A heterogeneous SLAM approach for improving map consistency

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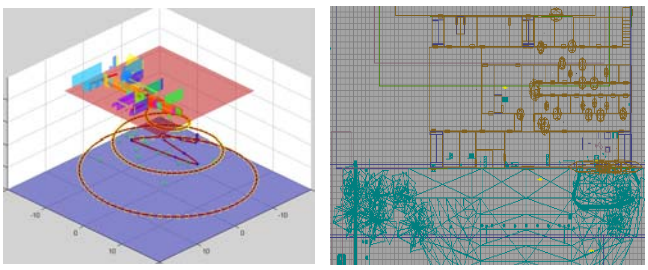
1. Introduction

Most SLAM approaches consider a homogeneous type of environment so that it can be either represented as a grid-based map or feature-based map. It is well-known that in a dense environment, the grid-based representation is often selected for its good ability to handle obstacle avoidance and scan matching[1]. Meanwhile, in a sparse environment, a feature-based representation is prefer for its light-weighted computation and easy feature association[2]. However, in an unobservable environment (e.g. a long spiral path (Fig.1a), there is almost no efficient representation until now. Since the real world is heterogeneous environment, which consists of dense, sparse structure environment as well as unobservable environment, it is our motivation to take them into account. Therefore, the paper proposes a novel heterogeneous SLAM approach for this problem.



a) b)

Fig. 1. a)A heterogeneous environments that contain large open spaces with sparse landmarks and a dense indoor structure connected by an unobservable path. b) Simulated environment for experiment

The basic idea of our approach is to classify the environment into observable and unobservable environments and to select the best filter accompanied with each type of environment. The observable environment can be dealt with as usual approaches while the unobservable environment should be treated differently. Since projected space, which is observable by the robot, is normally distorted, the filtering of this region should be more robust and the linking among these local map should be flexible. Hence, considering each unobservable path as a patch, we detect the changing point of environment and selecting the best suitable filter for each path based on current sensor observations and the state of the filter through using a classifier. As we will illustrate in the initial experiments, our approach gives more impressive results compare to other non heterogeneous approaches.

The paper is organized as follows. After introduction, a brief theory of SLAM and our approach are presented in Section II. Experiments are carried out in simulation in Section III. Finally, in Section IV, we draw the main conclusions before outlining some future research directions.

2. SLAM and our approach

In this section, we first brief about SLAM algorithm before presenting our approach. Basically, SLAM problem is to estimate the joint posterior of $P(x_{1:t},m|z_{1:t},u_{1:t-1})$ of a map m and a robot trajectory $x_{1:t}$ given the sensing and control history $u_{1:t-1}$, $z_{1:t}$ and respectively. SLAM is based on that:

$$P(x_{1:t},m|z_{1:t},u_{1:t-1}) = P(m|z_{1:t},z_{1:t})P(x_{1:t}|z_{1:t},u_{1:t-1}) \quad (1)$$

This factorization allows us to compute the trajectory and the map recursively to the first pose. The important step for every approach is to compute the posterior $P(x_{1:t},m|z_{1:t},u_{1:t-1})$.

Note that most SLAM approaches assume the environment is observable so it can be represented by either grid-based or feature based and depending on each representation a suitable filter is used to compute the maximum potential map. However, this is not always the case, especially for a complex environment. Ignoring this fact will produce an inconsistent map. Therefore, we propose to deal with this case by separating the unobservable path and use a more rigorous filter to keep the local map acceptable accurate. The detected changing point is kept as linking in global map to improve consistency.

Since the unobservable environment happens when the information matrix is under-constraint. This means we did not have enough correspondence to compute transformation. So we will use this character to detect the unobservable part. A measure that can be useful to detect such a situation is the likelihood $l(z_t,x_t,m_t)$ that the scan-matching seeks to maximize. To point-wise evaluate the observation likelihood of a laser observation, a "beam endpoint model" [1] in which the individual beams within a scan are considered to be independent, is used. The likelihood of a beam is computed based on the distance between the endpoint of the beam and the closest obstacle from that point. A heuristic th threshold for selecting map type can be trained to recognize :

$$\begin{cases} l \leq th \rightarrow maptype = unobservable \\ l > th \rightarrow maptype = observalble \end{cases} \quad (2)$$

Obtaining this classifier, the algorithm of our SLAM approach is summarized as follows:

1)From robot state, laser scan, feature and odometry of the current time step, determine maptype
2)**If** (maptype =observable)
3) Update map posterior using a normal light-weighted filter
4)**Elif** (maptype =unobservable)
5) Update map posterior using a more robust filter
6)Keep the changing point between environment

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3. Experimental Results

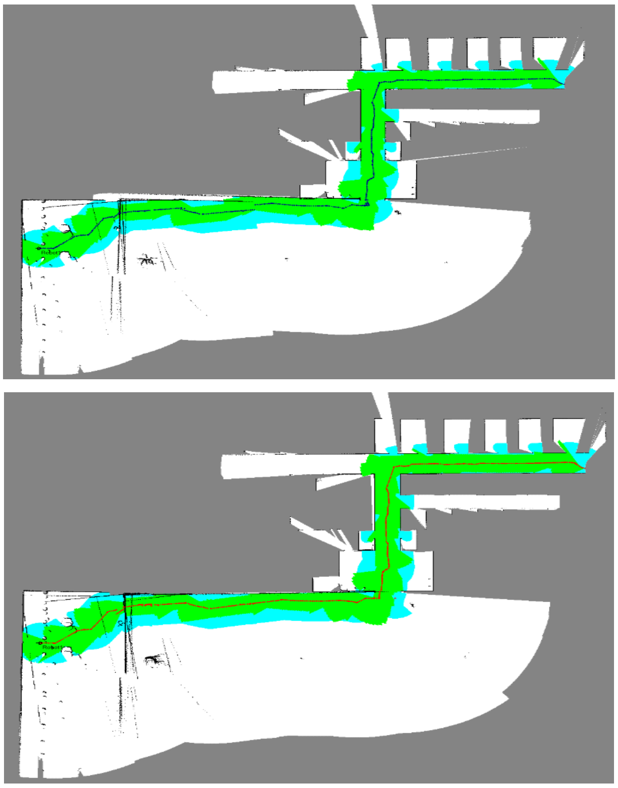

Fig. 2: Result of IDC scan matching [3] (up) and result of weighted scan matching [3] (down). The result is from USARSIM heterogeneous simulated environment which contain dense indoor, unobservable slope and sparse outside environment.

In order to show the improvement in consistency, we compared our method with a recent IDC scan matching [3] and weighted scan matching [3] in Fig. 2. In a simulated indoor environment (Fig. 1.b), we show the result of each algorithm. It could be seen that our method outperforms the other SLAM methods as it deals with unobservable environment more flexibly (Fig. 3).

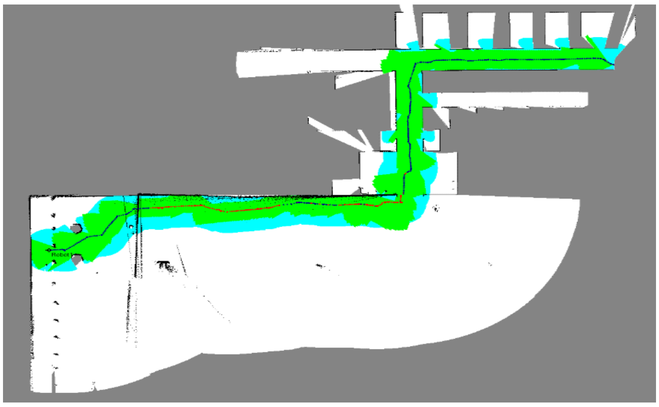

Fig. 3: Result of our approach. Blue and red means observable and unobservable while end points of each path mean changing point

4. Conclusion

We have proposed a novel heterogeneous SLAM approach for complex world environments. Since different region is categorized in harmony to observation likelihood, the filter of each region is selected accordingly. This leads to a significant improvement in consistency of the SLAM in a real world environment, especially when unobservable dimensions exist. Our future work will be a thorough investigation of both computational complexity and consistency improvement in a real world heterogeneous environment.

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