Improving Localisation Accuracy using Submaps in warehouses

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***Abstract*— This paper presents a method for localisation in hybrid metric-topological maps built using only local information that is, only measurements that were captured by the robot when it was in a nearby location. The motivation is that observations are typically range and viewpoint dependent and that a map a discrete map representation might not be able to explain the full structure within a voxel. The localisation system uses a method to select submap based on how frequently and where from each submap was updated. This allow the system to select the most descriptive submap, thereby improving the localisation and increasing performance by up to 40%.**

I. Introduction

A challenge in mapping is that objects may look different depending on where in the environment they were observed from. This is especially true for discrete surface map representations when a single surface, distribution or feature is not sufficient to explain the complete structure within a voxel. In that case, the final map has become general enough to reasonably explain the world from multiple view-points. Fig.1 shows mapping of a wall between two parallel corridors where the surface uncertainties are very high to explain the wall from each side respectively, this is because both sides of the wall has to be explained by the same voxel. On the other hand, a submap which uses local measurements is considerbly more specific as it only attempt to model the right-side wall surface. While this general discretisation problem applies to most environments, it's more significant e.g. in indoor intra-logistic environment where aisles generally are observed from two sides.

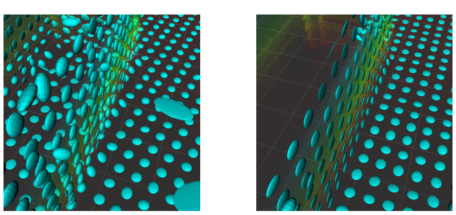

Fig. 1: Zoom-in on a corridor which has been observed from two sides of a wall. Discrete gaussian surface uncertainties are visualised in cyan. Left: global map with high uncertainty and noise. Right: local map with origin on right side of wall.

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II. Related work

The focus of this work lies in localisation in HMT frameworks. There is a great deal of research on methods that use an HMT structure [1]–[3]; however, to our knowledge there is very limited amount of work that focus on how the submaps could improve map descriptiveness and localization accuracy. One exception can be found in [4] where an approach of clustering observation nodes using an sensory based overlap criteria is presented to better assure that the generated submaps are consistent; however, the evaluation was done using visual inspection alone.

In the Atlas framework, new maps are added when the localization performance degrades [3]. Additionally, it uses a technique for selecting when to switch maps using a performance metric based on how well the current observation fits the different submaps. Finally, it is also common that many mapping approaches utilizes the submap representation only as an intermediate step in order to obtain a global map representation.

III. Method

In this work we utilize the NDT-OM [5] framework, which combines the NDT map representation with occupancy grid maps. The NDT-OM submap graph was created by selecting the closest node for mapping. If the condition I_{th}, $(\boldsymbol{m_{min}} = \arg\min_{i} \quad d(\boldsymbol{s_t}, \boldsymbol{m_i}) < I_{th})$ is not met, meaning that there are no submaps $\boldsymbol{m_i}$ at a distance d less then a threshold I_{th} from the sensor $\boldsymbol{s_t}$ a new submap is created where the origin is aligned with the sensor frame.

The localisation system is initially aligned with the ground truth pose (available through a pre-installed comercial reflector based system). The localisation is divided into three steps: predict the incremental pose of the robot based on wheel odometry, select the most descriptive map at the sensor pose and perform scan-to-map registration using NDT Distribution-to-Distribution (D2D) [6].

The map selection method based on distance as described above can be used in mapping and the localisation for map selection. However, the technique do not necessarily return the most descriptive map in that region as it has no notion of where the map was previously updated from. Additionally, this technique do not consider how frequently the maps were updated which is especially important in dynamic environments where the map needs to be updated in order to filter out non-static objects. Consequently, it is desirable to find a map selection method which uses information of where from and how frequently each submap was updated

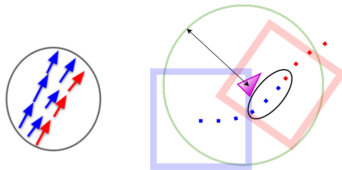

Fig. 2: Example of map selection using observation density search. (Left) Sensor poses when red and blue maps were updated. The blue map has been updated more times and which gives a higher density of blue poses. (Right) The blue and red squares are two local maps, located within a radius $2 * I_{th}$ of the robot (purple triangle). The majority of the observations belong to the blue submap, which was more densely updated in the region. Thus the blue map is selected for localisation.

to select the most descriptive. We propose that submaps is selected for localisation based on the density of the update sources' locations in the vicinity of the robot's sensor, see Fig. 2.

A. Update source density search

We propose a method called *update source density search* to find and select the most densely updated submap at a region. The prerequisite for the method is to store meta-data during the mapping, specifically we store tuples $S = \{\boldsymbol{m_{i,t}}, \boldsymbol{o_{i,t}}\}$ of the local map $\boldsymbol{m_i}$ that was updated from the sensor pose(which is the update source) $\boldsymbol{o_j}$ at time t. The selection process is divided into 3 steps. see fig 2

1) Let $C = \{\boldsymbol{m_i} : d(\boldsymbol{p_t}, \boldsymbol{m_i}) < 2 * I_{th}\}$. In other words, C is the set of all map nodes such that the distance between the estimated sensor pose $\boldsymbol{p_t}$ and the map node is less than 2 times the node distance.
2) For all $\boldsymbol{m_i}$ in C, calculate the distance $d(\boldsymbol{p_t}, \boldsymbol{o_j})$ (between the current sensor pose and the source of the map updates $\boldsymbol{o_j}$). This is done for all j coupled with $\boldsymbol{m_i}$.
3) Get all the tuples S_i corresponding to the $n * |C|$ smallest distances, where n is a constant set to 2. Calculate the histogram for the occurances of all $\boldsymbol{m_i}$ in S , the most frequent submap in the histogram is the output.

IV. Evaluation

The method was evaluated on a forklift equipped with a 3d range sensor (Velodyne 32), navigating manually in a warehouse and autonomously in a production dairy site, see fig 3. The absolute trajectory error wrt. the distance between nodes I_{th} is shown in fig 4. As the distance between nodes is reduced, (or the number of nodes are increased), the error decrease. This is because the submaps are updated by more local observations. When the resolution of the map discretisation is increased, (meaning that the voxels size is increased), the impact on localisation accuracy using submaps is higher compared to global maps. This is because

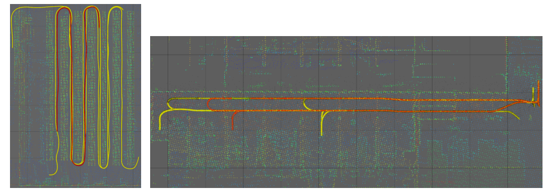

Fig. 3: Overview of the trajectories for the different data sets. Red and yellow depict the paths used for building the map and performing the localisation evaluations respectively. The warehouse set contain zig-zag navigation between the aisles.

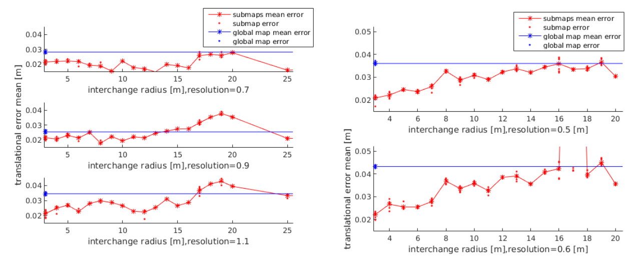

Fig. 4: Localisation error with respect to distance I_{th} between submaps Left: warehouse dataset. Right: dairy.

it's more likely that larger voxels need to represent multiple surfaces.

V. Conclusions and Future Work

The results obtained show that improvement in localisation accuracy in can be obtained using a submap-representation based on location-specific information. In the future we will compare our selection method with *closest node* as well as a method which directly measure the overlap between scan and adjecient submaps. We will also investigate map partitioning to group the observations to maximize the descriptiveness of the local maps dependently on the environment.

References

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