SIMPLE EMERGENT ACTION REPRESENTATIONS FROM MULTI-TASK POLICY TRAINING

Anonymous authors
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ABSTRACT

Low-level sensory and motor signals in the high-dimensional spaces (e.g., image observations or motor torques) in deep reinforcement learning are complicated to understand or harness for downstream tasks directly. While sensory representations have been widely studied, the representations of actions that form motor skills are yet under exploration. In this work, we find that when a multi-task policy network takes as input states and task embeddings, a space based on the task embeddings emerges to contain meaningful action representations with moderate constraints.Within this space, interpolated or composed embeddings can serve as a high-level interface to instruct the agent to perform meaningful action sequences. Empirical results not only show that the proposed action representations have efficacy for intra-action interpolation and inter-action composition with limited or no learning, but also demonstrate their superior ability in task adaptation to strong baselines in Mujoco locomotion tasks. The evidence elucidates that learning the action representations is a promising direction toward efficient, adaptable, and composable RL, forming the basis of abstract action planning and the understanding of motor signal space. Anonymous project page: `https://sites.google.com/view/emergent-action-representation/`

1 INTRODUCTION

Deep reinforcement learning (RL) can learn near-optimal policies to perform low-level actions with pre-defined reward functions. While the low-level actions are adequate for the specified tasks, it remains challenging to reuse this learned knowledge to accomplish new tasks efficiently. By contrast, when humans perform multiple tasks, the low-level muscle movements are naturally summarized into high-level action representations such as "pick up," or "turn left", which can be reused in novel tasks with slight modifications. As a result, though we are aware of our intent to perform a task, we carry out the most complicated movements without thinking about the detailed joint motions or muscle contractions (Kandel et al., 2021). By analogy with such abilities of humans, we ask the question: can RL agents have action representations of low-level motor controls, which can be reused, modified, or composed to perform new tasks?

As pointed out in Kandel et al. (2021), "the task of the motor systems is the reverse of the task of the sensory systems. Sensory processing generates an internal representation in the brain of the outside world or of the state of the body. Motor processing begins with an internal representation: the desired purpose of movement". In the past decade, representation learning has made tremendous progress in representing high-dimensional sensory signals such as images and audios for revealing the geometric and semantic structures hidden in the raw signals (Bengio et al., 2013; Chen et al., 2018; Kornblith et al., 2019; Chen et al., 2020; Baevski et al., 2020; Radford et al., 2021; Bardes et al., 2021; Bommasani et al., 2021; He et al., 2022). With the help of the generalization ability of sensory representation learning, downstream control tasks can be accomplished efficiently (Nair et al., 2022; Xiao et al., 2022; Yuan et al., 2022). In contrast to the advancement in sensory representation learning, action representation learning is yet under-explored. Thus, we make a step to study this topic with an aim to find generalizable action representations which can be reused or efficiently adapted to perform new tasks. A key idea in sensory representation learning is pretraining with a comprehensive task (or a set of tasks) and reusing the emergent latent representation. Inspired by this simple and powerful idea, we train a multi-task policy network, whereas a set of different tasks share the same latent action representation space. Further, the time-variant sensory and time-invariant ac-

tion representations are decoupled and concatenated as the sensory-action representation, which is transformed by a policy network to form the low-level action control. Surprisingly, when trained on a comprehensive set of tasks, we discover that such a simple structure learns an emergent self-organized action representation. The emergent action representation can be reused for intra-action interpolation, inter-action composition, and efficient task adaptation. In particular, we demonstrate the effectiveness of the emergent action representations with Mujoco locomotion environments and show zero-shot composition and few-shot task adaptation in the representation space. The agents adapt to new tasks in fewer steps than strong meta RL baselines. Besides the effectiveness of the action representation, we find the decoupled time-variant sensory representation exhibits equivariant properties. The evidence elucidates that reusable and generalizable action representations may lead to efficient, adaptable, and composable RL, thus forming the basis of abstract action planning and understanding motor signal space. The primary contributions in this work are listed as follows:

1. We put forward the idea of leveraging emergent action representations from multi-task learners to better understand motor action space and accomplish task generalization.
2. We decouple the state-related and task-related information of the sensory-action representations and reuse them to conduct action planning more efficiently.
3. Our approach is a strong adapter, which achieves higher rewards with fewer steps than strong meta RL baselines when adapting to new tasks.
4. Our method supports intra-action interpolation as well as inter-action composition by modifying and composing the learned action representations.

Next, we begin our technical discussion right below and leave the discussion of many valuable and related literature to the end.

2 PRELIMINARIES

Soft Actor-Critic. In this paper, our approach is built on Soft Actor-Critic (SAC) (Haarnoja et al., 2018). SAC is a stable off-policy actor-critic algorithm based on the maximum entropy reinforcement learning framework, in which the actor maximizes both the returns and the entropy. In SAC, there are three types of parameters to update during optimization: the policy parameter ω, the soft Q-function parameter θ and a learnable temperature α. The objectives are:

$$J(\alpha) = \mathbb{E}_{\mathbf{a}_t \sim \pi_\omega} \left[-\alpha \log \pi_\omega \left(\mathbf{a}_t \mid \mathbf{s}_t \right) - \alpha \overline{\mathcal{H}} \right] \tag{1}$$

$$J_\pi(\omega) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}} \left[\mathbb{E}_{\mathbf{a}_t \sim \pi_\omega} \left[\alpha \log \pi_\omega \left(\mathbf{a}_t \mid \mathbf{s}_t \right) - Q_\theta \left(\mathbf{s}_t, \mathbf{a}_t \right) \right] \right] \tag{2}$$

$$J_Q(\theta) = \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t) \sim \mathcal{D}} \left[\frac{1}{2} \left(Q_\theta \left(\mathbf{s}_t, \mathbf{a}_t \right) - \left(r \left(\mathbf{s}_t, \mathbf{a}_t \right) + \gamma \mathbb{E}_{\mathbf{s}_{t+1} \sim p} \left[V_{\bar{\theta}} \left(\mathbf{s}_{t+1} \right) \right] \right) \right)^2 \right] \tag{3}$$

where $\overline{\mathcal{H}}$ in Equation 1 is a pre-defined minimum expected entropy. The value function in Equation 3 is parameterized by the weights $V_{\bar{\theta}}$ in the target Q-network and can be defined by:

$$V \left(\mathbf{s}_t \right) = \mathbb{E}_{\mathbf{a}_t \sim \pi} \left[Q \left(\mathbf{s}_t, \mathbf{a}_t \right) - \alpha \log \pi \left(\mathbf{a}_t \mid \mathbf{s}_t \right) \right] \tag{4}$$

Task Distribution. We assume the tasks that the agent may meet are drawn from a pre-defined task distribution $p(\mathcal{T})$. Each task in $p(\mathcal{T})$ corresponds to a Markov Decision Process (MDP). Therefore, a task $\mathcal{T}$ can be defined by a tuple $(\mathcal{S}, \mathcal{A}, p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t), p(\mathbf{s}_0), R(\mathbf{s}_t, \mathbf{a}_t))$, in which $\mathcal{S}$ and $\mathcal{A}$ are respectively the state and action space, $p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$ the transition probability distribution, $p(\mathbf{s}_0)$ the initial state distribution and $R(\mathbf{s}_t, \mathbf{a}_t)$ the reward function.

The concept of task distribution is frequently employed in meta RL problems, but we have made some modifications and extensions on it to better match with the setting in this work. We divide all the task distributions into two main categories, the "uni-modal" task distributions and the "multi-modal" task distributions. Concretely, the two scenarios are defined as follows:

- *Definition 1 (Uni-modal task distribution):* In a uni-modal task distribution, there is only one modality among all the tasks in the task distribution. For example, in HalfCheetah-Vel, a Mujoco locomotion environment, we train the agent to run at different target velocities. Therefore, running is the only modality in this task distribution.

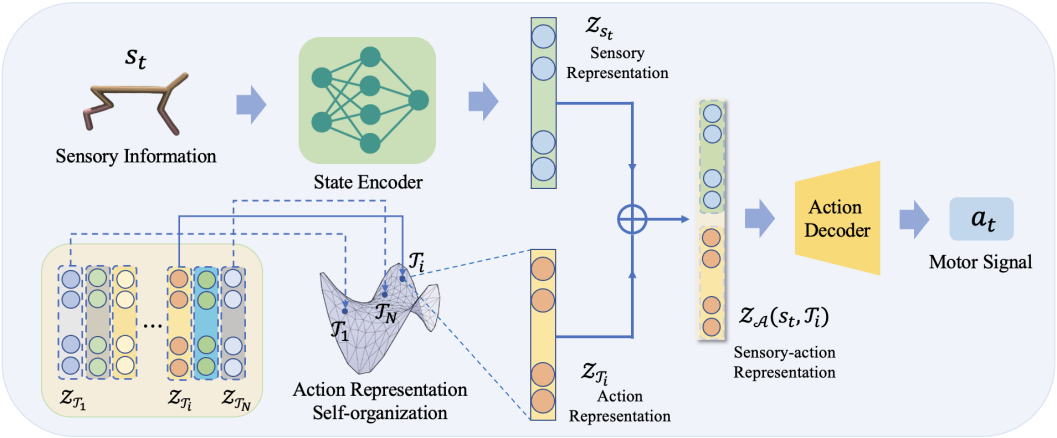

Figure 1: **Emergent action representations from multi-Task training.** The sensory information and task information are encoded separately. When both are concatenated, an action decoder decodes them into a low level action.

- *Definition 2 (Multi-modal task distribution):* In contrast to uni-modal task distribution, there are multiple modalities among the tasks in this task distribution. A multi-modal task distribution includes tasks of several different uni-modal task distributions. For instance, we design a multi-modal task distribution called HalfCheetah-Run-Jump, which contains two modalities including HalfCheetah-BackVel and HalfCheetah-BackJump. The former has been defined in the previous section, and the latter contains tasks that train the agent to jump with different reward weight. In our implementation, we actually train four motions in this environment, running, walking, jumping ans standing. We will leave more details in Section 4

3 Emergent Action Representations from Multi-Task Training

In this section, we first introduce the sensory-task decoupled policy network architecture. Next, we discuss the multitask policy training details, along with the additional constraints to the task embedding for the emergence of action representations. Lastly, we demonstrate the emergence of the action representations through various phenomena and applications.

3.1 Multitask Policy Network and Training

Decoupled embedding and concatenated decoding. An abstract high-level task, e.g., "move forward", typically changes relatively slower compared to the transient sensory states. As a simplification, we decouple the latent representation into a time-variant sensory embedding $\mathcal{Z}_{\mathbf{s}_t}$ and a time-invariant task embedding $\mathcal{Z}_{\mathcal{T}}$, which is shown in Figure 1. These embeddings concatenate to form a sensory-action embedding $\mathcal{Z}_{\mathcal{A}}(\mathbf{s}_t, \mathcal{T}) = [\mathcal{Z}_{\mathbf{s}_t}, \mathcal{Z}_{\mathcal{T}}]$, which is transformed by the policy network (action decoder) ψ to output a low-level action distribution $p(\mathbf{a}_t) = \psi(\mathbf{a}_t|\mathcal{Z}_{\mathbf{s}_t}, \mathcal{Z}_{\mathcal{T}})$, e.g., motor torques. The action decoder ψ is a multi-layer perceptron (MLP) that outputs a Gaussian distribution in the low-level action space $\mathcal{A}$.

Latent sensory embedding (LSE). The low-level sensory state information is encoded by an MLP state encoder ϕ into a latent sensory embedding $\mathcal{Z}_{\mathbf{s}_t} = \phi(\mathbf{s}_t) \in \mathbb{R}^m$. It includes the proprioceptive information of each time step. LSE is time-variant in an RL trajectory and the state encoder is shared among different tasks. We use LSE and sensory representation interchangeably in this paper.

Latent task embedding (LTE). A latent task embedding $\mathcal{Z}_{\mathcal{T}} \in \mathbb{R}^d$ encodes the time-invariant knowledge of a certain task. Let's assume we are going to train N different tasks, and their embeddings form a LTE set $\{\mathcal{Z}_{\mathcal{T}_N}\}$. These N different tasks share the same state encoder ϕ and action decoder ψ, or in other words these N tasks share the same policy network interface except that their task embeddings are different. Additionally, the LTE vectors are trainable during learning and we can always add a new task by adding a new trainable LTE vector to the set $\{\mathcal{Z}_{\mathcal{T}_N}\}$. After training,

the LTE interface can be reused as a high-level action interface. Hence, we use LTE and action representation interchangeably in this paper.

Training of the multitask policy networks. A detailed description of the multi-task training is demonstrated in Algorithm 1. When computing objectives and their gradients, we still use policy π parameterized by ω to indicate all the parameters in the encoders and the decoder. The overall training procedure is based on SAC. The only difference is that the policy network and Q networks additionally take as input the LTE $\mathcal{Z}_{\mathcal{T}}$ and a one-hot task label respectively.

During training, we also apply two techniques to constrain this space: 1) we normalize the LTEs so that they lie on a hypersphere; 2) we inject a random noise to the LTEs to enhance the smoothness of the space.

Algorithm 1 Multi-task Training

Input: Training task set $\{\mathcal{T}_N\} \sim p(\mathcal{T})$, θ_1, θ_2, ω
  $\overline{\theta}_1 \leftarrow \theta_1, \overline{\theta}_2 \leftarrow \theta_2, \mathcal{B} \leftarrow \emptyset$
  for each pre-train epoch **do**
    for $\mathcal{T}_i$ in $\{\mathcal{T}_n\}$ **do**
      Sample a batch $\mathcal{B}_i$ of multi-task RL transitions with π_ω
      $\mathcal{B} \leftarrow \mathcal{B} \cup \mathcal{B}_i$
    end for
  end for
  for each train epoch **do**
    Sample RL batch $b \sim \mathcal{B}$
    for all transition data in b **do**
      $\mathcal{Z}_{\mathbf{s}_t} = \phi(\mathbf{s}_t)$
      $\widetilde{\mathcal{Z}}_{\mathcal{T}_i} = normalize(\mathcal{Z}_{\mathcal{T}_i} + n \sim \mathcal{N}(0, \sigma^2))$
      Sample action $\mathbf{a}_t \sim \psi(\cdot|\mathcal{Z}_{\mathbf{s}_t}, \widetilde{\mathcal{Z}}_{\mathcal{T}_i})$
    end for
    for each optimization step **do**
      Compute SAC objectives $J(\alpha), J_\pi(\omega), J_Q(\theta)$ with b
      Update SAC objectives
    end for
  end for
Output: The optimal model of state encoder ϕ^* and action decoder ψ^* and a set of LTEs $\{\mathcal{Z}_{\mathcal{T}_N}\}$

3.2 The Emergence of Action Representation

After we train the multi-task policy network with a comprehensive set of tasks, where the LTE vectors in $\{\mathcal{Z}_{\mathcal{T}_N}\}$ share the same embedding space, we find that $\{\mathcal{Z}_{\mathcal{T}_N}\}$ self-organizes into a geometrically and semantically meaningful structure. Tasks from the same distribution are embedded in a continuous fashion, which facilitates intra-task interpolation. Surprisingly, the composition of task embeddings from different modalities leads to novel tasks, e.g., "run" + "jump" = "jump run". Further, the action representation can be used for efficient task adaptation. Visualization also reveals interesting geometric structures in task embedding and sensory representation spaces. In this subsection, we dive into these intriguing phenomena, demonstrating the emergence of action representation, and show the generalization of the emergent action representation.

Task interpolation & composition. After training the RL agent to accomplish multiple tasks, we select two pre-trained tasks and generate a new LTE through linear integration between the LTEs of the two chosen tasks. The newly-generated task embedding is expected to conduct the agent to perform another different task. The generated LTE is defined by

$$\mathcal{Z}' = f(\beta \mathcal{Z}_{\mathcal{T}_i} + (1 - \beta)\mathcal{Z}_{\mathcal{T}_j}) \tag{5}$$

where i, j are the indices of the selected tasks and $\mathcal{Z}_{\mathcal{T}_i}, \mathcal{Z}_{\mathcal{T}_j}$ are their corresponding LTEs. β is a hyperparameter ranging in (0,1). The function $f(\cdot)$ is a regularization function related to the pre-

defined quality of the LTE Space. For instance, in this paper, $f(\cdot)$ is a normalization function to extend or shorten the result of interpolation to a unit sphere.

A new task is interpolated by applying the aforementioned operation on the LTEs of tasks sampled from a uni-modal distribution. The interpolated task usually has the same semantic meaning as the source tasks while having different quantity in specific parameters, e.g., running with different speeds. A new task is composed by applying the same operation on tasks sampled from a multi-modal distribution. The newly composed task is usually lie in a new modality between the source tasks. For example, when we compose "run" and "jump" together, we will have a combination of an agent running while trying to jump.

Efficient adaptation. We find that an agent trained with the multi-task policy network can adapt to unseen tasks quickly by only optimizing the LTEs. This shows that the LTEs learn a general pattern of the overall task distribution. When given a new task after pre-training, the agent explores in the LTE Space to find a suitable LTE for the task. Specifically, We perform gradient-free cross-entropy method (CEM) (De Boer et al., 2005) in the LTE space for accomplishing the desired task. Detailed description can be found in Algorithm 2.

Geometric Structures of LTEs and the LSEs We visualize the LSEs and and LTEs to understand their geometric structures. The results are deferred to Section 4.5.

Algorithm 2 Adaptation via LTE Optimization

Input: Adaptation task $\mathcal{T} \sim p(\mathcal{T})$, ϕ^*, ψ^*, capacity of elite set m, number of sampling n
  Initialize the elite set $\mathbb{Z}_e$ with m randomly sampled LTEs from the LTE Space
  for each adapt epoch **do**
    Initialize the overall test set by $\mathbb{Z} \leftarrow \emptyset$
    for $\mathcal{Z}_i$ in $\mathbb{Z}_e$ **do**
      Sample n LTEs $\mathcal{Z}_{i1}, \ldots, \mathcal{Z}_{in}$ near $\mathcal{Z}_i$
      $\mathbb{Z} \leftarrow \mathbb{Z} \cup \{\mathcal{Z}_i, \mathcal{Z}_{i1}, \ldots, \mathcal{Z}_{in}\}$
    end for
    for $\mathcal{Z}_j$ in $\mathbb{Z}$ **do**
      while not done **do**
        $\mathcal{Z}_{\mathbf{s}_t} = \phi^*(\mathbf{s}_t)$,
        $\mathbf{a}_t \sim \psi^*(\cdot|\mathcal{Z}_{\mathbf{s}_t}, \mathcal{Z}_j)$
        $r_t = R(\mathbf{s}_t, \mathbf{a}_t|\mathcal{T})$
        $\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$
      end while
    end for
    Sort the task embeddings in $\mathcal{Z}$ by high cumulative reward in the trajectory
    Select the top m LTEs in $\mathcal{Z}$ to update $\mathbb{Z}_e$
  end for

4 EXPERIMENTS

In this section, we first demonstrate the training process and performance of the multi-task policy network. Then, we use the LTEs as a high-level action interface to instruct the agents to perform unseen skills through interpolation without any training. After that, we conduct experiments to evaluate the effectiveness of the LTEs in task adaptation. Lastly, we visualize the LSEs and LTEs to further understand the structure of the state and action representation. We use emergent action representation (EAR) to refer to the policy using the LTEs.

4.1 EXPERIMENTAL SETUPS

Environments. We evaluate our method on five continuous control environments (HalfCheetah-Vel, Ant-Dir, Hopper-Vel, Walker-Vel, HalfCheetah-Run-Jump) based on OpenAI Gym and the Mujoco simulator. Detailed descriptions of these RL benchmarks are listed in Appendix A.1.

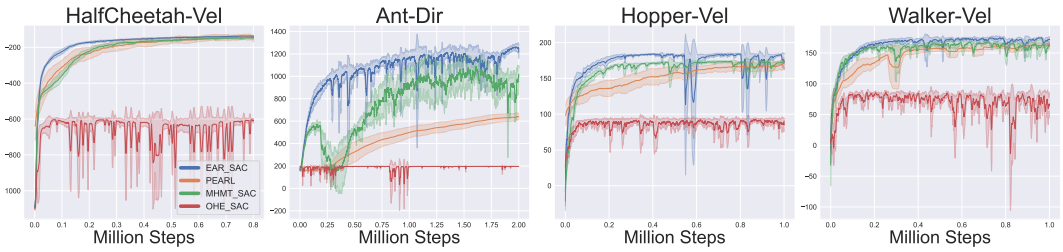

Figure 2: **Training performance of our method and baselines.** The x-axis represents the total training steps (in million steps) and the y-axis represents the average reward of all the training tasks. All the training are based on 3 seeds. The shaded area is one standard deviation.

Method	HalfCheetah-Vel	Ant-Dir	Hopper-Vel	Walker-Vel
EAR-SAC (Ours)	**-136.9±1.29**	**1216.7±54.97**	**173.5±11.09**	**172.7±4.05**
MAML	-500.9±47.33	422.8±29.40	34.0±41.92	-4.9±0.58
PEARL	-155.0±15.50	635.9±19.21	170.0±7.80	163.9±1.07
MHMT-SAC	-145.2±2.60	1020.0±54.90	172.9±1.17	160.6±5.21
OHE-SAC	-609.0±8.10	195.7±0.29	90.7±2.39	65.0±20.83

Table 1: **Comparison with baselines on the final performance** The metric is the return of the last epoch and the mean and standard deviation is calculated among 3 seeds.

Baselines. We compare EAR-SAC, the emergent action representation based SAC with several multi-task RL and meta RL baselines. For multi-task RL baselines, we use multi-head multi-task SAC (MHMT-SAC) and one-hot embedding SAC (OHE-SAC; for ablation). For meta RL baselines, we use MAML (Finn et al., 2017) and PEARL (Rakelly et al., 2019). Detailed descriptions of these baselines are listed in Appendix A.2.

4.2 Multi-task Training for Action Representations

In this section, we train the multi-task network and evaluate whether sensory-action representations can boost training efficiency. EAR-SAC is compared with all the multi-task RL and meta RL baselines on final rewards in Table 1 and additionally compared with off-policy baselines on the training efficiency in Figure 2. We find that EAR-SAC outperforms all the baselines in terms of training efficiency. In environments with high-dimensional observations (e.g., Ant-Dir), EAR-SAC achieves large performance advantage against the baselines. We attribute this to that the learned action representation space may provide meaningful priors when the policy is trained with multiple tasks.

4.3 Action Representation as a High-level Control Interface

In this section, we control the agent by recomposing the LTEs. We perform intra-action interpolation and inter-action composition in uni-modal task distributions and multi-modal task distributions respectively.

Intra-action interpolation. Intra-action interpolation is conducted in HalfCheetah-Vel, Ant-Dir, Hopper-Vel, and Walker-Vel. We interpolate the the action representations between two tasks using Equation 5. The coefficient β is searched to better fit the target task. An interpolation example in HalfCheetah-Vel is demonstrated in Figure 3. We select the tasks of running at 1 m/s and 2 m/s to be interpolated and get three interpolated tasks: run at 1.2 m/s, 1.5 m/s, 1.7 m/s. We perform evaluation on each task for a trajectory, and visualize them. In each task, we

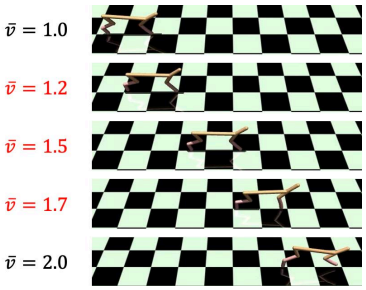

Figure 3: **Visualization of the interpolated tasks.**

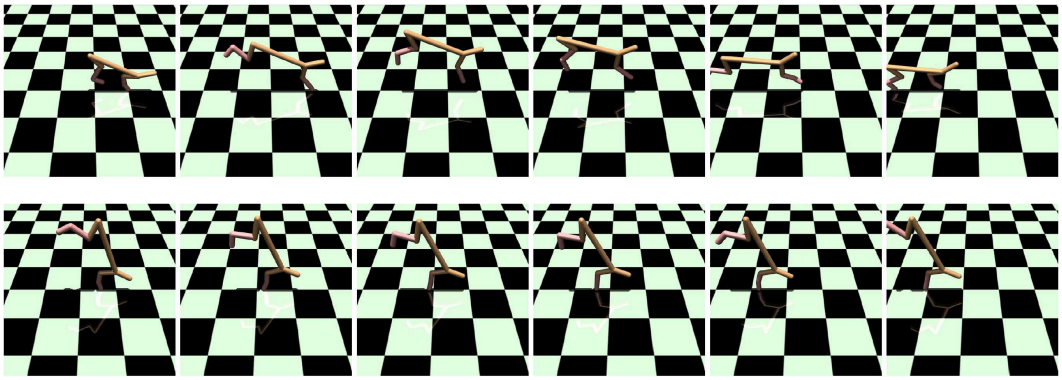

Figure 4: **Visualization of task compositions.** The first row represents part of a trajectory of run-jumping, and the second row represents part of a trajectory of walk-standing. Animated results are in the project page.

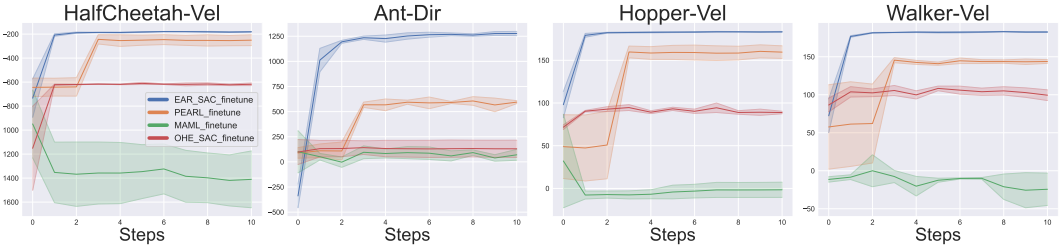

Figure 5: **Adaptation results.** The x-axis represents the adaptation steps and the y-axis represents the average reward of all the adaptation tasks. We fix the adaptation task set for all algorithms in the same environment.

make the agent start from the same point (not plotted in the figure) and terminate at 100 time steps. Only part of the whole scene is visualized in the figure. We find that through task interpolation, the agent manages to accomplish these interpolated tasks without any training. We leave other results in all environments to Appendix A.3.

Inter-action composition. Inter-action composition is conducted in HalfCheetah-Run-Jump, in which we merge two uni-modal task distributions. Taking HalfCheetah-BackRun and HalfCheetah-BackJump as an example, we find that the agent has learned four motions: walking backward, running backward, standing with its front leg, and jumping with its front leg. We select walk-standing as a composition task pair and run-jumping as the other and compose them with Equation 5. These two generated representations are evaluated in 1000 time steps and part of their evaluation trajectories are visualized in Figure 4. We find that the walk-standing representation enables the agent to walk backward with a standing posture despite some pauses to keep itself balance, while the run-jumping representation helps the agent to jump when running backward after some trials. These empirical results indicate that the LTEs can be used as action representations by composing them for different new tasks.

4.4 Task Adaptation with Action Representations

In this section, we assess how well an agent can adapt to new tasks by only updating the LTEs. We compare the agent's adaptation ability with the meta RL baselines (MAML,PEARL) and the ablation baseline (OHE-SAC). The results in Figure 5 demonstrate that EAR can adapt to new tasks and achieve to the converged performance within three epochs, outperforming the baseline meta RL methods. We note that , with the help of the LTE space, we can adapt to new tasks using zero-th order optimization method.

4.5 VISUALIZATION OF STATE AND ACTION REPRESENTATIONS

In this section, we further analyze and visualize the sensory-action representations based on the HalfCheetah environment.

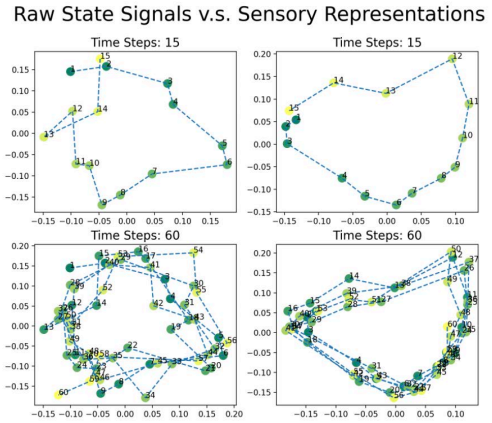

Figure 6: **Comparison between raw state signals (left) and sensory representations (right) in HalfCheetah-Vel.** To make the period of running motion easier to observe, we reduce the time interval between adjacent time steps. For now a period of the motion is 15 steps, while in the original setting it is only 6 steps.

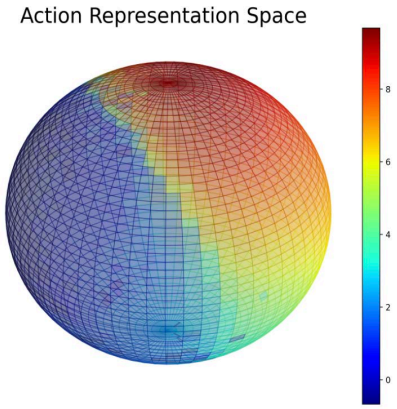

Figure 7: **Visualization of the action representation space in HalfCheetah-Vel.** Each grid on the unit sphere represents the terminal of an action representation and is colored based on how the agent performs when the policy is conditioned on the action representation. The redder the grid is, the faster the agent runs.

The sensory representations. In HalfCheetah-Vel, the halfcheetah agent is encouraged to run at a specific velocity, thus making its motion periodical. Therefore, the ideal raw signals and the LSEs in the trajectory should be periodical as well. After conducting Principal Components Analysis (PCA) (Abdi & Williams, 2010) to reduce the dimension of all the raw signals and the sensory representations collected in a trajectory, we visualize them for different time steps in Figure 6. We find that the raw state signals appear to be only roughly periodical due to the noise in the states. However, the LSEs show stronger periodicity than the raw signals, indicating that the sensory representations can reduce the influence of the noise in raw signals, thus helping the agent better understand and react to the environment.

The action representations. To better understand the intriguing fact that the agent can adapt to new tasks using the emergent action representations when only sparse training tasks are provided, we plot the LTE space in Figure 7. We find that the LTEs on the hypersphere automatically form a continuous space, constructing the basis of the composition of the representations in it. This also explains why the interpolation and composition of the LTEs result in meaningful new behaviors: when interpolated and normalized, the new LTE would still lie on this hypersphere, leading to new and meaningful action sequences.

4.6 A COMPARISON WITH ONE-HOT REPRESENTATION

Readers might be curious about whether the learned, manipulable LTEs better than a naive one-hot embedding. In this section, we compare EAR with a different policy network that takes in an one-hot embedding rather then the LTE. Specifically, in multi-task training, we concatenate the raw state vector with the one-hot embedding as the input of the policy network to form a multi-task RL architecture. We find that the one-hot embedded policy performs unsatisfactorily in all environments and fails completely in Ant-Dir environment. We attribute this to the fact that, without the sensory-action representation, the agent fails to understand the underlying relation among multiple tasks, especially in those environments with high-dimensional observations and a large training task set. We also compare both methods in the task adaptation setting. When optimizing the one-hot embedding to adapt to new tasks, the agent can barely reach a reasonable performance in any of the new tasks.

These facts echo with the idea that the simple emergent action representations are meaningful and effective in task learning and generalization.

5 Related Work

Representation learning in reinforcement learning. Representation learning has been widely applied in RL to generate representations of sensory information (Laskin et al., 2020; Chandak et al., 2019b; Yarats et al., 2021), policies (Edwards et al., 2019), dynamics (Watter et al., 2015).

In recent years, action representation has attracted more attention. In previous works (Dulac-Arnold et al., 2015), the action embeddings have been proposed to compress discrete actions to a continuous space based on prior knowledge. Recently, many researchers focus on mapping between the original continuous action space and a continuous manifold to facilitate and accelerate policy learning (Allshire et al., 2021) or simplify teleoperation (Losey et al., 2020). Moreover, such action representations are extended to high-dimensional real-world robotics control problems Jeon et al. (2020). In this area, a closely related work is Chandak et al. (2019a), which enables a policy to output a latent action representation with reinforcement learning and then uses supervised learning to construct a mapping from the representation space to the discrete action space. However, in our work, we discover emergent self-organized sensory-action representations from multi-task policy training without additional supervised learning, which can be further leveraged to generalize to new tasks.

Multi-task reinforcement learning. Multi-task reinforcement learning (multi-task RL) is an important problem in RL, which trains an RL agent to learn multiple tasks simultaneously with a single policy. A direct idea is to share parameters and learn a joint policy with multiple objectives (Wilson et al., 2007; Pinto & Gupta, 2017), but the gradients of different tasks may conflict with each other. Some works tackle this problem by directly reducing gradient conflicts (Yu et al., 2020), designing specific loss weighting (Hessel et al., 2019; Kendall et al., 2018), or leveraging regularization methods (Duong et al., 2015). Modular networks has also been proposed to perform multi-task learning by constructing the policy network with a combination of smaller sub-networks (Heess et al., 2016; Yang et al., 2020). In our work, we adopt the multi-task RL setting and train a multi-task policy network with a sensory-action representation layer.

Meta reinforcement learning. The adaptation part of this work also shares a similar goal as meta reinforcement learning (meta RL). (Finn et al., 2017; Xu et al., 2018a; Rothfuss et al., 2018; Wang et al., 2016; Levine et al., 2020), aiming to quickly adapt to new tasks. Meta RL executes meta-learning (Schmidhuber, 1987; Thrun & Pratt, 2012) algorithms under the framework of reinforcement learning, which aims to train an agent to quickly adapt to new tasks. A large number of meta RL methods are gradient-based, performing gradient descent on the policy (Finn et al., 2017; Xu et al., 2018a; Rothfuss et al., 2018), the hyperparameters (Xu et al., 2018b), or loss functions (Sung et al., 2017; Houthooft et al., 2018) based on the collected experience. Other meta RL algorithms are context-based methods (Wang et al., 2016; Rakelly et al., 2019). They embed context information into a latent variable and condition the meta-learning policy on such variables. Besides, recently offline meta RL algorithms (Levine et al., 2020; Mitchell et al., 2021) have also been widely explored, which enables the agent to leverage the existing offline data to perform meta-training. However, we exploit the emergent high-level representations to abstract low-level actions for adaptation rather than introduce complicated new techniques.

6 Conclusion

In this paper, we present our finding that the task embeddings in a multi-task policy network can automatically form a space where action representations reside. The emergent action representations abstract information of a sequence of actions and can serve as a high-level interface to instruct an agent to perform motor skills. Specifically, we find the action representations can be interpolated, composed, and optimized to generate novel action sequences for unseen tasks. Along with this work, a promising direction is to learn the action representation via self-supervised learning. Another intriguing direction is to learn hierarchical action representations that may capture different levels of semantics and geometric information in motor signals, thus facilitating future applications such as hierarchical planning LeCun (2022).

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A EXPERIMENTAL DETAILS

A.1 ENVIRONMENTS

The detailed descriptions of the reinforcement learning benchmarks in our experiments are listed as follows:

- **HalfCheetah-Vel (Uni-modal):** In this environment, we train the halfcheetah agent to run at a target velocity. The training task set contains 10 velocities. The target velocities during training range from 1 m/s to 10 m/s. For every 1 m/s, we set a training task. The adaptation task set contains 3 velocities that are uniformly sampled from [1,10]. The agent is penalized with the l_1 error between its velocity and the target velocity.
- **Ant-Dir (Uni-modal):** In this environment, we train the Ant agent to run in a target direction. The training task set contains 24 directions which are consecutive integers from 1 to 10. The adaptation task set contains 5 integer directions which are uniformly sampled from [0,360) degrees. The agent is rewarded with the velocity along the target direction and penalized with the velocity along the direction perpendicular to our target.
- **Hopper/Walker-Vel (Uni-modal):** Similar to HalfCheetah-Vel, Hopper/Walker-Vel contains 10 velocities in training task set and 3 in adaptation task set. The target velocities when training range from 0.2 m/s to 2 m/s and every 0.2 m/s we set a training task. The Hopper/Walker agent is penalized with the l_1 error between its velocity and the target velocity.
- **HalfCheetah-Run-Jump (Multi-modal):** There are two different uni-modal task distributions in this environment, respectively HalfCheetah-BackVel and HalfCheetah-BackJump. HalfCheetah-BackVel trains the halfcheetah agent to run backward at a target velocity, and the agent is penalized with the l_1 error between its velocity and the target velocity. HalfCheetah-BackJump trains the agent to raise its hind leg to jump, and the agent is rewarded with the height of its hind leg. HalfCheetah-Run-Jump contains 7 velocities for running backward (from 1 m/s to 7 m/s and every 1 m/s a training task is set) and 3 tasks for jumping (3 different weights for the leg height in the total reward function) in the training task set. In our implementation, the jumping task with smallest weight finally turns out to be a motion of "standing" instead of jumping.

A.2 BASELINES

The detailed descriptions of the multi-task RL and meta RL baselines are listed as follows:

- **MAML.** MAML (Finn et al., 2017) is a gradient-based meta-RL algorithm based on Trust Region Policy Optimization (Schulman et al., 2015). It aims to learn easily adaptable model parameters for tasks in a specific task distribution. MAML conducts explicit training on model parameters so that a small number of training data and gradient steps are required to adapt to a new task. In our implementation, we modify the range and density of task sampling, which will be discussed in the following section.
- **PEARL.** PEARL (Rakelly et al., 2019) is a context-based off-policy meta-RL algorithm based on Soft Actor Critic (Haarnoja et al., 2018) and variational inference method (Kingma & Welling). PEARL tackles the problem of limited sample efficiency in meta-RL domain. PEARL integrates off-policy RL algorithms with a latent task variable which infers how to adapt to a new task with small amount of history contexts.
- **Multi-head multi-task SAC (MHMT-SAC).** MHMT-SAC is a multi-task RL architecture, in which each training task has an independent head input, and the body of the policy network is shared among all the tasks. We compare our method with MHMT-SAC to evaluate the performance of an agent with emergent action representation in multi-task training.
- **One-Hot Embedding SAC (OHE-SAC).** The sensory-action representation is introduced when training the agent to learn multiple tasks in the training set. In OHE-SAC, We omit the representation layer to make the policy network a common multi-task RL structure, which concatenates a one-hot embedding and the raw state vector as the input of the policy network. Through comparison between the final performance of the two methods, OHE-SAC helps identify the effect of action representations in training and adaptation.

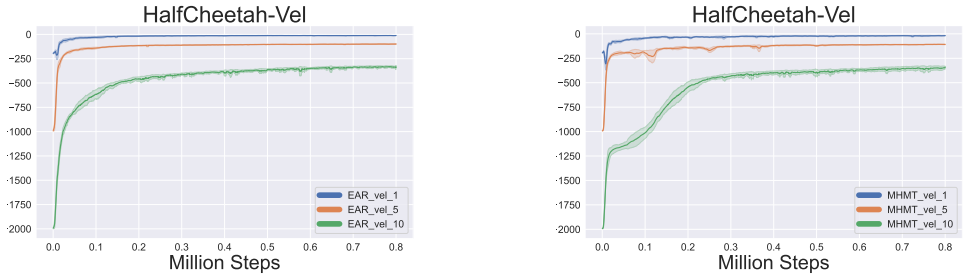

Figure 8: Training curves of tasks with different target velocities with multi-task RL method.

Method	HalfCheetah-Vel	Hopper/Walker-Vel	Ant-Dir
EAR-SAC (Ours)	**10 tasks in [0,10]**	**10 tasks in [0,2]**	**24 tasks in [0,360)**
MAML	100 tasks in [0,10]	40 tasks in [0,2]	40 tasks in [0,360)
PEARL	100 tasks in [0,10]	20 tasks in [0,2]	100 tasks in [0,360)
MTMH-SAC	10 tasks in [0,10]	10 tasks in [0,2]	24 tasks in [0,360)
OHE-SAC	10 tasks in [0,10]	10 tasks in [0,2]	24 tasks in [0,360)

Table 2: Density of task sampling in the training procedure.

A.3 Multi-task training

A.3.1 Task sampling density

In the experiments, we control control the range of task sampling to be unchanged for different algorithms in the same environment. We find that in HalfCheetah-Vel environment, multi-task RL methods get different final rewards for different tasks (in Figure 8). The reason is that when the agent is trained well enough, the penalty of velocity in the reward will become slight, thus making the control cost of the agent dominant. Therefore, it is natural that the faster the agent runs, the larger cost it should pay, leading to a relatively low reward. Thus to make our comparison valid and persuasive, the range of task sampling should be fixed. The detailed settings of the implementation in our paper are demonstrated in Table 2. Similarly, the adaptation tasks are also shared among all the algorithms in the same environment in Section 4.4.

A.3.2 Hyperparameters

Multi-task traing:

- Sensory representation size: 16
- Task embedding size: 3
- State encoder architecture: 2-layer MLP
- Action decoder: 4-layer MLP
- Learning rate: 3e-4

Adaptation:

- Elite set capacity m: 6
- Number of sampling n: 15

A.4 Task interpolation and composition.

Intra-action interpolation. We have performed interpolation between adjacent tasks in HalfCheetah-Vel in Section 4.3, where we can interpolate the LTEs of "running at 1m/s" and "running at 2m/s" to control the agent to run at 1.2, 1.5, 1.7m/s. The coefficient β of the task interpolation

is demonstrated in Table 3. We can find that as the coefficient of interpolation decreases, the cheetah tends to run faster, which indicates that the LTEs between the embeddings of "running at 1m/s" and "running at 2m/s" show some "continuity" in the LTE Space.

Meanwhile, to fully evaluate the performance of task interpolation, we conduct another experiment on other environments. We aim to adjust the interpolation coefficients to achieve 1:1 interpolation between pairs of tasks. For instance, in the experiment aforementioned, we find that when $\beta = 0.42$, the agent can run forward at 1.5m/s, which is a 1:1 interpolation of "running at 1m/s" and "running at 2m/s". The results of 1:1 interpolation are shown in Table 4,5,6,7.

Task	β	Evaluation
Vel-1.0 (pretrain)	1	0.98m/s
Vel-1.2 (interpolate)	0.52	1.20m/s
Vel-1.5 (interpolate)	0.42	1.49m/s
Vel-1.7 (interpolate)	0.35	1.70m/s
Vel-2.0 (pretrain)	0	1.98m/s

Table 3: Coefficients and evaluation results of task interpolation in HalfCheetah-Vel

Task	Vel-1.5	Vel-2.5	Vel-3.5	Vel-4.5	Vel-5.5	Vel-6.5	Vel-7.5	Vel-8.5	Vel-9.5
β	0.42	0.42	0.38	0.39	0.43	0.45	0.46	0.51	0.48
Evaluation	1.51	2.50	3.50	4.50	5.50	6.50	7.50	8.50	9.50

Table 4: 1:1 interpolation in HalfCheetah-Vel

Task	Vel-0.3	Vel-0.5	Vel-0.7	Vel-0.9	Vel-1.1	Vel-1.3	Vel-1.5	Vel-1.7	Vel-1.9
β	0.59	0.50	0.47	0.39	0.51	0.64	0.55	0.64	0.60
Evaluation	0.30	0.50	0.70	0.90	1.11	1.30	1.50	1.70	1.90

Table 5: 1:1 interpolation in Hopper-Vel

Inter-action composition We have performed task composition in the HalfCheetah-Run-Jump environment. The coefficient β of the task composition is demonstrated in Table 8.

Task	Vel-0.3	Vel-0.5	Vel-0.7	Vel-0.9	Vel-1.1	Vel-1.3	Vel-1.5	Vel-1.7	Vel-1.9
β	0.54	0.36	0.49	0.38	0.45	0.44	0.66	0.82	0.77
Evaluation	0.30	0.50	0.70	0.90	1.10	1.30	1.50	1.70	1.90

Table 6: 1:1 interpolation in Walker-Vel

Task	Dir-7.5	Dir-22.5	Dir-37.5	Dir-52.5	Dir-67.5	Dir-82.5	Dir-97.5	Dir-112.5
β	0.76	0.56	0.37	0.20	0.59	0.31	0.40	40
Evaluation	7.27	22.54	37.51	52.32	67.54	82.58	95.52	112.52
Task	Dir-127.5	Dir-142.5	Dir-157.5	Dir-172.5	Dir-187.5	Dir-202.5	Dir-217.5	Dir-232.5
β	0.34	0.22	0.52	0.48	0.41	0.47	0.38	0.27
Evaluation	127.69	142.80	157.56	172.39	187.50	202.50	217.44	232.61
Task	Dir-247.5	Dir-262.5	Dir-277.5	Dir-292.5	Dir-307.5	Dir-322.5	Dir-337.5	Dir-352.5
β	0.35	0.56	0.40	0.35	0.86	0.52	0.66	0.48
Evaluation	247.50	262.33	277.49	292.42	307.37	322.55	337.32	352.82

Table 7: 1:1 interpolation in Ant-Dir

Task	β
Run-jumping	0.27
Walk-standing	0.45

Table 8: Coefficients of task composition in HalfCheetah-Run-Jump