Interleaving Monte Carlo Tree Search and Self-Supervised Learning for Object Retrieval in Clutter

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Abstract—In this study, working with the task of object retrieval in clutter, we have developed a robot learning framework in which Monte Carlo Tree Search (MCTS) is first applied to enable a Deep Neural Network (DNN) to learn the intricate interactions between a robot arm and a complex scene containing many objects, allowing the DNN to partially clone the behavior of MCTS. In turn, the trained DNN is integrated into MCTS to help guide its search effort. We call this approach learning-guided Monte Carlo tree search for Object REtrieval (MORE), which delivers significant computational efficiency gains and added solution optimality. MORE is a self-supervised robotics framework/pipeline capable of working in the real world that successfully embodies the System 2 → System 1 learning philosophy proposed by Kahneman, where learned knowledge, used properly, can help greatly speed up a time-consuming decision process over time. Videos and supplementary material can be found at https://github.com/arc-l/more.

I. INTRODUCTION

Kahneman [1] proposed a thought-provoking hypothesis of human intelligence: in solving real-world problems, humans engage fast or “System 1” (S1) type of thinking for making split-second decisions, e.g., speech, driving, and so on. For other decision-making processes, e.g., playing chess, a slow or “System 2” (S2) approach is taken, where the brain would perform a search over some structured domain for the best actions to take. After repeatedly using S2 thinking to solve a given problem, patterns can be distilled over time and burned into S1 to speed up the overall process. In playing chess, for example, good chess players can instinctively identify good candidate moves. First-time or beginner drivers rely heavily on S2 and gradually converge to S1 as they gain more experience. This S2→S1 thinking has gained significant attention and has been explored in many directions in machine learning, including attempts at building machines with consciousness [2]. But, perhaps the most prominent line of work in reinforcement learning [3] that closely aligns with this paradigm is the application of Monte Carlo Tree Search (MCTS) for carrying out self-supervised learning in games [4], [5], where an “understanding” of a game emerges from a lifelong self-play and is gradually distilled so that it significantly reduces the search effort. Gradually, the overall system learns enough useful information that allows it to play perfect games with much less time and computing resources.

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clutter setting, the challenge lies in the difficulty of predicting the outcome of push actions, with the tip of the gripper, when many objects are involved. This is due to discontinuities inherent in object interactions; while a certain pushing action will move a given object, a slightly different direction can miss that same object entirely.

The main contribution of this work is proving the feasibility of applying the S2→S1 philosophy to build a self-supervised robotic object retrieval system capable of continuously improving its computational efficiency, through cloning the behavior of the time-consuming initial MCTS phase. Through the careful design and integration of two Deep Neural Networks (DNNs) with MCTS, our proposed self-supervised method, named Monte Carlo tree search and learning for Object REtrieval (MORE), enables a DNN to learn from the manipulation strategies discovered by MCTS. Then, learned DNNs are fed back to the MCTS process to guide the search. MORE significantly reduces MCTS computation load and achieves identical or better outcomes, i.e., retrieving the object using very few strategic push actions. In other words, our method “closes the loop”. This contrasts with [6], which only learns to replace the rollout function of MCTS.

II. RELATED WORK

Grasping. Grasping approaches can be classified as being analytical or data-driven [8]. Analytical methods examine precise object models to predict the stability of a grasp based on force-closure or form-closure [9]–[11]. However, high precision 3D models of objects, e.g., YCB objects [12], are hard to come by. In addition, other material properties, such as friction and inertia, are challenging to measure. These challenges have given rise to data-driven methods that learn from data, where many works focus on isolated objects [13]–[16]. Recently, grasping in clutter has received more attention [17]–[21]. Convolutional Neural Networks are widely used to construct grasp proposal networks such as Dex-net 4.0 [22], which are trained to detect 6D grasp poses in point clouds [23]. In this paper, we use a self-supervised Deep Q-Network similar to [24] for grasping in clutter.

Singulation. Singulation, i.e., isolating specific object(s) from the rest [25], is necessary for object retrieval. Usually, a sequence of pushing and grasping actions is used to clear the clutter that surrounds the target object. In [26], a model-free method was used to learn a reactive pushing policy without long-horizon reasoning. Later, other model-free reinforcement learning algorithms [24], [27] used learned push policies to improve grasping. In contrast to existing work on singulation, we explicitly seek to minimize the number of actions needed to isolate a target object for grasping sufficiently.

Object Retrieval. Object retrieval from clutter, the focus of this study, can be viewed as a form of rearrangement planning [6], [28], [29]. Online planning for object search with partial observations has been discussed in [30]. Retrieving objects under occlusion was also recently considered in [31] where parallel-jaw and suction grasping were used along with pushing to de-clutter surroundings of target objects. A model-free reinforcement learning technique has also been used for searching for objects in [32]. In [33], an agent was trained to find a continuous trajectory of a gripper that pushes away clutter or pushes the target object to free space, mimicking human-like behavior. A human-in-the-loop solution was proposed in [34] help with searching for objects in clutter. A deep Q-Learning method [35] considers a similar task and setup but uses additional primitives such as sliding objects from the top. Our work partially builds on [36], which explores the use of MCTS for the same object retrieval problem. In contrast to existing object retrieval works, we focus on developing the machinery that enables the S2→S1 philosophy to reduce the computational burden of the related search problem while using real robots and objects.

III. PRELIMINARIES

The object-retrieval-from-clutter task consists in using a robot manipulator to retrieve a hard-to-reach target object (Fig. 1). Objects are rigid bodies with various shapes, sizes, and colors; the target object is assigned a unique color. Similar to [36], a top-down fixed camera is installed to observe the workspace. The camera takes an RGB-D image of the workspace (e.g., the top-left image of Fig. 1), which serves as the only input to our system.

Pushing and grasping actions are allowed, the execution of each is considered as one atomic action. A grasp action is defined as a top-down overhead grasp motion \( a^g = (x, y, \theta) \), corresponding to the gripper’s target location and orientation, based on a coordinate system defined over the input image. A push action is defined as a quasi-static planar motion \( a^p = (x_0, y_0, x_1, y_1) \) where \((x_0, y_0)\) and \((x_1, y_1)\) are the start and the end locations of the gripper tip. The horizontal push distance is fixed and it is 10cm in our experiments. Each primitive action is transformed to the real-world coordinates for execution, but all the planning and reasoning are in image coordinates. The robotic arm keeps pushing objects until the target object can be grasped or until the target object is pushed outside of the workspace, in which case the task is considered a failure. The problem is to find a policy that maximizes the frequency of successfully grasping the target object, while also minimizing the number of pre-grasp pushing actions.

IV. METHODOLOGY

The MORE framework consists of three components: a Grasp Prediction Network (GPN), a Monte Carlo Tree Search (MCTS) routine, and a Push Prediction Network (PPN). GPN is a neural network that predicts the success probabilities of grasp actions. It is trained online similarly to [36]. The success probabilities can be interpreted as immediate rewards. MCTS uses a physics engine as a transition function to simulate long sequences of consecutive push actions that end with a terminal grasp action. Each branch in MCTS is composed of push actions as internal nodes, and a grasp action as a leaf. Grasp actions are evaluated with GPN, and the returned rewards are back-propagated to evaluate their corresponding branches. The branch with the highest discounted reward, or \(Q\text{-value}\), is selected for execution by the robot.
While highly effective in finding near-optimal paths, MCTS suffers from a high computation time that makes it impractical. To solve this, MORE employs a second neural network, PPN, to prioritize the action selection in the rollout policy. The robot starts by relying entirely on MCTS (S2 type of thinking) to solve various instances of the object-retrieval problem. Instead of throwing away the computation performed by MCTS for solving the various instances, we use the computed Q-values as ground-truth to train PPN. Note that this computation data is free, since it is generated by the simulations performed by MCTS as a byproduct of solving the actual problem. PPN is a neural network that learns to imitate MCTS and clone its behavior, while avoiding heavy computation and physics simulations by MCTS. As PPN becomes more accurate in predicting the outcome of MCTS, the robot starts relying on both MCTS and PPN for action selection. In a nutshell, PPN’s accuracy in predicting the Q-values of push actions matches that of MCTS, and the robot switches entirely to PPN to make decisions in a few milliseconds (S1 type of thinking).

A. Grasp Prediction Network (GPN)

GPN is a deep neural network based on the model proposed in [24] and further customized to estimate the expected grasp reward [36]. We used the pre-trained model from [36], with a ResNet-18 FPN [37], [38] backbone [39]. For training, only successful grasps are given fixed non-zero rewards. The Grasp Network takes a single RGB-D image \( s_t \) as input and outputs a pixel-wise reward map \( R_{gm}(s_t) \in [0, 1]^{H \times W} \) with the same size \( (H \text{ and } W \text{ are height and width of } s_t) \). To enable GPN to account for gripper orientation, \( s_t \) is rotated 16 times in the range of \([0, 2\pi]\), adding another dimension to the reward map and making it \( R_{gm}(s_t) \in [0, 1]^{H \times W \times k} \) with \( k = 16 \). Because the goal is to retrieve a specific object, a mask is imposed on the target object using Mask R-CNN [40], effectively truncating the reward map. If the largest reward from the map \( \max_{i,j,\theta} R_{gm}(s_t[i,j,\theta]) \) is larger than some preset threshold, \( R_{gs} \), GPN suggests grasping as the next action to execute. The location \([i, j]\) and rotation \( \theta \) of the best grasp is retrieved from the reward map \( R_{gm} \).

B. Monte-Carlo Tree Search

Monte-Carlo Tree Search (MCTS) [41] is used in MORE for both decision-making and training PPN. A typical MCTS routine has four steps: selection, expansion, simulation, and back-propagation. In our case, the goal of the search is to find the shortest action sequence; we can stop the search as soon as the best solution is found without exploring the rest. The search stops in two cases: 1) the number of iterations \( n \) exceeds a pre-set budget \( N_{max} \), or 2) the expanded node with state that the target object can be grasped, and all nodes in parent level are expanded. A node is considered as a leaf if \( \max_{i,j,\theta} R_{gm}(s_t[i,j,\theta]) > R_{gs} \) where \( R_{gm}(s_t) \) is obtained from GPN and \( R_{gs} \) is a pre-defined high probability. The maximum depth of the tree is limited to \( d \), where \( d \) is set to 4 in our experiments.

In the selection phase, we find an expandable node starting from the root according to the search policy

\[
\pi_n(s) = \arg \max_{a_p} (Q(s, a_p) + C \sqrt{\frac{\ln N(s)}{N(s, a_p)}})
\]

where \( N(s) \) is the number of visits to node (state) \( s \) and \( N(s, a_p) \) is the number of times push action \( a_p \) has been selected at node (state) \( s \). The Q-value is calculated as

\[
Q(s, a_p) = \sum_{i=1}^{m} r_i(s, a_p) \min_{n_i} \{N(n_i, m)\}
\]

where \( r(s, a_p) \) is the returned long-term reward and \( m \) is a pre-set maximum. Only the best \( m \) terms \( r_i(s, a_p) \) are used to compute the Q-value in the equation above. \( m \) is set to 10 when expanding nodes and 1 when selecting the best solution. \( C \) is the coefficient of the exploration term, and it is set to 2 when expanding nodes and 0 when selecting the best solution. In the expansion phase, we use a physics simulator to execute the chosen push action \( a_p \) at state \( s_t \) and predict new state \( s_{t+1} \). Then, a random policy is used to sample actions to simulate until a grasp is possible or a failure is encountered. The reward \( r \) is predicted by GPN at a terminal state \( s_t \). Reward \( r \) is set to 1 if \( \max_{i,j,\theta} R_{gm}(s_t[i,j,\theta]) > R_{gs} \), and 0 otherwise. One additional term \( \delta \max(R_{gm}(s_t)) \) is added to \( r \), to distinguish between good and bad push actions. We set \( \delta \) to be 0.2. In the last step, reward \( r \) is propagated back to its parent nodes to update their Q-values with a discount factor \( \gamma = 0.5 \).

As the push action space is enormous even after discretization, we further sample a subset of actions such that all push actions start around the contour of an object and point to the center of the object (Fig. 2). This action sampling method has been discussed in [36] and was empirically proven efficient for a similar setup of object retrieval.

In our implementation, \( N_{max} \) is set to 300 when MCTS is used to collect data to train PPN. The second and the third conditions for stopping the search are only activated after at least 50 roll-outs, so that the number of visits to a state is statistically significant and to reduce the variance of PPN.

C. Push Prediction Network (PPN)

As previously mentioned, PPN learns to imitate MCTS. PPN is a deep neural network with ResNet-34 FPN [37], [38] as the backbone, where the P2 level of the FPN connects to the head. It takes a two-channel input and outputs a single channel pixel-wise push Q-value map, similar to the reward map produced by GPN. An example input is shown in Fig. 3, where the first channel is a segmented image of all objects and the second channel is a binary image of the target object. The output is the image on the right of Fig. 3, where the arrow shows a push action with the highest Q-value. PPN estimates the Q-value (discounted rewards) \( Q_p(s_t) \) of executing push...
actions at the corresponding pixel, where the action is assumed to push 10cm to the right. \( \max(Q_p(s)) \) is limited to the range \([0, \eta]\), where \( \eta \) is the maximum reward of a terminal state.

When MCTS is used to generate training cases, it builds a tree and saves the transitions for each case: the state (image) \( s \), the push action \( a^p \), the Q-value \( Q(s, a^p) \), and the visited number \( N(s, a^p) \). As such, PPN is trained in a self-supervised manner. The input image is rotated based on a push action so that the corresponding push action points to the right. Because a single action is generated by MCTS (i.e., a \( \delta \) signal over the entire input), which is not conducive to training PPN, we “expand” the Q-value over a 3\( \times \)3 patch centered around MCTS action but set invalid pushes (e.g., if part of the patch is inside an object) to be zero. Now, the label is relatively dense compared to a one-hot pixel, so we can use Smooth L1 loss from Pytorch [42] with \( \beta \) equals to 0.8 to regress. Only gradients on the labeled pixels are used. Loss weighting is also applied: label values from the MCTS are weighted based on \( N(s, a^p) \), label values (zero Q-value) from void push actions are weighted with a small number, 0.001 for collision and 0.0001 for pushing thin air. We observe that PPN has difficulty learning to create clearance around the target object. Data augmentation is applied here so that for each training case, we also randomly choose the target object for the MCTS to solve; so each arrangement becomes many training cases. It mitigates over-fitting: given similar visual information, it could learn different strategies, as the target object could be anywhere.

The head model is an FCN with four layers, where the first two layers have a kernel size of 3, the last two 1, and the strides of four layers are all 1. Batch normalization is used at each layer of the head model except the last. Bilinear interpolation \((\times 2)\) is applied interleaved between the last three layers of the head model to scale up the hidden state to the same size as the input image. The training process has two stages, one to train the network with a batch size of 8, learning rate starts at 1e-4, epoch of 50. The learning rate decays with cosine annealing [43], where the maximum number of iterations is set to be the same as the epoch number 50 and the minimum learning rate is 1e-8. The second is a fine-tuning stage; we increase the batch size to 28 and the learning rate to 1e-5 with an epoch of 20.

D. Guided Monte-Carlo Tree Search

With the trained GPN and PPN, a guided MCTS is implemented to accelerate the search process, cutting cost from time-consuming expansion and simulation phases. GPN is again used to determine the terminal state and if so, calculate its estimated reward, as discussed in IV-B. PPN, trained with data from MCTS, can estimate how much reward can be gained from taking a push action at a certain state.

For this combination of MCTS with PPN, some additional updates are made (compared to IV-B) to incorporate the guidance from PPN. The exploration term is removed from the search policy, so \( C \) in equation (1) is set to 0. Similar to [44], we use the estimated reward from PPN as a prior, so the Q-value is calculated as follows

\[
Q_{\text{guide}}(s, a^p) = \frac{\max(Q_p(s)) + \sum_{i=1}^{m} r_i(s, a^p)}{N(s, a^p)},
\]

where \( m \) is set to 3 when expanding nodes and \( N(s, a^p) \) is initialized to 1 for all state-action pairs. Instead of computing an average as standard MCTS, only best \( m \) of \( Q_p \) are considered, this is due to the number of rollout is small, a good action could be averaged out. To select the best action as the next step solution, the Q-value is calculated without the denominator

\[
Q_{\text{best}}(s, a^p) = \max(Q_p(s)) + \max(r_i(s, a^p)),
\]

where only the best explored solution is considered.

The push action space of the guided MCTS is limited to a subset (like Fig. 2) so that the estimated reward from PPN is more accurate and the branching factor of the tree is of a reasonable size. To make the selection mimic the training data, we rotate the image for each sampled push action such that the push action in the rotated image is always pointing to the right. Then, we only use the estimated Q-value at the corresponding pixel (push action) of the output Q-value map. An example of guided MCTS is given in Fig. 4. The expansion of the tree is prioritized by PPN, where the push action with higher Q-value is sampled earlier, and the rollout policy is also prioritized. The maximum depth of the tree is limited to 3 instead of 4 as used in the earlier version of MCTS for collecting data to train PPN.

V. Experimental Evaluation

We evaluated the proposed technique both in simulation (PyBullet [45]) and on adversarial test cases on a UR5e robot with a Robotiq 2F-85 gripper using real objects. The robot, workspace, objects, and camera are the same in simulation and real-world experiments, so that we can seamlessly transfer from simulation to the real setup. The workspace is limited to a square with a side length of 0.48m; it is discretized as a grid of 224 \( \times \) 224 cells during the image processing step. The friction of objects and table cannot be accurately measured; nevertheless, high-fidelity physical properties do not seem to be needed for this particular application. The results demonstrate that the proposed method significantly outperforms MCTS [36] in terms of time efficiency while returning plans of equal quality. The plans returned by the
Simulate experiment results for 22 cases [36]. Budgets of MCTS and MORE are limited up to 50 iterations.

| Method          | Num. of Actions | Time  | Completion | Grasp Success |
|-----------------|-----------------|-------|------------|---------------|
| MORE-50         | 2.61            | 82s   | 100%       | 99.2%         |
| MCTS-50 [36]    | 2.69            | 208s  | 100%       | 99.1%         |
| PPN             | 3.68            | 8s    | 100%       | 97.7%         |

TABLE I: Simulate experiment results for 22 cases [36]. Budgets of MCTS and MORE are limited up to 50 iterations.

For the baseline go-PGN, results on 10 cases are directly quoted from the paper (at the time of our submission, we could not obtain the trained model or the information necessary for fully reproducing go-PGN). MORE uses the fewest number of actions to solve the task. Performance details on 22 cases can be found in Fig. 6 for the number of actions and 7 for the running time. PPN is fast as it is a one-stage DNNs solution. It learned a policy that creates free spaces around the target object, but it is less consistent and less stable than the tree search solutions. From our observation, PPN can propose non-prevailing pushing actions. MCTS provides a consistent and good quality solution, but requires a much longer planning time. MORE, combining the benefits of both, reduces the planning time and delivers high-quality solutions.
in simulation, we set to explore data efficiency in training, which can be important for building larger models in practice. For this purpose, we collected 243 training cases (65384 transitions in 30 hours with PyBullet) with MCTS as described in Section IV-B. Training on PPN on all data used around 22 hours. As shown in Fig. 8, we tested MCTS and MORE with different budgets. Also, MORE is trained on different numbers of training data. Clearly, the problem can be solved by all tested methods with fewer actions when the search iteration limits are increased. But the time for solving the problem also increases as a consequence. The proposed MORE technique can retrieve target objects with only 2.8 executed actions and using only 10 iterations of MCTS that last 36 seconds on average. This is close to the best that MCTS without PPN can achieve, 2.69 actions, after 50 iterations that last 208 seconds. When we limit the number of iterations of MCTS (without MORE) to 10, the number of executed actions increases to 3.19, and the search time remains relatively high (127 seconds). This clearly shows the out-performance of the proposed approach in terms of both time and action efficiency.

B. Robot Experiments

We evaluated the four methods on six real test cases (four from [35] and two from [36]). These six test cases are representative in that they contain more objects and often require at least two push actions to solve. For these real experiments, the results are shown in Table. III and Fig. 10. The budget of MCTS and MORE is limited to 10 iterations. We note that the results for go-PGN are taken from [35]. The execution time of PPN is not listed in Table. III as it is a near-constant small value as we had in the simulation experiments. From the result, we observe only negligible performance degradation in comparison to simulation, which may be due to differences in friction, slight differences in the dimensions of the objects between simulation and real world, statistical error, or a combination of these. Overall, the sim-to-real transfer was very successful and showed that MORE can learn in simulation and directly apply the learned skill to real-world tasks. We assume models of objects are known, such that simple pose estimation can be used to locate objects in the real world and placed in simulation for planning. We could also use sophisticated tracking systems [46]–[48] for general purpose.

![Fig. 6: The average number (out of 5 trials) of action used to solve one case for 22 cases.](image)

![Fig. 7: The average time (of 5 trials) used to solve one case for 22 cases.](image)

![Fig. 8: Different amounts of training data are used to train PPN, which are evaluated on MORE with different budgets (iteration). This is the evaluation of the 22 cases.](image)

![Fig. 9: Manually generated cases similar to [35], [36]. The target object is masked in purple. These cases are used also in simulation experiments as shown in Fig. 5.](image)

|        | Num. of Actions | Time | Completion | Grasp Success |
|--------|-----------------|------|------------|---------------|
| MORE-10| 2.83            | 36 s | 100%       | 100%          |
| MCTS-10 [36] | 3.67        | 190 s| 100%       | 95.8%         |
| PPN    | 3.72            | 3 s  | 94.5%      | 95.8%         |
| go-PGN [35] | 4.62        | –    | 95.0%      | 86.6%         |

TABLE III: Real experiment results for six cases as shown in Fig. 9. The budget of MCTS and MORE is limited to 10 iterations. For go-PGN, only the first four cases apply, and results are from [35]. Only planning time is recorded (robot execution was intentionally slowed down for safety). The computation time for PPN to solve a task is 3 seconds on average (estimated).

![Fig. 10: The number of action and time used on solving six cases. The budget is up to 10 iterations for MCTS and MORE.](image)

VI. DISCUSSION AND CONCLUSION

The main limitation of this work is that we need to know the models of the objects to do the planning. One possible solution is instead of using an explicit simulator, we can use a learned model [39] to simulate the push results. Generalization to novel objects could then be possible. We can further utilize the
Push Prediction Network to estimate the simulation (rollout) result instead of using a physics engine. However, this can introduce additional uncertainties that typically result from using DNNs, which can cause unexpected behaviors such as pushing objects out of the workspace. Building on the know-hows gains from developing MORE, we are exploring other real-world robotic manipulation tasks that would benefit from the S2→S1 search-and-learn philosophy. We point out that MORE can be further sped up by implementing a parallel version of MCTS, as we only utilized a single CPU thread in our implementation and PPN (on GPU) is not being used most of the time.

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