Efficient Collision Detection and Distance Computation with Realtime Sensor Data

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Abstract— **Most prior techniques for proximity computations are designed for synthetic models and assume exact geometric representations. However, real robots construct representations of the environment using their sensors, and the result is usually more cluttered and less precise when compared to synthetic models. Furthermore, this sensor data can be updated at high frequency, depending on the type of sensor used. In this paper, we present new algorithms for collision and distance queries, which can efficiently handle large amounts of point cloud sensor data received at high frequency. Our algorithms speed up the construction of broad phase data structures used for culling proximity checks in two ways: 1) we construct simple broad phase structures that are improved as proximity queries are processed and 2) we directly use an octree representation of the point cloud data as a proximity data structure. When the octrees used include a probability of occupancy for their leafs, our algorithms can optionally return the set of volumes where the probability of collision is high, for specified thresholds. In practice, our new approaches can be up to 15 times faster than previous methods. We demonstrate the performance of the new methods on both synthetic data and on data collected using a Kinect for motion planning for a mobile manipulator robot.**

I. Introduction

The problem of collision detection and distance computation has been widely studied in various fields including computer graphics, robotics, haptics and computational geometry. Many algorithms have been proposed to perform these queries on geometric models. Furthermore, efficient implementations of some of these algorithms are also available, including Bullet [1], ODE [2], V-Collide [3], PQP [4], Box2d [5], etc.

However, almost all these algorithms and libraries were originally designed for synthetic models and environments where objects are represented as meshes or primitive geometric shapes. These representations differ from the raw representation of the data collected by real robots using their sensors. In this work, we address the issue of collision detection and distance computation using algorithms that are designed to work better with data from a robot's sensors. We consider the use of visual sensors that report depth information in the form of a point cloud (e.g., laser sensors, stereo cameras, time-of-flight cameras)[1]. We further assume these sensors periodically generate point cloud data corresponding to their field of view. We call each view of the environment a "frame".

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[1]Here, we consider point clouds to be a collection of 3D points

The generated point clouds correspond to samples on the visible parts of the various objects in the environment. Dealing with these samples of the environment introduces many challenges: 1) it can be expensive to extract objects from the sensor data; such operations involve complex steps such as segmentation [6] or object recognition [7], among others; 2) tracking objects among different frames of sensor data is challenging due to noise and amount of sensor data; 3) amount of sensor data is large and is received at high frame rates; for example, typical RGB-D sensors like the Microsoft Kinect©sensor can generate a detailed point cloud with around 300,000 points at 30 Hz; 4) sensor data usually contains some level of noise and uncertainty and does not represent the environment fully (some parts are occluded). However, most collision and distance computation algorithms assume that a geometric model for each object in the environment is available. Furthermore, there are two additional issues in terms of applying existing algorithms to dynamically generated sensor data. First, most proximity algorithms need to compute complex acceleration data structures before performing actual queries. This computation overhead can be prohibitively high for sensor data. Second, parts of the environment can be modeled as uncertain or unknown in the sensor data. In traditional approaches such regions can only be considered either as free space (optimistic, but unsafe) or as occupied (safe, but perhaps too conservative).

In this paper, we present efficient collision detection and distance computation algorithms for point cloud sensor data. Our approach is general and applicable to all sensors that can generate point clouds. Given the sensor data, we first convert it into an octree, which is a compact data structure to model arbitrary environments and can encode the uncertainty in the sensor data, as well as occluded space [8]. Based on the octree representation, we present two techniques to perform efficient collision and distance queries on the sensor data:

- We amortize the cost of initialization over multiple or all proximity queries. That is, we initialize the acceleration data structure (a binary tree) for collision or distance queries using a simple technique which is not-optimal but fast, and then we incrementally improve the data structure as more queries are performed.
- In the second strategy, we completely avoid the initialization overhead by performing collision and distance queries directly with the octree representing the sensor. In this case, each query may be a bit more expensive than using traditional methods. However, the saving on

data preparation makes our approach more efficient on sensor data received at high frame rates.

The two strategies have different sets of advantages, but both of them can provide up to 15 times speedup in some particular cases, when compared to traditional methods. To handle occlusions and uncertainty in sensor data, our new algorithms assume that each leaf node in the octree specifies a probability of occupancy [8]. The probability of occupancy is initialized to 0.5 (thus unknown or occluded space has a probability of occupancy of 0.5). As sensor data is received, the probability of occupancy is maintained to be an average of occupancy over a number of previously observed frames. This uncertainty model is part of Octomap [8] and is not a contribution of this work. Our approach uses the probability of occupancy specified in the octree and can report a set of axis-aligned bounding boxes that correspond to intersections of robot links and octree nodes. These bounding boxes also specify the probability of occupancy carried over from the octree node. Using this set of bounding boxes a notion of cost can be defined for a collision check. A specific formula for this cost is outside the scope of this paper, as we believe such a definition is problem specific. A simple example of cost is the weighted sum of the box volumes using the probabilities of occupancy as weights.

We validate the performance of our new algorithms on both synthetic sensor data and real sensor data generated with a RGB-D sensor. The algorithms are implemented in the open source library FCL [9].

The rest of the paper is organized as follows. We survey related work on collision checking and distance computation on sensor data in Section II. Section III explains why previous methods are not efficient for sensor data and gives an overview of our new methods. Section IV discusses the details of our new approaches. We present the results in Section V and conclusions follow in Section VI.

II. Problem Definition and Related Work

The general collision query is defined as follows:

Given two sets of objects $\{A_i\}_{i=1}^n$ and $\{B_i\}_{i=1}^m$ with n and m objects, respectively, as well as their configurations, the collision detection query returns a yes/no answer about whether any pairs of objects, one from each set, are in collision with each other. Optionally, it also returns all the pairs of colliding objects.

A special case of the collision query is when the two sets of objects are the same, which is called the self-collision query. As an example, a self collision check is useful to test whether a configuration of an articulated model is valid.

The general distance query is defined as follows:

Given two sets of objects $\{A_i\}_{i=1}^n$ and $\{B_i\}_{i=1}^m$ with n and m objects, respectively, as well as their configurations, the distance query returns the minimum separation distance between the two sets. Optionally, it also returns the pair of objects that are closest to each other.

To avoid the quadratic worst-case complexity when performing collision checking or distance computation between two sets of objects, prior techniques use a two-phased approach: a broad phase and a narrow phase. Intuitively, the broad phase quickly excludes the object pairs that definitely are not colliding or are too far away, and identifies the pairs of objects that may be colliding or may contribute to the minimum distance between the two sets [10], [9]. The narrow phase corresponds to exact, pairwise collision or distance tests between the identified pairs.

To efficiently cull out object pairs that are definitely not colliding or are too far away, special data structures are used to manage all the objects in the given set. For example, interval trees [11] are used in sweep-and-prune based broad phase algorithms; spatial partitioning trees such as octrees and k-d trees can als be used [12]; hash tables are used in spatial-hashing based approaches [10]. These data structures are designed so they can be updated efficiently when the underlying objects change their positions or when objects are added into or removed from the environment. In traditional broad phase approaches, the overhead to initialize the broad phase data structure is usually ignored, because the broad phase data structure is typically used for a long time over many queries. As a result, the initialization overhead is negligible when compared to the total time of a large number of collision or distance queries performed by the application.

Previous work on proximity queries on sensor data tends to ignore the fact that the underlying data can be updated quickly, when a new frame is received from the sensor. For example, in [13], the sensor data is first converted into a set of boxes, and then ODE [2] is used to check for collisions between these boxes and the robot. Passing the sensor data to the collision checker in this manner is relatively slow when the frame rate of the sensor is high.

Some recent work attempts to handle collision checking with sensor data in a more sophisticated manner. For real-time haptics rendering, Leeper et al. [14] represent the point cloud using an implicit surface and use that implicit surface for collision checking. The accuracy of this method depends on the parameters used for the implicit surface fitting. Pan et al. [15] present a collision checking algorithm based on supported vector machines, which can handle collision queries for point clouds. If the given point clouds have noise, this approach can further compute a collision probability.

III. Overview

Current collision detection algorithm make assumptions that may no longer hold when dealing with data from real sensors.

All existing methods require a set of *objects* as input, where an object is a collection of geometry elements (points, triangles, etc) that have a well-defined boundary [16], for example, a desk, a cup on the desk, etc. In synthetic environments, the objects are provided by default, in the form of meshes or geometric primitives. However, for sensor data, the entire environment is in the form of a single point cloud, and different objects contained in the environment are not easily separable in the point cloud. To extract objects from the point cloud, expensive object recognition and reconstruction algorithms, such as [7], are necessary.

To bypass such difficulties, one widely used solution is to discretize the space into small axis-aligned cubes and model the sensor data as a collection of boxes which have sensor points inside. This representation is refered to as a *collision map* in [13], [17]. After converting the sensor data to a set of boxes, the collision or distance query between the robot and the environment becomes a query between the robot and the set of boxes. Broad phase structures for both the robot and for the boxes can be constructed, before performing actual queries. A diagram of this pipeline (used in [13], [17]) is shown in Figure 1a.

In pipelines such as ones presented in [13] and [17], the raw sensor data in the form of point clouds is first converted into a collision map structure. We denote the time required to construct the collision map as T_0, which is small compared to the timing cost of other components in the pipeline. It takes time T_1 to convert the collision map into a data structure suitable for broad phase approaches, which includes two parts: 1) $T_{1,1}$: the time cost from collision map to boxes; 2) $T_{1,2}$: the time cost from boxes to broad phase structures. $T_{1,2}$ can be expensive if the sensor data is large and there are many boxes. For example, the PR2 stereo sensor data usually contains tens of thousands of points and is converted to thousands of boxes. An additional challenge is that these generated data structures cannot be easily reused when new sensor data comes in, as is assumed by traditional approaches. The reason is that the boxes managed by the structure are not trackable objects: they are just spatial cells that contain several points belonging to one frame of the sensor data. Given a new frame of sensor data, it is difficult to identify each box's correspondence in the prior frames, which is necessary for traditional approaches to compute the objects' movements and update the broad phase structure accordingly. Therefore, once a new frame of sensor data is received, we need to discard the old broad phase structure and reconstruct a new one from scratch. Moreover, as the sensor data is received at high frame rates (e.g., Kinect frame rates can be 30 Hz and the stereo sensors on PR2 generates data at 20 Hz), we can only perform a few (e.g., $N < 1,000$) queries during the lifetime of a broad phase structure. As a result, for sensor data, it is possible that:

$$T_1 = T_{1,1} + T_{1,2} \quad \sim \quad T_2 = N \cdot T_q, \tag{1}$$

where T_q is the time cost for a single query. In other words, the overhead to prepare the sensor data for queries can be comparable to the total time spent on the actual queries and is in fact not negligible.

According to the analysis above, the overall time to handle one frame of sensor data is:

$$T = T_0 + T_1 + T_2 = T_0 + T_{1,1} + T_{1,2} + N \cdot T_q. \tag{2}$$

To improve performance, we provide two strategies. The first strategy tends to reduce the broad phase structure construction time $T_{1,2}$ by amortizing the cost over all the N queries. We first construct a low quality broad phase structure, which is less effective in culling but is much faster than the near-optimal broad phase structure used before, i.e., the new construction time is $\widetilde{T}_{1,2} \ll T_{1,2}$. When performing the actual queries, we can improve the broad phase structure gradually, along with each query. The new broad phase structure can slow down the actual queries because we may perform more narrow phase computations, i.e., $\widetilde{T}_q > T_q$. However, the gradual refinement of the broad phase structure guarantees that the decrease in performance is not obvious. As long as $T_{1,2} + N \cdot T_q > \widetilde{T}_{1,2} + N \cdot \widetilde{T}_q$, i.e.,

$$N \leq \frac{T_{1,2} - \widetilde{T}_{1,2}}{\widetilde{T}_q - T_q}, \tag{3}$$

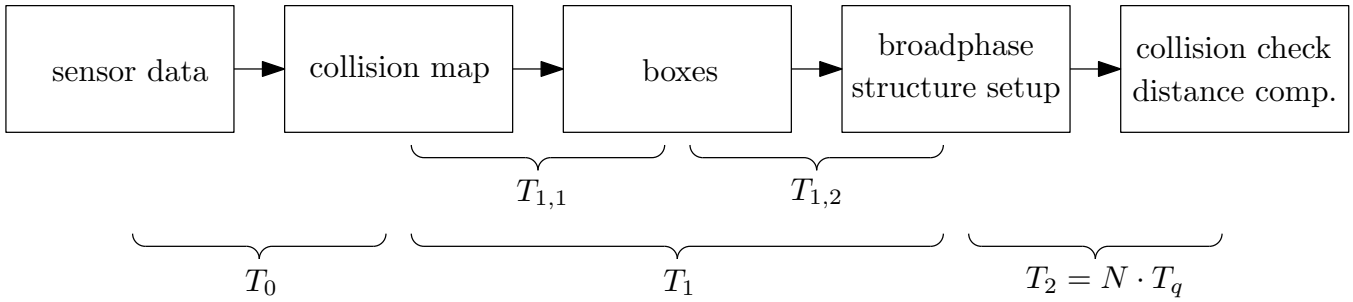
the amortized method will be faster than the original method.

The second strategy is to support collision or distance queries directly with the sensor data in the form of an octree and therefore we no longer need a broad phase structure to manage the sensor data. As shown in Figure 1b, this approach allows completely avoiding the data preparation overhead T_1, but may also make the actual queries slower, because it in fact uses the octree as a low quality broad phase structure. Suppose the time for actual query in this case is $\widetilde{T}'_q$, then the second strategy is better than the original methods if $N \leq \frac{T_{1,2}}{\widetilde{T}'_q - T_q}$.

Both the two strategies can be extended to handle sensor data with uncertain or unknown regions. The octree represents an uncertain or unknown region as a octree leaf node with occupancy probability smaller than 1 [8]. When using the first strategy, the boxes generated can store an occupancy probability with them, which will be considered in the narrow phase algorithms. If the second strategy is used, the octree's occupancy probability will directly be involved when performing collision or distance queries with the octree structure.

IV. Efficient Collision and Distance Query on Sensor Data

In this section, we discuss the details of our new algorithms, optimized to handle the sensor data. In all the descriptions that follow, we use the *dynamic AABB (Axis Aligned Bounding Box) tree* as the default broad phase data structure, which was used in visibility computation [18]. We remind the readers that a dynamic AABB tree is a binary tree structure used to organize objects in a hierarchical manner. Similar to the ordinary AABB tree, dynamic AABB tree recursively split a set of objects into two subsets, until the set contains only one object and is used as a leaf node. Previous methods try to construct a high quality AABB tree in order to perform broad phase culling effectively, e.g., the split axis is selected to minimize the bounding boxes of the children nodes. When new objects are added or old objects are removed from the tree, dynamic AABB tree needs to be re-balanced, i.e., we need to adjust the tree structure to keep it a balanced tree and to minimize the bounding volume of each tree node. Such re-balancing operation is also necessary when the objects have moved. The time complexity to construct a balanced dynamic AABB tree is $\mathcal{O}(n \log n)$ where n is the number of objects managed by the tree. This



(a) Pipeline for collision or distance computation: The sensor data is first represented as a collision map. The collision map can be directly constructed from the point cloud. The collision map is constructed in T_0 time. Next, the collision map is first converted into a set of boxes in $T_{1,1}$ time. Finally, a broad phase data structure is constructed in $T_{1,2}$ time in order to manage these boxes. The overhead to prepare the sensor data is $T_1 = T_{1,1} + T_{1,2}$. Once the data is prepared, the actual time to perform N collision or distance queries is $T_2 = N \cdot T_q$, where T_q is the time cost for a single query. In traditional approaches, N is assumed to be infinite, while for sensor data, N is usually small ($< 1{,}000$).

(b) By supporting the collision or distance query directly with the sensor data represented as octree, we no longer need the long conversion pipeline from octree to broad phase structures and thus can completely avoid the main overhead when preparing the sensor data for actual queries.

Fig. 1: Comparison between possible pipelines for environment representation and collision detection.

is because the tree has $\log n$ levels and each level needs $\mathcal{O}(n)$ time to rearrange the objects. If n is large, the construction step can be expensive. The objects are the geometric links for a robot and are the boxes converted from point clouds for sensor data. For example, for sensor data, n is the number of boxes converted from the sensor data and can be of magnitude more than 10,000.

A. Amortized Broad Phase Algorithm

Our first method attempts to reduce the construction time of a dynamic AABB tree, i.e., $T_{1,2}$ in Equation 2. Instead of constructing a high quality dynamic AABB tree, we start with a low quality binary tree and then gradually improve it during the following actual queries. The initial binary tree is constructed by using the well known space-filling Morton curve [19] – also known as the Lebesgue and z-order curve – to order all the boxes converted from the sensor data. We assume that the enclosing AABB of the entire environment is known. We take the barycenter of each of the n boxes as its representative point. By constructing a $2^k \cdot 2^k \cdot 2^k$ lattice within the enclosing AABB, we can quantize each of the three coordinates of the representative points into k-bit integers. The $3k$-bit Morton code for a point is computed by interleaving the successive bits of its quantized coordinates. Figure 2 shows a 2D-example of this construction. Sorting the representative points in increasing order of their Morton codes will lay them out in order along the Morton curve. Therefore, it will also order the corresponding boxes in a spatially coherent way, which directly determines a binary tree structure for the set of boxes. The time cost of this new tree construction method is dominated by the time to sort n $3k$-bit integers, which is of time complexity $\mathcal{O}(3k \cdot n)$ if we use radix sorting. If k is smaller than $\log n$, the Morton curve based construction method is cheaper than the traditional AABB tree construction method. Moreover, k also enables us to control the quality of the resulting initial tree: we can obtain broad phase structure with better culling efficiency by using larger k.

The AABB tree constructed as above may not be as effective at culling as the high quality AABB tree constructed with traditional approaches and therefore the timing cost of each actual query can increase, i.e., T_q item in Equation 2 can be larger. To overcome this problem, our solution is to incrementally refine the initial binary tree while performing each query. First, we encode each traversing path connecting the tree root node to one of the leaf nodes as an $\mathcal{O}(\log n)$-bit integer, according to whether the left or right child is selected during the traverse. Next, along with performing the actual query, we periodically select one of the traversing paths and re-compute the bounding boxes for all the nodes on the path, starting from the leaf node, which has time complexity $\mathcal{O}(\log n)$. Then after (at most) n iterations, the binary tree will become an AABB tree being able to culling effectively. In practice, we observe that the dynamic tree's culling efficiency can be almost as good as the near-optimal binary tree in only a few iterations. As a result, we can assume the actual query cost when using the amortized method is $\widetilde{T}_q = T_q + \mathcal{O}(\log n)$.

Suppose N queries are performed during the lifetime of the dynamic AABB tree. Then, according to Equation 2, if $N < \frac{c_1 \cdot n \log n - c_2 \cdot 3k \cdot n}{c_3 \cdot \log n}$ the amortized method will have better performance than the traditional methods. Here c_1, c_2 and c_3 are constant coefficients for $\mathcal{O}(n \log n)$, $\mathcal{O}(3k \cdot n)$ and $\mathcal{O}(\log n)$: c_1 is the cost to place a given AABB on one side of an axis-aligned plane according to its center coordinates; c_2 is cost to decide whether to exchange the position of two $3k$-bit integers by comparing one of the $3k$ bits; c_3 is the cost to test whether a given AABB is completely within another AABB and if not, enlarge the second AABB. There

is $c_3 > c_1 > c_2$, which implies that the above upper bound for N can be approximated by $N < \frac{c_1}{c_3} n$.

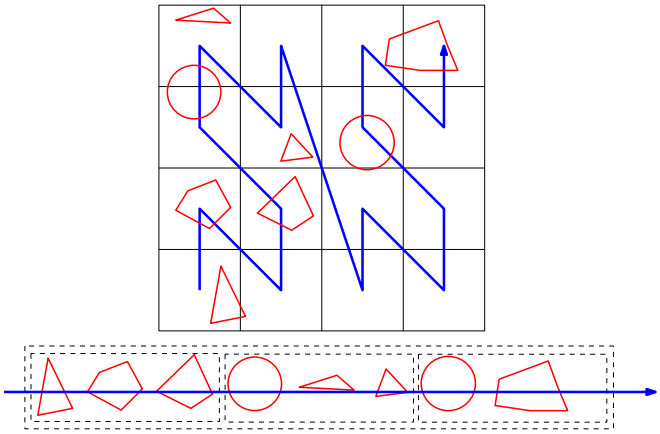


Fig. 2: Example 2-D Morton curve. According to the first two bits of the Morton code, we can order the objects in a hierarchical manner.

B. Collision Checking and Distance Computation using Octrees

The amortized method cannot avoid the overhead of $T_{1,1}$ in Equation 2, which can still be expensive for large sensor data. To avoid such overhead, our second method is to perform collision or distance query directly on the sensor data in the form of an octree as shown in Figure 1b, and therefore completely avoid the long pipeline as shown in Figure 1a to prepare sensor data. In other words, we use the octree as a low quality broad phase structure for the sensor data. Octree may not be as efficient at culling as a dynamic AABB tree, so the cost for a single collision or query cost can be larger than using the traditional pipeline, i.e., $\widetilde{T}'_q > \widetilde{T}_q > T_q$. However, as only a small number of queries are performed for one frame of sensor data, the saving on sensor data preparation time may make this strategy more efficient than the amortized strategy.

We will now illustrate the use of this algorithm to perform collision checking between an articulated robot and the sensor data. The desired query can be implemented as a collision query between trees: the sensor data is represented as an octree and the robot is represented as a binary dynamic AABB tree. The algorithm is shown in Algorithm 1, which is a recursive method. We start with two root nodes of the two trees. If both of them are leaf node, we perform the narrow phase collision between the object corresponding to the given dynamic AABB tree node and one cubic cell in the octree. Otherwise, we need to check for collisions between the subtrees rooted at the corresponding two nodes. If the given octree node is not a leaf node, we recursively perform collision between each of its eight children nodes and the given dynamic AABB node. Otherwise, we recursively perform collision queries between the given octree node and the two children of the given dynamic AABB node. The recursion continues until the collision is detected. One major issue is mentioned in Algorithm 1 at line 8: we only perform collision queries for octree cells with occupancy probability larger than a given threshold. This is because the octree representation of sensor data that we use can encode uncertain or unknown regions in the environment and we want the result computed by the new method to be consistent with result provided by the simple ad-hoc pipeline in Figure 1a, where octree cells are converted into boxes only if their occupancy probability is larger than a given threshold.

Algorithm 1: `collisionRecurse(node1,node2)`, `node1` is one node of the octree structure, and `node2` is one node from the other binary tree structure that is used to perform collision checking with the octree. The second tree structure can represent a dynamic AABB tree working as the broad phase structure for all the links of an robot, or an OBB tree for one mesh, or even a single geometric shape (i.e., a tree with only one node).

```
1  begin
2      if node1.isLeaf() and node2.isLeaf() then
3          if overlap(node1.bv,node2.bv) then
4              narrow phase collision between the octree box in
               node1 and the object in node2
5          return collision status
6      if node2.isLeaf() or (node1.hasChildren() and
       node1.bv > node2.bv) then
7          for i = 1 to 8 do
8              if node1.child(i).occupancy_prob() >
               threshold then
9                  collisionRecurse(node1.child(i),
                   node2)
10     else
11         collisionRecurse(node1, node2.leftChild())
12         collisionRecurse(node1, node2.rightChild())
```

Similar recursive traversal can be used to handle the distance computation between the robot and sensor data. Moreover, a binary tree can also be used to represent other types of data, e.g., a mesh can be represented as a binary AABB or OBB tree [9] and a geometric primitive (e.g., a sphere) can be represented as a binary tree with only root node. As a result, the same recursive formulation can be used to handle the collision and distance query between the sensor data and a mesh, or the sensor data and a geometric primitive.

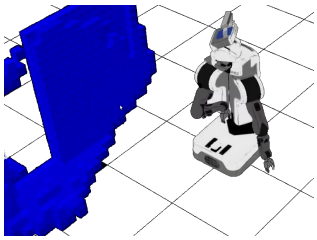
C. Collision Checking with Uncertain/Unknown Regions

The data gathered by various sensors tend to have error and noise. For example, the camera or laser may not be correctly calibrated and thus the generated point clouds may have systematic bias. Many sensors only have limited precision, which results in sampling error in the sensor data. Moreover, part of the environment may not be observed by the sensor, because sensors only have limited field of view and may have a large blind spot. It is important to handle the uncertain or unknown part of the sensor data so that robots can work robustly in real world scenarios.

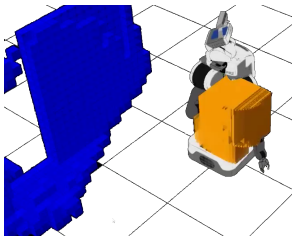
The unknown or uncertain regions are usually assumed to be collision-free, e.g., such an optimistic assumption is

made in [13]. This assumption can cause serious problems in some cases. In the example shown in Figure 3a, the sensor mounted on the robot's head cannot cover the region near the robot's left arm. Therefore, given a path for the left arm moving through the unknown region, the collision checking routine will always return collision-free, even if obstacles exist in that region. Our solution here is to compute a set of boxes representing different regions in the unknown space that intersect with the swept volume of the robot's path. Only boxes with the largest occupancy probability are returned, because they are the most important regions to check when determining whether the given path is collision free. Given these boxes as shown in Figure 3b, users can implement different strategies according to different applications. For example, the robot can try to avoid the unknown regions completely, minimize its motion through the unknown regions or actively sense the unknown regions to gain more information about them.

The intersection between the unknown space and the swept volume of the robot's path can be performed by checking the collisions between the octree and a series of samples on the path. Each collision query can be computed according to a recursive method which is similar to Algorithm 1. However, in this approach, we won't include the step shown in line 8, because we need to consider the unknown and uncertain octree cells besides the cells that are definitely occupied.



(a) Only perform collision checking between the planned trajectory and the regions that are known to be occupied (the blue part) in the sensor data



(b) Perform collision checking between the planned trajectory and both the known and unknown regions in the sensor data

Fig. 3: Environment representation can contain unknown or uncertain regions in the environment. In the case shown by (a), the sensor on the robot's head cannot cover the region near its left arm. Therefore, a path for the left arm will always appear valid if we ignore unknown regions of the environment and make an optimistic assumption, even though obstacles could possibly exist in that region. Our solution is shown in (b), where we compute a set of boxes (shown in brown) that cover the intersections of robot links and unknown parts of the environment. Using these boxes a notion of cost can be easily defined by the user, e.g., using the sum of the occupancy probability of all the boxes.

V. Results

In this section, we present the performance of our new collision checking and distance computation algorithms when handling the sensor data.

In the first experiment, we use a synthetic environment. First, we generate 300 randomly located objects (100 spheres, 100 boxes and 100 cylinders). We then construct a dynamic AABB tree broad phase structure to manage these objects. Next, we randomly generate an octree structure with $7,784$ cells to simulate the sensor data. Our task is to perform collision or distance queries between the dynamic AABB tree and the sensor data. The reported performance for a single query is the average of the cost for $1,000$ queries. For all experiments on collision query, we compare the overall timing when performing 10 and 100 queries. For all experiments on distance query, we only compare the overall timing when performing a single query, because distance query is much more expensive than collision query and thus the time slot for one sensor frame is usually only enough for a single query.

First we compare the performance between our amortized approach and the traditional non-amortized method and the results are shown in Table I. We can see that the amortized approach saves more than 50% of the broad phase structure construction time, while the actual collision query is only a bit slower. According to this result, the amortized approach is faster than traditional methods when the number of actural queries is 10 and 100. As a matter of fact, the amortized approach is faster than traditional methods if number of actual queries is smaller than $38,300$, which is much larger than the number of collision queries that can be performed during one sensor data frame.

Next, we compare the performance between the ad-hoc pipeline in [13] and our new pipeline. The results for the collision query are shown in Table II. In Table II(a), all the objects are represented as primitive shapes and the octree is also converted into primitive boxes for the ad-hoc pipeline, while in Table II(b), the objects and boxes generated from octree are in the form of meshes. In the first case, the actual collision cost in the new pipeline is about two times of the cost in the ad-hoc pipeline, but the saved overhead cost is much larger than a single query. As a result, the new pipeline performs better than the ad-hoc pipeline if the actual number of queries is smaller than 300. In the second case, even the cost of a single query in the new pipeline is smaller than the ad-hoc pipeline. The results for the distance query are shown in Table III. Similar to the collision case, the overhead cost is saved in distance query and the overall performance is improved in the new pipeline. However, as the distance query is much more expensive than the collision query, the performance improvement caused by saving the overhead of data preparation is not as large as in the collision case. Moreover, note that we assume all the steps in both pipelines can share the data efficiently and therefore we can ignore the data transmission overhead between different steps. For distributed robot systems, such transmission overhead can be large and therefore we underestimate the performance improvement caused by the new pipeline, because the new pipeline has fewer steps than the ad-hoc pipeline.

In the second experiment, we perform collision or distance query between a PR2 robot and the sensor data. The PR2 robot has 88 links, some are in the form of primitive geometric shapes (e.g., cylinders and spheres) and others are represented as meshes. The sensor data is an octree with $24,803$ cells. For collision queries, PR2's average penetration depth into the obstacles is 2.8 *cm*. For distance queries,

PR2's average distance to the obstacles is 3.4 *cm*. Note that collision or distance queries are slow for queries with small penetration depth or with small distance to the obstacles, because the AABB bounding box cannot perform culling effectively in these cases. As a result, the scene is challenging for collision and distance queries. The results are shown in Table IV and we observe similar performance improvement on real-world sensor data with PR2 robot, as in the synthetic case.

From these results, we can see the difference between the ad-hoc pipeline using amortized approach and the new pipeline. The amortized approach only reduces the overhead instead of completely avoiding it, but the performance reduction on a single actual query is small. The new pipeline completely avoids the overhead, but the time cost for one actual query may be notably larger than the traditional pipeline. As a result, the amortized approach is more suitable for the case where the number of actual queries per sensor frame is large, e.g., when the environment does not change frequently and the sensor frame rate is small; or when there are only a few obstacles in the environment. The method using the new pipeline is more suitable for dynamic environments with high sensor data frame rate or environments with many obstacles.

	T_1	T_q	$T_1+10\cdot T_q$	$T_1+10^2\cdot T_q$
non-amortized	2.07	$4.49\cdot 10^{-3}$	2.11	2.52
amortized	0.92	$4.52\cdot 10^{-3}$	0.96	1.37

TABLE I: Performance comparison between ad-hoc pipeline with and without amortized broad phase structure construction (in ms).

	$T_{1,1}$	$T_{1,2}$	T_q	$T_1+10\cdot T_q$	$T_1+10^2\cdot T_q$
ad-hoc pipeline	2.283	5.389	0.022	7.89	9.872
our pipeline	0	0	0.048	0.48	4.8

(a) Objects and boxes are in the form of geometric primitives

	$T_{1,1}$	$T_{1,2}$	T_q	$T_1+10\cdot T_q$	$T_1+10^2\cdot T_q$
ad-hoc pipeline	2.697	5.465	0.317	11.3	39.9
our pipeline	0	0	0.075	0.75	7.5

(b) Objects and boxes are in the form of meshes

TABLE II: Collision query performance comparison between the ad-hoc pipeline in [13] and our new pipeline (in ms). In both pipelines, the 300 objects in the environment are in the form of primitive geometric shapes or meshes. For the ad-hoc pipeline, the boxes generated from the octree are also represented as primitive boxes or meshes, respectively.

VI. Conclusions

We presented two approaches for efficiently performing collision and distance queries on sensor data, when compared to traditional methods. The first method amortizes the sensor data pre-processing overhead over all the queries and is suitable for static or simple environments. The second method shortens the traditional pipeline by directly performing queries between the robot links and an octree that represents sensor data. This approach completely avoids the data pre-processing overhead and is suitable for dynamic or complex environments. We demonstrated the performance of the two methods on synthetic benchmarks and on environments constructed using the RGB-D sensor mounted on the PR2 robot. Our new approach also supports collision queries for sensor data with uncertain or unknown regions. In summary, the techniques we propose in this paper will help in making collision checking and distance queries with real sensor data more efficient, improving the reactive behavior of robots operating in unstructured environments and allowing them to deal better with uncertain information about the environment.

For future work, we are interested in further improving the collision checking and distance query implementations. We are also interested in applications of this work to motion planning and active sensing, e.g. to design strategies for gaining more information about uncertain or unknown parts of the environment.

	$T_{1,1}$	$T_{1,2}$	T_q	T_1+T_q
ad-hoc pipeline	2.665	5.381	23.98	32.03
our pipeline	0	0	17.40	17.40

(a) Objects and boxes are in the form of geometric primitives

	$T_{1,1}$	$T_{1,2}$	T_q	T_1+T_q
ad-hoc pipeline	2.871	5.413	68.03	76.31
our pipeline	0	0	61.86	61.86

(b) Objects and boxes are in the form of meshes

TABLE III: Distance query performance comparison between the ad-hoc pipeline in [13] and our new pipeline (in ms). In both pipelines, the 300 objects in the environment are in the form of primitive geometric shapes or meshes. For the ad-hoc pipeline, the boxes generated from the octree are also represented as primitive boxes or meshes, respectively.

	T_1	T_q	$T_1+10\cdot T_q$	$T_1+10^2\cdot T_q$
ad-hoc pipeline	0.131	0.00127	0.1437	0.258
our pipeline	0	0.00135	0.0135	0.135

(a) PR2 collision

	T_1	T_q	T_1+T_q
ad-hoc pipeline	0.163	0.039	0.202
our pipeline	0	0.078	0.078

(b) PR2 distance

TABLE IV: Collision and distance query performance comparison between the ad-hoc pipeline in [13] and our new pipeline on the PR2 robot (in ms).

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