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Measuring 3D-reconstruction quality in probabilistic volumetric maps with the Wasserstein Distance

Stéphanie Aravecchia¹, Antoine Richard², Marianne Clausel³, Cédric Pradalier¹

Abstract—In this study, we address the challenge of measuring 3D-reconstruction quality in large unstructured environments, when the map is built with uncertainty in the robot localization. The challenge lies in measuring the quality of a reconstruction against the ground-truth when the data is extremely sparse and where traditional methods, such as surface distance metrics, fail. We propose a complete methodology to measure the quality of the reconstruction, on a local level, in both structured and unstructured environments. Building upon the fact that a common map representation in robotics is the probabilistic volumetric map, we propose, along this methodology, to use a novel metric to measure the map quality based directly on the voxels’ occupancy likelihood: the Wasserstein Distance. Finally, we evaluate this Wasserstein Distance metric in simulation, under different level of noise in the robot localization, and in a real world experiment, demonstrating the robustness of our method.

I. INTRODUCTION

In this work, we are interested in large scale natural environments, such as parks or forests, sometimes called “unstructured” ([1, 2]), in opposition to environments containing large geometrical shapes, such as buildings, called “structured”. In a large scale unstructured environment, not only computing an accurate 3D map, with a 3D-Lidar, is particularly difficult but also measuring the quality of the produced map is a challenging task in itself.

When building the map in unstructured environments, among the main challenges, we can specifically highlight the sparsity of the data and the robot localization ([1, 2]). To begin with the sparsity, the output from an affordable 3D-Lidar is sparse. For example, the Ouster-16 used in this study provides only 8,192 points at 10 Hz, whereas the number of points is generally 100 times higher and the frame rate at least 3 times higher when considering an RGBD camera or the point-cloud derived from visual odometry algorithms. In addition to the sparsity of the laser output, the environment itself leads to a sparse reconstruction. For example, trees, by their very structure, are sparse because they offer only an aggregation of small surfaces to the Lidar. Although the sampling of a trunk from a Lidar could be dense, the sampling of small branches or leaves, will generally not be high enough to recover the underlying structure. Moreover, from a laser’s perspective, trees can behave as semi-transparent structures, thereby inducing errors in the measurements. The reason is that when laser-rays – light cones in practice – reach a small object, like a branch, often only a portion of the energy

is reflected, causing inaccurate distance readings. Two other causes of errors in laser measurements, that are particularly abundant in large scale natural environments, are linked to the distance to the objects and the incidence angle: the error increases with each of them [3]. Finally, the localization of the robot in the map is also a source of errors because the 3D-reconstruction is a probabilistic accumulation of all the point-clouds transformed in the localization frame.

In a robotic monitoring or inspection task, an important question to consider is “how accurate is the map locally?”. With sparse 3D-reconstructions, in unstructured environments, answering this question is ambiguous. First, because the definition of ground-truth is not straightforward: how to acquire the real ground-truth of a park-like environment? Furthermore, because most classical methods, based on statistics on surface distances, require a reconstructed surface to measure the distance between the reconstruction and the ground-truth. We will show that for natural environments, attempting to reconstruct surfaces that match the actual surfaces of trees, trunks, small branches and leaves is doomed to fail. We circumvent this issue by measuring the quality of the reconstruction not on the surfaces, but directly on the probabilistic map. We propose to measure the “distance” between the occupancy likelihood in the 3D-reconstruction and the occupancy likelihood in the ground-truth. This measure is given by the Wasserstein Distance.

Finally, to obtain local information about the quality of the 3D-reconstruction, we propose a methodology to compare reconstruction to ground-truth on a local level. The code to reproduce the method and experiments is open-source ¹.

To summarize, our contributions are:

- a methodology to compare locally 3D-reconstruction and ground-truth, applicable both in structured and unstructured environments;
- a metric to measure the quality of a sparse 3D-reconstruction, also applicable to both structured or unstructured environments: the Wasserstein Distance.

II. RELATED WORK

A. Map building

The most common ways to represent maps are volumetric maps, i.e. 3D-grids, and meshes, i.e. 3D-surface maps.

Meshes are generally obtained from either a Lidar point-cloud or from the point-cloud derived from visual odometry. In a mesh, the surface is described by connected triangles.

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¹<https://github.com/stephanie-aravecchia/3d-reconstruction-metrics.git>

An optimization algorithm is applied on the point-cloud to build the mesh. Among the most widely used techniques, we can cite Ball-Pivoting Algorithm [4], Poisson Surface Reconstruction [5] or Delaunay triangulations [6]. Although results on the meshing of a single object is widely shown in the literature, meshing large scale natural environments is still a problem which is not solved. Some meshes can be derived, but they are generally a rough approximation of trees and bushes.

In this paper, we focus on a more common map representation for outdoor robotics: volumetric maps. Such a map is a discretization of the space in voxels, each voxel containing some information, such as its occupancy likelihood. [7] presented Octomap, a method to build and store an octree instead of a 3D-grid, saving memory and computation. The open-source Octomap library implements the complete probabilistic map building process. The map is constructed in a given map frame, and every point-cloud in the Lidar frame updates the map. For each point in the point-cloud, a ray-casting operation is performed. Between the robot and the returned point, the probability of occupancy of the leaves in the octree is decreased. The returned points are updated as occupied, their probability of occupancy is increased. A thorough update process has been implemented to be robust to noise in the Lidar’s point-cloud. We use Octomap to build the probabilistic volumetric map denoted as “reconstruction” in this paper.

It is also important to note that the quality of the map is intrinsically linked to the precision of the robot localization and that solving the localization in large scale natural environment is still challenging. Since the point-clouds are expressed in the Lidar frame (which is based on the robot’s localization), any error in the transformation from the Lidar frame to the map frame will lead to errors in the map [1]. In this work, we do not deal with solving the localization problem, but evaluate our method with different level of noise in simulation, and with a real experiment.

B. 3D-reconstruction metrics

In the context of 3D-reconstruction, several metrics exists to measure the quality of the 3D-reconstruction.

Generally, when considering 3D-reconstruction, the objective is to compare two surfaces: the mesh generated from the 3D-point cloud, and the ground-truth mesh. The traditional metrics in that case are based on surface distance errors. They consist in calculating, for all surface points of one surface, the distance to the closest on the other surface. Statistical metrics are then extracted, among which we typically see the Hausdorff Distance, the Root Mean Square Error (RMSE) or the MAE (Mean Average Error) ([8, 9, 10]).

In the context of robotics, the surface coverage is derived from those surface distance errors, and applied either on the meshes or on the 3D-grids. In that case, if the distance between a ground-truth point and its closest reconstructed point is less than a registration distance, the ground-truth point is considered as observed. The metric is the proportion of such points ([11, 12]).

The fact that those metrics aim at measuring the quality of a dense reconstruction, i.e. reconstructing dense objects

with high density point-clouds, is their main limitation. In the context of unstructured environments, the 3D-reconstruction tends to remain sparse, because only a few voxels will reach the threshold probability for them to be considered occupied. Therefore, in a sparse reconstruction, of an unstructured environment, the level of information is not sufficient to recover a surface, as we will also show later. This means that none of the previously seen metrics are adequate to evaluate sparse 3D-reconstructions of unstructured environments. Furthermore, those methods solely focus on the reconstruction of occupied voxels, and not on empty space. In the context of large scale environments with sparse objects, it is also interesting to measure how well empty space has been reconstructed.

C. Comparing probabilities

Since we are building a probabilistic volumetric map with Octomap, we could take advantage of that framework to measure the quality of the map. Each voxel in the probabilistic map has a probability of occupancy between 0%, the absolute certainty that the voxel is empty, and 100%, the absolute certainty that the voxel is occupied. Leveraging the probabilities inside a 3D-grid is not a novelty, and has been explored in [11]. However, they do not propose a mean to compare the reconstructed volume to a reference one. In this paper, we propose a methodology to compare two volumetric maps with probabilistic values. Something that, to the best of our knowledge, has not been done before.

Different methods allow comparing probabilities. The most common is probably the Kullback-Leibler divergence (DKL): a measure of how different two probability distributions are. Nonetheless, since we are considering a grid of probabilistic voxels, we have access to another information: the Euclidean distance between voxels. As an example, if a point is erroneously reconstructed 5 cm away from an actual object, the reconstruction is better than if the erroneous point is 50 cm away. The DKL is not sensitive to this difference. An alternative solution is then to calculate the Optimal Transport plan, linking one probability distribution to another one, with a cost function depending on the geometry [13]. From this Optimal Transport plan, we can calculate a distance, the Wasserstein Distance which is a generalization of the concept of Earth Mover’s Distance (EMD). To bypass computational issues, [14] regularizes the optimal transport problem by adding an entropic term, and solves it using a Sinkhorn’s fixed point iteration. [15] has implemented an open source Python library providing several solvers for Optimal Transport problems, including [14]’s algorithm. With the Wasserstein Distance, or its regularized variants, we can measure the quality of the 3D-reconstruction, comparing not only the ground-truth and reconstructed values of probabilistic maps but also taking into account the Euclidean distances in the errors.

III. METHOD

The objective of our method is to compare 3D-reconstruction to ground-truth, and to measure the quality of the reconstruction on a local level. To do so, we discretize the space into cuboid regions and calculate a reconstruction metric for each cuboid.

A. Cuboid region comparison

This section explains how we extract the cuboids regions from the reconstruction and from the ground-truth. The 3D-reconstruction is obtained from the full probability map constructed by Octomap, the ground-truth is either the mesh of the scene used in simulation, or the point-cloud obtained when scanning the area with a Total Station (Sec. IV-A).

To compare two cuboid regions of both the ground-truth and the reconstruction, we first construct two 3D-grids, of the ground-truth and of the reconstruction, in the same reference frame. We then compute the intersection, and finally we compare a cuboid region of the ground-truth to the cuboid region of the reconstruction, corresponding to the same volume in space (Alg. 1).

For the ground-truth in the simulated environment, we first slice the ground-truth mesh with horizontal planes, with a vertical space of res , our spatial resolution. In each plane, we then calculate the intersection of the mesh and the plane, and we store it in a 3D matrix of voxel size res . Each occupied voxel has a value of 1.0, each empty voxel a value of 0.0. For the ground-truth in the real experiment, we construct a 3D matrix of voxel size res containing zeros. We iterate on the point-cloud from the Total Station, and for each point, we set the value of the corresponding voxel to 1.0. Our ground-truth dataset, \mathcal{D}_{gt} , is then a 3D matrix of size (h_1, w_1, n_1) , with its associated bounding-box $B_{\text{box}1}$ in a reference frame R_f . For the reconstruction, we first create a full probability map with Octomap in the same reference frame R_f , and with the same resolution res . From this octree, we select a bounding-box in R_f , and we initialize a 3D matrix as unknown space, i.e. values of 0.5, corresponding to the equal probability of the voxel to be occupied or empty. The size of the matrix depends on the bounding-box and res . We then iterate on all the leaves in the octree and update the probability of the voxels corresponding to the leaves (the unknown space is implicitly described in Octomap with absent leaves). We finally obtain the reconstruction dataset, \mathcal{D}_{rec} , a 3D matrix of size (h_2, w_2, n_2) , with a voxel resolution res , with its associated bounding-box, $B_{\text{box}2}$, in the same reference frame, R_f .

Finally, we do the comparison in $B_{\text{box}1} \cap B_{\text{box}2}$. First, we load the intersection of both datasets in two 3D matrices, M_{gt} and M_{rec} : a voxel v_{gt}^{ijk} from M_{gt} corresponds to the same volume in R_f than v_{rec}^{ijk} from M_{rec} . Second, we go through both 3D matrices, and compare cuboid region by cuboid region, the reconstruction and the ground truth. A cuboid region is a group of $n \times n \times n$ voxels in each 3D matrix, and is noted C_{gt} or C_{rec} . Those cuboid regions are in fact voxels of size $RES = n \times res$, in the 3D-grid $B_{\text{box}1} \cap B_{\text{box}2}$, in R_f .

B. Comparison metrics

This section explains how, for each cuboid region, we compute different metrics to indicate the quality of the reconstruction (Alg. 2).

To measure the quality of reconstruction, we propose to partition the volume in two: the cuboid regions containing something to reconstruct, and the cuboid regions containing

only empty space. For the first part, we propose the Wasserstein Distance. For the second part, we simply propose the L_1 norm.

Furthermore, because measuring the quality of reconstruction of unknown space is pointless, we consider a threshold before calculating our metrics. If all the probabilities in C_{rec} are close to the unknown (0.5 ± 0.1), we do not calculate the metrics, but set them to the maximum values WD_{occ}^{max} and L_1^{max} .

1) *Wasserstein Distance*: The Wasserstein Distance is derived from the optimal transport plan to “move” the mass distribution from a query vector to match the mass distribution of a reference vector. The cost of moving the mass being a function of the Euclidean distance it has to be moved by. Here, we calculate the Wasserstein Distance between two cuboid regions.

First, we remap all the elements of C_{gt} and C_{rec} into two vectors of doubles, V_{gt} and V_{rec} , such that $\forall(i, j, k) \in \llbracket 0, n \rrbracket, V_*(i \cdot n^2 + j \cdot n + k) = C_*(i, j, k)$

Second, we derive from each vector, two different vectors. From V_{gt} , we derive $V_{gt}^{occ} = \max(2V_{gt} - 1, 0)$ and $V_{gt}^{free} = \max(1 - 2V_{gt}, 0)$. They contain respectively the probability of an element to correspond to an occupied voxel, and the probability of an element to correspond to an empty voxel. We then normalize each vector by their sum and obtain two vectors of probability distributions P_{gt}^{occ} and P_{gt}^{free} . Similarly, from V_{rec} , we obtain P_{rec}^{occ} and P_{rec}^{free} . We do this partition between occupancy and emptiness because we observed that the Wasserstein Distance between P_{rec}^{occ} and P_{gt}^{occ} , which embeds in each element the distance from its probability of occupancy to the unknown, contains more signal. Moreover, this corresponds better to what we intend to measure with this metric, that is how well the occupied space has been reconstructed.

Finally, we calculate WD_{occ} , the Wasserstein Distance between P_{rec}^{occ} and P_{gt}^{occ} , using the Sinkhorn algorithm described in [14], following the implementation of [15]. The cost matrix is set to contain the squared Euclidean distance between the voxels associated to the element of each vector.

2) L_1 norm: In a cuboid region of the ground-truth containing only free space, all the voxels have a probability of occupancy of 0. Therefore, when comparing the reconstruction to the ground-truth, we are comparing a vector containing some probabilities of occupancy V_{rec} to a vector of the same size containing only zeros (absolute certainty of emptiness). Calculating the optimal transport plan makes little sense, because there is no mass distribution on the reference vector. Hence, the Euclidean Distance the mass has to be moved by is not relevant, as long as the mass is evenly distributed to a uniform distribution at the end. Furthermore, what is interesting is only how different the emptiness likelihood is from actual emptiness. Such a measure is given by the L_1 norm of V_{rec} : the distance between V_{rec} and the vector of zeros that represent the empty space.

C. Evaluation Methodology

In order to evaluate our metric WD_{occ} , we first assess that the metric is meaningful. Then, we compare WD_{occ} against a

Algorithm 1 Reconstruction and ground-truth comparison

```

//  $\mathcal{D}_{gt}$  and  $\mathcal{D}_{rec}$  are the datasets
 $\mathcal{D}_{gt}(B_{\text{box}1}, (h_1, w_1, n_1), R_f)$ ,  $\mathcal{D}_{rec}(B_{\text{box}2}, (h_2, w_2, n_2), R_f)$ 
 $B_{\text{box}} \leftarrow B_{\text{box}1} \cap B_{\text{box}2}$ 
 $M_{gt} \leftarrow \mathcal{D}_{gt}(B_{\text{box}})$ ,  $M_{rec} \leftarrow \mathcal{D}_{rec}(B_{\text{box}})$ 
for all cuboid  $\in B_{\text{box}}$  do:
   $C_{gt} \leftarrow M_{gt}(\text{cuboid})$ ,  $C_{rec} \leftarrow M_{rec}(\text{cuboid})$ 
  if isObserved( $C_{rec}$ ) then
    cuboid.computeMetric( $C_{rec}$ ,  $C_{gt}$ )
  else
    cuboid.setMetricToMax()
  end if
end for

```

Algorithm 2 Metric Computation

```

 $V_{gt} \leftarrow \text{getVectorFromCube}(C_{gt})$ 
 $V_{rec} \leftarrow \text{getVectorFromCube}(C_{rec})$ 
if not isOnlyZeros( $V_{gt}$ ) then
   $V_{rec}^{occ}, V_{rec}^{free} \leftarrow \text{getFreeAndOccVectors}(V_{rec})$ 
   $V_{gt}^{occ}, V_{gt}^{free} \leftarrow \text{getFreeAndOccVectors}(V_{gt})$ 
   $P_{rec}^{occ}, P_{gt}^{occ} \leftarrow \text{normalizeToDistribution}(V_{rec}^{occ}, V_{gt}^{occ})$ 
  Metric  $\leftarrow \text{WassersteinDistance}(P_{rec}^{occ}, P_{gt}^{occ})$ 
else
  Metric  $\leftarrow L_1(V_{rec})$ 
end if

```

traditional metric: the surface coverage.

To assess that WD_{occ} is meaningful and is a distance that actually measures the 3D-reconstruction quality, we select randomly n cuboids C_{gt} from the ground-truth containing at least one occupied point. We then simulate several “ideal” reconstructions: we apply to C_{gt} a 3D Gaussian convolution, with different kernel size and sigmas, and then add a uniform noise. We also simulate a random reconstruction. Finally, we calculate WD_{occ} on those cuboids. If the value of WD_{occ} is significantly smaller for an ideal reconstruction than from a random reconstruction, we can conclude that WD_{occ} is a meaningful metric of 3D-reconstruction quality.

To calculate the surface coverage, we apply the classical methodology in a 3D-grid: all the points in the 3D-grid are considered belonging to the surface if their occupancy likelihood is above a threshold. We calculate the Euclidean distance between a ground-truth point S and the closest reconstructed point P . If the distance SP is below a registration distance, the point is considered reconstructed. The total number of ground-truth points is n_S , the total number of considered reconstructed points is n_{rec} . The surface coverage is then $cov = n_{rec}/n_S$.

Finally, to compare WD_{occ} and cov , we compare their ability to measure 3D-reconstruction quality. To assess if a metric is able to measure the reconstruction quality, we simply consider if the metric contains or does not contain information. Here, we do not consider the quality of the reconstruction in itself, but the ability of the metric to measure this quality. For cov , we simply consider that if $cov > 0$, it contains information.

For WD_{occ} , we consider that if $WD_{occ} < WD_{occ}^*$, then it contains information. We set the limit WD_{occ}^* to the mean of the values calculated before with random reconstructions, in the same environment. Lastly, we calculate, for each metric, the proportion of cuboids for which the metric contains information, in the population of cuboids for which a metric is calculated (observed cuboids containing at least one ground-truth voxel to reconstruct). The higher the proportion, the more informative the metric.

IV. EXPERIMENTS AND RESULTS

Our experiments are done in simulation and on the field. In both cases, we use the ROS framework and the robot is a Clearpath Husky, equipped with a 3D Lidar Ouster OS1-16 (16 planes of 512 points).

A. Experimental Setup in Simulation

The simulator is Gazebo. A mixture of noise is applied to the Lidar to simulate better the behavior of a Lidar in outdoor natural environments.

We generate randomly several environments. Each environment is a plane of dimension $60m \times 60m$ on which we place assets with a Poisson Cluster Point Process², to reproduce the natural implantation of trees. The assets can be either rectangular cuboids or randomly selected in our 15-trees library, where simulated trees are created with a space colonization algorithm³. Due to computational considerations in Gazebo, we create only trees without leaves. A random scaling factor is applied on the x, y and z dimensions of the assets, as well as on their orientation.

With the same point process generation, we create two different synthetic environments. The first one contains only rectangular cuboids: the structured environment. The second one contains only trees: the unstructured environment. With the open-source Blender software, we create a single shapefile (.stl) for each environment. This ensures that the mesh we slice to obtain the 3D-grid ground-truth is the same used in Gazebo to infer the collisions of the Lidar, hence to construct the map.

Next, we run a simulation for each environment where the robot is following the same list of waypoints, set manually.

Since the quality of the reconstruction is directly linked to the localization of the robot, we incrementally add noise in this localization. For each noise level, we build a probabilistic map with Octomap. To obtain the different noise levels, we use the perfect localization from Gazebo on which we apply a Gaussian noise on the position and on the orientation. The noise levels presented here are (with σ_p , standard deviation on position, in m, σ_q , on orientation, in rad): • **noise 0**: perfect localization; • **noise 1**: $\sigma_p = 0.005$, $\sigma_q = 0.005$; • **noise 2**: $\sigma_p = 0.05$, $\sigma_q = 0.01$; Errors in the orientation estimation lead to large errors in the position of far away points (i.e a 0.01 radian error in the orientation leads to a 0.25m error in the position of a 25m distant point in the Lidar point-cloud).

We generate 6 environments (3 different point processes with 1 structured, 1 unstructured each). For each environment,

²<https://pointpats.readthedocs.io/>

³<https://github.com/dsforza96/tree-gen>

and for each of the 3 noise levels, we build two 3D-grids with Octomap (max-range $25m$), one with resolution $res = 0.05m$, the other $res = 0.1m$. In total, we have 36 reconstructions to compare to 6 ground-truths.

B. Experimental Setup in the field

The experimental field is a small park containing trees, of an approximate area of $1500m^2$. Although it is not possible to acquire the ground-truth of such an environment, we consider that the 3D point-cloud obtained from the scan of the environment with a Total Station Leica TS60 is precise and dense enough to be considered as ground truth. The horizontal and vertical angular resolution of the scanning is set to 0.05 degrees. To scan the area, the Total Station is placed on three different locations, to have different point of views on the trees. Each scan takes 40 to 60 minutes. At the end, we obtain a single consistent point-cloud from the area. To localize the robot in this area, we track it with the Total Station. The robot is equipped with a prism, that is localized by the Total Station with centimeter accuracy. In a post-processing phase, we recover the orientation by fusing, in an Extended Kalman Filter, the localization from the Total Station, the wheel odometry of the robot, and the IMU. To avoid large errors due to large uncertainty in the orientation, we filter out the Lidar scans associated to turning motions of the robot when we build the map with Octomap. With this setup, we can consider we have a “good” localization for an outdoor robotics application. For this experiment, we obtain two reconstructions with Octomap (max-range $10m$): one with resolution $res = 0.05m$ and one with $res = 0.1m$: we have two reconstructions to compare to one ground-truth.

Ultimately, the volumetric maps are compared to the ground-truth as described in III, with a cuboid resolution of $RES = 10 \times res$. In the experiments, we are interested in comparing the reconstruction of salient objects, not the ground. To enforce it, we apply a threshold on the Z coordinates of the bounding-box on which we perform the comparison.



Fig. 1: Challenges with meshing: (a) the real tree, (b) the point-cloud from the Total Station (c) an example of mesh failing to describe the actual surface of the fine elements of the tree.

C. Results

After processing the data as explained in III, we obtain for each cuboid containing at least a voxel to reconstruct the reconstruction quality metric WD_{occ} and other metrics we will compare our method to.

1) *Surface Distance Metrics*: The underlying idea behind our method stems from the issues we encountered when trying to use surface distance metrics. Fig. 1 illustrates the difficulties when trying to reconstruct the surface of a tree. The point-cloud used here is the point-cloud from the Total Station (i.e.

our ground-truth). As we can see, it is dense on the trunk of the tree and on the larger branches, but really sparse on the small branches and on the leaves, where the sampling is not sufficient to recover the surface. As a consequence, classic meshing methods are able to reconstruct the surface of the trunk, but fail when it comes to the rest of the tree (i.e. the unstructured part). The example shown in Fig. 1 is the mesh reconstructed with the pivoting-ball algorithm with the open-source software MeshLab. We tried all the meshing algorithms available in MeshLab, with default parameters, and that mesh is the best result. We do not claim that there is no solution to compute a better mesh, but we illustrate the difficulties with off-the-shelf algorithms. This mesh, although computed on a single tree with the point-cloud from a Total Station, is also representative of the challenges involved when reconstructing meshes with robot-mounted Lidars in a natural environment. For these reasons, we cannot apply directly any surface distance metric (such as the RMSE) on the reconstruction of that type of environment.

In the context of 3D-grids, a common solution to circumvent the meshing is to calculate the distances not between surfaces but between points. We calculate the surface coverage cov , as described in III-C, with the following parameters (p , the occupancy likelihood; d , the registration distance): • **cov 1**: $p = 0.8$, $d = 0.05m$ (as in [11, 12]); • **cov 2**: $p = 0.8$, $d = 0.1m$; • **cov 3**: $p = 0.7$, $d = 0.1m$; • **cov 4**: $p = 0.7$, $d = 0.15m$. Doing so, we have surface coverages with different levels of permissiveness to compare our metric to.

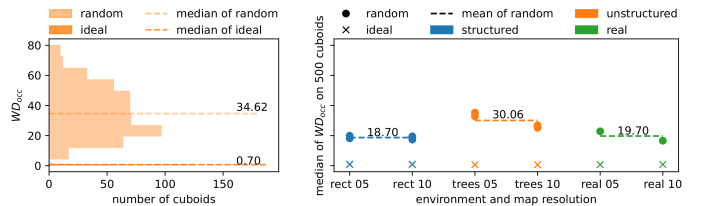


Fig. 2: Left: distribution of WD_{occ} on random and ideal reconstructions for an unstructured environment in simulation, on 500 cuboids, with the values of the medians. Right: summary of the medians of WD_{occ} on random and ideal reconstructions on all our environments. The dashed-lines are the limits for each environment (WD_{occ}^*).

2) *Our metric*: First, we demonstrate, as described in III-C, that our metric is meaningful. Fig. 2 shows the distribution of the calculated WD_{occ} . For visualization purposes on the “ideal” reconstruction, we only display the results for the one with kernel size 11, sigma 0.2 and uniform noise 0.1. The other results are similar. First, we can see that WD_{occ} is close to zero when the reconstruction is close to an ideal reconstruction. Our proposed metric is relevant to measure the 3D-reconstruction quality: it is small when the reconstruction is similar to the ground-truth, large if not. Second, we can see that the distribution of WD_{occ} when a random reconstruction is compared to the ground-truth is dependent on the environment. However, this is not significant with regard to the 3D-grid resolution. This figure also shows the limit WD_{occ}^* for each environment.

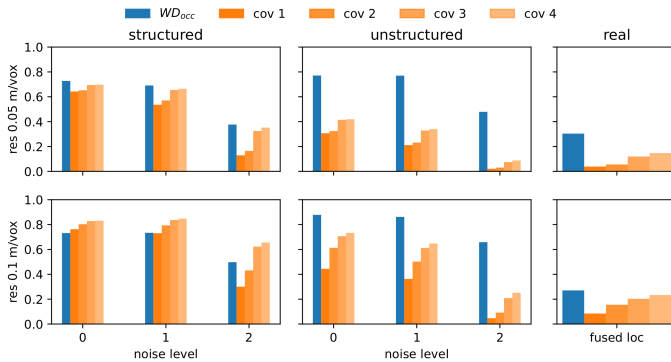


Fig. 3: Proportion of cuboids for which the metric is informative. Columns 1,2: results for the same point process simulation environment (1: structured, 2: unstructured), Column 3: real experiment. One line per map resolution (1: 0.05m/vox, 2: 0.10m/vox). Blue is the proportion of informative cuboids with our proposed metric (WD_{occ}), orange with different surface coverage (cov). The results are grouped by noise level.

Then, we demonstrate that our metric WD_{occ} is able to measure 3D-reconstruction quality in both structured and unstructured environments, whereas the more classic surface coverage cov tends to fail in unstructured environments, specifically when the robot localization is uncertain. We follow III-C. WD_{occ} is set to the values shown in Fig. 2. The results are shown in Fig. 3 for a single environment in simulation (structured and unstructured), and for the real experiment. The results for all the other simulated environments are similar. We can see that, as expected, cov is generally working in structured environments, although it is sensitive to uncertainty in the robot localization and to the map resolution. Additionally, in unstructured environments, with noise in the localization, the proportion of cuboids for which cov is informative is low. On the contrary, our proposed metric WD_{occ} is working both in structured and unstructured environments and is less sensitive than cov to map resolution or to noise in the localization. If we consider the map resolution of 0.05m/vox, that seems suitable for mapping trees in large scale natural environments, we can see that, in the case of noisy localization in simulation, WD_{occ} is 5 times more informative than the most permissive cov ($p = 0.7$, $d = 0.15m$). In the real experiment, even with what we can consider a good localization, WD_{occ} is still twice more informative than the most permissive cov .

V. CONCLUSION

We have shown that our proposed metric WD_{occ} is capable of measuring 3D-reconstruction quality both in structured and unstructured environments, even with noise in the robot localization, when traditional metrics such as surface coverage fail. Additionally, we have proposed a methodology to calculate the quality of the 3D-reconstruction on a local level, where the space is divided into cuboid regions. Based on these results, we can now foresee the integration of this metric into inspection and monitoring tasks, either by giving feedback to a human operator or by using them in an autonomous exploration framework. Looking even further, we intend to use this metric within the computation of a reward function for reinforcement learning algorithms.

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