Object Rearrangement Using Learned Implicit Collision Functions

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Abstract—Robotic object rearrangement combines the skills of picking and placing objects. When object models are unavailable, typical collision-checking models may be unable to predict collisions in partial point clouds with occlusions, making generation of collision-free grasping or placement trajectories challenging. We propose a learned collision model that accepts scene and query object point clouds and predicts collisions for 6DOF object poses within the scene. We train the model on a synthetic set of 1 million scene/object point cloud pairs and 2 billion collision queries. We leverage the learned collision model as part of a model predictive path integral (MPPI) policy in a tabletop rearrangement task and show that the policy can plan collision-free grasps and placements for objects unseen in training in both simulated and physical cluttered scenes with a Franka Panda robot. The learned model outperforms both traditional pipelines and learned ablations by 9.8% in accuracy on a dataset of simulated collision queries and is 75x faster than the best-performing baseline. Videos and supplementary material are available at https://sites.google.com/nvidia.com/scenecollisionnet.

I. INTRODUCTION

Rearranging objects is a fundamental robotic skill [2] with broad impacts in applications ranging from logistics in industrial settings to service robotics at home. The majority of existing approaches rely on known models of the objects and environment to generate collision-free trajectories for grasping, motion planning, and placing the objects in the scene [17, 22]. When only point cloud data for the scene and objects are available, these approaches may not correctly reason about occlusions or quickly react to a changing environment. We focus on a core ability that enables rearrangement of unknown objects in cluttered unknown environments: collision checking based on raw sensor measurements.

Existing techniques for collision checking between objects and scenes are limited in that they either rely on known object models or struggle to reason about occluded areas of a scene [13, 33, 34]. Recently, the computer vision community has introduced deep learning techniques with astonishing abilities to represent and reason about fine-grained 3D object geometries [5, 20, 37]. Unfortunately, these approaches are not efficient enough to handle the large number of collision queries necessary for efficient trajectory optimization and control in robotics. In this paper, we introduce an approach that overcomes these limitations and provides robust collision checking on point clouds with occlusions at speeds that are beyond model-based collision checkers used in robotics.

We present a neural network that takes as input raw point clouds of an object and a scene and a 6DOF pose of the object in the scene and outputs the likelihood that the object collides with the scene. We combine point features with voxel features to construct a scene representation that is both fast and memory efficient. We train the model entirely in simulation with 1 million randomly generated tabletop scenes and show it can generalize to real point cloud data. The resulting model can be used in any existing motion planning framework to generate collision-free motion plans; we demonstrate its capability in a model predictive control framework for real-time pick-and-place based on point cloud measurements.

This paper makes three contributions:

1) SceneCollisionNet: a model architecture and training procedure for collision checking between point clouds.
2) A rearrangement policy using SceneCollisionNet in a model predictive path integral controller.
3) Experimental results in simulation and on a real robot platform showing SceneCollisionNet achieves 93% accuracy on 2 million object-scene queries, taking only 10 µs per query, 75x faster than baselines.
II. RELATED WORK

A. Robot Collision Detection from Point Clouds

When mesh models for objects in a scene are known, there exist fast and accurate methods for checking collisions between robot links and the scene or between objects themselves [13, 34]. However, scenes containing unknown objects, only partial point cloud data may be available. One approach to collision checking for point cloud data is to expand each point as a sphere with a predefined radius [18], but the radius may be difficult to determine and may affect resolution of the collision queries. Similarly, voxel-based approaches are memory-intensive [7] and can suffer from resolution errors due to discretization. Bounding volume hierarchies that attempt to capture a representation of the shape from the points have also been considered [12, 23], but again may not capture occluded areas and may not be robust to noise in the point cloud. Pan et al. [33] cast the problem as a binary classification problem, use an SVM to learn a boundary surface between the point clouds, and determine collision probability based on the probability of points crossing the boundary. In contrast, our method encodes the scene into a single latent vector for the shape for better scene-level reasoning, rather than encoding the points in each voxel into a latent vector, but this method does not be robust to noise in the point cloud. Jiang et al. [20] and Chabra et al. [5] further encode the surface as a function in 3D space [6, 29, 37], showing ability to reconstruct objects with fine geometries. Merwe et al. [28] similarly reconstruct objects from partial point clouds without optimizing for a latent vector at run time. Jiang et al. [20] and Chabra et al. [5] further encode the surface into many latent vectors across discrete voxels as opposed to a single latent vector for the shape for better scene-level performance. We similarly discretize space into voxels and encode the points in each voxel into a latent vector, but optimize end-to-end for collision queries.

B. Point Cloud Surface Representations

Another approach to point cloud collision detection is to derive a representation of the underlying surface and check collisions against that representation. Adaptive meshes [44] or alpha shapes [1, 10] convert an unstructured array of 3D points into a triangular or tetrahedral mesh. Berger et al. [4] provide an excellent survey of surface reconstruction methods. Data-driven approaches also reconstruct underlying representations from point clouds or depth images [8, 14, 39]. They typically encode points using either point [8, 38, 41] or voxel [47, 52] representations, or a combination of the two [20]. Several recent approaches use fully-connected neural networks to encode an implicit representation of the surface as a function in 3D space [6, 29, 37], showing ability to reconstruct objects with fine geometries. Merwe et al. [28] similarly reconstruct objects from partial point clouds without optimizing for a latent vector at run time. Jiang et al. [20] and Chabra et al. [5] further encode the surface into many latent vectors across discrete voxels as opposed to a single latent vector for the shape for better scene-level performance. We similarly discretize space into voxels and encode the points in each voxel into a latent vector, but optimize end-to-end for collision queries.

C. Accelerating Collision Detection

As collision checking is considered one of the bottlenecks in motion planning, several methods accelerate it using nearby collision results [24, 50]. Pan et al. [35] developed a GPU implementation of bounding volume test tree traversal that dramatically increases the speed of generating collision-free motion plans for a PR2 robot. Fastron [9] and ClearanceNet [21] generate C-space models for collision checking. ClearanceNet also batches collision checks and does not need retraining when objects move. Tran et al. [45] use a contractive autoencoder and multi-layer perceptron to predict collisions in latent space between a robot and axis-aligned boxes. However, each of these methods assume knowledge of object geometry and do not use dynamic point cloud inputs.

D. Robotic Object Rearrangement

Robot grasping has seen recent advances in 6-DOF grasping [51, 52] and closed-loop grasping [50, 52]. Murali et al. [32] learn collisions between grippers and cluttered scenes centered around a target object, but this method does not easily lend itself to broader motion planning frameworks. Gualtieri et al. [15] learn pick and place actions for block, mug, and bottle objects, but use top-down point clouds and do not account for workspace dynamics. The Amazon Picking Challenge has also focused development of pick and place systems [51, 50, 49], and Yuan et al. [49], and Haustein et al. [16] learn policies to pick and place and rearrange via pushing directly from input images similar to our approach. However, their tasks are planar scenarios, which do not require the robot to reason about 3D collisions with other objects.

III. PROBLEM STATEMENT

We consider a problem setting where a robot with a parallel-jaw gripper must iteratively grasp and place objects on a tabletop to rearrange them. Observations of the scene are given by a single depth sensor with known camera intrinsics at an oblique angle to the scene, pointing toward the table and robot. The objective is to pick and place the objects in the least amount of time while reacting to changes in the environment and target object.

A. Definitions

We define the problem as having:

- **States** ($S$): A state $s_k$ at time $k$ consists of a valid robot joint configuration $q_k$ and a tabletop containing $N$ objects. No prior information is known about the $N$ objects. $S_{k,\text{free}} \subset S$ is the set of collision-free states with valid joint configurations at time $k$.
- **Observations** ($O$): An observation $y_k \in \mathbb{R}^{n \times 3}$ at timestep $k$ consists of a point cloud with $n$ points from the camera pointing at the scene.
- **Actions** ($A$): Actions are defined as a change in the joint configuration of the robot $a_k = \Delta q_k$.
- **Transitions** ($T$): The transition model $T(s_{k+1} \mid a_k, s_k)$ representing the dynamics of the scene and robot is executed by Isaac Gym for dynamics [25]. On the physical system, next states are determined by executing the action on a physical robot.
- **Value Function** ($V$): The value of a state $V(s_k)$ is defined as the negative Euclidean distance from the current robot joint configuration to the goal robot joint configuration (either grasp or placement).
Fig. 2: Network architecture for SceneCollisionNet, which predicts collisions between a scene point cloud and an object point cloud given a relative 6DOF pose of the object within the scene. Scene points are encoded by voxelizing, featurizing, and convolving the max-pooled voxels. Object points are encoded using Pointnet++ \cite{39} layers. Collision queries are created by feeding the concatenated voxel features, object features, and the relative object transform into a small classifier that predicts the likelihood of collision. Object transforms are specified relative to the voxel frame such that collision queries across different voxels can be predicted simultaneously.

### B. Objective

During the grasping and placement phases of rearrangement, the objective is to find a policy $\pi$ that maximizes the total value of the states visited over a finite horizon $H$ subject to kinematic constraints and that all states along the trajectory are collision-free:

$$
\pi^* = \arg \max_{\pi} \mathbb{E}_{a_k \sim \pi(s_k)} \sum_{k=1}^{H} V(s_k) \ s.t. \ s_k \in S_{k,\text{free}}
$$

### IV. SCENECOLLISIONNET

To predict collisions between two point clouds, we propose SceneCollisionNet, a deep neural network inspired by recent work in implicit surface representations from point clouds. Similar to Jiang \textit{et al.} \cite{20} and Chabra \textit{et al.} \cite{5}, we divide space into coarse voxels and use a local representation for each voxel based on the points contained within that voxel. However, our experiments show that extracting the full implicit surface representation for each voxel is not necessary for collision queries and scene information must be shared between voxel representations. Additionally, we seek to avoid the costly optimization of each latent vector for a new point cloud for real-time prediction.

Our model divides the scene point cloud into coarse voxels (side length of about 0.1 m) and assigns points to their voxels, normalizing each point within its voxel by subtracting the voxel’s center. We pass the points through a shared multi-layer perceptron and max-pool the features of the points per voxel, similar to Pointnet \cite{38}. The max-pooled voxel features are passed through 3D convolution layers, similar to Liu \textit{et al.} \cite{26}, incorporating global information from neighboring voxels. The target object point cloud is separately featurized using Pointnet++ set abstraction layers \cite{39}. Collision queries consist of transforms for the object; we form the query using the voxel features containing the object translation, the object features, and the transform of the object relative to the voxel center. This approach allows the scene and object features to only be generated only once and a very large number of collision queries can be made quickly in a single forward pass through the classifier, which predicts the likelihood of collision for each transformation. Figure 2 shows the network architecture.

### A. Dataset Generation and Training

We train SceneCollisionNet entirely using synthetic point clouds. For each scene, we place objects drawn from a dataset of 8828 3D mesh models \cite{11} in one of their stable poses with a uniformly random rotation applied about the world $z$-axis on a planar surface. Object positions are chosen uniformly at random such that they do not collide with any other objects. We draw the number of objects from a uniform distribution between 10 and 20. The camera, which renders a scene point cloud, is aimed at the origin of the scene and its extrinsics are taken from uniform distributions centered at their nominal values. A query object is also drawn from the dataset of mesh models; this object is placed at the origin in a random stable pose, where a point cloud is rendered using the same camera. We then generate $q$ collision queries by moving the query object along $t$ trajectories through the scene, recording its relative rotation, translation, and ground truth collisions with the scene using the flexible collision library (FCL) \cite{34}. The object’s start and end pose are chosen uniformly at random and is linearly interpolated along the trajectory. Generating one scene/target pair with $q = 2048$ queries over $t = 64$ trajectories takes roughly 2 seconds on an Ubuntu 18.04 machine with an Intel Core i7-7800X 3.50GHz CPU. Each epoch of training consists of 1,000 unique scene/object/trajectory inputs and we train...
each model for 1000 epochs, or a total of 1 million unique inputs and just over 2 billion total collision queries. We adopt a hard negative scheme, where we backpropagate the loss only from the 10% highest loss queries plus 10% random queries, which increases the true positive rate by 6% for similar accuracy. Training takes about 9 days on a NVIDIA V100 GPU. We use SGD with learning rate $1 \times 10^{-3}$ and momentum 0.9.

B. Robot Collision Checking

For robot collision checking, we pre-sample points from the 3D mesh of each link in the robot’s kinematic chain and featurize each set of points. This feature set only needs to be generated once for a given robot. The set of link features and link poses (using forward kinematics for a given configuration) are input to SceneCollisionNet with the scene features at run time and collision predictions can be generated for all links in a single forward pass. The same method can also be used to predict collisions between other known meshes and a partial scene point cloud, showcasing the flexibility of our method.

V. OBJECT REARRANGEMENT

Rearrangement of objects is a multi-stage task, so we incorporate a finite state machine into our policy with 5 states: reaching to the pre-grasp pose, attempting the grasp, lifting the object, placing the object, and releasing the placed object. We use a model predictive path integral (MPPI) policy for the reaching and placing states and preset actions for reaching from the pre-grasp to final grasp pose, lifting, and releasing the object. We use SceneCollisionNet to find both placements and collision-free trajectories for grasping and placing.

A. Grasps and Placements

We modify Contact-GraspNet \cite{43} to predict 6DOF grasps on a region of the raw point cloud in cluttered environments and the segmentation from Xiang et al. \cite{48}. We use the Trac IK solver \cite{3} to convert grasps poses for the gripper to robot configurations. For placement goal positions, we accept a point cloud mask that represents an area of the scene where the object should be placed, which by default includes the entire workspace. Points are sampled randomly within the placement zone and sorted by height in the scene, then SceneCollisionNet classifies whether the object would be in collision at the given point. The lowest collision-free points are chosen as placement locations. Figure 3 shows placement candidates for both empty and cluttered placement zones. Final placement goals (purple) must be both collision-free and have an inverse kinematics solution. Orange points show placement candidates without inverse kinematics solutions; this decoupling allows for the same placements to be used with a different robot.

B. MPPI Policy

We leverage the extreme parallelism provided by SceneCollisionNet in a model predictive path integral (MPPI) algorithm for object rearrangement in tabletop environments \cite{46}. The advantages of MPPI in this setting are: 1) the task can be specified entirely in the joint configuration space and robot joint constraints can be strictly enforced during rollouts, 2) rollout rewards can easily be specified using distances in joint space, 3) trajectory generation, reward calculation, collision checking, and forward kinematics can be parallelized on a GPU for the real-time capability necessary in closed-loop execution. In contrast, standard motion planning techniques, such as RRT or PRM, may provide guarantees of completeness and optimality, but are by nature sequential, require nearest neighbor search for connecting nodes, and must be adapted for dynamic environments.

We adapt MPPI such that trajectories are generated by sampling around a straight line in configuration space between the start and goal configurations. Specifically, we
create $T$ vectors by perturbing the straight-line trajectory $d$ with a vector drawn from a normal distribution and renormalizing: $d_i = \frac{N(d + \mathcal{N}(0, \Sigma))}{|d + \mathcal{N}(0, \Sigma)|}$. Trajectories consist of $H$ steps along $d_i$; actions are clipped to the robot joint limits at each timestep for all rollouts.

We specify goals in joint space and calculate reward for each rollout as the negative of the minimum Euclidean distance to any goal configuration. We check for both collisions between the robot and scene using the method in [9] and robot self-collisions using a model that predicts distance to self-colliding configurations [42] at discrete intervals between each waypoint in each rollout. Thus, at each policy call, we make $T \times H \times i$ collision checks for each robot link, which can be computed in a single forward pass using SceneCollisionNet. If there is an object being placed, collisions between the object and the scene at each point in the rollout are also checked. Then, we clip each rollout such that it is entirely collision-free (i.e., all waypoints beyond a waypoint in collision are removed) and such that its final waypoint has the maximum reward along the collision-free trajectory. The trajectory with the maximum reward is executed until the policy is called again. In experiments, we query the policy asynchronously with robot movement at 1 Hz with $H = 40$ for continuous execution. Figure 4 shows a sampling of four trajectories and their associated rewards, with the green box trajectory chosen to be executed.

One important point cloud processing step is to remove the points in the scene belonging to the robot or to the target object during placement, as if they remain in the scene, they will cause all MPPI rollouts to be in collision. In physical experiments, we use a combination of a learned robot point cloud segmentation model and particle filter to track the robot points and remove them. We segment the target object before grasping it and remove points within a bounding box that is transformed according to the relative transformation between the target points and the object end-effector as it moves through space. This approach does not account for any in-hand motion of the object, but avoids occlusion of the object by the robot during grasping. For simulation results we use ground truth segmentation masks for both the robot and the target object.

VI. SCENECOLLISIONNET EVALUATION

We benchmark SceneCollisionNet against baseline point cloud collision algorithms using synthetic data on two tasks: (1) a dataset of 1000 scene/object pairs with 2048 queries per scene/object pair where objects move on 16 linear trajectories through a scene, and (2) a dataset of 192,000 total grasps using the Franka Panda gripper [11], gathered from 5 scenes and 4 object categories (mugs, cylinders, boxes, and bowls), where each scene has between 7 and 10 objects from the same category. In both tasks, ground truth collisions between the robot and the scene are calculated using FCL and the mesh models of the objects and robot in the scene. For each method and task, we compare the overall prediction accuracy and the computation time per query or grasp. We additionally report average precision (AP) scores, a weighted mean of precisions achieved at each recall threshold, for the trajectory benchmark and precision and recall for the grasp benchmark.

A. Baseline Algorithms

We benchmark the learned collision model against 4 baseline collision checking algorithms on a simulated dataset of queries similar to those seen in training. The Marching Cubes baseline methods first create a mesh representation of the scene, object, or both from the raw point clouds [27]. The signed distance function (SDF) methods use the Kaolin library [19] for mesh to SDF conversion and SDF evaluation on the GPU. The baselines used in benchmarking are:

1) **Marching Cubes + SDF Scene (MC+SDFS)**: The points belonging to the object point cloud are transformed and evaluated using the scene SDF. If any point has distance, the object is in collision with the scene.

2) **Marching Cubes + SDF Object (MC+SDO)**: The points belonging to the scene point cloud are transformed and evaluated using the object SDF. If any point has a zero or negative distance, the object is in collision with the scene.

3) **Marching Cubes + FCL (MC+FCL)**: Collisions between the scene meshes and object meshes are determined using the flexible collision library (FCL) [34]. For fairer comparison, we parallelize this method across 10 processes. We also show performance when it receives points directly sampled from the underlying object meshes (FO).

4) **Pointnet Grid**: We divide the scene into coarse overlapping voxels and featureize each voxel and the object using Pointnet++ set abstraction layers [39], but no voxel convolution layers, and train on the same dataset used for SceneCollisionNet. Predictions are averaged across the 8 corresponding voxels.

B. Results

SceneCollisionNet outperforms all baselines in the linear trajectory collision environment, as shown in Table I with 9.8% and 15.8% gains in accuracy and AP score, respectively, over the FCL baseline. Additionally, SceneCollisionNet is nearly 20 times faster than the parallelized FCL baseline, taking only about 10µs per collision query. SceneCollisionNet can predict over 500,000 queries in a single forward pass on an NVIDIA GeForce RTX 2080 Ti GPU, further reducing the time per query on large batches of queries.

The comparison with Pointnet Grid shows the benefit of both the coarse voxel representation and the addition of voxel convolutions. If the scene is encoded in the same way as the object (Pointnet++ layers only), the network fails to converge. With coarse independent voxels (no voxel convolutions), the network converges, but accuracy and AP scores are 16.5% and 6.2% lower, respectively.

Table I shows the results on the grasping benchmark. In addition to evaluating each model on the grasp poses, we evaluate the models on pre-grasp poses that are offset along
unable to account for gaps in point cloud data. Beyond the points in the scene, while the other methods are to being in or out of collision, but dramatically improves accuracy. These results suggest SceneCollisionNet can struggle to predict collisions for geometries that are very close to the approach axis by 5 cm. The baseline methods slightly outperform SceneCollisionNet for the 5 cm offset while recalling over 70% of the collision-free grasps 15x faster.

| Algorithm           | Accuracy | AP   | Time / Query (ms) |
|---------------------|----------|------|-------------------|
| MC+SDFS             | 70.2%    | 0.651| 27 ± 12           |
| MC+FCL (10x)        | 75.4%    | 0.824| 0.49 ± 0.06      |
| MC+FCL (10x, FO)    | 83.4%    | 0.832| 0.74 ± 0.13      |
| PointNet Grid       | 76.7%    | 0.928| 0.026 ± 0.035    |
| SceneCollisionNet   | 93.2%    | 0.990| 0.010 ± 0.002    |

TABLE I: Benchmark results for 1000 scene/object pairs, with 16 linear trajectories and 2048 queries for each pair (2,048,000 total queries). SceneCollisionNet outperforms parallelized baselines that reconstruct meshes even from fully observed point clouds and learned baselines that do not share information between voxels.

The baselines slightly outperform SceneCollisionNet for the 5 cm offset while both accuracy and precision for the the 5 cm offset while recalling over 70% of the collision-free grasps 15x faster.

| Algorithm       | Grasps | Placements | Time (min) |
|-----------------|--------|------------|------------|
| MC+FCL (10x)    | 109    | 92         | 164        |
| SceneCollisionNet| 110    | 99         | 100        |

TABLE III: Simulation rearrangement results when using SceneCollisionNet and MC+FCL (10x) as collision checkers in the MPPI policy. SceneCollisionNet significantly speeds up scene interaction and leads to more placements.

We additionally evaluate the MPPI policy with SceneCollisionNet on a set of 10 physical tabletop scenes with a Franka Panda robot and an Intel RealSense LiDAR Camera L515. We divide the scenes into two categories: barrier scenes and rearrangement scenes, each with between 3 to 11 YCB objects. Examples are shown in Figures 1, 3 and 4. In barrier scenes a tall box divides the scene and objects must iteratively be grasped and placed on the opposite side of the barrier. Rearrangement scenes are similar to the simulated scenes, where objects are placed randomly on the table. However, in this case, placement is also restricted to a single side of the scene and both grasps and placements must be made among clutter. Placement becomes more difficult later in trials, when the zone fills with objects.

In the four barrier scenes, the policy grasps 16/17 objects and places 12/17 objects successfully. Three failures were due to collisions in the trajectory or incorrect placement choice, one was due to object motion in the gripper, and one was due to the policy being unable to find a placement. In the rearrangement scenes, 25/27 grasps and 20/27 placements were successful. Of these failures, five were due to collision errors in the trajectory or placement position, with one failure each due to motion in the hand and no placements found.

The policy’s grasping performance suggests it can consistently generate collision-free robot trajectories to specified goals in the presence of both clutter and a challenging divider that requires planning to significantly deviate from a straight line trajectory. The placement performance indicates that the addition of checking collisions with an object in the hand makes finding collision-free trajectories much more difficult, but the policy is still able to effectively reason about collisions along the trajectory and at the placement location.
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