Preprint, submitted to *IEEE Robotics and Automation Letters (RA-L)* 2021 with *International Conference on Robotics and Automation Conference Option (ICRA)* 2021

**Robotic self-representation improves manipulation skills and transfer learning**

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**Abstract**—Cognitive science suggests that the self-representation is critical for learning and problem-solving. However, there is a lack of computational methods that relate this claim to cognitively plausible robots and reinforcement learning. In this paper, we bridge this gap by developing a model that learns bidirectional action-effect associations to encode the representations of body schema and the peripersonal space from multisensory information, which is named multimodal BidAL. Through three different robotic experiments, we demonstrate that this approach significantly stabilizes the learning-based problem-solving under noisy conditions and that it improves transfer learning of robotic manipulation skills.

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**I. INTRODUCTION**

Humans and other biological agents depend on appropriate representations of their body and their surroundings to facilitate their activities in safety and comfort. These representations, known as body schema and peripersonal space (PPS) (see Fig. 1), result from the integration of different sensorimotor modalities that are involved when physically interacting with the environment [1]–[4]. Consequently, the body schema and peripersonal space are not innate but develop incrementally. This developmental process starts in infants through self-exploration and motor babbling, and continues later through goal-directed physical and social interactions [5]–[7]. Acquiring a body schema and a peripersonal space representation involves associative learning, a mechanism enabling infants to detect the sensorimotor contingencies in their environment. However, associative learning alone is not sufficient to explain the ability of humans to generate goal-directed actions. The conversion of the learned contingencies into goal-directed actions is related to another central ability that is only little investigated in computational methods: The ability to distinguish between self-caused body-schematic sensory effects and externally caused sensory effects [8], [9]. But how can we model these bidirectional body-schematic action-effect associations computationally, such that an agent can distinguish between its own body, the peripersonal space and the external world? And how does this affect the learning and problem-solving performance of artificial agents?

In this work, we argue that artificial agents/robots require two vital elements to develop the body-schema and peripersonal space representations: (1) a multimodal sensory

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**Fig. 1:** The body schema and peripersonal space representations during tool-use (from [10]).

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whether they are transferable to learn a new skill.

For this investigation, we extend Pathak et al.’s approach as follows: (i) We use multimodal sensory input instead of only visual input for our model; (ii) we build on intrinsic motivation to minimize the prediction error, especially in noisy conditions; and (iii) we investigate the transfer learning performance. In addition, we extend the discrete action space used by Pathak et al. towards a continuous action space. To realize these extensions, we build on several mechanisms and concepts related to multisensory representation learning, forward models and intrinsic motivation.

II. BACKGROUND AND RELATED WORK

Our proposed model in this paper relates to a body of literature in following main topics:

Multisensory representation learning of the body schema enables humans to perform pose estimation of their body parts, and coordinate transformation between sensory sources, which, ultimately, enables action [12], [13]. Robotic and computational models of body-schematic representations mostly focus on exploiting sensory information from proprioceptive and tactile sensing [14]–[16], or proprioceptive and visual sensing [17]–[19] and cast the representation learning as calibration, pose estimation or visuomotor mapping.

The peripersonal space representation serves as an interface between the agent’s body and the environment [3]. Existing robotic and computational models construct the PPS representation from sensory data including vision, audio, touch and proprioception [20]–[28]. Most of the approaches base on the random movements of joints inspired by infants’ motor babbling to generate the training data.

Forward models are computational models that map the current state of the system to the next state through actions. Some approaches utilize this model to learn the imitating actions from multisensory input [29]–[32]; others employ the forward model to learn the single sensory embedding for control, e.g. [11], [33]–[36]. Differently, in some neurorobotics models, forward model plays the core role in high-level cognitive functions such as self/o/other distinction, sense of agency or body ownership [37]–[39].

Intrinsic motivation is an internal system that drives human to “engage in particular activities for their own sake, rather than a step towards solving practical problem” [40]. Some recent models revisit this concept with the computational models of neural networks (cf. [41] for an overview). For example, Dilokthanakul et al. [42] implement the intrinsic motivation as the changes in the image features of two consecutive frames, allowing gaming agents to learn by maximizing the change of the visual representations. Pathak et al. [11] propose to use prediction error of an additional forward model as intrinsic motivation to drive gaming agents to explore the space. Pathak et al. [43] further extend the idea by using an ensemble of forward functions and exploiting the disagreement among prediction errors in the ensemble as the intrinsic motivation. Röder et al. [44] adopt the ideas of the intrinsic motivation from [11] but with only proprioceptive input instead of visual input.

III. METHODOLOGY

The objective of our research is to enable a robot to learn to solve a given task in a general goal-directed way, by generalizing the learnt knowledge to any goal \(g\) in the set of possible goals \(\mathcal{G}\). For example, considering the toy example of a planar reaching task (see Fig. 3a), we aim for a framework that enables a 2DoF-robot to learn to move its end-effector to every position in the plane within the robot’s reachable region. More advanced applications involve self-locomotion and object manipulation, where an agent should be able to generalize over goal locations of itself or of external objects.

A. Overview of the framework

To achieve the desired generalization and transfer learning abilities, we train a reinforcement learning policy in an abstract generalized state representation imposed by the agent’s body schema and peripersonal space model. This model is learned with the bio-inspired learning framework presented in Fig. 2. The forward model \(f(\cdot)\) predicts a sensory effect \(\hat{\phi}(s_{t+1})\) from a currently conducted action \(a_t\) and the currently perceived sensory state representation \(\phi(s_t)\). The policy \(\pi\) generates motor actions \(a_t\) under constraints exerted by the environment and under consideration of the prediction error \(\epsilon_{t+1}\) of the forward model. Both the forward model and the policy operate in the latent space of the multimodal sensory input, which is compressed by the multisensory integration process. We specify the operation of these modules as follows:

**Multisensory representations:**

\[
\phi(s_t) = \phi^{PPS}(s_t^{eui}) \cup \phi^{body}(s_t^i) \quad (1)
\]

Forward model:

\[
\hat{\phi}(s_{t+1}) = f(\phi(s_t), a_t; \theta_F) \quad (2)
\]

Prediction error:

\[
\epsilon_{t+1} = \frac{1}{2} \| \hat{\phi}(s_{t+1}) - \phi(s_{t+1}) \|^2_2 \quad (3)
\]

where \(\phi^{PPS}(s_t^{eui})\) denotes the representation of the PPS, \(\phi^{body}(s_t^i)\) denotes the body schema representation, and \(\theta_F\)
denotes parameters of a two-layer fully-connected neural network approximating the function \( f(\cdot) \).

Instead of using the prediction error as an intrinsic motivation to drive agents in seeking for the new information, which is suitable for the navigation task [11], we propose to use the prediction error for a different purpose in this work. For our agents, the lower the prediction error means the better their ability to anticipate their own action, which is represented by the intrinsic reward \( r^i_t \) as follows:

\[
r^i_t = -\frac{\lambda}{2} \| \hat{\phi}(s_{t+1}) - \phi(s_{t+1}) \|^2_2
\]

where \( \lambda \) is a hyperparameter to decide the importance of the intrinsic reward within the whole reward the agents receive.

In the following sections III-B and III-C we describe how the intrinsic reward is combined with the extrinsic reward to train an actor-critic reinforcement learning method (cf. Eq. 8). Herein, all modules learn simultaneously through the agent’s interactive experience in the environment.

### B. Multisensory integration with neural network

We aim to enable robots to exploit the relevant information from different sources of their sensory input, to construct a representation of the environment and finally to facilitate the task learning. Therefore, we first implement a neural network for visuo-motor integration based on Nguyen et al. [19], and construct our input preprocessing network with two branches, one for vision and one for proprioception. The former branch consists of four convolution layers with ELu activation and a fully-connected layer, while the latter branch contains one layer of fully-connected units. The visual and proprioceptive features are concatenated and combined by another fully-connected layer to produce a compressed latent feature \( \phi(s_t) \) of the environment (including the robot itself). The construction of multisensory network is presented in the left side of our general architecture in Fig. 2.

Unlike Nguyen et al. [19] and other methods that learn this representation separately, e.g. Watter et al. [33], Zambelli et al. [29], we adopt the approach by Pathak et al. [11] for state representation learning within the reinforcement framework. While Pathak et al. [11] consider only visual input, we extend it to multisensory input. In addition, we also employ the inverse model \( g(\cdot) \) for representation learning from multiple inputs by minimizing the inverse loss as follows:

\[
\mathcal{L}_i(\hat{a}_t, a_t) = \frac{1}{2} \| \hat{a}_t - a_t \|^2_2,
\]

where \( \hat{a}_t = g(s_t, s_{t+1}; \theta_f) \) is the estimated action of \( a_t \) through the inverse mapping function \( g(\cdot) \), approximated by a two-layer fully-connected neural network with parameters \( \theta_f \). By minimizing the difference between the estimated and real action, the learnt inverse model plays as an encoder of the relevant information for the task from multiple sensory input [11].

### C. Reinforcement learning policy

We consider a reinforcement learning setting, where an agent interacts with an environment and tries to maximize the long-term expected reward. The interacting environment can be defined as a set of state (or observation) \( S \), an action set \( A \), a reward function \( r: S \times A \rightarrow \mathbb{R} \), transition probability \( \rho(s_{t+1}, a_t): S \times S \times A, \) and a discount rate \( \gamma \in [0, 1] \).

In our setting, we employ the policy gradient approach that allows agent to select actions directly through a parameterized policy instead of consulting the value function. This means, at time \( t \), the agent takes an action \( a_t \) drawn from the policy \( \pi(a|s, \theta) \), a probability distribution over the action space given the current state \( s_t \) with parameter vector \( \theta \).

Any policy gradient-based reinforcement learning algorithm can be applied to construct the policy in our framework. In this work, we employ and validate the Deep deterministic policy gradient algorithm (DDPG) [45] with continuous actions in combination with our BidAL method. The previous implementation by Pathak et al. [11] uses AC3 [46] with a discrete action space. Moreover, we do not manually design any task-specific rewards, but employ the spare-reward scheme for the external reward \( r^e_t \) in our proposal. This means the robots receive 0 reward for successfully completing the desired task and -1 for failing the task, as defined in Eq. 6:

\[
r^e_t = -[\|g - s_t\| > \epsilon]
\]

where \( \epsilon \) is a reasonable threshold value to determine whether an achieved state \( s_t \) is close enough to an desired goal \( g \) to consider the goal achieved. We implement our goal-directed method using deep deterministic policy gradient (DDPG), universal value function approximators (UVFA)[47] and hindsight experience replay (HER)[48], as described below:

1) Deep deterministic policy gradient (DDPG): While policy gradient methods in general refer to a parameterized, stochastic policy, deterministic policy gradient methods aim to learn parameters for a deterministic policy, \( \mu_\theta: S \rightarrow A \). Silver et al. [49] shows that the deterministic policy gradient (DPG) exists as a special case of stochastic policy, but can be estimated more efficiently. The efficient exploration of a deterministic policy can be guaranteed with an off-policy algorithm in which actions are chosen according to a stochastic behaviour policy \( \beta(a|s) \), but to learn about a deterministic target policy [49]. The off-policy deterministic policy gradient is written as:

\[
\nabla_\theta J_\beta(\mu_\theta) \approx \int_S \rho_\beta(s) \nabla_\theta \mu_\theta Q(s, a) ds
= \mathbb{E}_{s \sim \rho_\beta} \left[ \nabla_\theta \mu_\theta(s) \nabla_s Q(s, a)|_{a = \mu_\theta(s)} \right]
\]

where \( \rho_\beta \) denotes the state distribution of \( \beta(a|s) \).

DDPG [45] extends the actor-critic approach of DPG with neural network function approximators. The actor network of \( \mu_\theta \) is updated with deterministic policy gradient as Eq. 7, while the critic network estimates the action-value function \( Q(s, a) \) by minimizing the loss in Eq. 8.

\[
\mathcal{L} = \mathbb{E}_{s_t \sim \rho_\beta, a_t \sim \beta} \left[ (Q(s_t, a_t | \theta^Q) - y_t)^2 \right]
\]

with target: \( y_t = r_t + \gamma Q(s_{t+1}, \mu_{s_{t+1}} | \theta^Q) \)

and reward: \( r_t = r^i_t + r^e_t \)
Both actor and critic neural networks are updated by sampling from a finite sized replay buffer where tuples of exploration \((s_t, a_t, r_t, s_{t+1})\) have been stored.

2) **Universal value function approximation (UVFA):** In order to generalize the learnt policy to both the state space and the goal space, [47] proposes the UVFA approach to represent a set of optimal action-value functions by using a unified function approximator. This is achieved by extending the Q-function to depend not only on the state-action \((s, a)\) pair but also the goal \(g\). In terms of function approximation with neural networks, we can concatenate \((s, g)\) or their embeddings \((\psi(s), \eta(g))\) for the actor network, and \((s, a, g)\) or \((\psi(s), a, \eta(g))\) for the critic network. Our networks follow the embeddings structure. This technique is important for our setup as it allow robots to learn a general goal-directed policy: Instead of achieving a specific task, e.g. reaching a certain position, they learn to complete a more general one, i.e. reaching every position within the reachable space. This also makes our approach different from the work by Pathak et al. [11].

3) **Hindsight experience replay (HER):** We employ this technique from Andrychowicz et al. [48] to enrich the replay buffer by assuming that some random unsuccessful achieved state is the goal state.

### D. Evaluation environments

![Planar reaching](image1.png) ![UR5 reaching](image2.png)

(a) Planar reaching  (b) UR5 reaching

![Object sliding](image3.png) ![Object lifting](image4.png)

(c) Object sliding  (d) Object lifting

Fig. 3: Experimental environments

We evaluate our method by conducting experiments in simulated environments based on the Mujoco software [50]. Depending on the specific environment, the setup can be varied but generally all robots have the common properties:

- They have access to cameras which provide rendered RGB frames of the environment, including parts of the robot itself. The rendered frames are then converted to gray format and scaled down to smaller dimension. This source of input is denoted as \(s^g_t\) in this work;
- The embeddings structure. This technique is important for our setup as it allow robots to learn a general goal-directed policy: Instead of achieving a specific task, e.g. reaching a certain position, they learn to complete a more general one, i.e. reaching every position within the reachable space. This also makes our approach different from the work by Pathak et al. [11].
- They handle \((s, g)\) or \((\psi(s), \eta(g))\) for the actor network, and \((s, a, g)\) or \((\psi(s), a, \eta(g))\) for the critic network. Our networks follow the embeddings structure. This technique is important for our setup as it allow robots to learn a general goal-directed policy: Instead of achieving a specific task, e.g. reaching a certain position, they learn to complete a more general one, i.e. reaching every position within the reachable space. This also makes our approach different from the work by Pathak et al. [11].

### TABLE I: Summary of experimental environments. For object manipulation tasks \(s^m\), i.e. sliding and lifting, the agent can control the position of the arm in the Cartesian space, roll and tilt its hand, and move all fingers and its thumb abduction.

| Env.  | \(s^m_t\) | \(s^m_{t+1}\) | \(a_t\) |
|-------|-----------|---------------|--------|
| Planar reaching | \([q, \dot{q}]_{(0.4)}\) | \([0,2]\) |
| UR5 reaching | \([q, \dot{q}]_{(0.6)}\) | \([0,3]\) |
| Object sliding | \([x, q, \dot{x}, \dot{q}]_{(0.4)}\) | \([0,7]^*\) |
| Object lifting | \([0,7]^*\) | \([0,7]^*\) |

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Fig. 4: Learning performance in different environment. Note that we use the term “proprioception” for both joint and Cartesian measurements. See Section III-D for more details.

Fig. 5: Learning performance in different noise conditions for the object sliding tasks: 5%–Left, 10%–Center and 15%–Right from the environment for achieving the task and an intrinsic reward computed from the prediction error.

Herein, we investigate four configurations: As baselines, we use DDPG+HER with proprioceptive input (proprio. baseline) and visual input (visual baseline). We compare these baselines with our proposed algorithm, where we combine the bidirectional associative learning (BidAL) method with the visual input (visual BidAL) and multisensory integration (multimodal BidAL). For these configurations, we perform training in all simulated environments presented in Section III-D.

The results in Fig. 4 show that our proposed algorithm learns all tasks efficiently, while the baselines with only visual input fail to learn any task. The baselines with proprioceptive input perform significantly better than those with visual input. Overall, our approach outperforms all baselines, especially in the object lifting task. This result provides direct evidence for our core hypothesis that the bidirectional associations improve the learning performance. The results suggest further that minimizing the prediction loss is beneficial for learning the multisensory representation, which is a prerequisite for the robots to learn the main desired task.

B. Robustness to noise

We further investigate the role of proprioception in the multimodal setting by adding observational noise to the end-effector pose and the object position. This experiment
focuses on the task of object sliding (see Fig. 3c), and aims to simulate that the robot’s end-effector and object pose cannot be measured directly in the real world. Normally, these information is obtained through additional estimation processes, mostly from visual input. These estimations may contribute to noise or inaccuracy in the general observation. We realize the noisy observations as follows:

\[ s_{\text{noisy}} = s + \kappa \cdot n \]  

where \( \kappa \) denotes the noise coefficient, \( n \) denotes noise and \( n \sim \mathcal{N}(0, \sigma) \), \( \sigma \) denotes the range between 75\(^{th}\) and 25\(^{th}\) percentile of the continuous history of \( s \).

We perform the training with the combined intrinsic and extrinsic rewards at three different values of the noise coefficient, namely 5\%, 10\% and 15\%. Fig. 5 illustrates that a high noise coefficient affects the performance significantly in all experiments. However, our BidAL approach is more robust to noise, performing significantly more stable than the baseline as we compare the mean and standard deviation of the success rate over the last \( N \) epochs\(^4\) over 5 training runs (see Table II).

![Fig. 6: The robot learns the task of object lifting from multimodal input, with and without transfer learning](image)

For the mean success rates, we see that a drop in the success rate when comparing 5\% noise with 15\% noise: by a factor of 0.70 and 0.66 for the multimodal BidAL and multimodal baseline, respectively. The higher factor of the BidAL approach illustrates a slight increase in the robustness to noise.

To investigate the stability of the learning under noisy conditions we consider the mean standard deviation of the success rate. With 10\% noise, the mean standard deviation of the multimodal BidAL approach is 0.022, compared to a significantly larger value of 0.054 for the multimodal baseline. Hence, the mean standard deviation with the BidAL approach is less than half (factor of 0.4) of the multimodal baseline. In the case of 15\% noise, these numbers are 0.032 and 0.041 respectively: BidAL mean standard deviation is around 3/4 (factor of 0.78) of the baseline.

Furthermore, both metrics favor our multimodal BidAL over the proprioceptive baseline.

### C. Transfer learning from a simple to a complex skill

This experiment addresses our hypothesis that previously learned peripersonal space and body schema representations, encoded in the forward and inverse model, foster the learning of new tasks. We propose to pre-train these representations first with a simple skill, and then re-use the representations later to learn a novel skill. Therefore, we first train the NICOL robot to slide objects (see Fig. 3c), and then continue

![Table II: Evaluation of robustness to noise.](image)

\( N = 30 \) for 10-15\% noise and \( N = 5 \) for 5\% noise.

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**ACKNOWLEDGMENT**

We thank Nicolas Frick for the help on the NICOL design and part of the NICOL simulation used in this paper. The authors acknowledge funding by the German Research Foundation (DFG) through the IDEAS and LeCAREbot projects.

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\( 5^{th} \) and \( 25^{th} \) percentile
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