

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***Abstract*— The enactivist perspective on social cognition emphasizes the roles of action and perception in social contexts; the mind is viewed as intrinsically embodied. By conducting synthetic neurorobotic experiments, this study aims to examine how the reciprocal information exchange of embodied robotic minds can lead to different types of social alignment. Future work will show whether and how neurocognitive mechanisms of the model can lead to spontaneous alignment shifts, from one mutual interaction context to another.**

I. INTRODUCTION

Our social cognitive abilities allow us to recognize, understand, and predict dynamics in the surrounding social environment [1]. By observing other individuals and their interactions, we infer their intentions and learn to understand them [2], [3]. Theory of Mind attempts to explain how one agent infers the mental states of another agent; closely related, the concept of self-other distinction, where we aim to understand how a 'self' agent develops internal models to understand 'other' agents' mental states. In many other cases, the study of social cognition, including the subdomain of social interaction, has been dominated by such individualistic perspective [4].

Motivated by the idea that bidirectional information exchange is one key component of social interaction, the individualistic approach to social cognition has started shifting toward a collective consideration. This reciprocity emphasizes the role of action and perception in social contexts and can be explained by an enactivist perspective. Here the mind is viewed as embodied, thus, deeply grounded in the world. Actions serve as the means to interact with the physical and social environment [4]. To model related cognitive mechanisms computationally, we may consider recent formulations of predictive models, those that emphasize active inference and embodiment [5].

Research in human-robot interaction and robot-robot interaction faces a shift toward enactivism as well. However, to the best of our knowledge, the main focus is still on the individual, not on the collective level [7], [8], on static, rather than dynamic intersubjective contexts [9], and on limited behavioral primitives with identical agents [10].

In this work, we propose an embodied predictive coding framework that considers the reciprocal exchange of information between two agents on a collective level. We designed synthetic neurorobotic experiments that allow us to study the mutual information exchange in different interagent contexts. We train two robotic minds to analyze how their interaction relates to varying types of social alignment. Alignment shift, i.e. spontaneous shifts in collective intent from one social context to another, is the second part of our study.

II. APPROACH

A. Model Architecture

The cognitive architecture used in this study is Variational Bayes Predictive Coding Multiple Timescale Recurrent Neural Network (VBP-MTRNN) [11]. This generative model is based on a predictive coding framework [12], [13] and employs the concept of variational inference [14]. The model comprises multiple recurrent layers k with N_k stochastic and deterministic variables z and d. A time constant τ_k exhibits temporal scales on the neural activity in each layer and allows the network to form a self-organizing hierarchy [15]. In every time step t, the network receives input x_t; based on its prior expectations encoded in the latent variables z, the network predicts $\hat{x}_{t+1}$.

B. Training objective

The network is optimized with respect to two training objectives. First, reconstruction error $\mathcal{L}_{reconstruction}$ is minimized. This is the difference between the network prediction $\hat{x}_{t+1}$ and the actual sensory evidence x_{t+1}. The second objective is to constrain the stochastic variable z to follow a Gaussian distribution $z \sim N(\mu, \sigma)$. This is represented as regularization error $\mathcal{L}_{regularization}$. A meta-parameter $w \in [0, 1]$ balances $\mathcal{L}_{reconstruction}$ and $\mathcal{L}_{regularization}$; thus, it controls the level of stochasticity that z brings to the network. z is intended to form a meaningful representation of input x while following a Gaussian distribution. In every training step, the respective training error is back-propagated to minimize $\mathcal{L}$ as following:

$$\mathcal{L} = (1 - w)\mathcal{L}_{reconstruction} + w\mathcal{L}_{regularization}$$

C. Robotic Platform

To study the aforementioned mechanisms in social interactions, we used two humanoid systems as proxies for two human experimenters. Via two master controllers Rakuda the

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experimenters controlled eight DoFs in the upper body of the OP2 robotic systems[1] (Fig. 1).

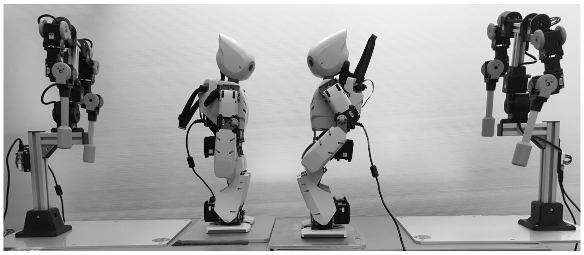

Fig. 1. The robot experiment was conducted with two Rakuda robotic systems (at the outer edges of the picture) and two humanoid OP2 systems (in the center of the picture).

D. Social Interaction Task

Social alignment is considered to be a multi-level, dynamic, interactive mechanism present in social interactions [16]. We designed synthetic experiments to reproduce various forms of social interactions. Here, the dyadic information exchange requires different forms of social alignment.

III. Experiment

While two experimenters performed a set of social interaction tasks, actuator data of the Rakuda devices were collected at a speed of 15 Hz. These motion data were sent via serial communication to two 'slave' robots OP2. Rakuda has the same DoF as OP2, so that trajectories were directly mapped to the OP2 actuators. Note, the playback of Rakuda motion on the OP2 system was done for quality assurance only; this step is not a technical requirement.
Motion data were used to train two models, one for each embodied agent. We provided sensory evidence of 'self' perception as well as the 'other'-robot proprioceptive sensation (Fig. 2) to two distinct VBP-MTRNN networks.

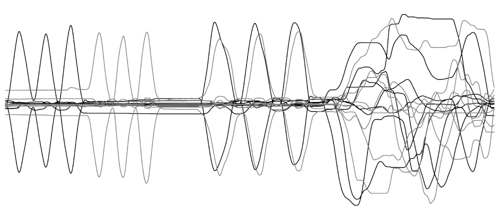

Fig. 2. Sample training trajectory of switching between three social interaction tasks. The plot shows the magnitude over time of eight DoFs of the robot "OP2-black" (black trajectory) together with eight DoFs of "OP2-gray" (gray trajectory).

[1]Both systems, OP2 and Rakuda, are developed by Robotis: www.robotis.us/robotis-op2-us/

IV. Future Work

Next, the two trained networks will be tested in an online setting. Each OP2 will be equipped with one pre-trained network. In a predictive open-loop, both agents will try to predict each other (i.e. predicting their sensory evidence) while inferring the cause of their perception (i.e. calculating, and if necessary, updating latent states z to better explain the observed sensory evidence.). Future analysis will focus on those prediction and inference behaviors of individual robotic minds, plus the respective intersubjective information exchange.
We hypothesize that the neurocognitive mechanism represented by the proposed framework demonstrates dynamic coupling and decoupling behaviors. Expected findings include (1) self-organized mutual alignment in different social contexts, plus (2) spontaneous alignments switching from one social context to a new one.

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