The whole picture of the technical solution

FastSLAM2.0 is used to get the Gaussian Mixture Model. The Gaussian Mixture Model is then converted to a Single Gaussian. Finally, EKF update is conducted by incorporating the single Gaussian Distribution of the local features to the corresponding features in the global to generate a consistent estimation of the common features. And a whole cycle of Hybrid-SLAM update is finished.

Gaussian Mixture Model from FastSLAM2.0

The FastSLAM algorithm factors distribution as:

Formula(3)

This factored distribution is represented as a set of *P* samples, which can be represented as:

Formula(5)

Where ……

Single Gaussian from Gaussian Mixture Model

The parameters of a Single Gaussian, the mean xt and covariance Pt, can be computed from Gaussian Mixture Model by using formula(6) and (7) known as Moment Matching:

Formula(6)

Formula(7)

In Equation 7, the first term in the square brackets is the covariance of the particle’s individual map. The second term is from the variation between particle’s maps, which represents cross correlations.

Setting Correspondences form(from?) Voting Mechanism

It is necessary to set correspondences for each observation. For a single observation, each particle can make the following data association decisions:

1. associate the observation to an existing feature in its individual local map,

2. associate the observation with a new map feature initialized in its individual local map.

Each particle votes in proportion to its weight. The voting mechanism considers the number of particles and their weights to determine the winner and set it as the correspondence for this single observation. In the end, this voting mechanism forms a consensus about the common set of features while allowing each particle to make distinct decisions in its individual map.

Forming a Gaussian Given Correspndences

The correspondences are then used to map the features in each particle’s individual map to the common set of features. The function xx is used as the reverse mapping: formula ,where ….. Thus each particle can be represented by its weight, mean and covariance. The mean and covariance matrix can be simply written as: formula(9). Thus each particle’s individual map can be represented by a single multidimensional mean and covariance.

The difficulties occur in two corner cases. Firstly, a particle’s individual map may contain multiple features corresponding to the same feature in the common set. Secondly, a feature in the common set may have no corresponding features in each particle’s individual map. For case one, the algorithm simply pick one feature as random to compute the mean and covariance for the corresponding common feature. For case two, the algorithm ignores that common feature.

Map Fusion

During the HybridSLAM process, the filter consists of two maps, the Gaussian global map and the Gaussian local map. By fusing the local map to the global map periodically, the required number of particles can be reduced compared with pure FAST-SLAM. The filter takes two steps to do the Map Fusion:

1. Initialize the local features in the global map.

2. Features are associated and fused.

The initialization step requires initialization of both the local features and the robot pose because the robot pose in the local map is obviously different from that in the global map during local map initialization. The mean and covariance are computing as follows:

Formula

Formula

Where x-,x+,P-,P+ represents the mean and covariance of the global map before and after fusion, xL and PL represents the mean and covariance of the local map, and g(x-,xL) (formula) transform the local map into the global coordinates by using the Head-to-Tail[5] and x-: the robot’s global pose at the time of the previous fusion.

The association step:

Word

Word

Formula (many)

[5]smith,Self,and cheesemen

y^{+}=\begin{bmatrix}

y^{-}\\

g(x^{-},x\_{L})

\end{bmatrix}

P^{+}=\begin{bmatrix}

P\_{xx}^{-} & P\_{xm}^{-} & P\_{xx}^{-}^{T}\bigtriangledown \_{xg}^{T} \\

P\_{xm}^{-} & P\_{mm}^{-} & P\_{xm}^{-}^{T}\bigtriangledown \_{xg}^{T}\\

\bigtriangledown \_{xg}P\_{xx}^{-} & \bigtriangledown \_{xg}P\_{xm}^{-} & \bigtriangledown \_{xg}P\_{xx}^{-}\bigtriangledown \_{xg}^{T}+\bigtriangledown \_{zg}P\_{L}^{-}\bigtriangledown \_{zg}^{T}

\end{bmatrix}

g(x^{-},x\_{L})

The condition that features *Ei* from the loacal map and *Fji* from the global map coincide can be expressed using an ideal measurement equation which does not consider noise. This is taken as the difference of the coordinates in the global map.

z\_{i}=h\_{ij\_{i}}(x)=0

The measurement equation can be expanded around the mean, which is actually precise here because the measurement function is linear.

h\_{ij\_{i}}(x)\simeq h\_{ij\_{i}}(\hat{x})+H\_{ij\_{i}}(x-\hat{x})

with

H\_{ij\_{i}}={\partial}h\_{ij\_{i}}/{\partial}x|\_{\hat{x}}=\begin{bmatrix}

0 & ... & H\_{Fj\_{i}} & ... & H\_{Ej\_{i}} & ... & 0

\end{bmatrix}

H\_{Fj\_{i}}={\partial}h\_{ij\_{i}}/{\partial}x\_{Fj\_{i}}|\_{\hat{x}}

H\_{Ej\_{i}}={\partial}h\_{ij\_{i}}/{\partial}x\_{Ej\_{i}}|\_{\hat{x}}

H represents the innovation of the pairing and H is the associated Jacobian

h\_{gai}(x)=0

h\_{gai}(x)=\begin{bmatrix}

h\_{ij\_{i}}(x)\\...

\\ h\_{mj\_{m}}(x)

\end{bmatrix}\simeq h\_{gai}(\hat{x})+H\_{gai}(x-\hat{x})

H\_{gai}={\partial}h\_{gai}/{\partial}x|\_{\hat{(x)}}=\begin{bmatrix}

H\_{1j\_{1}}\\ ...

\\ h\_{mj\_{m}}

\end{bmatrix}

The validity of the hypothesis *H* can be determined using an innovation test on the joint innovation h*H*(ˆx) as follows:

D\_{gai}^{2}=h\_{gai}(\hat{x})^{T}(H\_{gai}PH\_{gai})^{-1}h\_{gai}(\hat{x})< \chi \_{d,\alpha }^{2}

Once this hypothesis has been determined, a new estimate ˆx*0* of the state vector and its covariance P*0* can be obtained by applying the modified EKF update equations

d=dim(h\_{gai})

\hat{x}^{'}=\hat{x}-Kh\_{gai}(\hat{x})

{P}'=(I-KH\_{gai})P

K=PH\_{gai}^{T}(H\_{gai}PH\_{gai}^{T})^{-1}

After the modified EKF update, the associated features become fully correlated with the same mean and covariance, and one of the duplicate can be eliminated.

Adaptive Step Number

Another difficulty to get a good SLAM result is to determine when to conduct map fusion. Map fusion right after a sharp turn can be susceptible to linearization error of covariance propagation, resulting in wrong data association. adaptive number of step for local SLAM is applied to avoid fusion under large uncertainty, delaying the fusion process until sufficient number of pairings appears for robust JCBB.