A Robust Back-end Based on Feature Maps in SLAM

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Abstract. Simultaneous Localization and Map (SLAM) Building belongs to the category of the autonomous robot navigation. The solution of SLAM makes robots move by themselves. The current SLAM is based on least square optimization, while it requires all data associate correct. This paper proposed a robust algorithm based on feature maps. According to the relation of topological and mathematical model, a kind of switchable variable were added into the topological graph, and also some constraints were added into the back-end formulation. Our algorithm not only is able to recognize the false data association, but also could modify the data association in feature maps. The feature maps could be corrected by the robust back-end. The evaluation shows that the approach can deal with up to 500 false data association constraints on the datasets. This approach makes the back-end more powerful and the front-end would be easier than before.

Introduction

SLAM [1,2] is a hot topic in the fields of autonomous robot navigation, and there are many methods to solve it. There are a lot of literature [3, 4, 5] suggests their solutions to the problem of SLAM, even some had been implemented using the software like g2o [6]. The g2o is a least squares optimizers, but it is not robust against false data association in feature maps. This is because the topological could not change through the optimizer of g2o, so the false data association cannot be removed through least squares optimizers. If the front-end makes a false data association, general optimization in the back-end would fail. The estimates of robot state and the landmarks of environment would have a huge error.

To get accurate feature map about SLAM, Back-end should be robust when system has false data association. Therefore, this paper presents a robust back-end for SLAM system. This robust back-end compare to other methods [7, 8] are the switchable variable and the feature maps. It has be used to victoria-park dataset which is a feature map and is a large scale real-world urban dataset. Through some experiments, feasibility and effectiveness of this method has been validated. Exemplary results of the victoria-park datasets are shown in Fig.1. The next section reviews the switchable variable and the feature maps. The experiments results are discussed in the section III. The section IV is the conclusion.
Switchable Variable and Feature Maps

Feature Maps and Factor Graphs

There are many kinds of maps which are created in SLAM. If the sensor equipment on the robot are different, the maps that are created in SLAM also would be different, for example the occupancy grid maps, feature maps and pose graphs. In this paper, feature maps are only considered, while other maps are not considered. The SLAM’s feature maps are sparse and contain only the position of distinct landmarks or features in the environment. The Fig. 2(a) illustrates a feature map which is a part of victoria-park datasets. The yellow dots are the landmarks which represent the tree in the real environment, the yellow line is the robot states and the blue line is the true path of robot. While the factor graph is different from the feature map, it is a topological graph. The Fig. 2(b) illustrates the factor graph of victoria-park. The robot state is the $x_k$ and the landmark is $l_i$, while probabilistic relationships between them are expressed by the small vertices. So the blue node represents odometry factors and green nodes are landmark observations.

Switchable Variable

According to the factor graphs (Fig. 2(b)) in SLAM, we could see that factor graphs with landmarks could represent feature map made by robot. This paper’s main idea is to remove the false data association, and increase the robustness of back-end, so we add a switchable variable into the factor graph like the Fig. 3.

Figure 1. Victoria-Park Datasets after Optimization
a). the initial feature map; b). no robust back-end solution;
  c). true feature map; d). robust back-end.

Figure 2. Feature Map of Victoria-Park and Factor Graph.

The data association is the green nodes with the red line, it represents that one landmark observed again after it run some distance. The front-end processes the data association. But it cannot guarantee 100% correct when analyzing data association from a large amount of data. If false data association cannot be avoided in front-end, robust back-end is a better choice.

Switchable Variable

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In the Fig. 3, the switchable variable $S_{k2}$ links the green node which represents data association. The red node is the relationship between switchable variable $S_{k2}$, robot state $x_k$ and landmark $l_i$. Depending on the value assigned to the switchable variable $S$, the data association is switched on or off. If the variable $S$ is switched on, it means that this data association is correct and the factor graph like Fig. 3(a). If it is switched off, it means that data association is wrong, and the factor graph is Fig. 3(b). So this robust back-end can distinguish wrong data association from all data association.

Robust Back-end

Robust Back-end Formulation

To achieve the desired robustness behavior, a new kind of variable is added in the factor graph. According to the iSAM2 and SC [7], the SLAM can be described from the perspective of probability. In a word, it is a max posterior probability estimate problem. In this paper, the SLAM we want to estimate can be written as:

$$
(X^*, L^*, S^*) = \arg \max_{X, L, S} P(X_T, L, S | Z_T, U_T, \Gamma_T).
$$

We should note that the variable $X_T$ represent the robot states, the variable $L$ represent the map composed by landmarks, The $Z_T$ is the observation, the $U_T$ is the odometry and the $\Gamma_T$ is the initial value of variable $S$. In the factor graph (Fig. 3), there are three kids of constraints that among variable $X, L$ and $S$. The first constraints is the robot odometric constraints that connect $x_k$ and $x_{k+1}$ via a motion model, the second constraints is the observation constraints that connect $x_k$ and landmark $l_i$ via an observation model, the third constraints is the switch constraints which is added for variable $S_{ki}$.

To solve this problem, we can factor the probability distribution as

$$
P(X_T, L, S | Z_T, U_T, \Gamma_T) \propto \prod_k P(x_{k+1} | x_k, u_k) \cdot \prod_{li} P(l_i | x_k, z_{li}) \cdot \prod_{li} P(s_{li} | \alpha_{li}).
$$

As we all know the motion model and observation model in robot system, so the probability distribution is $x_{k+1} \sim N(f(x_k, u_k), \Sigma_k)$ and $z_{li} \sim N(h(x_k, l_i), \Lambda_{li})$ in Eq. 2. While as the switch constraints, the probability can be written as $s_{li} \sim N(\alpha_{li}, \Xi_{li})$. This paper assumes the conditional probabilities above are all Gaussian, we can write for the odometry constraints:
\[
P(x_{k+1} | x_k, u_k) = \frac{1}{\sqrt{2\pi |\Sigma_{k}|}} \exp \left( -\frac{1}{2} \| f(x_k, u_k) - x_{k+1} \|^2_{\Sigma_k} \right)
\]

\[
\propto \exp \left( -\frac{1}{2} \| f(x_k, u_k) - x_{k+1} \|^2_{\Sigma_k} \right)
\]

where \( \| f(x_k, u_k) - x_{k+1} \|^2_{\Sigma_k} = (f(x_k, u_k) - x_{k+1})^T \Sigma_k^{-1} (f(x_k, u_k) - x_{k+1}) \). By the same steps for the observation constraints and switch constraints, we can gain:

\[
P(l_i | x_k, z_{ki}) \propto \exp \left( -\frac{1}{2} \| h(x_k, l_i) - z_{ki} \|^2_{\Lambda_{ki}} \right)
\]

\[
P(s_{ki} | \alpha_{ki}) \propto \exp \left( -\frac{1}{2} \| s_{ki} - \alpha_{ki} \|^2_{E_{ki}} \right)
\]

According to the Eq. 3 and Eq. 4, the Eq. 1 can be written as:

\[
(X^*, L^*, S^*) = \arg \min_{X, L, S} \log \left( P(X, L | Z_T, U_T, \Gamma_T) \right)
\]

\[
\propto \arg \min_{X, L, S} \sum_k \| f(x_k, u_k) - x_{k+1} \|^2_{\Sigma_{ki}} + \sum_{li} \| h(x_k, l_i) - z_{li} \|^2_{\Lambda_{ki}} + \sum_{ki} \| s_{ki} - \alpha_{ki} \|^2_{E_{ki}}.
\]

In order to remove the wrong data association, the information matrix of observation constraints should be added the switch function \( \phi^2(s) \). Thus the information matrix is \( \phi^2(s) A^{-1} \) and the observation constraints will change to \( \sum_{ki} \| \phi(s_{ki}) (h(x_k, l_i) - z_{ki}) \|^2_{\Lambda_{ki}} \), so the robust back-end formulation is

\[
(X^*, L^*, S^*) \propto \arg \min_{X, L, S} \sum_k \| f(x_k, u_k) - x_{k+1} \|^2_{\Sigma_{ki}} + \sum_{li} \| \phi(s_{ki}) (h(x_k, l_i) - z_{li}) \|^2_{\Lambda_{ki}} + \sum_{ki} \| s_{ki} - \alpha_{ki} \|^2_{E_{ki}}.
\]

**Switch Function and Switch Constraints**

The observation constraints have been augmented by a multiplication with switch function \( \phi(s_{ki}) \). This switch function is a mapping from the continuous real numbers to the interval \([0, 1]\). There are many switch function can be defined, this paper use a linear function:

\[
\phi(s) = \begin{cases} 
0 & s \leq 0 \\
0 & 0 < s < 1 \\
1 & s \geq 1 
\end{cases}
\]

In the probabilistic interpretation, the switch function influences the information matrix and drives it from its original value to zero. In the topological interpretation, the switch function can remove the edge it is associated with, and get a correct topological graph.

In order to get correct solution of SLAM, switch constraints are necessary to be added. The first thing is to confirm the initial value of variable \( s_{ki} \). As the switchable variable represents the data
association, all data association are right when the optimization hold the initial state. Thus the initial value $\alpha_i$ is set to 1.

Now the covariance of switch constraints should be fixed. There are much information created by the front-end. We can analysis it and get the covariance $\Xi_i$. In the experiments of this paper, the covariance is equal to the covariance of observation constraints. May be it is not the real covariance, but it has good results in the experiments.

**Experiments and Results**

This paper uses a Victoria-Park dataset from ACFR which created by an intelligent car, the car records the measured values when it runs through Victoria-Park in 30min. For the Victoria-Park from ACFR has no false data association, we add some synthetic false data association into the dataset. See the Fig. 3, we could know the consequence. Compare to Fig. 3(b) and (c), the general method has a bad solution after optimization. However, the robust back-end method could have a good solution compare to Fig. 3(d) and (c). So the robust back-end could be robust against wrong data association.

<table>
<thead>
<tr>
<th>Wrong data association number</th>
<th>Wrong data association ratio</th>
<th>RMSE[m]</th>
<th>Recall</th>
<th>Precision</th>
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</thead>
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<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>100%</td>
</tr>
<tr>
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<td>1.3</td>
<td>100%</td>
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<td>0.2</td>
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<td>91.98%</td>
</tr>
<tr>
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<td>10.8%</td>
<td>1.2</td>
<td>100%</td>
<td>98.80%</td>
</tr>
<tr>
<td>500</td>
<td>13.5%</td>
<td>0.47</td>
<td>100%</td>
<td>86.73%</td>
</tr>
</tbody>
</table>

The robust back-end can deal with up to 500 wrong data association, and the result is shown in Table 1. The precision is 100%, and the recall also has high value.

**Conclusions**

With the robust back-end in SLAM, the wrong data association cannot be a problem when robot moves in the unknown environment. This method allows the front-end brings wrong data association into the back-end, and it can get a correct feature map using the switchable variable. It changes the back-end performance and makes back-end more robust.

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**References**


