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Proprioceptive Feedback Plays a Key Role in Self-Other Differentiation

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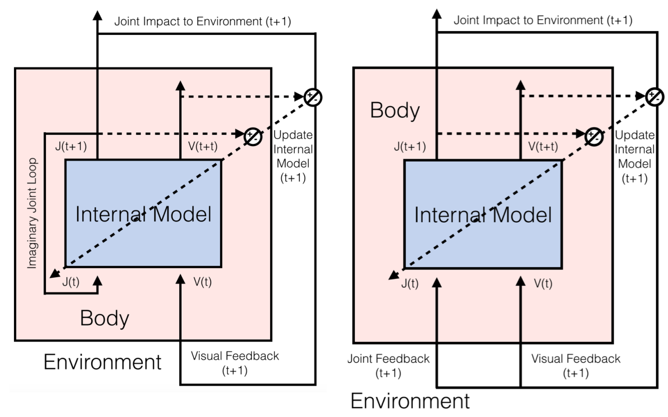
***Abstract*—How do humans know whether the hand in front of their sight belongs to themselves? The question concerning the development of self-other differentiation remains one of the fundamental problems before we can truly understand and simulate the cognitive process of human social behaviors. Opposing to the traditional associative sequence learning models, our proposed model adds a closed loop of the proprioceptive perception of an agent, which conceptually simulates the imaginary body scheme. During a learning phase, this simulated body representation is corrected by the feedback of the actual sensation of the agent. Therefore, after learning, the agent becomes to be able to visually distinguish self-produced actions from others' even without proprioceptive information. This paper presents how the utilization of predicted proprioceptive feedback enables the agent to better differentiate the self from others.**

I. Introduction

In the field of cognitive developmental robotics, many implementations of associative sequence learning made robotic agents learn the mapping between the desired sensory and motor signals through previous experiences of the agents [1]–[3]. These approaches assumed that the agents had the predefined knowledge to utilize their proprioceptive information. In other words, the agents made prediction of their actions directly based on the sensory signals they perceive. We here define the 'self' as the body schema as mentioned above, which is the preconscious and sub-personal understanding of the self's body [4]. One concern about the existing computational models is that, using a real time proprioceptive input already encodes the knowledge of the self and contradicts the purpose of letting the model learn to visually differentiate itself from others, as a change of proprioceptive signal indicates a self action and vice versa. However, human can differentiate self even if proprioceptive input is missing or wrong. As in the example of rubber hand illusion, people will predict the rubber hand as a part of self even when the proprioceptive input from the real hand should be different against such prediction [5].

We suggest that the process of learning how to utilize the proprioceptive feedback plays a crucial role in the emergence of self-other differentiation. This idea is supported by a similar phenomenon called Experiential Blindness [6]. Even though long-term blind patients can regain their visual sensation through surgeries, they are not able to make sense of the visual input and to acquire the ability to see for a period of time. This approach of explaining perception is called enactivism, which



(a) Proposed model (b) Conventional model

Fig. 1. The comparison between the proposed model (a) and the conventional model (b). These two models utilize the proprioceptive signals (i.e., joint angles of an agent) differently. The proposed model (a) always makes predictions based on the joint signals perceived at the last time step, whereas the conventional model (b) utilizes the target joint signals given by the environment. The solid lines show how data are pipe-lined in each model and the dashed lines show which data are used to update the models.

suggests that perceiving is not merely mental computation but rather the outcome of interaction with the environment and finding the correlation between sensors and actions. There were several computional models trying to instantiate enactive self onto robots [7].

We propose a new computational model by which a robotic agent learns to utilize the sensory feedback from its own body. Conceptually, the agent tries to become aware of its body parts during the process of acting and observing. The internal model of the agent is implemented using a recurrent neural network based on predictive coding, which tries to minimize the difference between the actual sensory signals and the predicted ones based on the information from the previous time steps. Figure 1(a) illustrates the key idea of our model in comparison to the conventional models shown in Figure 1(b). In the proposed model, the prediction of the proprioceptive signals (i.e., joint angles of the agent) are always closely looped, which means that the agent relies on the proprioceptive information anticipated by the internal model instead of the actual sensory signals. The visual prediction, in contrast, always depends on the actual visual input, which aligns with the visual dominant nature of humans [5], [8]. Only for training but not for testing, the actual proprioceptive signals as well as the actual visual signals are used to update the internal model, which are obtained through own action experiences. Our experiment using a humanoid robot demonstrates that the model enables the agent to acquire the ability to differentiate whether an action is done by the agent itself or not only using the visual input.

II. Our Assumptions

Assume that there are several agents oriented differently, and that one of them is picked up as the self-agent (see Figure 2 in the case of two agents). The self-agent learns to predict the visual signal $\boldsymbol{V}(t)$ and the proprioceptive signal (i.e., joint angles) $\boldsymbol{J}(t)$ for both the self and others in its own perspective under the following assumptions:

1) All agents share the same repertoire of motions and body structures.
2) The self-agent only has the observation of either its own body $\boldsymbol{V}_{self}(t)$ or one of the other agents' body $\boldsymbol{V}_{other}(t)$ at any given time t, that is, it can only focus on one agent at a time.
3) The visual perception of both $\boldsymbol{V}_{self}(t)$ and $\boldsymbol{V}_{other}(t)$ contains sufficient information about the entire motion. In other words, the overlapping of the body parts during the motion does not affect how the motion is perceived.
4) The agents do not have predefined knowledge of their body parts. No object detection is performed for the visual perception.
5) The self-agent obtains only the proprioceptive perception of its own body $\boldsymbol{J}_{self}(t)$ and cannot access the proprioceptive signals of other agents.

Based on these assumptions, we investigate whether the self-agent can acquire the ability of differentiating the self from others in the visual perception.

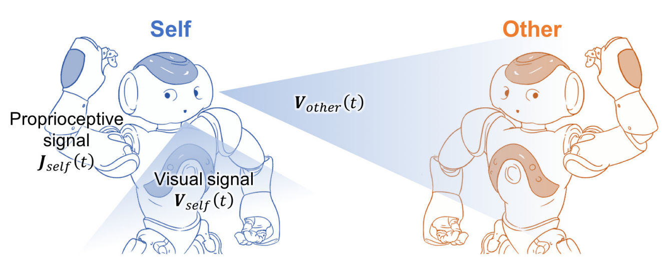


Fig. 2. Assumptions for the current experiment. The self-agent learns to differentiate the actions produced by itself $\boldsymbol{V}_{self}(t)$ from those by others $\boldsymbol{V}_{other}(t)$ utilizing the proprioceptive feedback $\boldsymbol{J}_{self}(t)$.

III. A Computational Model of Sensorimotor Learning for Self-Other Differentiation

A. Basic idea

When doing sensorimotor learning on desired motion sequences, the most common way is to provide the desired sensorimotor signals along the time steps and to let a model learn the correct prediction for each time step. However, this procedure has several downsides for the purpose of this study. This study aims to simulate the real world situation, where only the motion executed by the self has proprioceptive feedback from its own body. It means that not every dataset for training has both sensory and motor signals. Observation of other agents, for example, provides only visual signals but no proprioceptive signals corresponding to their body motion.

To address this issue, we introduce some modifications to the conventional models [1]–[3]. The proposed model shown in Figure 1(a) adds a closed loop of proprioceptive signals. The joint signals $\boldsymbol{J}(t+1)$ for the next time step $t+1$ are anticipated by the imaginary perception of the joint signals $\boldsymbol{J}(t)$ at the current time step t. The desired joint signals $\hat{\boldsymbol{J}}(t)$ only serve for the purpose of updating the proposed model but not for making prediction, which means its existence is not necessary for execution. The visual signals of the desired motion sequence $\hat{\boldsymbol{V}}(t)$, on the other hand, are always provided as the visual input to predict the signals $\boldsymbol{V}(t+1)$ at the next time step as well as to minimize the visual prediction error for the current signals $\boldsymbol{V}(t)$.

The closed loop of proprioceptive signals works as an imaginary body simulation. When the actual proprioceptive feedback is provided, the proposed internal model tries to utilize the feedback and update itself to adapt to the real body schema. This feature results in the ability of adapting to changes in the body representation, which confronts to the body schema extension after tool usage [9] and the phantom limb symptom [10], where the human assumes the existence of missing body parts. Furthermore, the proposed model becomes more robust and coherent when executing in real situations, since the closed loop is more stable against the variance produced by proprioceptive sensors. However, the advantage in robustness is still a hypothesis and requires future experiments. The current study aims to investigate the role of the proprioceptive feedback in learning for self-other discrimination. Comparing the models with and without the feedback loop would reveal advantages of integrating the imaginary proprioceptive loop. Note that these models are the functional abstractions of human cognition and that the overall cognitive process can be the combination of both models.

B. Internal model design

The internal sensorimotor learning model for both proposed and conventional ones is implemented using three layers of Gated Recurrent Units (GRU) as illustrated in Figure 3. GRU is a sophisticated type of recurrent neural network, similar to long short-term memory (LSTM) [11], [12], which has a built-in gating mechanism to enhance the performance of long term sequential modeling. The type of recurrent units used in the internal model should not change the generality of LSTM.

The three GRU layers have 120, 40, and 120 neurons respectively. The purpose of limiting the middle layer with a smaller size is to acquire a compressed representation of the sensorimotor association that is used for self-other discrimination. The input and output layers consist of 8 neurons for the

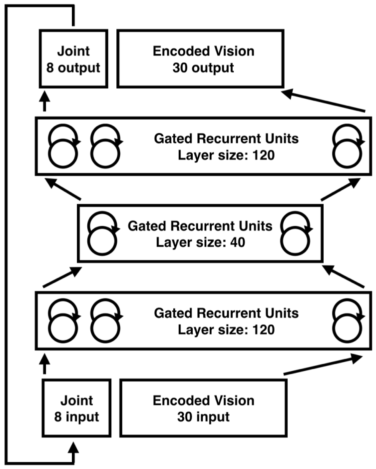


Fig. 3. The internal model takes in the joint signals predicted from the last time step and the visual feedback of the desired motion sequence. Three GRU layers are featured by sizes of 120, 40, and 120, respectively.

proprioceptive information (i.e., joint angles of a humanoid robot) and of 30 neurons for the visual information (i.e., compressed signals of the robot's camera image using a deep autoencoder).

IV. Experimental Setting

The experiments were designed to show how the proposed model successfully predicted own actions and achieved self-other differentiation when incorporating the proprioceptive closed loop. We introduced eight identical agents using humanoid robots NAOs. Figure 4(a) represents the visual perception observed from the self-agent's perspective (i.e., $\boldsymbol{V}_{self}(t)$ and $\boldsymbol{V}_{other}(t)$) using a USB camera placed above the self-agent to capture the entire range of motion. Every two neighboring agents differed 45 degrees in the orientation. The bottom agent in Figure 4(a) was selected as the self-agent, and all the other agents were named after their orientation differences clock wisely. For instance, the two agents next to the self-agent were named 45-deg agent on the left and 315-deg agent on the right, respectively.

The agents were endowed with three possible motion primitives: 'right hand raise', 'left hand raise', and 'both hands raise'. For each of the motion primitives, the execution started from the standing still body posture (or the starting posture), moved to the hand raised posture (or the destination posture), and then went back to the starting posture. Figure 4(b) shows the images of the self-agent moving from the starting posture to the three destination postures. We designed three actions formed by the combination of the three repertoires of motions. Action 1, or 'both hands' action, was formed by a sequential execution of 'left hand raise' for two times, 'right hand raise' for two times, and 'both hands raise' for two times. Action 2, or 'left hand' action, was formed by a sequential execution of 'left hand raise' for four times. Action 3, or 'right hand' action, was formed by a sequential execution of 'right hand raise' for four times. The visual perception of all the eight agents executing the above actions was recorded separately from the perspective of the self-agent. The visual data streams were then compressed frame by frame from 1200 dimensional images (30 $\times$ 40 [pixels]) to 30 dimensional signals using an autoencoder [13], [14] so that its dimension became small enough to be learned by the internal model. The proprioceptive perception of the self-agent was also recorded while the self-agent was producing the actions. The data of joint angles contained the roll and pitch angles of the shoulder and the yaw and roll angles of the elbow of both arms. For example, the joint signals recorded during the execution of Action 1 are plotted in Figure 4(c).

During the training phase, the self-agent perceived the desired actions executed by the eight agents clock wisely, starting from itself. Each epoch consisted of the observation of the actions produced by all the agents. When observing the actions executed by others, the self-agent received only the visual signal at the current time step. The actual joint feedback existed only during the execution of the self action, which was then used for training together with the corresponding visual signal.

V. Experiment 1: Prediction of Self Proprioceptive Signals Using Visual Input

A. Purpose of experiment

The first experiment was conducted to demonstrate the basic ability of the proposed model to predict the joint signals during the observation of own actions. For the training of this experiment, the self-agent only executed the 'both hands' action and updated its internal model using the visual and joint feedback of the desired action. After enough training epochs, or when the prediction error of the internal model converged to a stable state, the model stopped learning and then examined the prediction accuracy of all the three actions performed by the self.

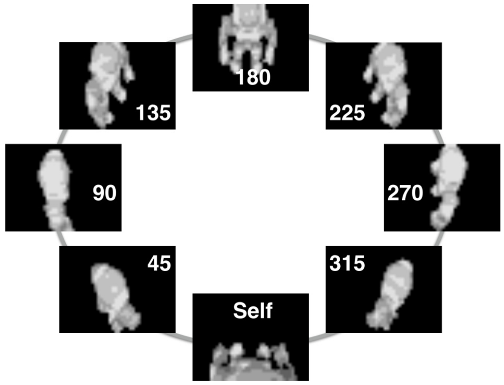
B. Results and discussion

Figure 5 shows the prediction (red) and the desired proprioceptive signals (blue) while the self-agent observed the three actions produced by itself: (a) Action 1, (b) Action 2, and (c) Action 3. The graphs demonstrate the successful prediction of the joint signals of the self produced actions. Note that only Action 1 was used for the training, and Actions 2 and 3 were given only for the testing. We thus conclude from these results that the imaginary body representation produced by the closed loop of the proprioceptive signals successfully acquired the mapping to the corresponding visual perception.

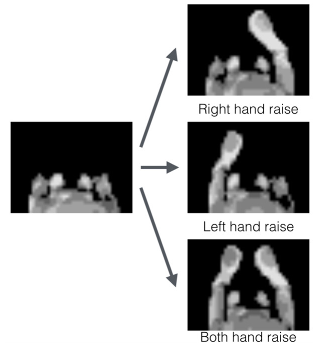
VI. Experiment 2: Self-Other Differentiation Represented by Internal Model

A. Purpose of experiment

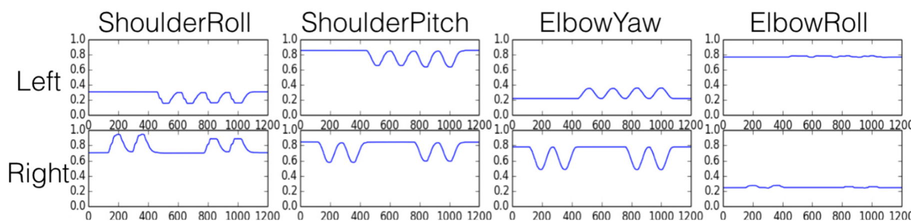
The second experiment was conducted to investigate whether the proprioceptive feedback facilitated the proposed internal model acquiring the ability to visually distinguish the self from others. Learning experiments under two conditions were carried out for the comparison. The first condition made



(a) Visual perception of eight agents in different orientations



(b) Three motion primitives with starting posture (left) and destination postures (right)



(c) Desired joint signals for Action 1 (i.e., 'both hands' action)

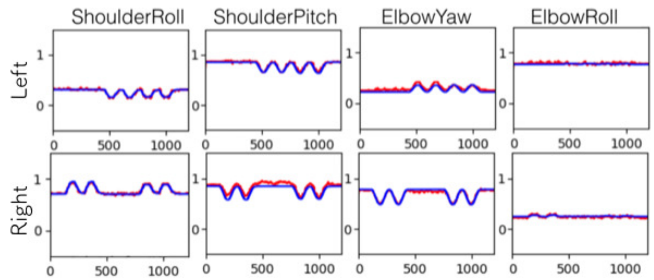
Fig. 4. The self-agent and seven other agents orientated every 45 degrees clock wisely. How the agents were perceived visually by the self-agent is shown in (a). The repertoires of the agents' actions consisted of three motion primitives: 'right hand raise', 'left hand raise', and 'both hands raise' as shown in (b). The 'both hands' action, for example, was defined as the combination of all three primitives, of which the joint signals are plotted in (c). Note that the joint feedback was observable only when the action was performed by the self-agent.

the self-agent receive *no* proprioceptive feedback from its body even when producing own actions. The self-agent learned the internal model only using the visual information. The second condition enabled the self-agent to perceive the proprioceptive signals during the execution of own actions and to update the internal model using the signals as well as the visual feedback. During the observation of others' actions, in contrast, the internal model was trained only using the visual information under both conditions. All the three actions produced by the eight agents were used for training, and the representations acquired in the internal model were compared to assess the ability of self-other discrimination.

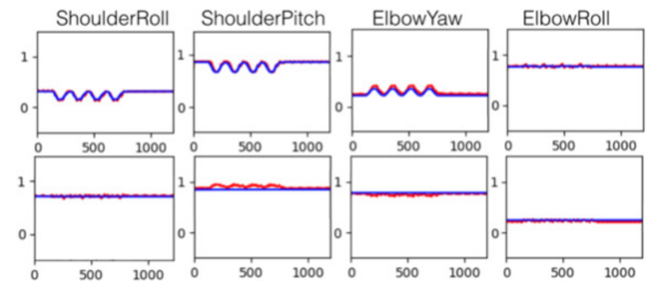
B. Results and discussion

We first examined the ability of sensory prediction. After learning, the self-agent exhibited the ability to visually predict other agents' actions as well as own actions for both conditions. Despite the difference in the perspective observing their actions (see Figure 4(a)), the internal model properly represented the temporal sequences of the visual perception. However, there was no evidence showing the ability to predict the proprioceptive signals of other agents. Figure 6 highlights the difficulty in anticipating the proprioceptive signals of other agents (b) in comparison to the self-agent (a). Prediction of the proprioceptive signals of the 45-deg agent generated significant error, whereas only marginal error was observed in the self produced action. There have been computational models to cope with this problem. For example, models that learn to acquire the perspective taking ability were proposed (e.g., [1], [2], [15], [16]). Our experiment, by contrast, focuses on the early stage of cognitive development, in which agents do not yet have the ability of spatial perspective taking.

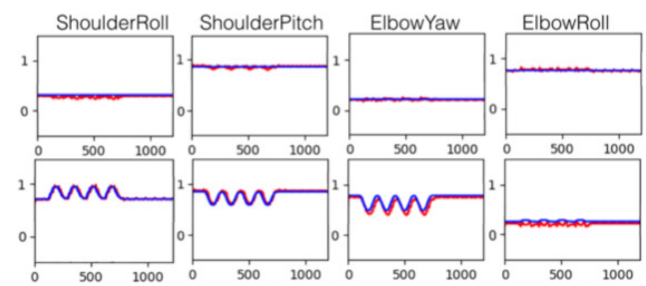
Next, we investigated the ability of self-other differentiation by analyzing the internal representation acquired in the internal model. We applied principle component analysis (PCA) to the activation of the middle GRU layer (with the size of 40). PCA extracts the largest variances among the high dimensional data, and therefore it is expected to demonstrate how the activations relevant to the self and others are differentiated. Figure 7 illustrates the internal activations corresponding to the actions generated by the eight agents: blue crosses for the self, red for the 45-deg, green for the 90-deg, blue dots for the 135-deg, yellow for the 180-deg, magenta for the 225-deg, cyan for the 270-deg, and black for the 315-deg. The first and second principal components (PC1 and PC2) were used to visualize the results in a two dimensional space. The results for Actions 1, 2, and 3 under the condition *without* the proprioceptive feedback were shown in Figures 7(a) to 7(c), whereas the the results under the condition *with* the proprioceptive feedback were shown in Figures 7(d) to 7(f). As shown in Figures 7(a) to 7(c), the self-agent trained without the proprioceptive feedback could not distinguish the actions executed by the self and by



(a) Proprioceptive signals for Action 1

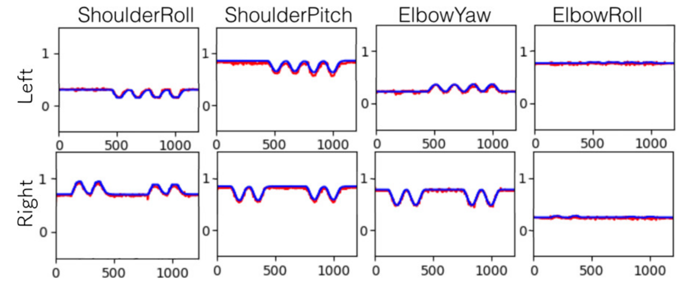


(b) Proprioceptive signals for Action 2

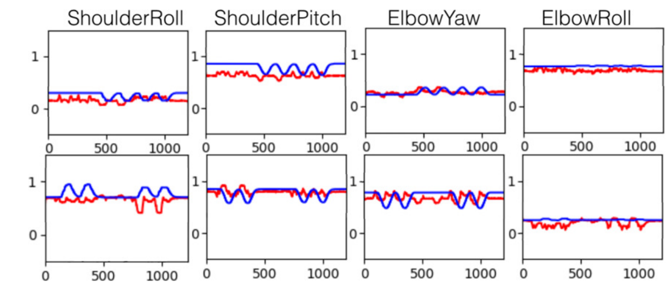


(c) Proprioceptive signals for Action 3

Fig. 5. The comparison between the actual joint signals and the prediction made by the proposed model during the observation of (a) 'both hands', (b) 'left hand', and (c) 'right hand' actions. The blue curves indicate the desired joint signals corresponding to the observed actions, whereas the red curves show the predicted joint signals by the internal model.



(a) Proprioceptive signals of the self-agent performing Action 1



(b) Proprioceptive signals of the 45-deg agent performing Action 1

Fig. 6. Prediction of the proprioceptive signals of the self-agent (a) and the 45-deg agent (b) when they were performing Action 1. The blue curves indicate the actual joint signals corresponding to the observed actions, and the red curves show the predicted joint signals by the internal model. The self-agent successfully predicted its joint signals, whereas it failed in anticipating the joint signals of the 45-deg agent. Note that the proprioceptive signals of other agents were recorded with a small time offset against the self-agent. Thus the actual joint signals might not align perfectly with the predicted ones.

others among the PC space. The trajectories of the self actions (being circled) overlapped with other trajectories. Despite the difference in the visual perspective observing the self's and others' actions (see Figure 4(a)), the self-agent could not distinguish them in the internal model. In contrast, the self-agent that received the proprioceptive feedback for self actions managed to separate the actions executed by the self from those of others along the PC1. Figures 7(d) to 7(f) demonstrate that the trajectories corresponding to the self actions (being circled) is isolated from those corresponding to the actions by other agents. These results suggest that the proprioceptive feedback of the self-executed actions plays a crucial role in the acquisition of self-other discrimination.

VII. Conclusion

Through the experiments, we demonstrated the capability of our model to represent the self body schema by predicting the proprioceptive signals and differentiating the self actions from those done by others. However, the model was not able to predict others' body schema when observing. Our interpretation for the lack of this ability is that self-other differentiation emerges earlier than the perspective taking. As the body schema represents the preconscious control of the body, the perception of the 'self' must emerge at a very early stage, while infants first learn to control their bodies. Only later than 24 months old, infants start realizing a difference between what they see and what other persons see [17]. There are hypotheses trying to explain and fill in the gap between these two stages, such as expecting spatial perspective taking as a result of the accumulation of goal sharing experiences with a caregiver [18]. Future research should be conducted to investigate how the knowledge from these experiments can be used to explain the emergence of perspective taking and to facilitate human-robot and robot-robot interaction.

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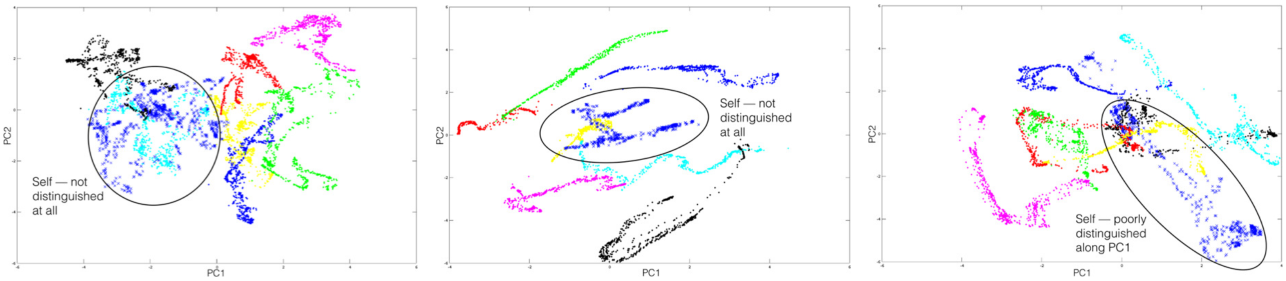
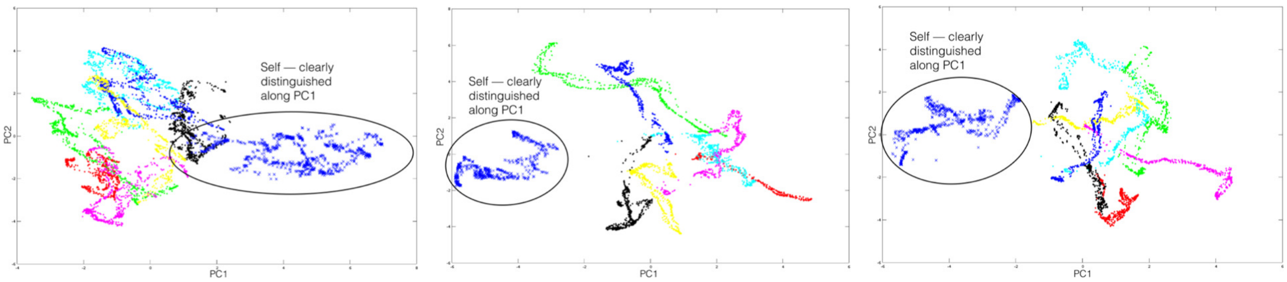


(a) Action 1 w/o proprioceptive feedback (b) Action 2 w/o proprioceptive feedback (c) Action 3 w/o proprioceptive feedback



(d) Action 1 w/ proprioceptive feedback (e) Action 2 w/ proprioceptive feedback (f) Action 3 w/ proprioceptive feedback

Fig. 7. PCA of the middle layer activation of the internal models, which were trained with all the three actions generated by the eight agents. The blue crosses, as being circled, represent the activation when observing the self actions. The rest of the dots represent the other agents as following: red for 45-deg, green for 90-deg, blue dots for 135-deg, yellow for 180-deg, magenta for 225-deg, cyan for 270-deg, and black for 315-deg. Only the self-executed actions trained with the proprioceptive feedback were differentiated from those presented by other agents.

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