Dense Outdoor 3D Mapping and Navigation with Pose SLAM

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***Abstract*— Pose SLAM is the variant of SLAM where only the robot trajectory is estimated and in which landmarks are solely used to compute relative constraints between robot poses. In previous work, we have developed efficient methods to build Pose SLAM maps that ponder the information content on odometry and measurement links to keep the graph of poses sparse. In this paper we show results of Pose SLAM mapping with our custom built 3D laser and an outdoor all-terrain mobile robot. Finally, we argue that Pose SLAM graphs can be directly used as belief roadmaps and, thus, used for path planning under uncertainty. We show how to plan trajectories with the lowest accumulated robot pose uncertainty, i.e., the most reliable path to the goal, taking into account the encoded uncertainty in the map. Results of this navigation strategy are demonstrated with our outdoor robot.**

I. Introduction

State of the art simultaneous localization and mapping (SLAM) methods can now manage thousands of features [6], [14], [21]. Unfortunately, feature-based representations can not be directly used for collision-free path planning since they do not provide much information about which routes in the map have been previously traversed safely, or about the nature of the obstacles they represent. Feature-based maps could be somehow enriched with obstacle or traversability-related information [15], but at the expense of a significant increase in complexity.

Further scalability is possible with trajectory-based representations [4], [10], [12]. In this case only the robot trajectory is estimated and landmarks are solely used to produce relative constraints between robot poses. In this context we have developed Pose SLAM, a very efficient trajectory-based representation that ponders the information content on odometry and measurement links to keep the graph of poses sparse [7].

An added advantage of Pose SLAM is that the poses stored in the map are, by construction, reachable and obstacle-free since they were already traversed by the robot when the map was originally built. Furthermore, since the robot trajectories are usually human-driven, they even satisfy mobility constraints not usually modeled in the robot controller, such as the existence of restricted traversable regions (grass or sidewalks), or the right of way along paths.

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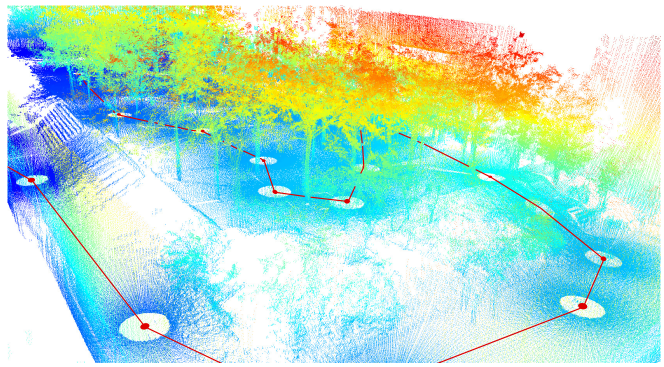

Fig. 1. A close in on the computed 3D range map and the robot trajectory.

In that sense, Pose SLAM graphs can be used to plan safe navigation paths, and we showed recently how this can be achieved for 2D laser-based maps [22]. We present in this paper results of the same technique for 3D laser-based mapping as shown in Fig. 1.

From the point of view of SLAM, this approach constitutes a step forward to actually use the output of the mapping process for path planning. Other approaches that attempt to use SLAM for path planning either ignore the uncertainty in the robot pose [11], [18] or in the map [3] whereas our approach takes both of them into account. From the point of view of motion planning, this algorithm contributes with a method to generate belief roadmaps without resorting to stochastic sampling on a predefined model of the environment [17].

Remapping and replanning, situations that arise upon contingency between expectations and measurements, should also be taken into account. We decide to keep these issues out of the scope of this contribution.

In Section II we summarize Pose SLAM and describe in Section III how to plan navigation paths using as roadmap the PoseSLAM graph. We show in Section IV an experiment that exemplifies the method with real data, and finally, in Section V we give some concluding remarks.

II. 3D Mapping with Pose SLAM

The Pose SLAM algorithm belongs to the variant of SLAM algorithms where only the robot trajectory is estimated and landmarks are solely used to produce relative constraints between robot poses. Pose SLAM maintains a compact state representation by limiting the number of links and nodes added to the graph using information content measures [7].

Formally, in Pose SLAM, the state vector $\mathbf{x} = [x_0^\top, x_1^\top, ..., x_n^\top]^\top$, contains the history of robot poses from time 0 to n, which is estimated from the history of odometric observations U and proprioceptive observations Z using a canonical parameterization of Gaussian distributions

$$p(\mathbf{x}|Z, U) = \mathcal{N}^{-1}(\mathbf{x}; \boldsymbol{\eta}, \mathbf{\Lambda}) \,, \tag{1}$$

where $\boldsymbol{\eta}$ is the information vector, and $\mathbf{\Lambda}$ is the information matrix.

Predictions and updates using this parametrization lead to an information filter, which compared to the traditional Kalman form, has the advantage of being exactly sparse for trajectory-based state vectors, such as ours [4].

New poses are added to the state vector as a result of the composition of odometric observations u_n with previous poses,

$$x_n = f(x_{n-1}, u_n) = x_{n-1} \oplus u_n. \tag{2}$$

And, for highly uneven and unpredictable terrain, such as the one in the experiments reported here, odometric data from the platform is unreliable and odometric observations are in fact computed by running the Iterative Closest Point (ICP) algorithm over two consecutively acquired point clouds.

As said, to keep the graph of poses sparse, redundant poses are not fed to the estimator. A new pose is considered redundant when it is too close to another pose already in the trajectory, and not much information is gained by linking this new pose to the map. However, if the new pose allows the establishment of an informative link, both the link and the pose are added to the map. The result is a uniform distribution of poses in the information space, as opposed to other more common methods that trim the number of odometric relations by distributing them uniformly in Euclidean space [10].

To determine if the current pose x_n is close to any other pose in the trajectory x_i, we estimate the relative displacement between them

$$d = h(x_i, x_n) = \ominus x_i \oplus x_n \tag{3}$$

as a Gaussian with parameters

$$\mu_d = h(\mu_i, \mu_n) \tag{4}$$

$$\mathbf{\Sigma}_d = \begin{bmatrix} \mathbf{H}_i & \mathbf{H}_n \end{bmatrix} \begin{bmatrix} \mathbf{\Sigma}_{ii} & \mathbf{\Sigma}_{in} \\ \mathbf{\Sigma}_{ni} & \mathbf{\Sigma}_{nn} \end{bmatrix} \begin{bmatrix} \mathbf{H}_i & \mathbf{H}_n \end{bmatrix}^\top \tag{5}$$

where $\mathbf{\Sigma}_{ii}$ and $\mathbf{\Sigma}_{nn}$ are the marginal covariances for the state variables at stake, $\mathbf{\Sigma}_{in}$ is their cross correlation, and $\mathbf{H}_i$ and $\mathbf{H}_n$ are the measurement Jacobians of the relative displacement d with respect to poses x_i and x_n, respectively. Marginalizing the distribution on the displacement for each one of its dimensions we get a set of 1-D Gaussian distributions that allow to compute the probability of each variable in pose x_i of being closer than a threshold to its corresponding variable in pose x_n. If, for all dimensions, these probabilities are above a given threshold s, then pose x_i is considered close enough to the current robot pose x_n, and there is no need to include x_n in the map, unless it establishes a highly informative link.

The amount of information of a link between any two poses is decided in terms of the amount of uncertainty that is removed from the state when such link is added to the pose graph; and measured as the mutual information gain, which for Gaussian distributions is given by the logarithm of the ratio of determinants of the covariance prior to performing the state update, and after the state update is made [2], [24]. This ratio is a multiple of the number of times state uncertainty shrinks once a loop is asserted. In [7] we show, that despite being a measure of global entropy reduction, it can be computed in constant time with a single compact expression:

$$\mathcal{I} = \frac{1}{2} \ln \frac{|\mathbf{S}|}{|\mathbf{\Sigma}_y|} \,, \tag{6}$$

where $\mathbf{S} = \mathbf{\Sigma}_d + \mathbf{\Sigma}_y$, and $\mathbf{\Sigma}_y$ is the measurement covariance.

Sensor registration is an expensive process, and in practical applications, it is convenient to hypothesize whether a candidate link is informative enough before actually aligning sensor readings. To that end, Eq. 6 is first evaluated using an approximation of the measurement covariance. If the result is above a given threshold g, sensor registration is needed to assert data association. The real sensor covariance is computed during sensor registration and can be used to recompute the gain measure to ultimately decide whether or not to update the state with the new link.

When establishing such a link, the update operation only modifies the diagonal blocks i and n of the information matrix $\mathbf{\Lambda}$, and introduces new off-diagonal blocks at locations in, and ni. These links enforce graph connectivity, or loop closure in SLAM parlance, and revise the entire state, reducing overall uncertainty. The operation has linear time complexity but takes place very sparsely. Hence Pose SLAM can be executed in amortized constant time [8].

III. Path Planning with Pose SLAM

Originally, research in motion planning assumed deterministic setups where a perfect model of the environment was available and where the configuration of the robot was known too. Many extensions have been introduced recently to deal with different sources of uncertainty, either in the model of the environment [13], by estimating the collision probability of drawn samples using a multivariate probability density of the world model; in the robot configuration [16], or in the effect of robot actions [1]. The extension that best matches the stochastic nature of the SLAM problem is the Belief Roadmap (BRM) [17]. In this approach, the edges defining the roadmap include information about the uncertainty change when traversing such edge. However, the main drawback of BRMs is that it still assumes a known model of the environment.

We overcome this limitation arguing that the map generated by Pose SLAM, or any other trajectory-based SLAM algorithm, is perfectly suited to be used as a belief roadmap. And have shown recently that using this map, planning can take place in belief space, allowing to compute optimal paths to previously visited locations taking into account the uncertainty along the path [22].

The main advantage of this method is that, marginal poses with small uncertainty estimates lead to more reliable sensor registration. Therefore, a plan to navigate through these areas would suggest lower risk of becoming lost during path execution.

We assume maximum likelihood actions and measurements during path planning. This implies that the mean estimate after a sequence of controls will lie at the mean of a node in the Pose SLAM graph and that the observation previously obtained at that position will be repeated. Given the Pose SLAM graph, and a goal destination, the objective of path planning is then to find an optimal collision-free path in the graph from the current robot pose to the goal.

Thus, the task at hand is to search for the minimum uncertainty path on the graph implicitly defined by the neighboring relations between the poses stored in the map built by Pose SLAM. Two considerations are necessary: a) graph connectivity must be increased with guaranteed reachability, and b) we need to define a cost function of cumulative uncertainty along a path.

A. Increasing graph connectivity

Note that only odometry-based links ensure the existence of collision-free transitions between poses. However, a graph with only odometry-based edges is too sparse. Loosely connected graphs are not best suited for path planning and we need to increase the number of edges to allow the system to jump from one exploration sequence to another in the quest for an optimal path. Thus, besides odometry related poses, we consider the possible transition to all neighboring nodes during path planning.

We use Eq. 3 to measure the distance between candidate neighbor nodes in the very same way it is used to decide whether two nodes are sufficiently close to add a measurement link between them. If for all dimensions, the probability of nodes x_i and x_n is above a given threshold s, then configuration x_i is considered kinematically reachable from configuration x_n.

Adding these node transitions to the graph does not guarantee a collision free path between them. These cases, however, can be easily detected during path execution, the poses be removed from the list of neighbors, and a re-plan process be triggered. One advantage of the method is that the original odometry-based links present in the Pose SLAM map ensure the existence of collision-free way-outs for every pose, thus guaranteeing reachability.

Given that candidate paths lie on top of the graph, we can safely assume that, after path execution, sensor registration will close a loop and the final robot uncertainty will be close to the original marginal at that node. Thus, a cost function that only evaluates the belief state at the goal is unsuitable. We are interested instead in those paths that maintain the robot well localized throughout the whole trajectory.

B. Minimum uncertainty along a path

In [22] we developed a cost function that considers cumulative relative uncertainty during localization, independent of the map reference frame. Finding trajectories that accumulate the least uncertainty can be seen as searching for a path of minimal mechanical work in an information surface over the space of robot poses [9], [19]. In this case, the cost of traversing a link from node x_i to node x_j is proportional to the conditional entropy at node j given full confidence about node i, $H(x_j|x_i)$, which for Gaussians is proportional to $|\bar{\boldsymbol{\Sigma}}_{jj} - \bar{\boldsymbol{\Sigma}} ji \bar{\boldsymbol{\Sigma}} ii^{-1} \bar{\boldsymbol{\Sigma}}_{ij}|$, where $\bar{\boldsymbol{\Sigma}}$ is the compound localization estimate of the pair (x_i, x_j).

For a discrete trajectory $\mathbf{u}_{1:T}$, the cumulative relative uncertainty can thus be computed as the sum of relative entropy increments $\Delta H_i = H(x_{i+1}|x_i) - H(x_i|x_{i-1})$ along the path

$$W(T) = \sum_{i=1}^{T} \Delta H_i \quad \forall \Delta H_i > 0. \tag{7}$$

With these two considerations, increased graph connectivity and a suitable cost function, we have the necessary tools to search for the minimum uncertainty path in the Pose SLAM graph. We perform breadth first search from an initial configuration to a goal configuration. The distance between two nodes is computed from relative entropy measures obtained simulating maximum likelihood localization estimates. If for a node transition from i to j the so far computed path is cheaper than the best known, the cost to reach j is updated, we set i as the predecessor of j, we update the marginal covariance for the best path to the node, and we store the marginal entropy for this node. When the goal is reached, the minimum uncertainty path to the goal is reconstructed using the chains to predecessor nodes.

Finally, should a map change significantly during path execution (i.e., a new highly informative loop closure is found), re-planning is enforced. Note that this is seldom the case since the optimal path traverses already visited regions in the environment as best localized as possible. Moreover, re-traversing a path on an already optimized map will seldom lead to map improvements as no new information is introduced. The map can only be improved or extended by joining different paths closing a loop or when exploring new paths to cover a larger area. However, exploration is out of the scope of this work.

IV. Experiments

Exhaustive experiments that demonstrate the benefits of Pose SLAM and the viability of using Pose SLAM for path planning for the 2D case were presented in [7] and [22], respectively. The goal of the experiment shown here is to demonstrate that the method is also applicable to dense 3D mapping using range data, and in particular, to plan a minimum uncertainty escape route on a previously mapped area.

The experimental data, acquired at the interior plaza of the FME building at UPC, encompasses a 100×40 sqm. rectangular area with various terrain types (gravel, earth, grass) and ramps. The robot used is Teo, a Segway RMP 400 platform equipped with a custom built 3D scanner with Hokuyo UTM-30LX sensor mounted on a slip ring (see

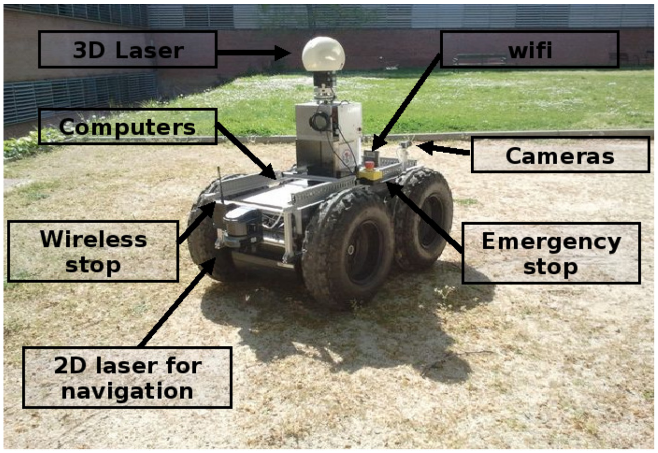

Fig. 2. Our robot Teo at the FME plaza.

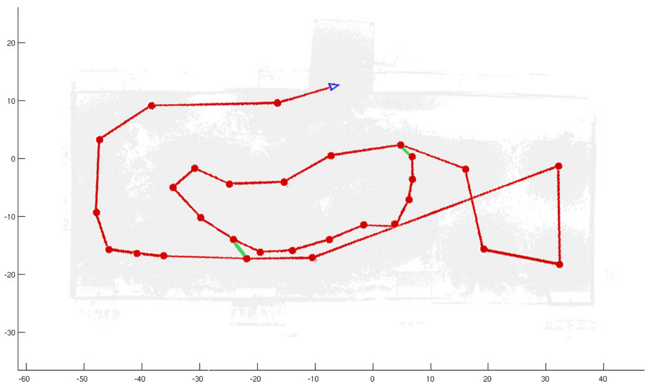

Fig. 3. 2D projection of the 3D pose graph. The robot trajectory is shown in red, and the sparse loop closures are shown in green.

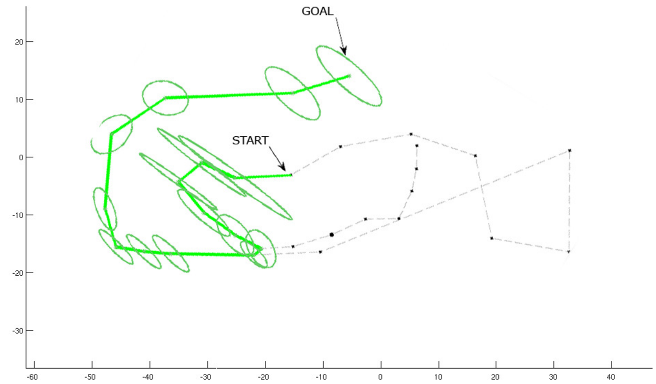

Fig. 4. Planning in configuration space we obtain the shortest path to the goal and related covariances.

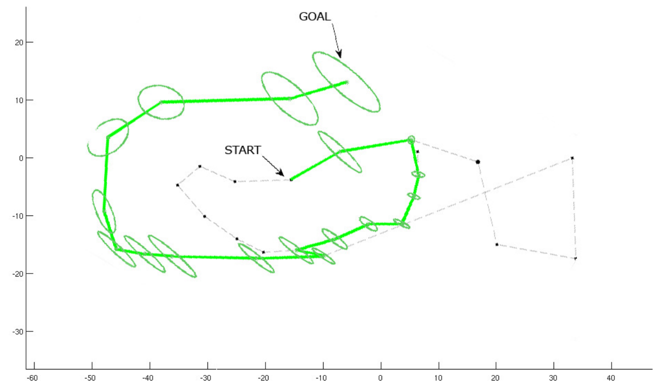

Fig. 5. Planning in belief space we obtain the minimum uncertainty path to the goal.

Fig. 2). Each aggregated laser scan has $194,500$ points with resolutions of $0.5\,$deg azimuth and $0.25\,$deg elevation and range of $30\,$m, with a noise level of $5\,$cm in depth. The Pose SLAM map built contains 30 dense point clouds with a maximum separation between consecutive poses of $18\,$m. The robot was teleoperated during data collection.

For the experiment reported in this paper, sensor registration is computed in the very same way as odometric relations, by aligning the range scans with hierarchical ICP. The point clouds were subsampled uniformly using a voxel size of $35\,$cm and noise was removed using a density policy [20].

Sensor covariance is approximated with first order error propagation by computing the implicit function Jacobian for ICP's point-to-point unconstrained minimization as shown in [5]. Two factors make this computation suboptimal. On the one hand, it is only a first order approximation, thus conservative. On the second hand it is formulated only for the point-to-point error metric, whilst our ICP implementation is optimized for performance with a hierarchical structure that uses a point-to-plane error metric at the coarsest level and a point-to-point metric at finer levels, and that weights differently rotations and translations [20]. Our experiments have shown empirically that the computation of $\mathbf{\Sigma}_y$ is accurate enough and does not jeopardize the rest of the method.

A 6DOF version of Pose SLAM is used to map the environment [23]. Given the relative small size of the pose graph, and that interval-based data association as described in [7] is not mature for 3D mapping yet, data association was asserted manually. The resulting Pose SLAM is shown in Fig. 7. The map contains one situation between poses 20 and 21 for which the displacement is so large it precludes sensor registration. For that case, the link in the graph was updated purely with platform odometry data and constant noise covariance $\mathbf{\Sigma}_u = \mathrm{diag}(0.0158\,\mathrm{m},\ 0.0158\,\mathrm{m},\ 0.0791\,\mathrm{m},\ 0.0028\,\mathrm{rad},\ 0.0028\,\mathrm{rad},\ 0.0001\,\mathrm{rad})^2$. The covariance of the initial pose was set to $\mathbf{\Sigma}_0 = \mathrm{diag}(0.01\,\mathrm{m},\ 0.01\,\mathrm{m},\ 0.01\,\mathrm{m},\ 0.0087\,\mathrm{rad},\ 0.0087\,\mathrm{rad},\ 0.0087\,\mathrm{rad})^2$.

During path planning, neighboring poses are linked for a threshold of $\pm 5\,$m in x and y and no orientation restriction, thanks to the omnidirectional characteristic of our range sensor. Path search is performed over a 2D projection of the 3D pose graph, marginalizing the x, y and θ variables from the full state vector and state covariance for the computation of the cost function and other path-planning related routines. Fig. 3 shows the 2D pose graph used for path planning.

The task at hand is to plan a minimum uncertainty escape

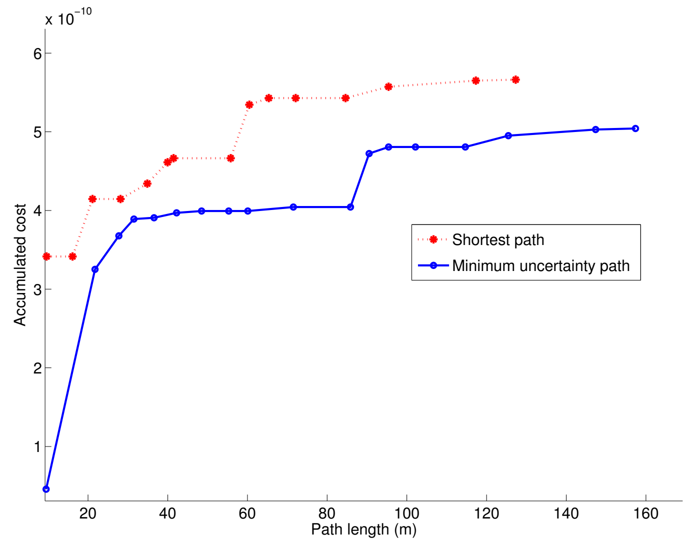

Fig. 6. Accumulated cost along the shortest path (red) and the minimum uncertainty path (blue).

route from the center of the plaza to the exit of the building. A plan in configuration space finds the shortest path to the goal (see Fig. 4). This route is about 130 meters long, but had the drawback of having higher localization uncertainties at the beginning of the path, as shown by the projected hyperellipsoids of equiuncertainty. Taking this route to escape has higher probability of failure getting the robot lost.

A safer route is a path searched in belief space. The plan is a little longer, about 160 meters, but with higher guarantee of good sensor registration during path execution, and hence good localization estimates throughout the trajectory (see Fig. 5). The covariances shown in the plots indicate absolute localization uncertainty.

The savvy reader might note how the covariance in robot pose at the start of the plan is not zero, but that of the precomputed PoseSLAM map. This is not counterintuitive and refers to the fact that even at the start of the plan, absolute localization can only be guaranteed to a certain level. In consequence, the method is capable of finding an escape route even when no full certainty about the initial robot pose is available.

The plot in Fig. 6 compares the cost of executing both the shortest path and the minimum uncertainty path as well as the corresponding path lengths.

V. Conclusions

This paper shows how pose graphs that are built with Pose SLAM can readily be used to plan minimum uncertainty navigation routes. The proposed metric has two advantages over previous approaches: on the one hand it is defined in belief space, and thus it takes into account localization uncertainties along the path; and secondly, it encodes only relative information about the poses and thus is independent of the chosen reference frame. Results are demonstrated densely mapping an outdoor setting with a range sensing device, and then planning an evacuation route. The final path obtained is the safest evacuation route with the highest guarantee of good sensor registration during path execution.

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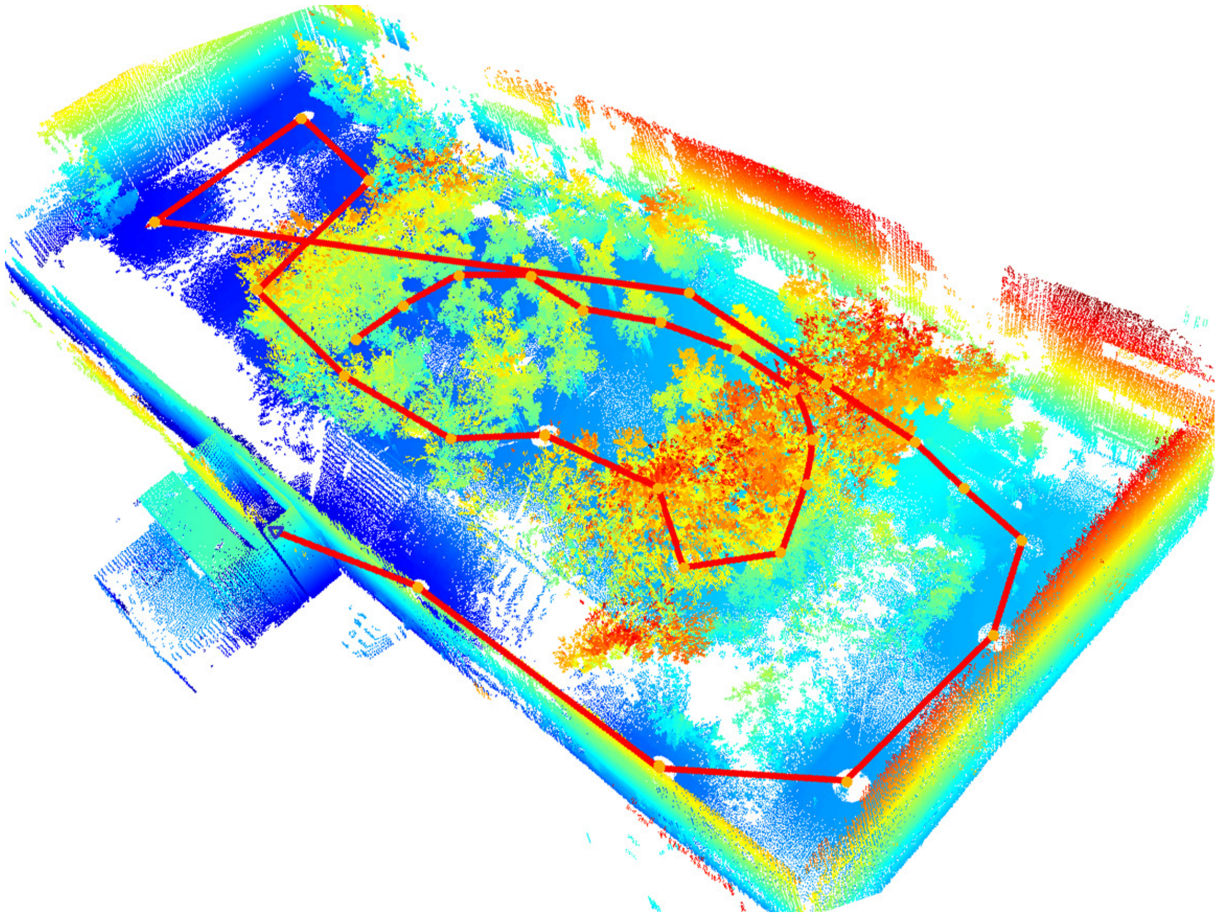

Fig. 7. 3D Pose SLAM map of the FME plaza.

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