

Graph SLAM Formulation

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1 Problem Formulation

Let a robot's trajectory through its environment be represented by a sequence of N poses: $\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_N$. Each pose lies on a manifold: $\mathbf{p}_i \in \mathcal{M}$. Simple examples of manifolds used in Graph SLAM include 1-D, 2-D, and 3-D space, i.e., \mathbb{R} , \mathbb{R}^2 , and \mathbb{R}^3 . These environments are *rectilinear*, meaning that there is no concept of orientation. By contrast, in $SE(2)$ problem settings a robot's pose consists of its location in \mathbb{R}^2 and its orientation θ . Similarly, in $SE(3)$ a robot's pose consists of its location in \mathbb{R}^3 and its orientation, which can be represented via Euler angles, quaternions, or $SO(3)$ rotation matrices.

As the robot explores its environment, it collects a set of M measurements $\mathcal{Z} = \{\mathbf{z}_j\}$. Examples of such measurements include odometry, GPS, and IMU data. Given a set of poses $\mathbf{p}_1, \dots, \mathbf{p}_N$, we can compute the estimated measurement $\hat{\mathbf{z}}_j(\mathbf{p}_1, \dots, \mathbf{p}_N)$. We can then compute the *residual* $\mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j)$ for measurement j . The formula for the residual depends on the type of measurement. As an example, let \mathbf{z}_1 be an odometry measurement that was collected when the robot traveled from \mathbf{p}_1 to \mathbf{p}_2 . The expected measurement and the residual are computed as

$$\begin{aligned}\hat{\mathbf{z}}_1(\mathbf{p}_1, \mathbf{p}_2) &= \mathbf{p}_2 \ominus \mathbf{p}_1 \\ \mathbf{e}_1(\mathbf{z}_1, \hat{\mathbf{z}}_1) &= \mathbf{z}_1 \ominus \hat{\mathbf{z}}_1 = \mathbf{z}_1 \ominus (\mathbf{p}_2 \ominus \mathbf{p}_1),\end{aligned}$$

where the \ominus operator indicates inverse pose composition. We model measurement \mathbf{z}_j as having independent Gaussian noise with zero mean and covariance matrix Ω_j^{-1} ; we refer to Ω_j as the *information matrix* for measurement j . That is,

$$p(\mathbf{z}_j \mid \mathbf{p}_1, \dots, \mathbf{p}_N) = \eta_j \exp\left((- \mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j))^T \Omega_j \mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j)\right), \quad (1)$$

where η_j is the normalization constant.

The objective of Graph SLAM is to find the maximum likelihood set of poses given the measurements $\mathcal{Z} = \{\mathbf{z}_j\}$; in other words, we want to find

$$\arg \max_{\mathbf{p}_1, \dots, \mathbf{p}_N} p(\mathbf{p}_1, \dots, \mathbf{p}_N \mid \mathcal{Z})$$

Using Bayes' rule, we can write this probability as

$$\begin{aligned}p(\mathbf{p}_1, \dots, \mathbf{p}_N \mid \mathcal{Z}) &= \frac{p(\mathcal{Z} \mid \mathbf{p}_1, \dots, \mathbf{p}_N) p(\mathbf{p}_1, \dots, \mathbf{p}_N)}{p(\mathcal{Z})} \\ &\propto p(\mathcal{Z} \mid \mathbf{p}_1, \dots, \mathbf{p}_N),\end{aligned} \quad (2)$$

since $p(\mathcal{Z})$ is a constant (albeit, an unknown constant) and we assume that $p(\mathbf{p}_1, \dots, \mathbf{p}_N)$ is uniformly

distributed [3]. Therefore, we can use (1) and (2) to simplify the Graph SLAM optimization as follows:

$$\begin{aligned}
\arg \max_{\mathbf{p}_1, \dots, \mathbf{p}_N} p(\mathbf{p}_1, \dots, \mathbf{p}_N \mid \mathcal{Z}) &= \arg \max_{\mathbf{p}_1, \dots, \mathbf{p}_N} p(\mathcal{Z} \mid \mathbf{p}_1, \dots, \mathbf{p}_N) \\
&= \arg \max_{\mathbf{p}_1, \dots, \mathbf{p}_N} \prod_{j=1}^M p(\mathbf{z}_j \mid \mathbf{p}_1, \dots, \mathbf{p}_N) \\
&= \arg \max_{\mathbf{p}_1, \dots, \mathbf{p}_N} \prod_{j=1}^M \exp \left(-(\mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j))^T \Omega_j \mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j) \right) \\
&= \arg \min_{\mathbf{p}_1, \dots, \mathbf{p}_N} \sum_{j=1}^M (\mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j))^T \Omega_j \mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j).
\end{aligned}$$

We define

$$\chi^2 := \sum_{j=1}^M (\mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j))^T \Omega_j \mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j),$$

and this is what we seek to minimize.

2 Dimensionality and Pose Representation

Before proceeding further, it is helpful to discuss the dimensionality of the problem. We have:

- A set of N poses $\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_N$, where each pose lies on the manifold \mathcal{M}
 - Each pose \mathbf{p}_i is represented as a vector in (a subset of) \mathbb{R}^d . For example:
 - An $SE(2)$ pose is typically represented as (x, y, θ) , and thus $d = 3$.
 - An $SE(3)$ pose is typically represented as $(x, y, z, q_x, q_y, q_z, q_w)$, where (x, y, z) is a point in \mathbb{R}^3 and (q_x, q_y, q_z, q_w) is a *quaternion*, and so $d = 7$. For more information about $SE(3)$ parameterizations and pose transformations, see [1].
 - We also need to be able to represent each pose compactly as a vector in (a subset of) \mathbb{R}^c .
 - Since an $SE(2)$ pose has three degrees of freedom, the (x, y, θ) representation is again sufficient and $c = 3$.
 - An $SE(3)$ pose only has six degrees of freedom, and we can represent it compactly as (x, y, z, q_x, q_y, q_z) , and thus $c = 6$.
 - We use the \boxplus operator to indicate pose composition when one or both of the poses are represented compactly. The output can be a pose in \mathcal{M} or a vector in \mathbb{R}^c , as required by context.
- A set of M measurements $\mathcal{Z} = \{\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_M\}$
 - Each measurement's dimensionality can be unique, and we will use \bullet to denote a “wildcard” variable.
 - Measurement $\mathbf{z}_j \in \mathbb{R}^\bullet$ has an associated information matrix $\Omega_j \in \mathbb{R}^{\bullet \times \bullet}$ and residual function $\mathbf{e}_j(\mathbf{z}_j, \hat{\mathbf{z}}_j) = \mathbf{e}_j(\mathbf{z}_j, \mathbf{p}_1, \dots, \mathbf{p}_N) \in \mathbb{R}^\bullet$.
 - A measurement could, in theory, constrain anywhere from 1 pose to all N poses. In practice, each measurement usually constrains only 1 or 2 poses.

3 Graph SLAM Algorithm

The ‘‘Graph’’ in Graph SLAM refers to the fact that we view the problem as a graph. The graph has a set \mathcal{V} of N vertices, where each vertex v_i has an associated pose \mathbf{p}_i . Similarly, the graph has a set \mathcal{E} of M edges, where each edge e_j has an associated measurement \mathbf{z}_j . In practice, the edges in this graph are either unary (i.e., a loop) or binary. (Note: e_j refers to the edge in the graph associated with measurement \mathbf{z}_j , whereas \mathbf{e}_j refers to the residual function associated with \mathbf{z}_j .) For more information about the Graph SLAM algorithm, see [2].

We want to optimize

$$\chi^2 = \sum_{e_j \in \mathcal{E}} \mathbf{e}_j^\top \Omega_j \mathbf{e}_j.$$

Let $\mathbf{x}_i \in \mathbb{R}^c$ be the compact representation of pose $\mathbf{p}_i \in \mathcal{M}$, and let

$$\mathbf{x} := \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_N \end{bmatrix} \in \mathbb{R}^{cN}$$

We will solve this optimization problem iteratively. Let

$$\mathbf{x}^{k+1} := \mathbf{x}^k \boxplus \Delta \mathbf{x}^k = \begin{bmatrix} \mathbf{x}_1 \boxplus \Delta \mathbf{x}_1 \\ \mathbf{x}_2 \boxplus \Delta \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_N \boxplus \Delta \mathbf{x}_N \end{bmatrix} \quad (3)$$

The χ^2 error at iteration $k+1$ is

$$\chi_{k+1}^2 = \sum_{e_j \in \mathcal{E}} \underbrace{[\mathbf{e}_j(\mathbf{x}^{k+1})]^\top}_{1 \times \bullet} \underbrace{\Omega_j}_{\bullet \times \bullet} \underbrace{\mathbf{e}_j(\mathbf{x}^{k+1})}_{\bullet \times 1}. \quad (4)$$

We will linearize the residuals as:

$$\begin{aligned} \mathbf{e}_j(\mathbf{x}^{k+1}) &= \mathbf{e}_j(\mathbf{x}^k \boxplus \Delta \mathbf{x}^k) \\ &\approx \mathbf{e}_j(\mathbf{x}^k) + \frac{\partial}{\partial \Delta \mathbf{x}^k} [\mathbf{e}_j(\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)] \Delta \mathbf{x}^k \\ &= \mathbf{e}_j(\mathbf{x}^k) + \left(\frac{\partial \mathbf{e}_j(\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)} \Big|_{\Delta \mathbf{x}^k=0} \right) \frac{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial \Delta \mathbf{x}^k} \Delta \mathbf{x}^k. \end{aligned} \quad (5)$$

Plugging (5) into (4), we get:

$$\begin{aligned} \chi_{k+1}^2 &\approx \sum_{e_j \in \mathcal{E}} \underbrace{[\mathbf{e}_j(\mathbf{x}^k)]^\top}_{1 \times \bullet} \underbrace{\Omega_j}_{\bullet \times \bullet} \underbrace{\mathbf{e}_j(\mathbf{x}^k)}_{\bullet \times 1} \\ &+ \sum_{e_j \in \mathcal{E}} \underbrace{[\mathbf{e}_j(\mathbf{x}^k)]^\top}_{1 \times \bullet} \underbrace{\Omega_j}_{\bullet \times \bullet} \underbrace{\left(\frac{\partial \mathbf{e}_j(\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)} \Big|_{\Delta \mathbf{x}^k=0} \right)}_{\bullet \times dN} \underbrace{\frac{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial \Delta \mathbf{x}^k}}_{dN \times cN} \underbrace{\Delta \mathbf{x}^k}_{cN \times 1} \\ &+ \sum_{e_j \in \mathcal{E}} \underbrace{(\Delta \mathbf{x}^k)^\top}_{1 \times cN} \underbrace{\left(\frac{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial \Delta \mathbf{x}^k} \right)^\top}_{cN \times dN} \underbrace{\left(\frac{\partial \mathbf{e}_j(\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)} \Big|_{\Delta \mathbf{x}^k=0} \right)^\top}_{dN \times \bullet} \underbrace{\Omega_j}_{\bullet \times \bullet} \underbrace{\left(\frac{\partial \mathbf{e}_j(\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)} \Big|_{\Delta \mathbf{x}^k=0} \right)}_{\bullet \times dN} \underbrace{\frac{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial \Delta \mathbf{x}^k}}_{dN \times cN} \underbrace{\Delta \mathbf{x}^k}_{cN \times 1} \\ &= \chi_k^2 + 2\mathbf{b}^\top \Delta \mathbf{x}^k + (\Delta \mathbf{x}^k)^\top H \Delta \mathbf{x}^k, \end{aligned}$$

where

$$\mathbf{b}^\top = \sum_{e_j \in \mathcal{E}} \underbrace{[\mathbf{e}_j(\mathbf{x}^k)]^\top}_{1 \times \bullet} \underbrace{\Omega_j \left(\frac{\partial \mathbf{e}_j(\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)} \Big|_{\Delta \mathbf{x}^k = \mathbf{0}} \right)}_{\bullet \times dN} \underbrace{\frac{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial \Delta \mathbf{x}^k}}_{dN \times cN}$$

$$H = \sum_{e_j \in \mathcal{E}} \underbrace{\left(\frac{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial \Delta \mathbf{x}^k} \right)^\top}_{cN \times dN} \underbrace{\left(\frac{\partial \mathbf{e}_j(\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)} \Big|_{\Delta \mathbf{x}^k = \mathbf{0}} \right)^\top}_{dN \times \bullet} \underbrace{\Omega_j \left(\frac{\partial \mathbf{e}_j(\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)} \Big|_{\Delta \mathbf{x}^k = \mathbf{0}} \right)}_{\bullet \times dN} \underbrace{\frac{\partial (\mathbf{x}^k \boxplus \Delta \mathbf{x}^k)}{\partial \Delta \mathbf{x}^k}}_{dN \times cN}.$$

Using this notation, we obtain the optimal update as

$$\Delta \mathbf{x}^k = -H^{-1} \mathbf{b}. \quad (6)$$

We apply this update to the poses via (3) and repeat until convergence.

References

- [1] BLANCO, J.-L. A tutorial on $SE(3)$ transformation parameterizations and on-manifold optimization. *University of Malaga, Tech. Rep 3* (2010).
- [2] GRISETTI, G., KUMMERLE, R., STACHNISS, C., AND BURGARD, W. A tutorial on graph-based SLAM. *IEEE Intelligent Transportation Systems Magazine 2*, 4 (2010), 31–43.
- [3] THRUN, S., AND MONTEMERLO, M. The graph SLAM algorithm with applications to large-scale mapping of urban structures. *The International Journal of Robotics Research 25*, 5-6 (2006), 403–429.