ROBUST ROBOTIC CONTROL FROM PIXELS USING CONTRASTIVE RECURRENT STATE-SPACE MODELS

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ABSTRACT

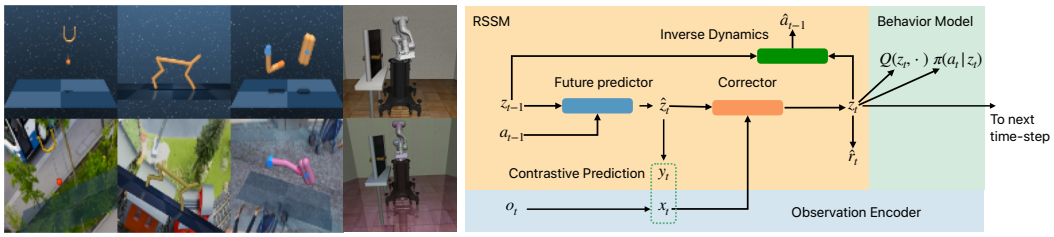
Modeling the world can benefit robot learning by providing a rich training signal for shaping an agent's latent state space. However, learning world models in unconstrained environments over high-dimensional observation spaces such as images is challenging. One source of difficulty is the presence of irrelevant but hard-to-model background distractions, and unimportant visual details of task-relevant entities. We address this issue by learning a recurrent latent dynamics model which contrastively predicts the next observation. This simple model leads to surprisingly robust robotic control even with simultaneous camera, background, and color distractions. We outperform alternatives such as bisimulation methods which impose state-similarity measures derived from divergence in future reward or future optimal actions. We obtain state-of-the-art results on the Distracting Control Suite, a challenging benchmark for pixel-based robotic control.

1 INTRODUCTION

For a robot, predicting the future conditioned on its actions is a rich source of information about itself and the world that it lives in. The gradient-rich training signal from future prediction can shape a robot's internal latent representation of the world. Predictive models can generate imagined interactions, facilitate model-predictive control, and dynamically attend to mispredicted events. Video prediction models (Finn et al., 2016) have been shown to be effective for planning robot actions. Model-based Reinforcement Learning (MBRL) methods such as Dreamer (Hafner et al., 2020) and SLAC (Lee et al., 2020) have been shown to reduce the sample complexity of learning control tasks.

These methods learn an action-conditioned model of the observations received by the robot. This works well when observations are clean, backgrounds are stationary, and only task-relevant information is contained in the observations. However, in a real-world unconstrained environment, observations are likely to include extraneous information that is irrelevant to the task (see Figure 1a). Extraneous information can include independently moving objects, changes in lighting, colors, as well as changes due to camera motion. High-frequency details, even in task-relevant entities, such as the texture of a door or the shininess of a door handle that a robot is trying to open are irrelevant. Modeling the observations at a pixel-level requires spending capacity to explain all of these attributes, which is inefficient.

The prevalence of extraneous information poses an immediate challenge to reconstruction based methods, e.g. Dreamer. One promising approach is to impose a metric on the latent state space which groups together states that are indistinguishable with respect to future reward sequences (DBC (Zhang et al., 2021)) or future action sequences (PSE (Agarwal et al., 2021)) when running the optimal policy. However, using rewards alone for grounding can be sample inefficient, especially in tasks with sparse rewards. Similarly, actions may not provide enough training signal, especially if they are low-dimensional. On the other hand, observations are usually high-dimensional and carry more bits of information. One way to make use of this signal while avoiding pixel-level reconstruction is to maximize the mutual information between the observation and its learned representation (Hjelm et al., 2019). This objective can be approximated using contrastive learning models where the task is to predict a learned representation which matches the encoding of the true future observation (positive pair), but does not match the encoding of other observations (negative pairs). However, the performance of contrastive variants of Dreamer and DBC has been shown to be inferior.



(a) Environment Examples

(b) Recurrent Contrastive State-Space Model

Figure 1: **Left**: Examples of visual control tasks in canonical (top row) and distracting environments (bottom row). Background, color, and camera pose distractions significantly increase observation complexity. **Right** Our proposed **Co**ntrastive **Re**current State-Space Model (CoRe).

In this work, we show that contrastive learning can in fact lead to surprisingly strong robustness to severe distractions, provided that a recurrent state-space model is used. We call our model CoRe: **Co**ntrastive **Re**current State-Space Model. The key intuition is that recurrent models such as GRUs and LSTMs maintain temporal smoothness in their hidden state through time because they propagate their state using gating and incremental modifications. When used along with contrastive learning, this smoothness ensures the presence of informative hard negatives in the same mini-batch of training. Using CoRe, we get state-of-the-art results on the challenging Distracting Control Suite benchmark (Stone et al., 2021) which includes background, camera, and color distractions applied simultaneously. Video results from our model can be seen at supplementary/index.html.

2 Model Description

We formulate the robotics control problem from visual observations as a discrete-time partially observable Markov decision process (POMDP). At any time step t, the robot agent has an internal state denoted by $\boldsymbol{z}_t$. It receives an observation $\boldsymbol{o}_t$, takes action $\boldsymbol{a}_t$, and moves to state $\boldsymbol{z}_{t+1}$, receiving a reward r_{t+1}. We present our model with continuous-valued states, actions, and observations. A straightforward extension can be made to discrete states. The objective is to find a policy that maximizes the expected sum of future rewards $\sum_{t=0}^{\infty} \gamma^t r_t$, where γ is a discount factor.

2.1 Model Components

As shown in Figure 1b, our model consists of three components: a recurrent state space model (RSSM) (Hafner et al., 2019) which encodes the learned dynamics, a behavior model based on Soft-Actor-Critic (SAC) (Haarnoja et al., 2018) which is used to control the robot, and an observation encoder.

Observation encoder: This component is a convolutional network f which takes an observation as input and outputs its encoding $\boldsymbol{x}_t = f(\boldsymbol{o}_t)$. LayerNorm (Ba et al., 2016) is applied in the last layer of the encoder.

Recurrent State Space Model (RSSM): This component consists of the following modules,

$$
\begin{aligned}
\text{Future predictor} \quad & p(\hat{\boldsymbol{z}}_t | \boldsymbol{z}_{t-1}, \boldsymbol{a}_{t-1}), \\
\text{Observation representation decoder} \quad & \boldsymbol{y}_t = g(\hat{\boldsymbol{z}}_t), \\
\text{Correction Model} \quad & q(\boldsymbol{z}_t | \hat{\boldsymbol{z}}_t, \boldsymbol{x}_t), \\
\text{Inverse Dynamics model} \quad & \hat{\boldsymbol{a}}_{t-1} = a(\boldsymbol{z}_t, \boldsymbol{z}_{t-1}), \\
\text{Reward predictor} \quad & \hat{r} = r(\boldsymbol{z}_t).
\end{aligned}
$$

Each module is parameterized as a fully-connected MLP (typically 3-layers), except the future predictor which uses GRU cells (Cho et al., 2014). The future predictor outputs a prior distribution $\hat{\boldsymbol{z}}_t$ over the next state, given the previous state and action. This is decoded into $\boldsymbol{y}_t$ which corresponds to an encoding of the observation that the agent expects to see next. The correction model is given access to the current observation encoding $\boldsymbol{x}_t$, along with the prior and outputs the posterior distribution $\boldsymbol{z}_t$, i.e., it corrects the prior belief given the new observation. The posterior state $\boldsymbol{z}_t$ is used to predict the reward, and also feeds into the actor and critic models that control the agent's behavior. The inverse

dynamics model predicts the action that took the agent from state $\boldsymbol{z}_{t-1}$ to $\boldsymbol{z}_t$. The RSSM is similar to the one used in Dreamer and SLAC except that it includes the inverse dynamics model and that the observation representation is predicted from the *prior* latent state, whereas these models reconstruct the observation from the posterior latent state. These differences lead to slightly better results and a different probabilistic interpretation of the underlying model which we discuss in Section 2.2. Similar to Dreamer, the latent state $\boldsymbol{z}_t$ consists of a deterministic and stochastic component.

Behavior Model: This component consists of an actor $\pi_\phi(a_t|z_t)$ and two critic networks $Q_{\theta_i}(z_t, a)$, $i \in \{0, 1\}$ which are standard for training using the SAC algorithm (Haarnoja et al., 2018).

2.2 Representation Learning with CoRe

Our goal is to learn a representation of the agent's latent state space by extracting task relevant information from the observations, while ignoring the distractions. Therefore, we formulate representation learning as dynamics-regularized mutual information maximization between the observations $\boldsymbol{o}_t$ and the model's prediction of the observation's encoding $\boldsymbol{y}_t$. Mutual information maximization (Hjelm et al., 2019) has been used extensively for representation learning. In our case, it can be approximated using a contrastive learning objective defined over a mini-batch of sequences, in a way similar to Contrastive Predictive Coding (CPC) (van den Oord et al., 2018). At time-step t in example i in the mini-batch, let $\boldsymbol{x}_{i,t}$ and $\boldsymbol{y}_{i,t}$ denote the real observation's encoding and the reconstructed observation encoding, respectively. The loss function is

$$L_c = -\sum_{i,t} \log \left(\frac{\exp(\lambda \boldsymbol{x}_{i,t}^\top \boldsymbol{y}_{i,t})}{\sum_{i',t'} \exp(\lambda \boldsymbol{x}_{i,t}^\top \boldsymbol{y}_{i',t'})} \right) - \sum_{i,t} \log \left(\frac{\exp(\lambda \boldsymbol{x}_{i,t}^\top \boldsymbol{y}_{i,t})}{\sum_{i',t'} \exp(\lambda \boldsymbol{x}_{i',t'}^\top \boldsymbol{y}_{i,t})} \right), \tag{1}$$

where λ is a learned inverse temperature parameter and i' and t' index over all sequences and time-steps in the mini-batch, respectively. Intuitively, the loss function makes the predicted observation representation match the corresponding real observation's encoding, but not match other real observation encodings, and vice-versa. In addition, the predicted latent state distribution should match the corrected latent state distribution, which can be formulated as minimizing a KL-divergence term

$$L_{\text{KL}} = \text{KL}\left(q(\boldsymbol{z}_t|\hat{\boldsymbol{z}}_t, \boldsymbol{x}_t)||p(\hat{\boldsymbol{z}}_t|\boldsymbol{z}_{t-1}, \boldsymbol{a}_{t-1})\right).$$

An additional source of training signal is the reward prediction loss, $(r_t - \hat{r}_t)^2$. Modeling the inverse dynamics, i.e. predicting $\boldsymbol{a}_t$ from $\boldsymbol{z}_t$ and $\boldsymbol{z}_{t+1}$ is a different way of representing the transition dynamics. This does not provide any additional information because we already model forward dynamics. However, we found that it helps in making faster training progress. We incorporate this by adding an action prediction loss. The combined loss is

$$J_M(\Theta) = L_c + \beta L_{\text{KL}} + \alpha_r (r_t - \hat{r}_t)^2 + \alpha_a ||\boldsymbol{a}_t - \hat{\boldsymbol{a}}_t||^2,$$

where $\beta, \alpha_r, \alpha_a$ are tunable hyperparameters and Θ is the combined set of model parameters which includes parameters of the observation encoder, the RSSM, and the inverse temperature λ.

Relationship with Action-Conditioned Sequential VAEs The above objective function bears resemblance to the ELBO from a Conditional Sequential VAE which is used as the underlying probabilistic model in MBRL algorithms such as Dreamer and SLAC. The objective function there is the sum of an observation reconstruction term $||\boldsymbol{o}_t - \hat{\boldsymbol{o}}_t||^2$ and L_{KL} scaled by β, corresponding to a β-VAE formulation (Higgins et al., 2017). This formulation relies on decoding the *posterior* latent state to compute $\hat{\boldsymbol{o}}_t$. Since the posterior latent state distribution $q(\boldsymbol{z}_t|\hat{\boldsymbol{z}}_t, \boldsymbol{x}_t)$ is conditioned on the true observation $\boldsymbol{x}_t$, observation reconstruction is an auto-encoding task. Only the KL-term corresponds to the future prediction task. On the other hand, in our case the *prior* latent state is decoded to a representation of the observation, which already constitutes a future prediction task. The KL-term only provides additional regularization. This makes the model less reliant on careful tuning of β (empirically validated in Appendix C.3). In fact, setting it to zero also leads to reasonable performance in our experiments (though not the best).

2.3 Behavior Learning

Behavior is learned simultaneously with the state representation using SAC. This involves learning an actor π_ϕ that parameterizes a stochastic policy and two critics Q_{θ_i} which use the latent state $\boldsymbol{z}_t$ as

the representation of the state of the agent. The critic is trained by minimizing Bellman error,

$$J_Q(\theta_i, \Theta) = \mathop{\mathbb{E}}_{\boldsymbol{z}_{t:t+1} \sim q} \left[(Q_{\theta_i}(\boldsymbol{z}_t, \boldsymbol{a}_t) - \text{sg}(r_t + \gamma V_{\text{target}}(\boldsymbol{z}_{t+1})))^2 \right], \tag{2}$$

$$V_{\text{target}}(\boldsymbol{z}_{t+1}) = \mathop{\mathbb{E}}_{\boldsymbol{a}_{t+1} \sim \pi_\phi} \left[\min_{i=1,2} Q_{\bar{\theta}_i}(\boldsymbol{z}_{t+1}, \boldsymbol{a}_{t+1}) - \alpha \log \pi_\phi(\boldsymbol{a}_{t+1} | \boldsymbol{z}_{t+1}) \right], \tag{3}$$

where $\bar{\theta}_i$ represents an exponentially moving average of θ_i, 'sg' denotes the stop-gradient operation, and α is the weight on the entropy regularization. Note that J_Q is a function of Θ as well. In other words, the RSSM and observation encoder model are also trained using the gradients from the critic loss. Appendix C.2 explores this design choice in more detail. The parameters Θ are shared between the two critics. The actor is updated using the following loss function

$$J_\pi(\phi) = \mathop{\mathbb{E}}_{\boldsymbol{z}_t \sim q, \boldsymbol{a}_t \sim \pi_\phi} [\alpha \log \pi_\phi(\boldsymbol{a}_t | \boldsymbol{z}_t) - \min_{i=1,2} Q_{\theta_i}(\boldsymbol{z}_t, \boldsymbol{a}_t)]. \tag{4}$$

Overall training consists of three steps: collecting data using the current actor, using the data to update the representation model, and using the data to update the actor and critic as shown in Algorithm 1.

3 Experiments

We use the Distracting Control Suite (DCS) (Stone et al., 2021) and Robosuite (Zhu et al., 2020) to benchmark our model's ability to withstand visual distractions. DCS consists of six simulated robotic control tasks derived from the DeepMind Control Suite (Tassa et al., 2018). There are three types of distraction: background, camera, and color. They can either be fixed for the duration of the episode (static) or changed smoothly during the episode (dynamic). Three benchmarks are defined: easy, medium, and hard, which have increasing levels of difficulty along all 3 distraction types. We focus our experiments on two settings: dynamic-background-only and dynamic-medium. Results on other settings follow the same trends (Appendix B). In the dynamic-background-only case, the backgrounds for training and validation environments are drawn from the 60 training and 30 validation videos in the DAVIS dataset (Pont-Tuset et al., 2017). Our experiments show that (1) CoRe enables visual robotic control in the presence of severe distractions, performing better than strong baselines, (2) recurrence and latent dynamics alone are not sufficient to achieve this performance (i.e. contrastive prediction is important), (3) recurrent architectures are important to make contrastive learning work well, (4) CoRe can solve a challenging simulated robotic manipulation task, and (5) interpretable attention masks emerge that help visualize how CoRe works. We report the mean validation reward over 10 random seeds and 100 episodes per seed along with the standard error. Details of the network architectures and training hyper-parameters are provided in appendix A.

Algorithm 1: The CoRe Model

Require: Environment E, initial Θ, ϕ, θ_1, θ_2
for *each iteration* **do**
  $\boldsymbol{o}_1 \sim E_{\text{reset}}()$, $\boldsymbol{z}_0 \leftarrow \mathbf{0}$, $\boldsymbol{a}_0 \leftarrow \mathbf{0}$;
  $\mathcal{D} \leftarrow \{\}$;
  for *each environment step* **do**
    $\boldsymbol{x}_t \leftarrow f_\theta(\boldsymbol{o}_t)$;
    $\boldsymbol{z}_t \leftarrow \text{RSSM}(\boldsymbol{z}_{t-1}, \boldsymbol{a}_{t-1}, \boldsymbol{x}_t)$;
    $\boldsymbol{a}_t \sim \pi_\psi(\boldsymbol{a}_t | \boldsymbol{z}_t)$;
    $r_t, \boldsymbol{o}_{t+1} \leftarrow E_{\text{step}}(\boldsymbol{a}_t)$;
    $\mathcal{D} \leftarrow \mathcal{D} \cup (\boldsymbol{o}_t, \boldsymbol{a}_t, r_t)$;
  end
  for *each gradient step* **do**
    $B \sim N$ samples of length T from $\mathcal{D}$;
    Train the model: $\mathbb{E}_B[J_M(\Theta)]$;
    Train the critic: $\mathbb{E}_B[J_Q(\theta_i, \Theta)]$;
    Train the actor: $\mathbb{E}_B[J_\pi(\phi)]$;
  end
end

3.1 Comparison of robustness to distractions

The goal of this set of experiments is to quantify the robustness of our proposed model to visual distractions. We compare our model to a model-free RL baseline **SAC-RAD**, a state-of-the-art method based on bisimilarity metrics **PSE** (Agarwal et al., 2021), **Recon**, a reconstruction variant of our model, where we replace the contrastive loss with an observation reconstruction loss (making it similar to SLAC), and **CURL** (Laskin et al., 2020a) which also uses contrastive learning but does not use recurrence or future prediction. Figure 2 shows the comparison as a function of environment steps for 4 of the 6 environments. We use the published code for PSE and CURL and only change the distraction settings.

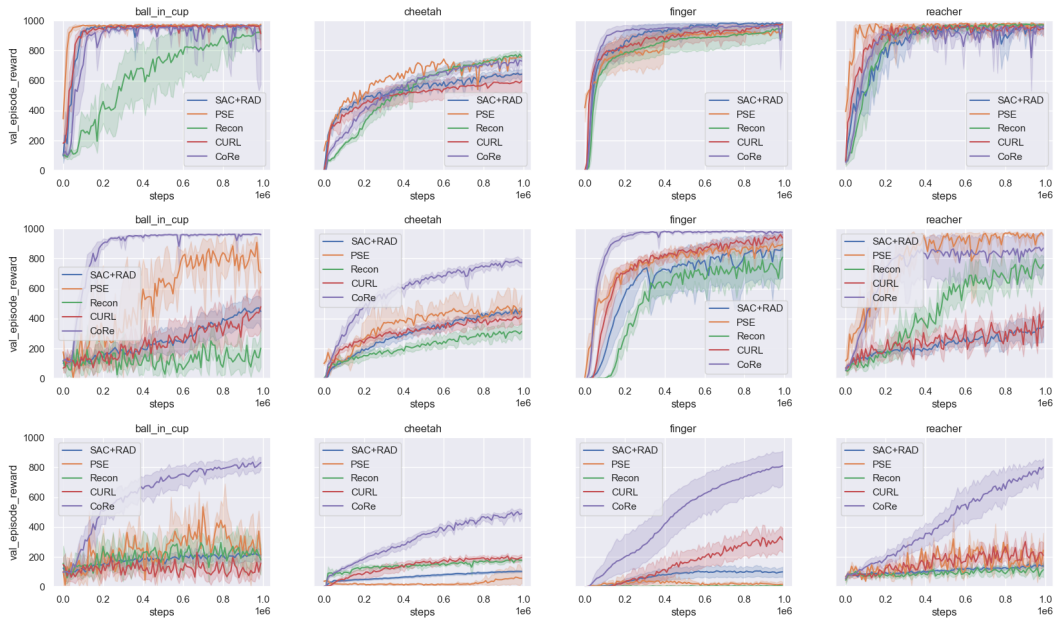


Figure 2: **Top**: No distractions. **Middle**: Background distractions only. **Bottom** Background, color, and camera distractions.

Method	Env Steps	Video dataset	BiC-Catch	C-swingup	C-run	F-spin	R-easy	W-walk
DBC	500K	Kinetics (Driving)	–	650 ± 40	260 ± 40	800 ± 10	100 ± 20	550 ± 50
DBC	500K	DAVIS (2 videos)	170 ± 57	198 ± 11	93.7 ± 6	443 ± 15	74 ± 11	158 ± 9
PSE	500K	DAVIS (2 videos)	$\mathbf{821 \pm 17}$	$\mathbf{749 \pm 19}$	308 ± 12	779 ± 49	$\mathbf{955 \pm 10}$	$\mathbf{789 \pm 28}$
CURL	500K	DAVIS (2 videos)	580 ± 53	624 ± 38	313 ± 20	$\mathbf{851 \pm 19}$	416 ± 68	$\mathbf{773 \pm 35}$
CoRe (Ours)	500K	DAVIS (2 videos)	802 ± 15	578 ± 32	$\mathbf{483 \pm 19}$	743 ± 22	610 ± 96	$\mathbf{773 \pm 16}$
CoRe (Ours)	1M	DAVIS (2 videos)	784 ± 25	635 ± 23	527 ± 26	752 ± 20	620 ± 90	775 ± 17
CURL	500K	DAVIS (60 videos)	220 ± 42	697 ± 20	332 ± 17	847 ± 14	302 ± 29	750 ± 41
PSE	500K	DAVIS (60 videos)	667 ± 21	762 ± 10	392 ± 6	829 ± 4	$\mathbf{943 \pm 6}$	718 ± 81
CoRe (Ours)	500K	DAVIS (60 videos)	$\mathbf{957 \pm 3}$	$\mathbf{810 \pm 9}$	$\mathbf{659 \pm 13}$	$\mathbf{978 \pm 4}$	843 ± 83	$\mathbf{880 \pm 23}$
CoRe (Ours)	1M	DAVIS (60 videos)	961 ± 4	821 ± 15	773 ± 14	975 ± 6	869 ± 81	950 ± 6

Table 1: Background distractions only. Mean $\pm$ Standard Error. **Bold** indicates best results at 500K steps.

In the **no-distraction** setting (Figure 2, top row), we can see that all methods perform well. In the **dynamic-background-only setting** (Figure 2, middle row), CoRe and PSE both perform better than the other methods. On the 'cheetah-run' task CoRe trains faster and gets better asymptotic performance. The performance of SAC-RAD is significantly worse. This confirms the conclusion in Stone et al. (2021) that data-augmented model-free RL methods are insufficient to solve these tasks. Recon also does not work well, as expected, because it wastes capacity on modeling the background. In the **dynamic-medium setting** (Figure 2, bottom row), we see that the performance of CoRe is far better than other baselines. CoRe trains more slowly here compared to the dynamic-background-only setting, which is expected because of the higher difficulty of this task. However, it keeps improving with more environment steps. Other methods saturate at a low score.

In Table 1, we compare the performance of our proposed model with bisimulation-based methods (DBC and PSE) and CURL. Results from DBC and PSE have been reported with different background videos making them hard to compare directly. DBC results were reported using videos from the Car Driving class in the Kinetics dataset (Kay et al., 2017), while PSE results were reported when training on 2 videos from DAVIS and testing on 30 validation videos. To do a fair comparison, we train CoRe as well as DBC (using their published code) in the same setting as PSE. This setting is denoted as DAVIS (2 videos) in Table 1. We can see that here, PSE outperforms DBC. CoRe performs similar to PSE. However, when we use all 60 training videos, CoRe performs better.

3.2 Ablation Experiments

The goal of this set of experiments is to ablate the design of our model and show that contrastive learning contributes significantly to the outcome. We compare the following models

Method	Env Steps	Mean	BiC-Catch	C-swingup	C-run	F-spin	R-easy	W-walk
SAC	500K	86 ± 3	102 ± 24	175 ± 6	57 ± 4	1 ± 0	103 ± 10	78 ± 15
SAC + RAD	500K	89 ± 5	139 ± 7	192 ± 6	14 ± 2	63 ± 24	93 ± 6	31 ± 2
QT-Opt + RAD	500K	103 ± 3	132 ± 20	241 ± 7	52 ± 3	25 ± 6	105 ± 10	64 ± 2
Recon	500K	147 ± 14	211 ± 55	219 ± 12	147 ± 9	3 ± 1	105 ± 5	199 ± 26
CURL	500k	223 ± 14	136 ± 24	320 ± 11	170 ± 10	163 ± 37	222 ± 37	328 ± 19
R-SAC	500K	198 ± 20	257 ± 89	277 ± 19	244 ± 17	90 ± 47	112 ± 17	211 ± 15
R-SAC + Dynamics	500K	289 ± 35	277 ± 114	$\mathbf{410 \pm 31}$	322 ± 38	129 ± 115	114 ± 26	$\mathbf{483 \pm 65}$
CoRe (Ours)	500K	$\mathbf{480 \pm 23}$	$\mathbf{706 \pm 39}$	354 ± 26	$\mathbf{354 \pm 10}$	$\mathbf{540 \pm 73}$	$\mathbf{445 \pm 48}$	$\mathbf{479 \pm 31}$
CoRe (Ours)	1M	684 ± 24	832 ± 22	483 ± 29	490 ± 13	810 ± 60	801 ± 32	686 ± 42

Table 2: Results on Distracting Control Suite Benchmark (dynamic-medium setting). Mean $\pm$ Standard Error. **Bold** indicates best results at 500K steps.

CoRe: Our proposed model, which uses Recurrent SAC + Dynamics + Contrastive Prediction.
R-SAC + Dynamics: The above model but with contrastive prediction removed.
R-SAC: The above model but without any dynamics (or reward) modeling.
All of these methods use the same SAC-based behavior training along with the same observation encoder and recurrent state space architecture. They differ only in terms of the representation learning objective that is used to shape the latent state space. Table 2 tabulates results from these methods in the dynamic-medium distraction setting, along with other baselines. We can see that model-free methods such as SAC and QT-Opt trained with data augmentation are not able to solve these tasks. Adding recurrence and dynamics improves results. Further addition of contrastive prediction gives a major boost to performance. More ablation experiments that study the relative effects of modeling reward and forward and inverse dynamics are presented in appendix C.1.

3.3 Importance of having a recurrent state space model

Contrastive models have been reported to underperform DBC in previous works (Zhang et al., 2021). However, in our experiments we found that contrastive models can in fact work quite well. We hypothesize that this difference is because we use a recurrent state space whereas previous work used contrastive learning in an MDP setting in which a feed-forward encoder operating on stacked observation frames is used. To validate this hypothesis, we compare our model to its non-recurrent version. The models both do contrastive future prediction and use similar network architectures, but the non-recurrent one consumes stacked frames. The training mini-batches are also sampled similarly using 32 sequences of 32 time-steps each. Therefore, even the non-recurrent model has access to observations that are semantically close. The results at 500K environment steps in the dynamic-medium setting on DCS are shown in Figure 3 (Top). We can see that, in the absence of recurrence, contrastive learning does not perform well. This indicates that just having nearby observations is not sufficient to provide hard negatives and a recurrent network has help fix this problem.

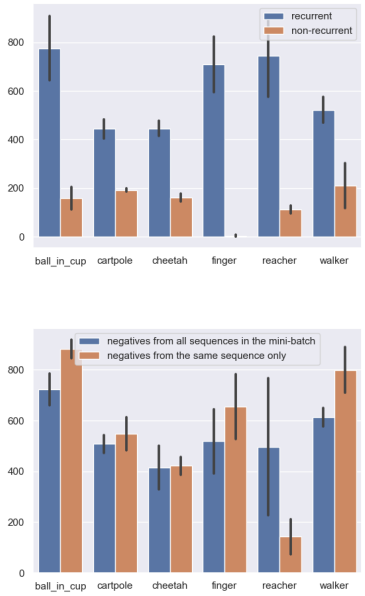


Figure 3: **Top:** Performance drops if recurrence is removed. **Bottom:** Only using negatives from the same sequence is often helpful.

An intuitive explanation for this is the following. A recurrent network (in our case, a GRU-RNN) has a smoothness bias built-in because at each time step, it carries forward previous state and only modifies it slightly by gating and adding new information. This is true to a large extent even during training, and not just at convergence. Therefore, when CoRe is trained, it generates hard negatives throughout training in the form of nearby future predictions. This is true even when the observations have distractions present which change the overall appearance of the observation dramatically. On the other hand, in an MDP setting, feed-forward encoders are trained, starting from random initialization. Untrained feed-forward networks are less likely to map observations that are semantically close but visually distinct to nearby points. Therefore, hard negatives may not be found easily during training.

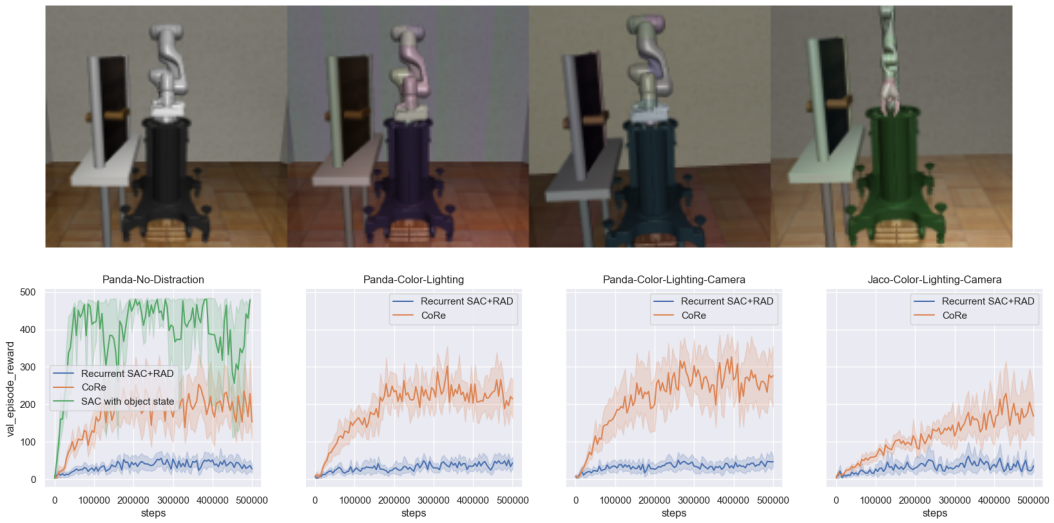


Figure 4: Examples of observations and results in the Robosuite (Zhu et al., 2020) Door Opening Task. In each of the four columns, the top image is an example of an observation in that setting and the plots below are results obtained in that setting as training progresses. The left-most column corresponds to a distraction-free environment with the Panda arm. The next column is for the setting where color and lighting distractions are added. The last two involve color, lighting, as well as camera distractions.

To confirm this further, we train CoRe with a modified contrastive loss in which for each sample in the mini-batch, only samples from the same temporal sequence are used as negatives. As shown in Figure 3 (bottom), ignoring negatives from other sequences is actually beneficial to performance on all tasks, except reacher. The fact that CoRe doesn't rely on other episodes in the mini-batch means that we can avoid a major concern in contrastive learning, which is finding good negative examples. Essentially, recurrence gives good negative samples for free. Performance degrades on the reacher task because observations there contain a goal position for the arm. Contrastive learning tries to remove this information because it is constant throughout the episode. Therefore, the actor and critic may not get access to the goal information, causing the agent to fail. This highlights a **key limitation** of contrastive learning – it discourages retaining constant information in the latent space. For that type of information, it is important to have negative examples coming from other episodes.

3.4 Results on Robosuite

In this section, we present results of our method on Robosuite (Zhu et al., 2020), a MuJoCo-based simulator for robotic manipulation tasks. Examples from this environemnt are shown in Figure 4 (Top). We experiment with two kinds of arms: Panda and Jaco, and two distraction settings: (1) Color and lighting only, and (2) Color, lighting, and camera. Each episode lasts for 500 environment steps. Visual observations were rendered from the front-view camera at a 256×256 resolution and a 128×128 crop near the center of the image was fed as input to the model. The same model as that used for Distracting Control Suite was applied here, except the observation encoder was changed to accept 128×128 inputs and proprioceptive state was fed as an additional observation. The RGB observations were encoded using a convolutional network. Two convolutional layers with 32 filters of kernel size 3×3 with a stride of 2 were applied to reduce the spatial size from 128×128 to 32×32. This was followed by 3 layers of 3×3 convolutions with a stride of 1. The Operational Space Controller (OSC_POSE) was used, in which the end-effector position and orientation is controlled by the actor, leaving the actual joint controls to be computed using inverse kinematics.

Figure 4 shows the results. We obtain significant speed-ups in training compared to a recurrent SAC+RAD baseline in all cases. In the distraction-free case, we also compare to results from SAC operating on ground-truth object state instead of using image observations, as reported by Zhu et al. (2020). This can be interpreted as an upper bound on how well a pixel-based controller can be expected to perform. CoRe learns slower than this model, as expected, but much faster than the recurrent SAC+RAD baseline. In the case where distractions are added, CoRe continues to train much faster than the baseline. The same trend is observed for the Jaco arm.

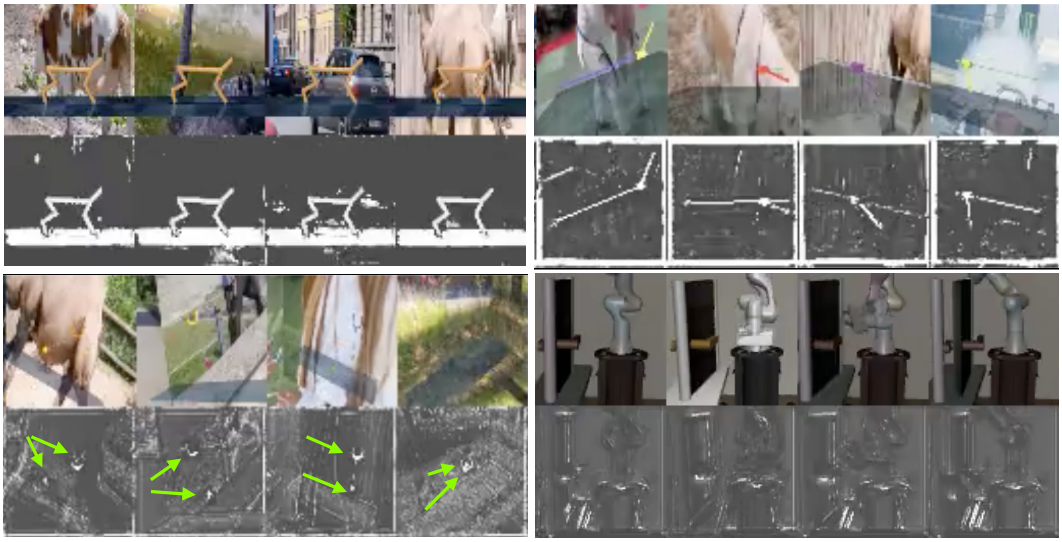


Figure 5: Gating masks showing that CoRe learns to remove distractions. Green arrows indicate the locations of the ball and cup, which are tiny, but CoRe can still find them. In the door opening task in Robosuite (bottom right), the lower edge of the door handle is very bright when the door is closed, indicating strong attention to that part of the image. In addition, the agent attends to the edges of the door and the table, as well as its own base. Since the camera position can change randomly, the agent needs to find the robot's position relative to the door, for which the robot's base and the door's edges are important. Proprioception is provided separately. Therefore, the agent doesn't need to attend to the arm itself.

3.5 Visualizations

In this section, we present qualitative visualizations to help understand what the model does to cope with distractions. We make visualization easier by modifying the observation encoder to include a pixel-level gating network. This is done using a four-layered CNN which takes the observation as input and outputs a full-resolution sigmoid mask. This mask is multiplied into the observation image, and the result is fed to the encoder. The gating network is trained along with the rest of the model. We expected this gating to improve performance but found that it actually has no effect. This lets us use it as a diagnostic tool that factors out the attention mask that the model is otherwise applying implicitly. Figure 5 shows the attention masks inferred by the gating network. We can see that the model learns to exclude distractions in the background, even in the dynamic-medium distraction setting for the ball_in_cup task where the task-relevant objects are very small. For the door opening task, the model learns to attend to the bottom edge of the door handle, the top and right edges of the door, the edge of the table, and some parts of the robot's base. This includes all the information needed to find the relative position of the door with respect to the agent. Proprioception is provided separately. Therefore, the agent doesn't need to attend to the arm itself.

4 Discussion and Related Work

Our work uses contrastive learning in the context of world modeling and pixel-based robotic control. In this section, we review related work in these areas.

Pixel-based robotic control Controlling robots directly from raw environment observations is a general framework for robotic problem solving since it avoids the use of specific modules such as object detectors and instead relies on the data and reward function to learn a representation of the observations. Model-free methods such as QT-Opt (Kalashnikov et al., 2018) and SAC (Haarnoja et al., 2018) have been applied to pixel-based control. However, learning encoders for high-dimensional observations from reward only is sample inefficient. Simply adding observation autoencoding to SAC as an auxiliary task has been shown to work well in Yarats et al. (2019). Instead of using a generative model, CURL (Laskin et al., 2020a) uses contrastive learning to learn observation encoders yielding similar results. Data augmentation techniques RAD (Laskin et al., 2020b) and DrQ (Yarats et al., 2021) dramatically improve sample efficiency. However, these methods are still not sufficient to solve visual tasks in the presence of distractions (Stone et al., 2021). Other approaches shape

the learned encoders to produce a latent space that is amenable to locally-linear control algorithms (Watter et al., 2015; Cui et al., 2020; Levine et al., 2020). Improvements in the encoder architecture, for example, using attention Tang et al. (2020) and efficient transformer-based models (Choromanski et al., 2021) have been proposed. Our proposed model can potentially benefit from the use of these better architectures. We use a simple convolutional encoder for our experiments and focus on the modeling aspect of the problem.

World Modeling World models aim to learn how the world changes as a result of the agent's action instead of just learning the optimal policy. Finn et al. (2016) used video prediction parameterized as pixel-level flow to predict the future video frames. Dreamer (Hafner et al., 2020) and SLAC (Lee et al., 2020) model observations using a sequential action-conditioned VAE. However, these methods are not designed to deal with distractions since they would waste capacity on reconstructing them along with the task-relevant portion of the observations. In order to avoid observation reconstruction, Gelada et al. (2019) proposed DeepMDP, a method that embeds the given high-dimensional RL problem into a latent space which preserves the essence of the problem (i.e. the reward and transition function). While this method only preserves the current reward, Deep Bisimulation for Control (Zhang et al., 2021) uses the future sequence of rewards to extract a stronger learning signal. In this case, the learned state space is trained to impose a bisimulation metric, under which similarity between states is determined by the similarity in future reward sequences produced from those states. PSE (Agarwal et al., 2021) further extends this idea to use similarity in future action distributions. While these models use dynamics to get more training signal, they do not make use of structure in the observation space itself. In our proposed model, we seek to find a middle ground between modeling observations and not modeling them at all. This is done in a principled way using mutual information maximization between the observation and its prediction from the internal dynamics. While previous work often found contrastive learning to be ineffective, we show that combining it with recurrent state space models makes it work. Recently, a contrastive variant of Dreamer (Okada & Taniguchi, 2020) has been proposed which shares the same motivation. Concurrent with our work, Nguyen et al. (2021) explore a formulation similar to ours based on temporal predictive coding, but do not evaluate it on the difficult camera and color distractions we do here.

Contrastive Learning: Learning to contrast positive and negative examples is a general representation learning tool since it can be applied to many scenarios by changing what positive and negative pairs mean. They can be defined based on identity, for example, in face verification (Weinberger et al., 2006; Schroff et al., 2015), object identity for tracking (Wang & Gupta, 2015), closeness in temporal order in the case of time-contrastive models (Sermanet et al.; Hyvarinen & Morioka, 2016), word and sentence ordering in the case of language models such as Log-Bilinear models Mnih & Hinton (2007), Word2Vec (Mikolov et al., 2013) and Skip-thoughts (Kiros et al., 2015). Contrastive Predictive Coding (CPC) (van den Oord et al., 2018) proposes an auto-regressive model to do future prediction at multiple time steps and applies it to various domains including image patches, audio, and RL. In this case, positives are the corresponding predicted and observed representations, and negatives are all other pairs. Our model uses a similar contrastive loss as CPC. However, it also uses dynamics modeling in latent space to improve the representation quality. Subsequent works have improved on CPC using momentum in the learned encoder (MoCo (He et al., 2020)), adding projection heads before computing contrastive loss (SimCLR (Chen et al., 2020)), avoiding negative examples altogether (BYOL (Grill et al., 2020) and SwAV (Caron et al., 2020)). Our model can potentially be improved using these techniques but we found that the simple contrastive loss is already sufficient to solve challenging visual control problems.

5 Conclusion

We show that a contrastive objective can be a viable replacement for reconstructing observation pixels in solving visual robotics control problems using model-based RL. It works even in the presence of severe distractions. In addition, we show that having a recurrent architecture helps contrastive learning work well. Even though our results are only in simulated environments, the surprisingly high degree of robustness indicates that this approach should transfer well to a real-world setting. In future work, we plan to test this approach on real-world robots.

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