SEMI: Self-supervised Exploration via Multisensory Incongruity

Jianren Wang*, Ziwen Zhuang* and Hang Zhao

Abstract-Efficient exploration is a long-standing problem in reinforcement learning since extrinsic rewards are usually sparse or missing. A popular solution to this issue is to feed an agent with novelty signals as intrinsic rewards. In this work, we introduce SEMI, a self-supervised exploration policy by incentivizing the agent to maximize a new novelty signal: multisensory incongruity, which can be measured in two aspects, perception incongruity and action incongruity. The former represents the misalignment of the multisensory inputs, while the latter represents the variance of an agent's policies under different sensory inputs. Specifically, an alignment predictor is learned to detect whether multiple sensory inputs are aligned, the error of which is used to measure perception incongruity. A policy model takes different combinations of the multisensory observations as input, and outputs actions for exploration. The variance of actions is further used to measure action incongruity. Using both incongruities as intrinsic rewards, SEMI allows an agent to learn skills by exploring in a self-supervised manner without any external rewards. We further show that SEMI is compatible with extrinsic rewards and it improves sample efficiency of policy learning. The effectiveness of SEMI is demonstrated across a variety of benchmark environments including object manipulation and audio-visual games.

I. INTRODUCTION

Efficient exploration is a major bottleneck in reinforcement learning problems. In many real-world scenarios, rewards extrinsic to an agent are extremely sparse or completely missing, leading to nearly random exploration of states. A common remedy to exploration is adding intrinsic rewards, i.e., rewards automatically computed based on the agent's model of the environment. Existing formulations of intrinsic rewards include maximizing "visitation count" [3] of less-frequently visited states, "curiosity" [4], [5], [6] where future prediction error is used as reward signal and "diversity rewards" [7], [8] which incentivizes diversity in the visited states. These rewards provide continuous feedback to the agent when extrinsic rewards are sparse, or even absent. However, it is challenging to deploy these methods in practice. For "visitation count" based method, it is hard to count in a continuous space. And for "predictive model" based method, the key challenge is to model and interact with a stochastic world where multiple futures are available.

As humans, we experience our world through a number of simultaneous sensory streams, such as vision, audition and touch. The novel sensory streams from different modality motivate us to explore the world and gain knowledge actively.

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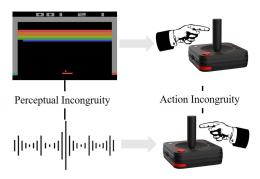


Fig. 1: SEMI: a self-supervised exploration policy by incentivizing the agent to maximize multisensory incongruity, including *perceptual incongruity* and *action incongruity*. *Perceptual incongruity* indicates the misalignment between the multisensory perceptual inputs, and *action incongruity* refers to the discrepancy of actions under different perceptual inputs.

In modern robot design, sensors with different modalities are ubiquitous in order to augment the performance of the robot perception. However, few exploration policies are designed around multimodal feedback for reinforcement learning agents. The difficulties are mainly reflected in two aspects: how to leverage multiple modalities with very different dimensions, frequencies and characteristics; and how to measure novelty with multimodal feedback.

In this work, we introduce **SEMI**, a self-supervised exploration method by incentivizing the agent to maximize multisensory incongruity, including *perceptual incongruity* and *action incongruity*, as shown in Figure 1.

Perceptual incongruity is defined as the misalignment between multisensory inputs. As humans, the coincidence of senses gives us strong evidence that they were generated by a common, underlying event [9], since it is unlikely that they co-occurred across multiple modalities merely by chance. Thus, the misalignment or incongruity between multisensory streams can be used as a strong signal of novelty. Researches in psychology suggested that this incongruity can attract human's attention and trigger further exploration [10], [11], which has been widely used in product design [12], [13]. In SEMI, we use such novelty to guide robot exploration. Specifically, an alignment predictor is trained to detect misalignment between multisensory inputs. The model observes raw sensory streams — some of which are paired, and some have been shuffled — and we task it with distinguishing between the two. This challenging task forces the model to fuse information from multiple modalities and meanwhile learn a useful feature representation. The prediction error of the sensor fusion model serves as a metric of perceptual incongruity, which is further used as an intrinsic reward to guide the agent's exploration.

Action incongruity is defined as the discrepancy of an agent's decisions when it perceives different senses of the same underlying event. This is inspired from the fact that humans are able to integrate multimodal sensory information in a near-optimal manner for decision making [14], [15], and are even robust to the loss of some senses [16], [17]. Sensory compensation empowers humans to make similar decisions when different senses are used [18], [19], [20]. In SEMI, a policy network is learned with multi-modal dropout during multisensory fusion. Concretely, we randomly drop one or several modalities during multisensory fusion to imitate loss of senses. The variance of actions suggested by the policy network under different dropout states is used to measure action incongruity, which is also used as an intrinsic reward for better exploration.

SEMI is evaluated in two challenging scenarios: object manipulation (vision and depth) and audio-visual games (Gym Retro). We show that SEMI outperforms "predictive model" based exploration policy by a large margin in both scenarios.

The contributions of this paper can be summarized as follows. Inspired by psychology, we propose SEMI, a novel self-supervised exploration policy through discovering multisensory perceptual and action incongruity; SEMI enables agents to learn compact multimodal representation from hard examples; we demonstrate the efficacy of this formulation across a variety of benchmark environments including object manipulation and audio-visual games; furthermore, we show that SEMI is complementary to other intrinsic and extrinsic rewards.

II. RELATED WORKS

a) Explore with Intrinsic Rewards.: Consider an agent that sees an observation, takes an action and transitions to the next state. We aim to incentivize this agent with a reward relating to how informative the transition was, so that the agent can explore the complicated environment more efficiently. One simple approach to encourage exploration is to use state visitation counts [1], [21], [22], where one maximizes visits on less frequent states. However, counting in the continuous space is usually challenging. Recently a more popular line of works are using prediction error [5], [6], [23], [24], prediction uncertainty [25], [26], or improvement [2] of a forward dynamics or value model as intrinsic rewards. As a result, the agent is driven to reach regions of the environment that are difficult to reason with the current model. Our proposed method also follows these works, but instead studies the exploration problem in a multisensory perception setting, which is becoming more common for modern robots.

A concurrent work from Dean *et al.* [27] has also demonstrated the effectiveness of using multisensory signals as intrinsic rewards. Specifically, they focus on the association of audio and visual signals as intrinsic rewards for reinforcement learning exploration. Different from them, our multisensory incongruity contains both perceptual incongruity and action incongruity.

- b) Multimodal Self-supervised Learning.: Selfsupervised methods learn features by training a model to solve a pretext task derived from the input data itself, without human labeling. A variety of pretext tasks have been proposed to learn representations from different modalities. Several works leverage the natural correspondence [28], [29] and synchronization [30], [31] between the audio or tactile and RGB streams to learn representations. In our work, we also used the natural correspondence and synchronization of different modalities and we proposed the novel method to utilize these relations and compute intrinsic reward signal for the exploration algorithm. Recent works have also found that multi-modal learning can lead to more robust representations as they can partly account for the different learning speeds of the different modalities [32].
- c) Noise-contrastive Estimation.: Noise-contrastive estimation [33], [34], [35] measures the compatibility between sample pairs in a representational space and is at the core of several recent works on unsupervised feature learning [36], [37], [33], [29], [38]. It reduces a density estimation problem into a simpler probabilistic classification problem, circumventing the need to design handcrafted tasks in the raw signal space. Contrastive learning has recently been shown to yield good performance for image and video representation learning [39], [37], [40]. Prominently, Chen et al. [38] demonstrated that proper combination of data augmentation strategies and noise-contrastive re-identification achieves superior unsupervised learning results. In our work, we build the positive-negative pair of data augmentation by utilizing the temporal correspondence throughout the experience of the agent.

III. METHOD

SEMI is a self-supervised exploration policy that incentivizes agents to maximize multisensory incongruities, which we formulate as two aspects: perceptual incongruity (Section III-A) and action incongruity (Section III-B). Both incongruities are fed to the agent as intrinsic rewards to encourage its exploration. Figure 2 gives an overview of the pipeline of SEMI, and we will detail each sub-module in the following.

a) Notation.: Given an agent's current observation O_t at time t, our goal is to generate intrinsic curiosity reward r_t so that the agent learns a policy π to explore unknown and difficult environment. In this paper, we focus on the multisensory setting, where the agent observes a set of perceptual inputs $O_t = \{o_t^1, o_t^2, ..., o_t^M\}$, where M is the number of modalities, which could represent vision, audio, touch, etc. By executing an action a_t produced by the policy, the agent further observes the next state, which we denote as $O_{t+1} = \{o_{t+1}^1, o_{t+1}^2, ..., o_{t+1}^M\}$.

A. Multisensory Perceptual Incongruity

The synchrony of multiple senses is a fundamental property of natural event perception. We humans are extremely sensitive to the incongruity between these senses, which is a strong signal of novelty. For example, if a common

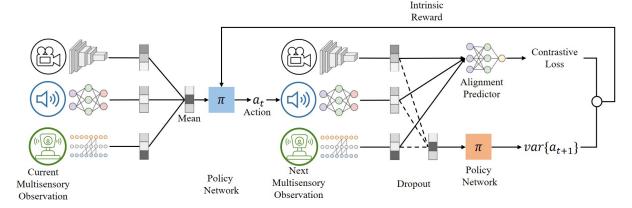


Fig. 2: SEMI pipeline overview: at time step t, an agent takes action a_t given a multisensory observation O_t as input and ends up in a new state. The multisensory fusion model takes a new observation O_{t+1} as input and predicts whether these sensory inputs are aligned. The prediction loss is used as the measure of perceptual incongruity. The variance of actions suggested by the policy network given different combination of multisensory inputs is used to measure action incongruity. Both incongruities are used as intrinsic rewards to train the policy π .

object makes an uncommon sound, we are motivated to further interact with this object to gain better knowledge about it. Inspired by this observation, we aim to use such novel association signals as curiosity to drive an RL agent to explore unfamiliar states.

To guide an agent to explore novel states, we propose an alignment predictor to discover the perceptual incongruity. Alignment prediction can take various forms, one possible design is to predict one sensory stream from other streams. For example, we could generate sounds from a corresponding visual input, or generate images from its sounds. However, generating data in the raw signal space is proved to be challenging, since (1) it does not handle the cases of multiple possible targets, (2) it suffers from overfitting to trivial details or noises [5].

A better idea is to predict the compatibility of multisensory streams in the latent space. Along the idea of contrastive learning [39], [38], our design of alignment predictor directly maximizes the agreement between different modalities of the same event. This is achieved by predicting positive (aligned) modality streams from negative ones via a contrastive loss penalty in the latent space. The predicted alignment score can then be used as an indicator of perceptual incongruity.

Concretely, the alignment predictor comprises the following two major components.

- ullet A set of neural network base encoders $(f_1(\cdot),...,f_M(\cdot))$ that extracts representation vectors from each modality. Our framework is agnostic to the choices of neural network architectures. In the following experiments, we use a 2D ConvNet to extract RGB visual features, another 2D ConvNet to obtain depth features, and a Short Time Fourier Transform (STFT) followed by a 1D ConvNet to extract the audio features.
- A contrastive loss function defined for a contrastive learning. Given one sensory stream o^j from a multisensory observation $O = \{o^i\}|_{i=1,\dots,M}$ (we omit time t in the following for brevity), we define the other M-1 simul-

taneous sensation streams $\{o^i\}|_{i\neq j}$ as positive examples. In a minibatch of N observations, there are $M\times (N-1)$ sensory streams from other modalities, which can be used to build misaligned examples. The contrastive prediction task aims to identify aligned sensory streams from these misaligned examples.

The similarity of a pair of multimodal observation (o^i, o^j) are measured by the cosine distance, *i.e.*

$$sim(o^{i}, o^{j}) = cos(\mathbf{f_i}, \mathbf{f_j}) = \frac{\mathbf{f_i^{T} \cdot f_j}}{||\mathbf{f_i}|| \cdot ||\mathbf{f_j}||},$$
 (1)

where $\mathbf{f_i} = f_i(o^i)$, $\mathbf{f_j} = f_j(o^j)$ are features from different modalities. Then the contrastive loss function for a pair of positive observation (o_k^i, o_k^j) is defined as

$$\mathcal{L}(o_k^i, o_k^j) = -\log \frac{\exp(\sin(o_k^i, o_k^j)/\tau)}{\sum_{n=1}^{N} \sum_{m=1}^{M} \exp(\sin(o_k^i, o_n^m)/\tau)}, \quad (2)$$

where τ denotes a temperature parameter.

The multisensory perceptual incongruity of an observation O_k is then defined numerically as the sum of losses of all possible multisensory pairs from the same timestep, which can be used as an intrinsic reward $r^p = \sum_{i=1}^M \sum_{j=i+1}^M \mathcal{L}(o_k^i, o_k^j)$.

B. Multisensory Action Incongruity

Congruity in actions is inspired from the fact that human perception is robust to the partly loss of senses, and humans have an exceptional ability to compensate for the loss with other senses. For example, an experienced driver can predict if cars are coming up from nearby lanes just from sound noise, without turning his/her head to look. If we make different decisions with different sensory inputs, it suggests we have low confidence of the event we experienced, *e.g.* an inexperienced driver might change lane recklessly without a good understanding of the distance of cars from the sound noise. Inspired by the above observation, we further aim to use the action incongruity as an indicator of novelty in RL exploration.

Here we implement the action incongruity via drop of senses. Proposed by Srivastava *et al.* [41], *dropout* has been widely used to prevent neural networks from overfitting [42], [43]. Gal *et al.* [44], [45] further cast dropout training in deep neural networks as approximate Bayesian inference in deep Gaussian processes, which offers a mathematically grounded framework to reason about model uncertainty.

We adopt a similar approach by taking a sensory-wise dropout strategy during sensor fusion for the policy network. Then multisensory action incongruity is defined as the divergence of actions suggested by the policy network given different combinations of multisensory observations.

Specifically, we combine features of different modalities with dropout to obtain a fused perceptual feature z,

$$z = \frac{1}{\sum_{i=1}^{M} 1^{i}} (\sum_{i=1}^{M} 1^{i} \mathbf{f_{i}})$$
 (3)

where $\mathbb{1}^i \in \{0,1\}$ indicates the existence of $\mathbf{f_i}$. Apparently, different combinations of $\mathbb{1}^i$ will lead to different z. We collect the action outputs from the policy network π_r given all possible inputs z's (2^M-1) possible inputs in total), and define the variance of these actions as the *multisensory action incongruity*. The action incongruity is further used as an intrinsic reward r^a for exploration,

$$r^{a} = \frac{1}{2^{M} - 1} \sum_{k=1}^{2^{M} - 1} ||\pi_{r}(z^{k}) - \frac{1}{2^{M} - 1} \sum_{k=1}^{2^{M} - 1} \pi_{r}(z^{k})||_{2}^{2}.$$
(4)

C. Multisensory Incongruities as Intrinsic Rewards

To summarize, we use both multisensory perceptual incongruity and multisensory action incongruity as intrinsic rewards. It is worth noting that the policy network π_r used to calculate intrinsic reward r_t^a is different from that used for exploration π . Inspired by Double Q-learning [46] and Dual Policy Iteration [47], π_r , with parameters θ being the same as π except that its parameters are copied every τ steps from the π . This simple strategy not only reduces the observed overestimations, but also leads to better convergence.

At time step t, the agent takes action a_t given multisensory observation O_t with modality dropout as input and receives a new observation O_{t+1} and intrinsic reward in calculated as $r_t = r_t^p + \gamma \times r_t^a$, where γ is a weight factor. The agent is optimized using PPO [48] to maximize the expected reward according to

$$\max_{\theta} \mathbf{E}_{\pi(O_t;\theta)}(\sum_{t} r_t). \tag{5}$$

IV. EXPERIMENTS

We evaluate the performance of SEMI in two environments, *OpenAI Robotics* and *Atari*. Three settings are considered and discussed: exploration with multisensory incongruity only (Section IV-A), combining multisensory incongruity with extrinsic reward (Section IV-B), and combining multisensory incongruity with other intrinsic rewards (Section IV-C).

A. Exploration via Multisensory Incongruity

- 1) Environment and Setting:
- a) OpenAI Robotics: We evaluate our method on OpenAI Robotics [49], where robot receives RGB image and Depth image as two modalities, and controls the gripper Cartesian movement, gripper rotation as well as gripper open or close.
- b) Atari: We also evaluate our method on Atari games, where vision and audio are considered as multi-modal inputs. We use Gym Retro [50] in order to access game audio.

Further details for the two evaluation environments are described in the supplementary materials.

2) Training Details: In general, we used 5 convolutional layers to extract RGB features, a similar network to extract depth features or 5 consecutive frames channel-wise spectrum to represent audio feature. We used a 4-layer multilayer perceptron (MLP) as our policy network and used PPO to maximized the intrinsic reward with an Adam Optimizer. During training, all rewards that are collected in trajectories will be replaced or added by intrinsic reward. Further details in training the agent in OpenAI Robotics and Atari Games are described in supplementary materials.

3) Results:

a) OpenAI Robotics: Table I shows the exploration performance of object manipulation using the multisensory incongruity, which are measured by the frequency at which our agent interacts (i.e., touches) with the object (i.e., interaction rate). The interaction rate is defined as #trials robot interact with object/#total trials.

We evaluate two different versions of our method. We first use only the multisensory perceptual incongruity as our intrinsic reward, as described in Section III-A. Second, we use both multisensory perceptual incongruity and multisensory action incongruity as our intrinsic reward.

We compare SEMI to Curiosity [5], [23] and Disagreement [51] as our baselines. Also, we compared with a random policy as a sanity check, which samples its action uniformly from the action space.

As shown in Table I, our method outperforms all of these baselines. The method of Disagreement [51] has a performance close to that of our method.

We perform an ablation analysis to quantify the performance of each component of our system (4th and 5th row in Table I). We see that both multisensory perceptual incongruity and multisensory action incongruity contribute to the robot exploration.

b) Atari: We also test out method in Atari MsPacman, Assault, AirRaid, Alien, Space Invaders, Breakout, and Beam Rider. Figure 3 shows the extrinsic reward of some Atari games during exploration with SEMI in comparison of intrinsic reward via RND, Curiosity and Disagreement. It should be pointed that during training the agent only has access to the intrinsic reward. As illustrated in Figure 3, our method converges faster and achieves better performances comparing with all baseline methods. The reason is that audio signals are always triggered by significant events (e.g. eating pellets). The highly temporal-aligned signal from

Exploration Strategy		Interaction Rate (1 objects)	Convergence Iteration	Interaction Rate (1 of 3 objects)
Uni-IR	Curiosity	2.7%	25	8.3%
	Random	8.4%	0	22.6%
	Disagreement	26.3%	23	64.3%
	SEMI (P)	30.5%	20	81.4%
	SEMI (PA)	34.4%	33	82.1%
Multi-IR	Curiosity + SEMI (PA)	35.8%	36	83.3%
	Disagreement + SEMI (PA)	37.1%	35	83.8%

TABLE I: We measure the exploration quality by evaluating the object interaction frequency of the agent trained with different intrinsic rewards (Row 1-5) and a combination of intrinsic rewards (Row 6-7).

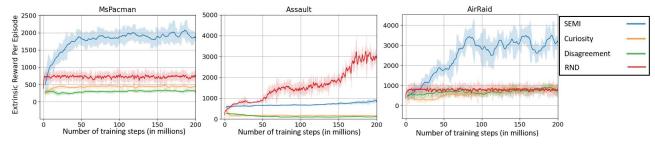


Fig. 3: We compare different intrinsic reward formulations across different Atari games. We run three independent runs of each algorithm and show the mean extrinsic reward during training. SEMI far outperforms curiosity-based baseline and disagreement-based baseline, and also learns more efficiently.

different sensory modalities can be explicitly utilized when we are computing the contrastive loss function. Thus, the multisensory incongruity is more indicative compared with curiosity and disagreement baselines, which are influenced by the stochasticity of the environments.

B. Combining with Extrinsic Reward

Considering our proposed intrinsic rewards are designed to guide the agent to explore the environment, will they allow the agent to explore well when the extrinsic reward is sparse? To verify this, we conduct additional experiments in OpenAI Robotics and Atari Games. While the network architecture and training schema are exactly the same as Section IV-A, we use the sum of SEMI and extrinsic rewards as training signal,

$$R_t = r_t + \beta \times r_t^{(e)} \tag{6}$$

where $r_t^{(e)}$ is the external reward provided by the environment. We set β to 1 in all the experiments.

Figure 4 shows the episodic extrinsic reward of the FetchPush, Pickup and Place, FetchSlide task training with multisensory incongruity against without using intrinsic rewards. The extrinsic rewards are sparse and binary: The agent obtains a reward of 0 if the goal has been achieved (within some task-specific tolerance) and -1 otherwise. Training with SEMI significantly improves the learning efficiency compared with training with only sparse extrinsic reward. By adding action variance in SEMI paradigm (PA), the performance improves further when policy model learns meaningful mapping from observation to action.

We also tested the experiments on Atari MsPacman, Air-Raid, Assault, and Alien. Figure 5 shows the effectiveness of our method for efficient exploration in these Games.

Training with SEMI always leads to a faster convergence, which indicates that it is able to speed up exploring the environments. Besides, the final performance of the agent does not deteriorate with faster convergence, showing the compatibility of SEMI with any extrinsic rewards.

C. Combining with Other Intrinsic Rewards

We further show that exploration via multisensory incongruity is complementary to some other self-supervised exploration methods, *e.g.* prediction-based curiosity. To demonstrate this, we simply sum the multisensory incongruity with other intrinsic rewards, and use it to train the agents. We evaluate this setup in both OpenAI Robotics and Atari Games. The network architecture and training schema are exactly the same as mentioned in Section IV-A.

Table I (5th and 6th row) shows the interaction rate of object manipulation during exploration with a combination of intrinsic rewards, which sums two intrinsic reward directly as the total intrinsic reward for the agent. The agent maximizing the sum of multiple intrinsic rewards explores better than an agent maximizing single intrinsic rewards, which shows that SEMI is complementary to many existing intrinsic rewards.

Similarly, We combine our method with other intrinsic rewards on MaPacman, Assault and AirRaid. Figure 6 shows the extrinsic reward of Atari during exploration with a combination of intrinsic rewards. On environment such as AirRaid, the extrinsic reward converge significantly faster than trained with only visual prediction or SEMI method. But on environments like Alien and Space Invaders, the performance does not improve compared to the visual prediction baselines no matter whether multisensory incongruity outperforms curiosity. Since it is unclear how the intrinsic rewards will affect each other when trained jointly, it is possible that optimizing some rewards can bring negative

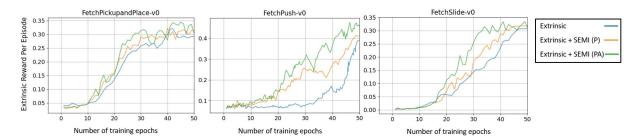


Fig. 4: Comparison of episodic extrinsic rewards of the agent trained with and without multisensory incongruity in the Fetch-Pushing task. Training with SEMI significantly improves the learning efficiency compared with training with only sparse extrinsic reward.

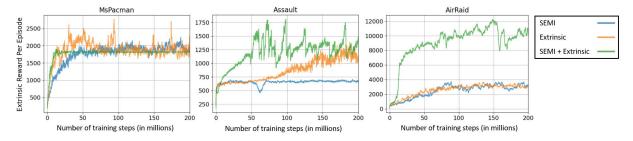


Fig. 5: Comparing the performance of the agent trained with multisensory incongruity against without using intrinsic rewards across different Atari games. We run three independent runs of each algorithm and show the mean extrinsic reward during training. Training with SEMI always leads to a faster convergence.

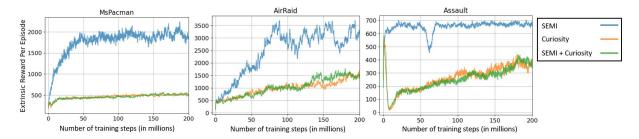


Fig. 6: Comparing the performance of the agent trained with multisensory incongruity joint with other intrinsic rewards against trained with multisenory incongruity alone across different Atari games. We run three independent runs of each algorithm and show the mean extrinsic reward during training.

impacts on the others, which will lead to a worse exploration efficiency.

D. Failure Cases

While SEMI generally shows improvement in exploring the environment and is compatible with training with extrinsic reward, there are still some Atari environments where it does not improve exploration efficiency. We dig into the games and analyze the feature of them to explain why these environments lead to failures.

- a) The game presents constant sound patterns: For example in Beam Rider, there is a fixed background sound whenever the agent makes a move. Thus, the multisensory incongruity method will not learn useful patterns to distinguish the incongruity even in the basic situations, therefore the agent cannot learn from any meaningful intrinsic reward signal.
- b) The game shows trivial multisensory association: In environments like Breakout, the audio is almost the same when the agent is interacting with the environment, *i.e.* the

sound in Breakout only indicates the ball is making contact with objects in the scene. The multisensory incongruity module could easily distinguish the incongruity in almost all cases in the game. A newly reached game situation will not lead to high intrinsic rewards. Therefore, multisensory incongruity method cannot motivate the agent to explore unseen situations.

V. CONCLUSION

In conclusion, we proposed SEMI, a self-supervised exploration strategy by incentivizing the agent to maximize multisensory incongruity. We showed that through the use of multisensory perceptual incongruity and multisensory action incongruity, our learned policy can explore the environment efficiently. We also showed the compatibility of our proposed method with extrinsic rewards and other intrinsic rewards.

We hope that our work paves the way towards to a direction for intelligent agents to continually develop knowledge and acquire new skills from multisensory observations without human supervision.

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