g2o versus Toro: Format and Cost Functions

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I. Format for 2D datasets

Both g2o [1] and Toro [2] input files contain two "sections":

- VERTICES (lines starting with "VERTEX2" in TORO, or "VERTEX_SE2" in g2o): description of the vertices of the pose graph. Each line follows the format: "ID x y th", where "ID" is a unique index assigned to the corresponding pose, and "x", "y", "th" describe the initial guess (usually obtained from odometry) of the pose. "x" and "y" are the initial guess of node's planar position, while "th" is the initial guess for node's orientation (in radians);
- EDGES (lines starting with "EDGE2" in TORO, or "EDGE_SE2" in g2o): description of the edges of the pose graph. In TORO, each line follows the format: "IDout IDin dx dy dth I11 I12 I22 I33 I13 I23", and describes an edge going from node with index "IDout" to node with index "IDin". The edge describes a measurement of the pose of node "IDin" in the reference frame of node "IDout". The relative (planar) pose is coded in the elements "dx", "dy", "dth". The remaining elements describe the uncertainty on the relative pose measurement: the six elements completely define the (symmetric) 3x3 Information matrix:

$$I = \begin{bmatrix} I11 & I12 & I13 \\ I12 & I22 & I23 \\ I13 & I23 & I33 \end{bmatrix} \tag{1}$$

  In g2o, the ordering of the elements in the EDGES description is slightly different from TORO, and becomes: "IDout IDin dx dy dth I11 I12 I13 I22 I23 I33". Moreover, for letting g2o optimize the same cost function as TORO, the corresponding information matrices need to be changed as described in the next section.

II. Cost Functions

When comparing results from g2o [1] and Toro [2] it is important to realize that the two solvers use slightly different cost functions. The optimization problem solved in Toro is:

$$\min_{\boldsymbol{R}_i, \boldsymbol{t}_i} \sum_{(i,j)\in\mathcal{E}} \left\| \mathrm{Log}\left(\bar{\boldsymbol{R}}_{ij}^{\mathsf{T}} \boldsymbol{R}_i^{\mathsf{T}} \boldsymbol{R}_j\right) \right\|_{\Omega_{ij}^r}^2 + \left\| \bar{\boldsymbol{t}}_{ij} - \boldsymbol{R}_i^{\mathsf{T}}(\boldsymbol{t}_j - \boldsymbol{t}_i) \right\|_{\Omega_{ij}^t}^2 \tag{2}$$

where $\boldsymbol{R}_i$ and $\boldsymbol{t}_i$ are the (to-be-computed) rotation and translation at node i (for $i = 1, \ldots, n$), $\bar{\boldsymbol{R}}_{ij}^{\mathsf{T}}$ and $\bar{\boldsymbol{t}}_{ij}$ are the relative rotation and translation measurements between node i and j, Ω_{ij}^r is the rotation measurement information matrix, Ω_{ij}^t is the translation measurement information matrix, and $\mathcal{E}$ is the set of node pairs (i, j) for which a measurement is available. The symbol $\mathrm{Log}(\cdot)$ denotes the logarithm map for the rotation group, which, roughly speaking, converts a rotation to a vector (in 3D) or a scalar angle (in 2D).

The error definition in g2o is similar, with a small difference in the second summand:

$$\min_{\boldsymbol{R}_i, \boldsymbol{t}_i} \sum_{(i,j)\in\mathcal{E}} \left\| \mathrm{Log}\left(\bar{\boldsymbol{R}}_{ij}^{\mathsf{T}} \boldsymbol{R}_i^{\mathsf{T}} \boldsymbol{R}_j\right) \right\|_{\Omega_{ij}^r}^2 + \left\| \bar{\boldsymbol{R}}_{ij}^{\mathsf{T}}(\bar{\boldsymbol{t}}_{ij} - \boldsymbol{R}_i^{\mathsf{T}}(\boldsymbol{t}_j - \boldsymbol{t}_i)) \right\|_{\Omega_{ij}^t}^2 \tag{3}$$

Developing the Mahalanobis norms on the right, we get:

$$\begin{aligned}
&\min_{\boldsymbol{R}_i, \boldsymbol{t}_i} \sum_{(i,j)\in\mathcal{E}} \left\| \mathrm{Log}\left(\bar{\boldsymbol{R}}_{ij}^{\mathsf{T}} \boldsymbol{R}_i^{\mathsf{T}} \boldsymbol{R}_j\right) \right\|_{\Omega_{ij}^r}^2 + \left(\bar{\boldsymbol{R}}_{ij}^{\mathsf{T}}(\bar{\boldsymbol{t}}_{ij} - \boldsymbol{R}_i^{\mathsf{T}}(\boldsymbol{t}_j - \boldsymbol{t}_i))\right)^{\mathsf{T}} \Omega_{ij}^t \left(\bar{\boldsymbol{R}}_{ij}^{\mathsf{T}}(\bar{\boldsymbol{t}}_{ij} - \boldsymbol{R}_i^{\mathsf{T}}(\boldsymbol{t}_j - \boldsymbol{t}_i))\right) \\
&\Updownarrow \\
&\min_{\boldsymbol{R}_i, \boldsymbol{t}_i} \sum_{(i,j)\in\mathcal{E}} \left\| \mathrm{Log}\left(\bar{\boldsymbol{R}}_{ij}^{\mathsf{T}} \boldsymbol{R}_i^{\mathsf{T}} \boldsymbol{R}_j\right) \right\|_{\Omega_{ij}^r}^2 + \left(\bar{\boldsymbol{t}}_{ij} - \boldsymbol{R}_i^{\mathsf{T}}(\boldsymbol{t}_j - \boldsymbol{t}_i)\right)^{\mathsf{T}} \bar{\boldsymbol{R}}_{ij} \Omega_{ij}^t \bar{\boldsymbol{R}}_{ij}^{\mathsf{T}} \left(\bar{\boldsymbol{t}}_{ij} - \boldsymbol{R}_i^{\mathsf{T}}(\boldsymbol{t}_j - \boldsymbol{t}_i)\right) \\
&\Updownarrow \\
&\min_{\boldsymbol{R}_i, \boldsymbol{t}_i} \sum_{(i,j)\in\mathcal{E}} \left\| \mathrm{Log}\left(\bar{\boldsymbol{R}}_{ij}^{\mathsf{T}} \boldsymbol{R}_i^{\mathsf{T}} \boldsymbol{R}_j\right) \right\|_{\Omega_{ij}^r}^2 + \left\| \bar{\boldsymbol{t}}_{ij} - \boldsymbol{R}_i^{\mathsf{T}}(\boldsymbol{t}_j - \boldsymbol{t}_i) \right\|_{\bar{\boldsymbol{R}}_{ij} \Omega_{ij}^t \bar{\boldsymbol{R}}_{ij}^{\mathsf{T}}}^2
\end{aligned} \tag{4}$$

which also shows that for a fair comparison between Toro and g2o we should use $\bar{\boldsymbol{R}}_{ij} \Omega_{ij}^t \bar{\boldsymbol{R}}_{ij}^{\mathsf{T}}$ as information matrices in g2o.

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[2] G. Grisetti, C. Stachniss, and W. Burgard. Non-linear constraint network optimization for efficient map learning. *Trans. on Intelligent Transportation systems*, 10(3):428–439, 2009.