Touch-based Curiosity for Sparse-Reward Tasks

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Abstract: Robots in many real-world settings have access to force/torque sensors in their gripper and tactile sensing is often necessary in tasks that involve contact-rich motion. In this work, we leverage surprise from mismatches in touch feedback to guide exploration in hard sparse-reward reinforcement learning tasks. Our approach, Touch-based Curiosity (ToC), learns what visible objects interactions are supposed to "feel" like. We encourage exploration by rewarding interactions where the expectation and the experience do not match. We test our approach on a range of touch-intensive robot arm tasks (e.g. pushing objects, opening doors), which we also release as part of this work. Across multiple experiments in a simulated setting, we demonstrate that our method is able to learn these difficult tasks through sparse reward and curiosity alone. We compare our cross-modal approach to single-modality (touch- or vision-only) approaches as well as other curiosity-based methods and find that our method performs better and is more sample-efficient.

1 Introduction

Most successes in reinforcement learning (RL) come from games [1, 2] or scenarios where the reward is strongly shaped [3, 4]. In the former, the environment is often fully observable, and the reward is dense and well-defined. In the latter, a large amount of work is required to design useful reward functions. While it may be possible to hand-craft dense reward signals for many real-world tasks, we believe that it is a worthwhile endeavor to investigate learning methods that do not require dense rewards.

Closely related to the sparse rewards problem is the issue of exploration. One reason that traditional RL agents struggle with sparse-reward problems is a lack of exploration. An agent may not obtain useful rewards without an intuitive exploration strategy when rewards are sparse. Exploration based on intrinsic curiosity comes naturally to many animals and infants (who start crawling and exploring the environment at around 9 months [5] and oftentimes even before they can crawl by using their hands and mouth to touch and probe objects). Touch is a local experience and encodes accurate geometrical information while handling objects. Developmental research in infants has suggested that tactile and visual sensory modalities play a central role in systematic learning of tasks related to object understanding, interaction and manipulation [6, 7].

Ideally, we would like our RL agents to explore the environment in an analogous self-guided fashion to learn the dynamics and object properties, and use this knowledge to solve downstream tasks. Just as how humans utilize different sensory modalities to explore and understand the world around them, exploration in robots should be more embodied and related to a combination of vision and touch and potentially other sensor modalities. We believe that building autonomous agents that are self-driven and seek to explore via multi-modal interaction are crucial to address key issues in developmental robotics.

Recent works in RL have focused on a curiosity-driven exploration through prediction-based surprise [8, 9, 10]. In this formulation, a forward dynamics model predicts the future, and if its prediction is incorrect when compared to the real future, the agent is surprised and is thus rewarded. This encourages the agent to look for novel states while improving its visual forward model in return. However, this formulation can be practically challenging to optimize since there are many states that are visually dissimilar but practically irrelevant (e.g. for a pushing task, moving a robotic end-effector without touching the object creates visual novelty but contributes little to task-related knowledge). One way to constrain this search space over curious behaviors is by involving another modality like touch.

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In this work, we demonstrate that a self-guided cross-modal exploration policy can help solve sparse-reward downstream tasks that existing methods without this curiosity struggle to solve. Our method uses cross-modal consistency (mismatch between visual and touch signal) to guide this exploration. To use self-play knowledge in downstream tasks, we relabel past experiences, providing a dense reward signal that allows modern off-policy RL methods to solve the tasks. While there are many existing methods that use artificial curiosity/intrinsic motivation, the majority of these methods either rely on strong domain knowledge (e.g. labels of state dimensions in Forestier et al. [4], a goal-picking strategy in Andrychowicz et al. [11]) or are prone to get stuck in local optima when a single meaningless stimulus creates enough surprise to capture the attention of the agent (e.g. noisy-TV experiment from [12]). Other approaches depend on unrealistic assumptions and goal conditioning [11]. Our method presents a novel approach in the family of prediction-based models [8, 13, 9] and yields better performance on a wide range of robotic manipulation tasks than purely vision-based and touch-based approaches [8, 9]. The tasks are chosen with careful consideration—they comprise of preliminary robotic manipulations such as grasping, pushing, and pulling. In this work, we present the following contributions:

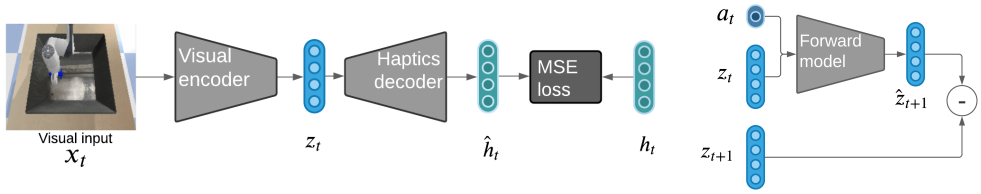
- A new curiosity method to help solve sparse-reward tasks that use cross-modal consistency (predicting one modality from another) to guide exploration. We implement it in this work as vision and touch modalities, but the formulation of our method does not require any knowledge about the underlying modalities and can thus be applied to other settings.
- We create and maintain a manipulation benchmark of simulated tasks, *MiniTouch*, inspired by Chen et al. [14], Andrychowicz et al. [11], where the robotic arm is equipped with a force/torque sensor. This allows evaluation of models' performance on different manipulation tasks that can leverage cross-modal learning.
- We validate the performance of our method on MiniTouch environment comprising of four downstream tasks. We compare purely vision-based curiosity approaches and standard off-policy RL algorithms. Our method improves both performance and sample efficiency.

2 Related Work

Intrinsic Motivation Intrinsic motivation is an inherent spontaneous tendency to be curious or to seek something novel in order to further enhance one's skill and knowledge [15, 16, 17]. This principle is shown to work well even in the absence of a well-defined goal or objective. In reinforcement learning, intrinsic motivation has been a well-researched topic [18, 19, 20, 21, 22, 23]. An intuitive way to perform intrinsic motivation is through the use of "novelty discovery". For example, incentivize the RL agent to visit unusual states or states with substantial information gain [24]. In its simplest form, this can be achieved with up-weighting mechanisms such as state visitation counts [25]. Count-based methods have also been extended to high-dimensional state spaces [26, 12, 27]. Alternative forms of intrinsic motivation include disagreement [28], empowerment [29, 30].

Exploratory intrinsic motivation can also be achieved through "curiosity" [18, 31]. In this setting, an agent is encouraged to visit states with high predictive errors [10, 8, 9] by training a forward dynamics model that predicts the future state given the current state and action. Instead of making predictions in the raw visual space, Pathak et al. [9] mapped images to a feature space where relevant information is represented via an inverse dynamics model. Burda et al. [8] demonstrate that random features are sufficient for many popular RL game benchmarks. This approach may work well with tasks that require navigation to find a reward because each unseen position of the agent in the world leads to high intrinsic reward when unseen. However, in the case of manipulative tasks, we are less interested in the robot visiting all the possible states and more interested in states where the robot interacts with other objects. In this work, we leverage multimodal inputs that encourage the agent to find novel combinations of visual and force/torque modalities.

Self-Supervised Learning via Cross-modality Exploiting multimodality to learn unsupervised representations dates back to at least 1993 [32]. Multimodal signals are naturally suitable for self-supervised learning, as information from one modality can be used to supervise learning for another modality. Different modalities typically carry different information, e.g., visual and touch sensory modalities emerge concurrently and often in an interrelated manner during contact-rich manipulation tasks [33]. Specifically, force/torque motor signal has always been a major component in the literature of perception and control [34, 35, 36].



(a) Touch Control module

(b) Forward module

Figure 1: **Touch-based Curiosity Model.** (a) The input image x_t at time t is transformed into a 256-dimensional feature vector $z_t = enc(x_t)$ using a CNN encoder. The touch decoder network predicts corresponding force/torque vector $\hat{h}_t = dec(z_t)$. The $L2$ norm between predicted haptics $\hat{h}_t$ and observed haptics h_t is used as exploration reward. (b) To stabilize training, an additional network is used to predict the forward dynamics, and the difference between predicted next latent state $\hat{z}_{t+1}$ and actual next latent state $\hat{z}_t$ is used as weighted additional term in the exploration reward.

The most common ways to leverage multimodal signals to learn representations are through vision and language [37, 38], or through visual and audio [39, 40]. Gao et al. [41], Li et al. [42] demonstrated a unified approach to learning representations for prediction tasks using visual and touch data. In robotics and interactive settings, the use of additional modalities such as tactile sensing [43, 44, 45] is increasingly popular for grasping and manipulation tasks. Lee et al. [46] showed the effectiveness of self-supervised training of tactile and visual representations by demonstrating its use on a peg insertion task.

While the mentioned approaches have used multiple sensory modalities for learning better representations, in this work we demonstrate its utility for allowing agents to explore. Similar to ours, Dean et al. [47] use multimodal sensory association (i.e. audio and visual) to compute the intrinsic reward. Their curiosity-based formulation allows an agent to efficiently explore the environment in settings where audio and visual signals are governed by the same physical processes. In addition to the different nature of sensory signals, they use a discriminator that determines whether an observed multimodal pair is novel. This might not work in our case as touch is a more sparse signal and using a discriminator could lead to ambiguous outcomes.

3 Proposed Approach

The goal of our method, Touch-Based Curiosity (ToC), is to encourage the agent to interact with objects. ToC provides a reward signal for a RL agent to explore the state space of a task that involves interacting with objects. The exploration phase is independent of the downstream task, i.e., relying solely on visual and force/torque signals, without a reward signal from the downstream task.

Similar to how people spend more time exploring stimuli that are more incongruous [7], ToC guides the agent to focus its experience on different novel cross-modal associations. We augment this intrinsic objective with a future visual state prediction objective similar to the one in Pathak et al. [9] to avoid getting stuck in undesired inactive configurations. Note that we sometimes refer to the future state prediction objective in the text as forward dynamics objective. In this work, we focus on the cross-modality between vision and touch, but the same idea could be applied to other pairs of sensory domains, such as vision and sound, or touch and acoustics.

3.1 Problem Formulation

The learning problem is formalized as a Markov decision process (MDP) defined by a tuple $\{\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \rho, \gamma\}$ of states, actions, transition probability, reward, initial state distribution, and discount factor. The goal is to find the optimal policy that maximizes the discounted sum of rewards, $\pi^* = \mathbb{E}_\pi[\sum_t^\infty \gamma^t r(\mathbf{s}_t, \mathbf{a}_t)]$. In our case, each state s_t in the trajectory is composed of both visual and corresponding touch features as detailed in the following section. We use soft actor-critic policy gradients (SAC) [48] to train our policies, but in principle, our proposed approach is algorithm-agnostic. The policy π is evaluated with an estimation of the soft Q-value:

$$Q(\mathbf{s}_t, \mathbf{a}_t) \triangleq r(\mathbf{s}_t, \mathbf{a}_t) + \gamma \mathbb{E}_{\mathbf{s}_{t+1} \sim p}[V(\mathbf{s}_{t+1})] \ , \tag{1}$$

where $V(\mathbf{s}_t) = \mathbb{E}_{\mathbf{a}_t \sim \pi}[Q(\mathbf{s}_t, \mathbf{a}_t) - \log \pi(\mathbf{a}_t|\mathbf{s}_t)]$ is the soft value function.

3.2 Touch-based Prediction

Our core prediction framework consists of two modules: (i) a *touch control* module, which learns to predict expected touch signal from the visual input, and (ii) a *forward dynamics* model, which predicts the next latent state from the current latent state and the current action (see Figure 1). Let the state of the environment $\mathbf{s}_t = (z_t, h_t)$ at time t be composed of a visual feature z_t (the encoded visual input) and a touch signal h_t. The touch prediction model consists of a convolutional encoder $z_t = enc(x_t)$ that transforms the image x_t into a latent representation z_t and a fully-connected decoder $\hat{h}_t = dec(z_t)$ that transforms the latent into a predicted haptic signal $\hat{h}_t$. The encoder-decoder is trained with a L2 reconstruction loss, i.e. for every image x_t and force/torque sensor h_t:

$$L_{touch} = \left\| \hat{h}_t - h_t \right\|_2 \ . \tag{2}$$

A high prediction error on a given image indicates that the agent has had few interactions like this. Therefore, to harness this "surprise" to guide exploration, we define the intrinsic reward at time t during exploration to be proportional to this reconstruction loss. This essentially allows the agent policy to visit under-explored configurations of the state space by encouraging interactions where the system does not know what the target object "feels" like. In addition to efficient exploration, being aware of such incongruity via touch prediction aids learning local regularities in the visual input. This in turn could assist better generalization to unseen states. An overall pipeline of the framework is shown in Figure 1a.

3.3 Regularization Through Forward Dynamics Model

We found empirically (and we demonstrate in the experiments section below) that the surprise stemming from haptic novelty was not enough to cause object-centric interaction. We postulate that by incorporating visual surprise (i.e. the mismatch between predicted forward dynamics and observed dynamics) [9], we can create an agent that seeks out visual novelty as well as haptic one and thus leads to better state space coverage. To this end, our model is augmented with a forward dynamics model (see Figure-1b) $\hat{z}_{t+1} = fdm(z_t, a_t)$ that learns to map the latent state z_t (obtained from the visual encoder enc) and action a_t at time t to the predicted latent state $\hat{z}_{t+1}$ at the next timestep. This model is also trained with L2 loss:

$$L_{fdm} = \|\hat{z}_{t+1} - z_{t+1}\|_2 \ = \|fdm(enc(x_t), a_t) - enc(x_{t+1})\|_2 \ . \tag{3}$$

The intrinsic reward is defined as the convex combination of the cross-modal prediction loss (Eq. 2) and the forward dynamics model loss (Eq. 3):

$$r_t = (1 - \lambda) \cdot L_{touch} + \lambda \cdot L_{fdm} \ , \tag{4}$$

where $\lambda \in [0, 1]$ is a balancing factor. The effect of the factor λ on overall performance is studied in the ablation experiments described in Section 5.1.

3.4 Training

Learning is divided into two stages: (i) an *exploratory* step, where the agent performs free exploration following ToC, and (ii) an *adaptation* step, where the agent is tasked to solve a downstream problem, given a sparse reward.

During the exploratory step, each trajectory consists of pairs of image and force/torque features, (z_1, h_1), (z_2, h_2),..., (z_n, h_n). These trajectories are used for two purposes: (i) updating the parameters of the prediction model to help shape the representations and (ii) updating the exploration policy based on the intrinsic reward r_t. Note that we use the touch features only to craft the intrinsic rewards and the input to RL agent consists of visual features alone. For vision-based curiosity models, Burda et al. [8] observed that encoding visual features via a random network constitute a simple and effective strategy compared to learned features. In Section 5.1, we investigate the performance of our model in both scenarios, i.e., when the features are learned vs random. The overall optimization problem at this step consists of the policy learning (driven by intrinsic reward), the touch reconstruction loss (Eq. 2), and the forward dynamics loss (Eq. 3). During the downstream adaptation step, the parameters of the policy network, the Q network and the replay buffer are retained from the exploratory phase. The objective of the down-stream task is computed as:

$$\min_{\theta} \left[-\mathbb{E}_{\pi} \left[\sum_t r_t^e \right] \right] \ , \tag{5}$$

where r_t^e in this phase is task-specific external sparse reward. In both steps, the objectives are optimized with Adam [49].

Implementation Details: The encoder is a four-layered strided CNN followed by a fully connected network. We use LeakyReLU [50] as non-linear activation in all the layers. The decoder network is a two-layerd MLP that maps 256-dimensional visual features to touch vectors. For a more detailed description of the networks (SAC policy network and ToC networks, including the forward model) and hyper-parameters, please refer to the supplementary material Section 7.2.

4 Experimental Setting

Our experiments focus on a tabletop robot manipulation from raw image observations and raw force/torque sensory values, which we refer to as "touch vector". For our experiments, we use a 7-DoF Franka Emika Panda arm with a two-finger parallel gripper. Each of the fingers is equipped with a simulated force/torque sensor that measures the joint reaction force applied to it. We utilize PyBullet [51] to simulate the robot arm and haptic sensor[1].

4.1 MiniTouch Benchmark

Our proposed benchmark, MiniTouch, consists of four manipulation tasks: Playing, Pushing, Opening, Pick-up. Each of the tasks along with corresponding actions, observations, and rewards is described in detail in the Supplementary Material Section 7.1 and further illustrated in Figure 7. MiniTouch is an active repository[1] and we expect to update the benchmark with new tasks and datasets. The tasks are inspired by Yu et al. [52] but are *not* based on a proprietary simulator, feature an arm that we have access to for real-world experimentation (in follow-up work), and where the arm is equipped with a haptic sensor.

4.2 Baseline Comparisons and Metrics

For the task evaluation, we study two versions of our model: (i) ToC-Pure considering the touch vector reconstruction intrinsic reward alone, and (ii) ToC, considering the full intrinsic reward (Eq. 4). We compare our model with SAC and several well-known intrinsic exploration based baselines:

- **SAC**: The unmodified Soft Actor-Critic algorithm from Haarnoja et al. [48].
- **ICM**: SAC augmented with the state-of-the-art visual curiosity approach Intrinsic Curiosity Module (ICM) [12], which uses a visual forward model to guide exploration.
- **Disagreement**: It uses model disagreement as objective for exploration [53, 28]. It leverages variance in the prediction of an ensemble of latent dynamics models as the reward.
- **RND**: Random Network Distiallation [54] utilizes a randomly initialized neural network to specify an intrinsic reward for visiting unexplored states in hard exploration problems.

We built a Pytorch [55] version of these baselines based on their open source code (details in supplementary material). We use the following metrics to evaluate our method and the baseline models:

Exploration success: measures the percentage of times that the agent attained the goal state in the *exploratory* phase, i.e. with no external reward. Higher is better.
Success: denotes the percentage of times that the agent attained the goal state during the *downstream* task phase.
Episode steps: quantifies the number of steps required for each episode to succeed. This metric is an indicator of sample efficiency. The lesser the number of steps, the faster the agent's ability to succeed.
Touch-interaction: Amount of interaction the agent's fingers have with the underlying object. We measure this by computing the variance of force/torque sensory signal across the whole episode. Higher variance indicates better interaction.
Object movement: The agent can resort to constantly engaging with the object in a passive manner in order to satisfy the objective. We, therefore, compute the variance of door angle (for the Opening task) and the variance of object position (for the remaining tasks) over the course of training. A higher motion indicates diverse state space and that the agent does not get stuck with pointless subtle movements of the objects.

[1]Based on code from the official Franka Emika repo https://github.com/frankaemika/libfranka
[1]https://github.com/xxxxx

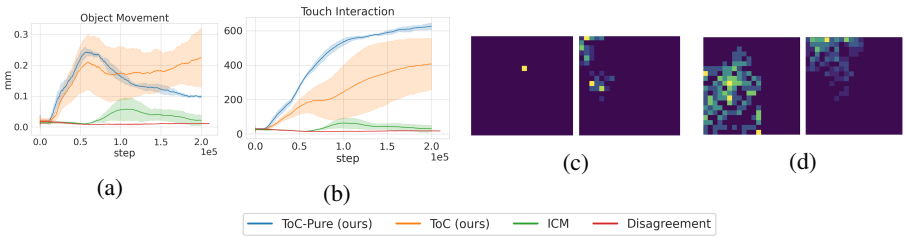


Figure 2: **Object Interaction for Playing task.** To quantitatively evaluate an agent's object interaction, we consider both touch interaction and object displacement. (a) shows the object movement evaluation (avg displacement in mm from the starting point) of our method compared with the baseline methods over training steps; (b) depicts the number of touch interactions, evaluated on the "playing" task. (c) Heat maps showing the object position at the beginning (*left*) and end (*right*) of the ToC training. The object is moving more often towards the end. (d) shows heat maps showing the end-effector position at the beginning (*left*) and end (*right*) of the training. Robot's fingers are spread every where at starting while learn to focus near the object towards the end of training.

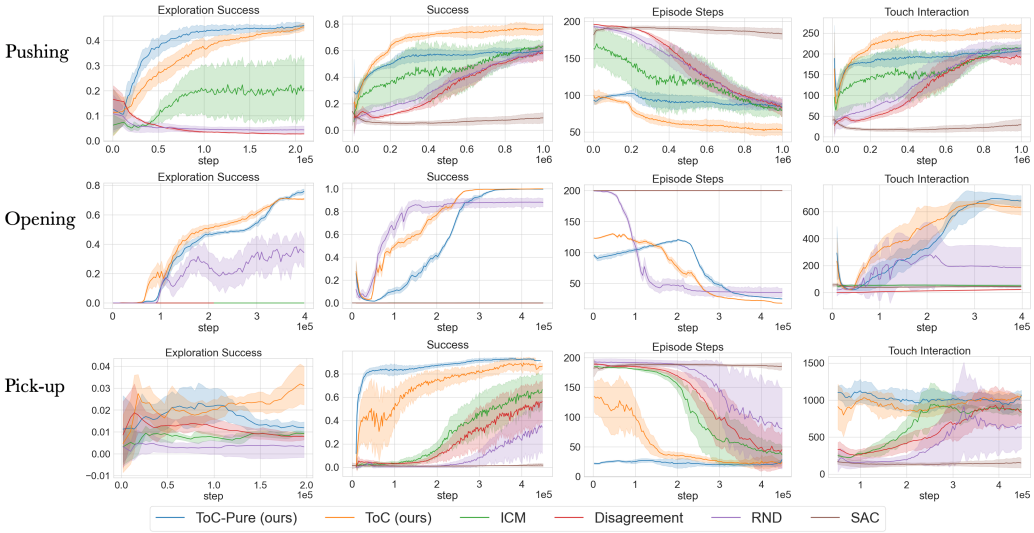


Figure 3: **MiniTouch Evaluations**. Each row in the figure outlines the performance of the ToC variants and the baselines on a MiniTouch task. Each column marks performance on the four specified evaluation metrics over a number of training steps on the x-axis expressed in $1e^5$. The results are averaged across 5 random seeds and shaded areas represent mean ± one standard deviation while darker line represents mean. In the majority of the tasks, ToC agents attain success in the *exploratory* phase with no external reward (see text). *Note*: We exclude the single object playing task as success in this task is equivalent to object interaction as depicted in Figure. 2.

5 Results and Discussion

ToC and baselines were trained on a Panda robot agent [51] for one million steps. In the *exploratory* phase of the training, we pre-train our method only with the curiosity-based intrinsic reward. We then progress to the *adaptation* phase. Also, note that across all tasks, ToC-Pure is based purely on cross-modal prediction, while ToC includes visual forward prediction reward in addition.

Figure 2 shows results on the basic task of playing with a single object. Since single object interaction does not have explicit goal states to evaluate, we instead measure the agent's ability to constantly engage and play with the underlying object. ToC-Pure displays four times better interaction with the underlying object when compared to SAC (see Figure 2b). Also, the plot depicting object movement metric in Figure 2a indicates that ToC is slightly more dynamic in the interaction in contrast to ToC-Pure. Note from the plots that there is a trade-off when using ToC and ToC-Pure between constant interaction (i.e. touch interaction performance) and object movement dynamics.

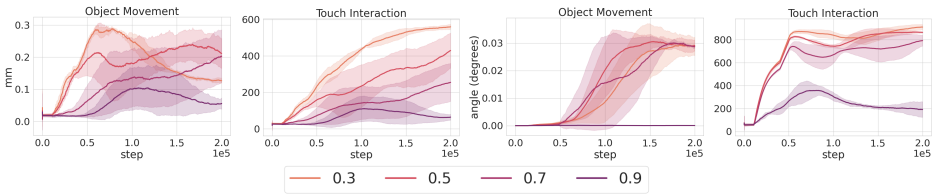


Figure 4: **Forward Prediction weight.** Performance on Touch interaction and Object movement metrics evaluated on the playing task and Open-door task for different forward prediction weightings sampled $\sim [1, 0]$. Large weight (darker plot) favors object-movement towards the end of training, where as smaller weight improves touch-interaction. Middle value in the sweep range (*e.g.* 0.5) balances the trade-off.

Metric	Pushing			Open Door			Pick-up			Playing		
	ToC	ToC-*fut*	ICM	ToC	ToC-*fut*	ICM	ToC	ToC-*fut*	ICM	ToC	ToC-*fut*	ICM
Exploration ↑	**0.403**	0.291	0.187	**0.669**	0.355	0.083	**0.063**	0.051	0.013	-	-	-
Success ↑	**0.733**	0.678	0.597	**0.983**	0.571	0.114	**0.891**	0.825	0.780	-	-	-
Episode steps ↓.	**57.84**	87.61	95.24	**23.34**	97.10	199.3	**30.54**	33.77	42.19	-	-	-
Touch-interaction ↑	**247.79**	210.11	202.66	**600.1**	287.97	43.56	980.7	**984.2**	952.3	**388.15**	267.021	63.31

Table 1: **Touch-based future prediction** This table compares the mean evaluations for ToC and ToC-Pure on all the four tasks emphasizing the importance of the cross-modal association(see text). We omit measuring success and episode steps for playing task since success there is equivalent to object-interaction and has no explicit goal.

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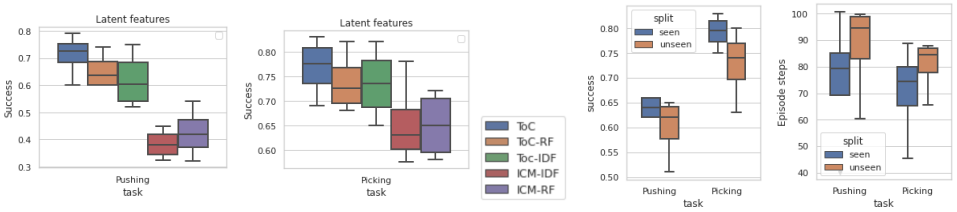
Collecting a variety of such interesting data during the *exploratory* phase helps the agent in terms of sample efficiency while solving the downstream tasks. Figure 8 in the supplemental material section shows similar plots for door opening task. We also include short video clips displaying qualitative performance on each of the tasks in the supplementary material.

We compare ToC and ToC-Pure with SAC and state-of-the-art vision-based curiosity baselines on the remaining downstream tasks in MiniTouch. From Figure 3 it is evident that ToC and ToC-Pure perform better than SAC in all the tasks and better than the vision-based curiosity models in the majority of the tasks. Using SAC alone hinders the performance and is often unable to solve any of the three tasks. This is not surprising since the model is not motivated enough to collect diverse and useful data through interaction. ICM performs better than ToC-Pure in the pushing task, however, ToC dominates in performance by about 15%. Recall that the goal is not just to succeed but to help attain success in a sample efficient manner in fewer steps. The results support our hypothesis that cross-modal curiosity enables an RL agent to succeeds at an early stage in training and often without any external reward. Similarly, our model outperforms on the opening task without external reward. However, ToC initially has lower success compared to RND, but surpasses towards the end. Although ToC and ToC-Pure attain similar success in the pick-up task towards the end of the training, it is compelling to note that ToC-Pure attains faster convergence. This is because the picking task requires constant touch interaction (where ToC-Pure has an advantage), as opposed to diverse object movement. In the following section, we examine the role of the forward objective term on touch interaction and possible ways to encode agent's observation in our ablation studies.

5.1 Ablations

Importance of forward objective. Visual forward prediction L_{fdm} plays a handy role when it is used in the right proportion. Intrinsic reward is a weighted combination of cross-modal prediction and forward prediction as defined in Eq.4. Figure 4 illustrates the performance of the model with different levels of emphasis on the forward loss term, with λ uniformly sampled between 0 and 1. Higher weights indicate that the future prediction dominates force/torque prediction. We notice that both larger and smaller values of λ hurt the overall performance. Larger weight leads to more object movement but hurts the robot's constant touch-interaction with the underlying objects, while smaller value leads to inactive behavior while satisfying the objective as shown in Figure.4.



(a) Latent feature space ablations

(b) Generalization to novel objects.

Figure 5: (a) Comparing different latent space performance on *pushing* and *grasping* tasks. Features learned via touch prediction perform better than those learned using IDF or Random. (b)Generalization performance on *success* and *episode steps* for the *pushing* and *picking* task.

Touch-based future prediction. The goal of this experiment is to strengthen the argument of cross-modal association. While conducting experiments, it is important to deduce information of one modality from another modality in a related manner than simply adding another modality on top of visual information. We created an additional touch-based baseline, ToC-*future*, where in addition to the visual future prediction model we include the touch-based future prediction model. The touch-based future prediction model takes a touch vector as input and predicts the touch vector for the next time step. Table 1 compares ToC and ToC-*future* on MiniTouch tasks and we observe that ToC-*future* is better than ICM in general but compares below ToC.

Robustness to diverse shapes. It is desirable for an agent to be able to handle diverse shapes in order to be robust across arbitrary manipulation settings. We study this using an environment in which an object is sampled from a thousand procedurally generated objects. The objects are dissimilar with respect to shape and mass but are sampled from the same generative distribution. Out of 1000 different objects, 800 of them are used in the training phase, and we evaluate the agent's effectiveness on the remaining 200 unseen object shapes. Figure 5b shows touch interaction and object movement evaluations for a single object exploration task. The results validate that our model generalizes to unseen object configurations.

Latent features for forward dynamics. Choosing ideal embedding space for decoding the touch vector (Figure 1a) and for predicting future state (Figure. 1b) is important. Existing approaches rely on a pretext inverse dynamics task of predicting the agent's action given its current and next states [9]. Another simple yet strong method is to use features from a random but fixed initialization of the encoder [12]. In our work, we learn the features by leveraging the self-supervised pretext task of predicting one modality from the other. Figure.5a compares (1) encoder, i.e. learned through cross-modal prediction(ToC) (2) random feature encoder(ToC-RF) (3) encoder learned through IDF task (ToC-IDF). In each case, the decoder network is optimized through touch prediction. We observe that the random features variant is stable and effective on both ToC and ICM models.

Real world validation: While no real robot data have been used in the experiments, our method is data agnostic. We note that the physics engine can be replaced by real-world data as there is no bias introduced in process. The networks used for the curiosity prediction task can be easily adapted, if needed, to accommodate inputs from a real robotic platform. As a next step and when restrictions are eased, we plan to implement this method on a physical system and replicate our experiments.

6 Conclusion

Building self-seeking RL agents that can leverage cross-modal associations could be a key research direction in developmental Robotics. Sense of touch is ubiquitous in human routine. Borrowing insights from how infants learn to explore out of curiosity by touching what they visually perceive, we formulated Touch-based Curiosity (ToC) that is aimed at encouraging exploration via haptic interaction with the environment. We demonstrated in this work, that by involving additional modalities, the performance of curiosity-based systems on downstream tasks can be increased. We observed increased interaction with target objects, and presented evidence that ToC learns to solve the MiniTouch benchmark tasks in an efficient manner while vanilla RL algorithms and vision-based curiosity formulations struggled. Force/torque sensing is widespread in the lab and industrial robots but while there are plenty of robotic benchmarks, we believe that tactile feedback is an under-explored modality and by releasing our benchmark, we hope to enable future research in this exciting area.

References

[1] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. A. Riedmiller. Playing atari with deep reinforcement learning. *CoRR*, 2013.

[2] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. V. D. Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, and M. Lanctot. Mastering the game of go with deep neural networks and tree search. *nature*, 2016.

[3] Y. Zhu, Z. Wang, J. Merel, A. A. Rusu, T. Erez, S. Cabi, T. Saran, J. Kramár, R. Hadsell, N. de Freitas, and N. Heess. Reinforcement and imitation learning for diverse visuomotor skills. *CoRR*, 2018.

[4] S. Forestier, Y. Mollard, and P. Oudeyer. Intrinsically motivated goal exploration processes with automatic curriculum learning. *CoRR*, 2017.

[5] D. Vernon, C. Hofsten, and L. Fadiga. A roadmap for cognitive development in humanoid robots. *978-3-642-16903-8*, 11, 2011.

[6] A. E and R. CH. The importance of touch in development. *Paediatr Child Health*, 2010;15(3).

[7] M. R. Connolly and L. Harris. Effects of stimulus incongruity on children's curiosity as measured by looking time and expression change. *Psychonomic Science*, 1971.

[8] Y. Burda, H. Edwards, D. Pathak, A. Storkey, T. Darrell, and A. A. Efros. Largescale study of curiosity-driven learning. *ICLR*, 2019.

[9] D. Pathak, P. Agrawal, A. Efros, and T. Darrell. Curiosity-driven exploration by self-supervised prediction. *ICML*, 2017.

[10] R. Raileanu and T. Rocktäschel. RIDE: Rewarding impact-driven exploration for procedurallygenerated environments. *ICLR*, 2020.

[11] M. Andrychowicz, F. Wolski, A. Ray, J. Schneider, R. Fong, P. Welinder, B. McGrew, J. Tobin, O. Pieter Abbeel, and W. Zaremba. Hindsight experience replay. In *NeurIPS*, 2017.

[12] Y. Burda, H. Edwards, A. Storkey, and O. Klimov. Exploration by random network distillation. *ICML*, 2019.

[13] S. H. Huang, M. Zambelli, J. Kay, M. F. Martins, Y. Tassa, P. M. Pilarski, and R. Hadsell. Learning gentle object manipulation with curiosity-driven deep reinforcement learning. *CoRR*, 2019.

[14] A. S. Chen, H. Nam, S. Nair, and C. Finn. Batch exploration with examples for scalable robotic reinforcement learning. *arXiv*, 2020.

[15] R. White. Motivation reconsidered: the concept of competence. *Psychological review*, 1959.

[16] A. G. Barto, S. Singh, and N. Chentanez. Intrinsically motivated learning of hierarchical collections of skills. In *International Conference on Development and Learning(ICDL)*, 2004.

[17] S. I. Di Domenico and R. M. Ryan. The emerging neuroscience of intrinsic motivation: A new frontier in self-determination research. *Frontiers in Human Neuroscience*, 2017.

[18] J. Schmidhuber. A possibility for implementing curiosity and boredom in model-building neural controllers. *ICSAB: From animals to animats*, 1991.

[19] P.-Y. Oudeyer, F. Kaplan, and V. V. Hafner. Intrinsic motivation systems for autonomous mental development. *IEEE transactions on evolutionary computation*, 2007.

[20] P.-Y. Oudeyer and F. Kaplan. What is intrinsic motivation? a typology of computational approaches. *Frontiers in neurorobotics*, 2009.

[21] N. Lair, C. Colas, R. P. J.-M. Dussoux, P. F. Dominey, and P.-Y. Oudeyer. Language grounding through social interactions and curiosity-driven multi-goal learni. *arXiv*, 2019.

[22] K. Marino, A. Gupta, R. Fergus, and A. Szlam. Hierarchical rl using an ensemble of proprioceptive periodic policies. *ICLR*, 2019.

[23] N. Savinov, A. Raichuk, R. Marinier, D. Vincent, M. Pollefeys, T. Lillicrap, and S. Gelly. Episodic curiosity through reachability. *aarXiv preprint arXiv:1810.02274*, 2018.

[24] R. Houthooft, X. Chen, Y. Duan, J. Schulman, F. D. Turck, and P. Abbeel. Curiosity-driven exploration in deep reinforcement learning via bayesian neural networks. *CoRR*, 2016.

[25] A. L. Strehl and M. L. Littman. An analysis of model-based interval estimation for markov decision processes. *Journal of Computer and System Sciences*, 2008.

[26] M. Bellemare, S. Srinivasan, G. Ostrovski, T. Schaul, D. Saxton, and R. Munos. Unifying count-based exploration and intrinsic motivation. *NeurIPS*, 2016.

[27] G. Ostrovski, M. G. Bellemare, A. van den Oord, and R. Munos. Count-based exploration with neural density models. *ICML*, 2017.

[28] R. Sekar, O. Rybkin, K. Daniilidis, P. Abbeel, D. Hafner, and D. Pathak. Planning to explore via self-supervised world models. In *ICML*, 2020.

[29] A. S. Klyubin, D. Polani, and D. L. Nehaniv. Empowerment: A universal agent-centric measure of control. *In 2005 IEEE Congress on Evolutionary Computation*, 2005.

[30] K. Gregor, D. J. Rezende, and D. Wierstra. Variational intrinsic control. *CoRR*, 2016.

[31] R. Dubey and T. L. Griffiths. Understanding exploration in humans and machines by formalizing the function of curiosity. *Current Opinion in Behavioral Sciences*, 2020.

[32] V. R. de Sa. Learning classification with unlabeled data. In *NeurIPS*, 1993.

[33] R. Blake, K. V. Sobel, and T. W. James. Neural synergy between kinetic vision and touch. *Psychological Science*, 15:397–402, 2004.

[34] M. Kalakrishnan, L. Righetti, P. Pastor, and S. Schaal. Learning force control policies for compliant manipulation. In *IROS*, 2011.

[35] S. Levine, C. Finn, T. Darrell, and P. Abbeel. End-to-end training of deep visuomotor policies. *JMLR*, 2016.

[36] G.-H. Liu, A. Siravuru, S. Prabhakar, M. Veloso, and G. Kantor. Learning end-to-end multimodal sensor policies for autonomous navigation. In *CoRL*, 2017.

[37] N. Srivastava and R. R. Salakhutdinov. Multimodal learning with deep boltzmann machines. *NeurIPS*, 2012.

[38] Z. Gan, Y.-C. Chen, L. Li, C. Zhu, Y. Cheng, and J. J. Liu. Large-scale adversarial training for vision-and-language representation learning. In *NeurIPS*, 2020.

[39] R. Gao, R. Feris, and K. Grauman. Learning to separate object sounds by watching unlabeled video. *ECCV*, 2018.

[40] A. Owens and A. A. Efros. Audio-visual scene analysis with self-supervised multisensory features. *ECCV*, 2018.

[41] Y. Gao, L. A. Hendricks, K. J. Kuchenbecker, and T. Darrell. Deep learning for tactile understanding from visual and haptic data. In *ICRA*, 2016.

[42] Y. Li, J.-Y. Zhu, R. Tedrake, and A. Torralba. Connecting touch and vision via cross-modal prediction. In *CVPR*, 2019.

[43] H. van Hoof, N. Chen, M. Karl, P. van der Smagt, and J. Peters. Stable reinforcement learning with autoencoders for tactile and visual data. In *IROS*, 2016.

[44] R. Calandra, A. Owens, D. Jayaraman, J. Lin, W. Yuan, J. Malik, E. H. Adelson, and S. Levine. More than a feeling: Learning to grasp and regrasp using vision and touch. *IEEE Robotics and Automation Letters*, 2018.

[45] A. Murali, Y. Li, D. Gandhi, and A. Gupta. Learning to grasp without seeing. *International Symposium on Experimental Robotics*, 2018.

[46] M. A. Lee, Y. Zhu, K. Srinivasan, P. Shah, S. Savarese, L. Fei-Fei, A. Garg, and J. Bohg. Making sense of vision and touch: Self-supervised learning of multimodal representations for contact-rich tasks. *ICRA*, 2019.

[47] V. Dean, S. Tulsiani, and A. Gupta. See, hear, explore: Curiosity via audio-visual association. In *NeurIPS*, 2020.

[48] T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. *arXiv preprint arXiv:1801.01290*, 2018.

[49] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. In Y. Bengio and Y. LeCun, editors, *ICLR*, 2015.

[50] B. Xu, N. Wang, T. Chen, and M. Li. Empirical evaluation of rectified activations in convolutional network. *arxiv*, 2015.

[51] E. Coumans and Y. Bai. Pybullet, a python module for physics simulation for games, robotics and machine learning, 2016–2019.

[52] T. Yu, D. Quillen, Z. He, R. Julian, K. Hausman, C. Finn, and S. Levine. Meta-world: A benchmark and evaluation for multi-task and meta reinforcement learning. *CoRR*, 2019.

[53] D. Pathak, D. Gandhi, and A. Gupta. Self-supervised exploration via disagreement. In *ICML*, 2019.

[54] Y. Burda, H. Edwards, A. J. Storkey, and O. Klimov. Exploration by random network distillation. *ICLR*, 2019.

[55] A. Paszke, S. Gross, Massa, and et al. Pytorch: An imperative style, high-performance deep learning library. *NeurIPS*, 2019.

[56] V. Mnih, A. P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, and K. Kavukcuoglu. Asynchronous methods for deep reinforcement learning. *ICML*, 2016.