Robust Pose Graph Optimization Without An Accurate Measurement Covariance Model

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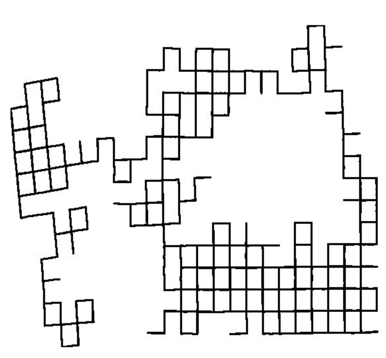
Motivation

The factor graph provides a popular way to represent the navigation state estimation problem. Methods for optimizing factor graphs work well when the Gaussian assumption holds and the measurement model is known a priori. However, robust models aimed at addresses graph optimization when the above mentioned assumptions do not hold fall short on several fronts.

Introduction

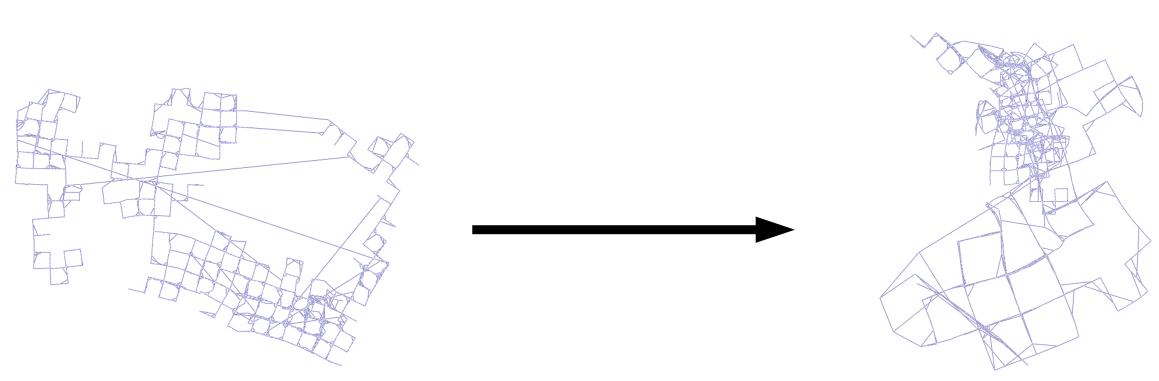
- The factor graph provides a convenient tool for factorizing a function of many variables into a product of smaller subsets



$$e_i = H_i(X_i) - Z_i$$

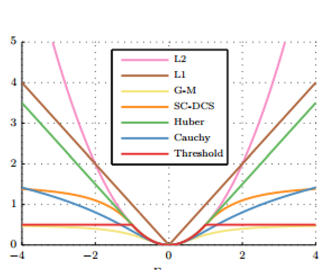
$$\hat{X} = \operatorname{argmin} \sum_i ||e_i||^2_\Sigma$$

- What happens when the Gaussian assumption is not valid?

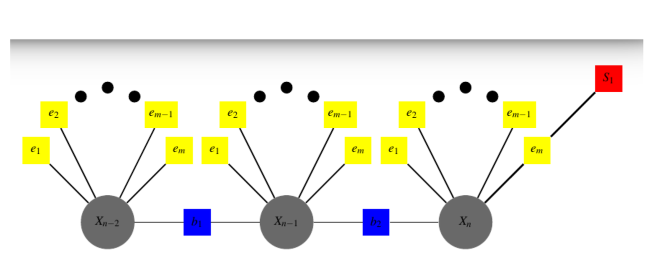


- Current Methods of robust graph optimization.

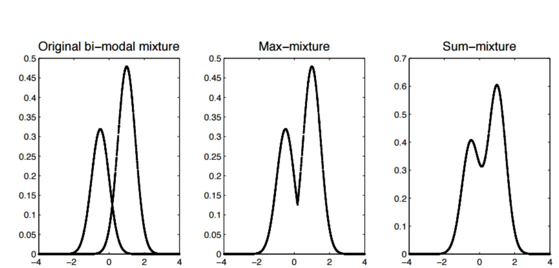
M-Estimator



Switch Factors

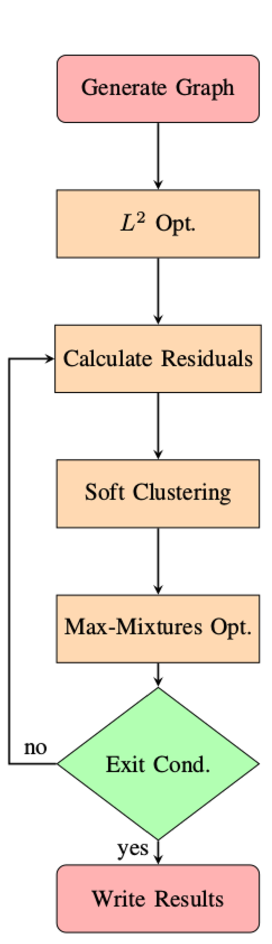


Max-Mixtures

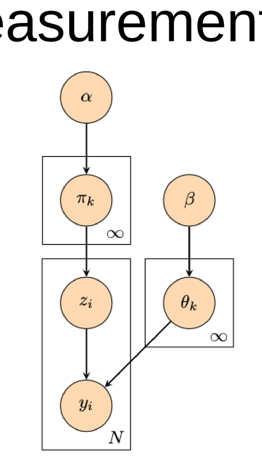


- These methods works well when the input measurement covariance is known. However, that is not always a safe assumption. Additionally, these methods are sensitive to hyper-parameters

Technical Approach



- Utilize collapsed Gibb's Sampling to estimate a infinite Gaussian Mixture Model (G.M.M) to characterize the measurement covariance matrix.



Define $p(\pi|\alpha)$ and $p(\mu_k, \Sigma_k|\beta)$ in such a way that we can analytically integrate out latent variables ($\pi,\ \mu_k,$ and Σ_K) and only sample the component assignments.

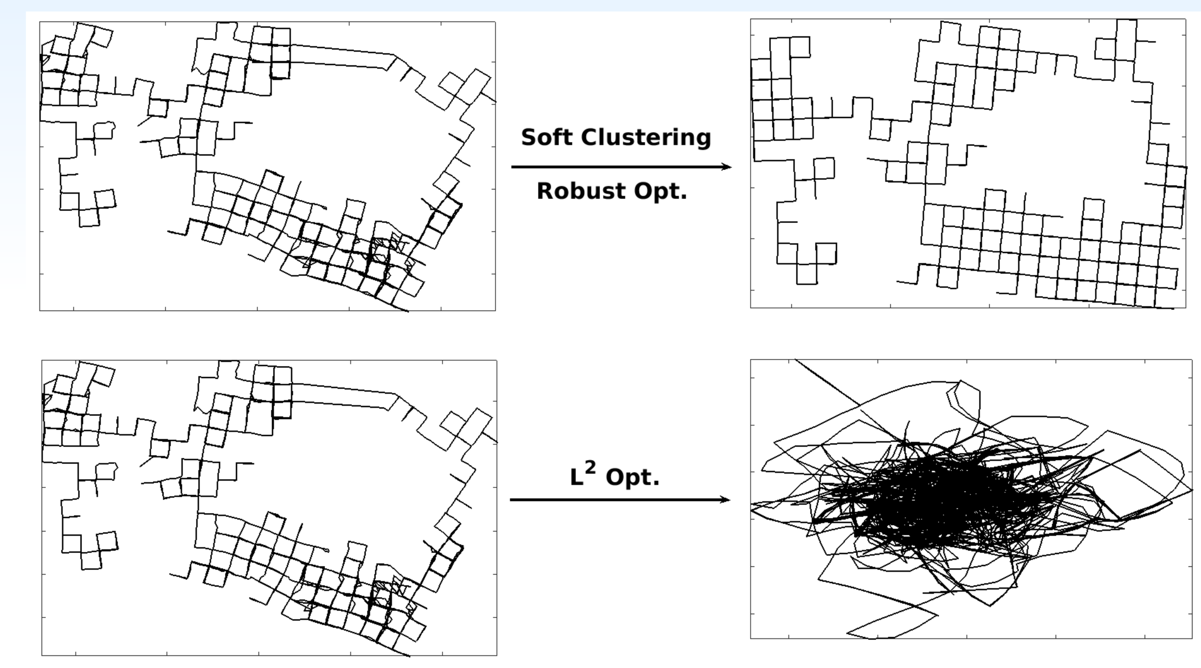
- Now, we have an n-component mixture model that characterizes the measurement covariance.

$$p(z_i|x) = \Sigma_i \omega_i\ \mathcal{N}(\mu_i, \Sigma|i)\ \approx\ max\ \omega_i\ \mathcal{N}(\mu_i, \Sigma_i)$$

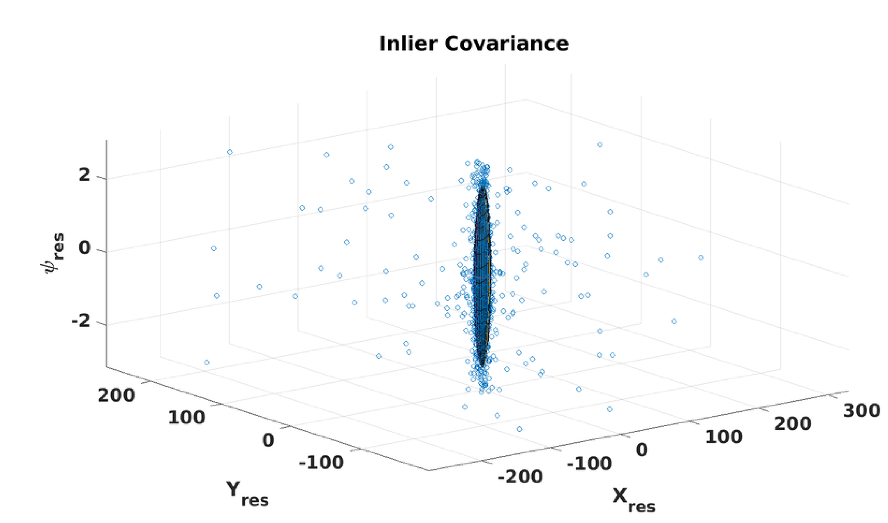
- Now, all constraints are iteratively tested against the model, which allows the information and Jacobian matrices to be scaled accordingly.

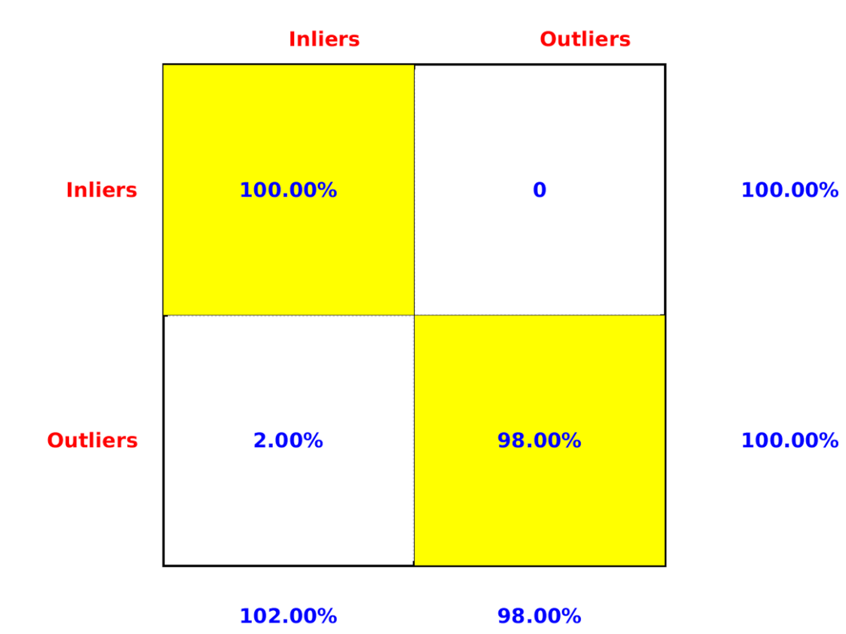
Results

- Robust to false constraints

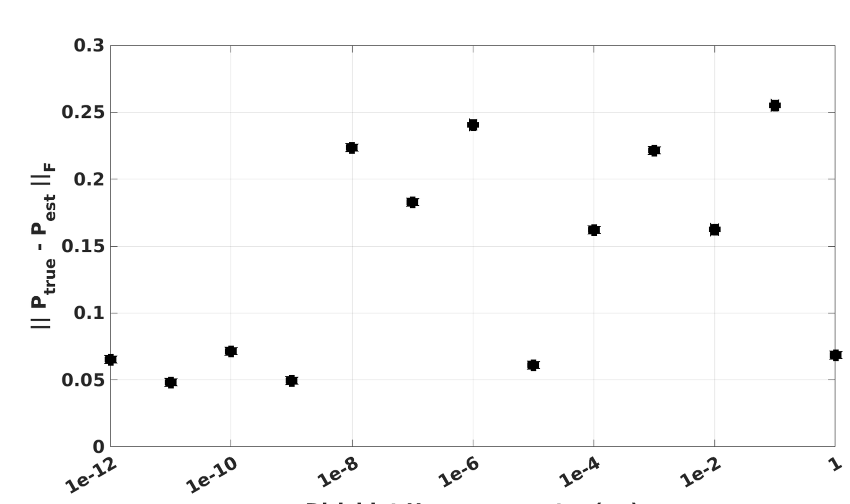


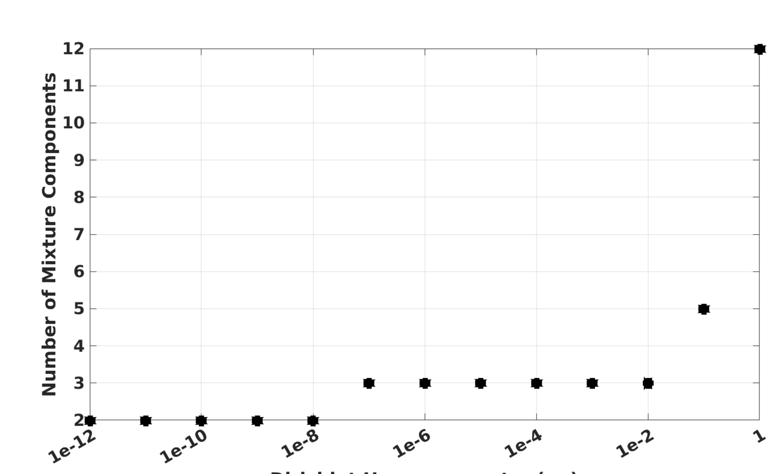
- Accurate Covariance





- Insensitivity to Hyper-parameters





Contribution

We've provided a method of robust factor graph optimization that handle erroneous constraints and provides a reliable estimate of the inlier measurement covariance, while not being sensitive to hyper-parameters.

Future Work

We would like to advance this method on two fronts:

1) Reduce run-time
   - The method discussed in this poster utilizes collapsed Gibb's sampling to approximate the posterior distribution.
   - We can make the current method faster by moving from a sampling approach to a closed form solution. Specifically, we can apply variational inference to approximate the true posterior distribution in closed form.
   - Additionally, we can store the measurement residuals in a kd-tree to efficiently access them during inference.

2) Scale the final covariance estimate proportional to its likelihood of being a false positive.
   - Utilize the Neyman-Pearson lemma.

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