Autonomous drone cinematographer

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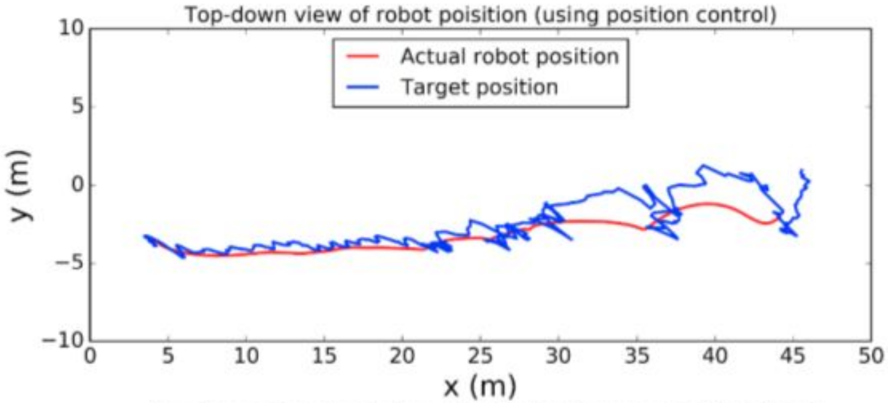
Motivation

Drones are revolutionizing the way people film: more flexibility in shots. However...

Project Goals

Design costs functions to ensure:

Artistic intent + smoothness + obstacle avoidance + occlusion



[1] N. Ratli, M. Zucker, J. A. Bagnell, and S. Srinivasa, “Chomp: Gradient optimization techniques for ecient motion planning," in Robotics and Automation, 2009. ICRA'09. IEEE International Conference on , pp. 489{494, IEEE, 2009.

[2] Jing Dong et. al. “Motion Planning as Probabilistic Inference using Gaussian Processes and Factor Graphs”

Cost functionals to be optimized

$$C_{obstacle} = \int_{t=0}^{1} \int_{u \in B} c(x(\xi(t), u)) || \frac{d}{dt} x(\xi(t), u) || du dt$$

$$\mathcal{F}_{smooth}[\xi] = \frac{1}{2} \int_0^1 \left\| \frac{d}{dt} \xi(t) \right\|^2 dt$$

$$J_{\text{shot}}(\xi_q, \xi_{shot}) = \frac{1}{t_f} \frac{1}{2} \int_0^{t_f} ||\xi_q(t) - \xi_{shot}(t)||^2 dt$$

$$J_{\text{occ}}(\xi_q, \xi_a) = \int_{t=0}^{t_f} \int_{\tau=0}^{1} c(p(\tau)) \left|\left| \frac{d}{d\tau} p(\tau) \right|\right| d\tau \left|\left| \frac{d}{dt} \xi_q(t) \right|\right| dt$$

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In this project we explored two different trajectory optimizers:

- CHOMP [1]
- Gaussian Process Motion Planning - GPMP [2]

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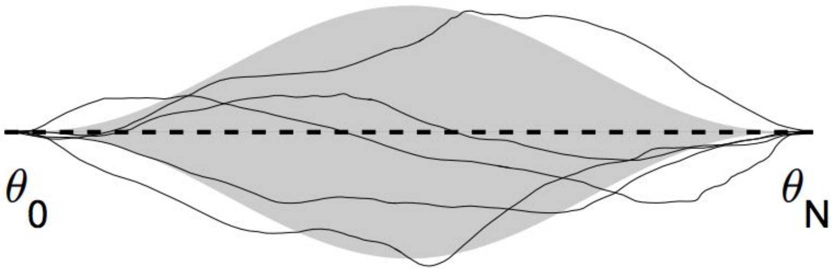
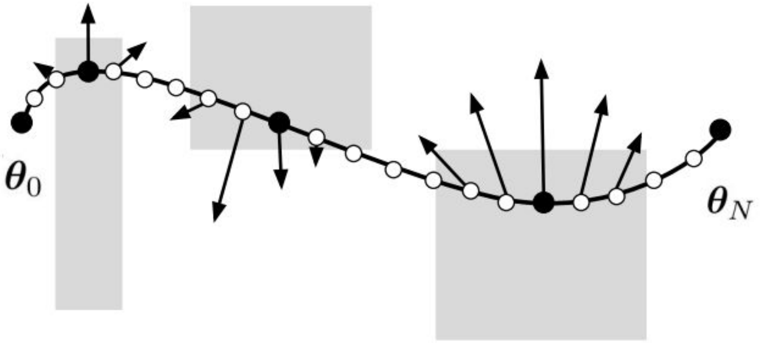
Methodology - GPMP



Gaussian Process Prior

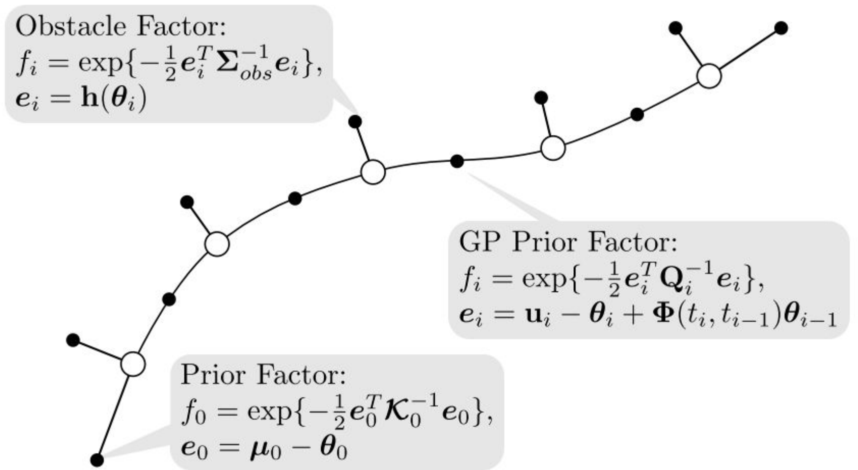


Optimizes interpolated states

$$\xi'(t) = A(t)\xi(t) + F(t)w(t)$$
$$w(t) \sim \mathcal{GP}(0, Q_c\delta(t - t')), \quad t_0 < t, t' < t_{N+1}$$

[4] Mustafa Mukadam et. al. “Continuous-time Gaussian process motion planning via probabilistic inference”

Methodology - GPMP



- Smoothness is ensured from the GP prior
- Gaussian Process reduces to nonlinear least squares optimization

$$\boldsymbol{\theta}^* = \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \left\{ \frac{1}{2} \parallel \boldsymbol{\theta} - \boldsymbol{\mu} \parallel_{\boldsymbol{\mathcal{K}}}^2 + \frac{1}{2} \parallel \boldsymbol{h}(\boldsymbol{\theta}) \parallel_{\boldsymbol{\Sigma}_{obs}}^2 \right\},$$

Solve iteratively:

$$\delta\boldsymbol{\theta}^* = \underset{\delta\boldsymbol{\theta}}{\operatorname{argmin}} \left\{ \frac{1}{2} \parallel \bar{\boldsymbol{\theta}} + \delta\boldsymbol{\theta} - \boldsymbol{\mu} \parallel_{\boldsymbol{\mathcal{K}}}^2 + \frac{1}{2} \parallel \boldsymbol{h}(\bar{\boldsymbol{\theta}}) + \mathbf{H}\delta\boldsymbol{\theta} \parallel_{\boldsymbol{\Sigma}_{obs}}^2 \right\}$$

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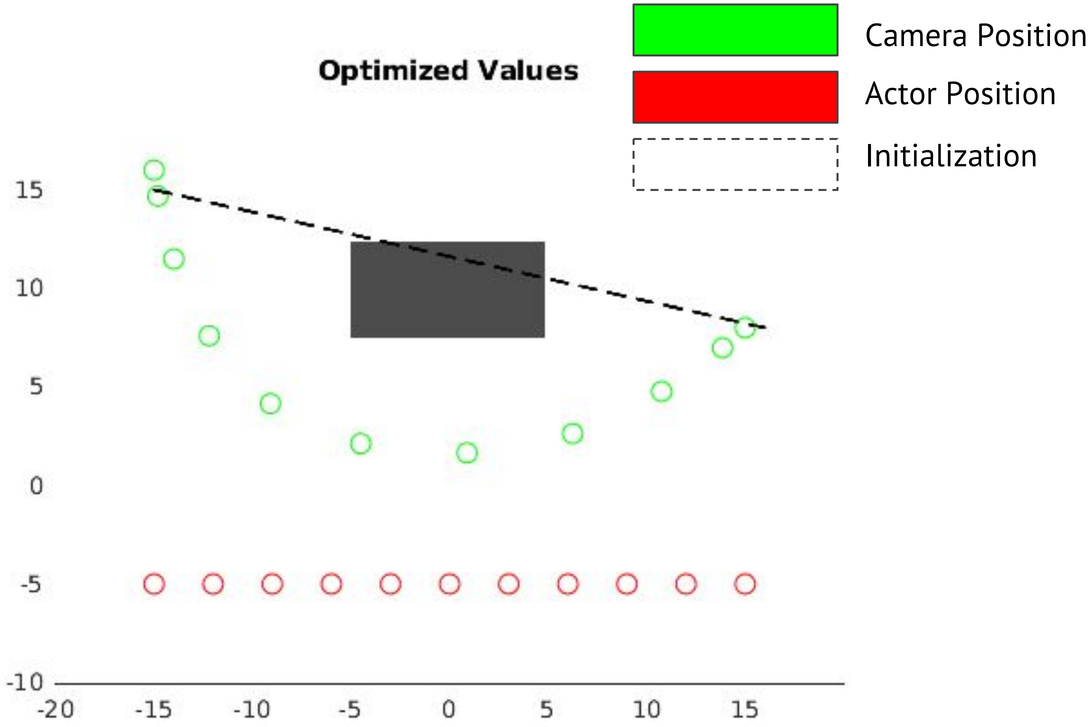
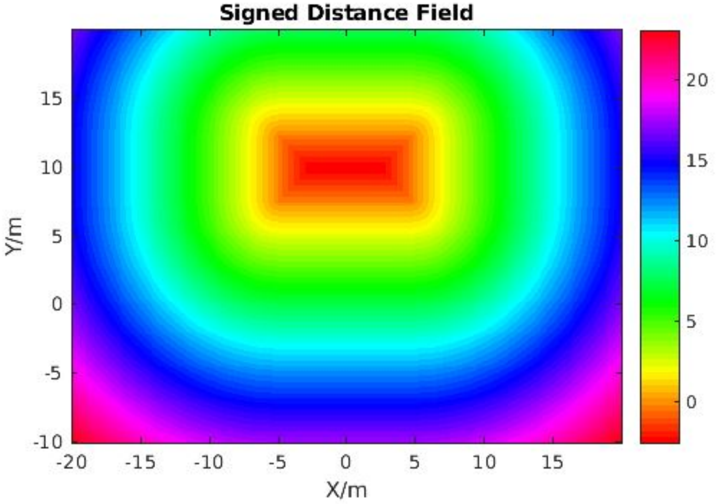
Results: GPMP





Methodology - CHOMP

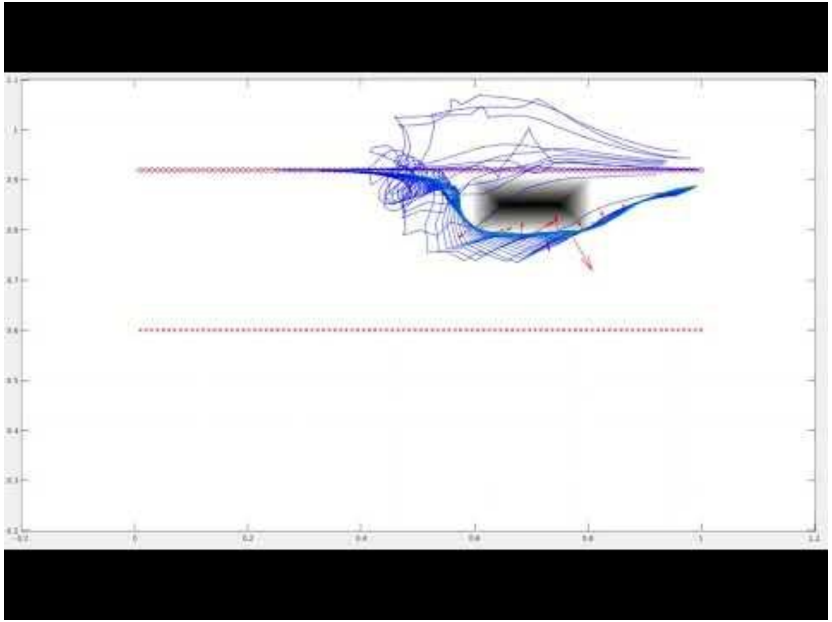
- Steepest descent optimization using covariant gradient descent on the trajectory
- gk is the gradient of the cost functional

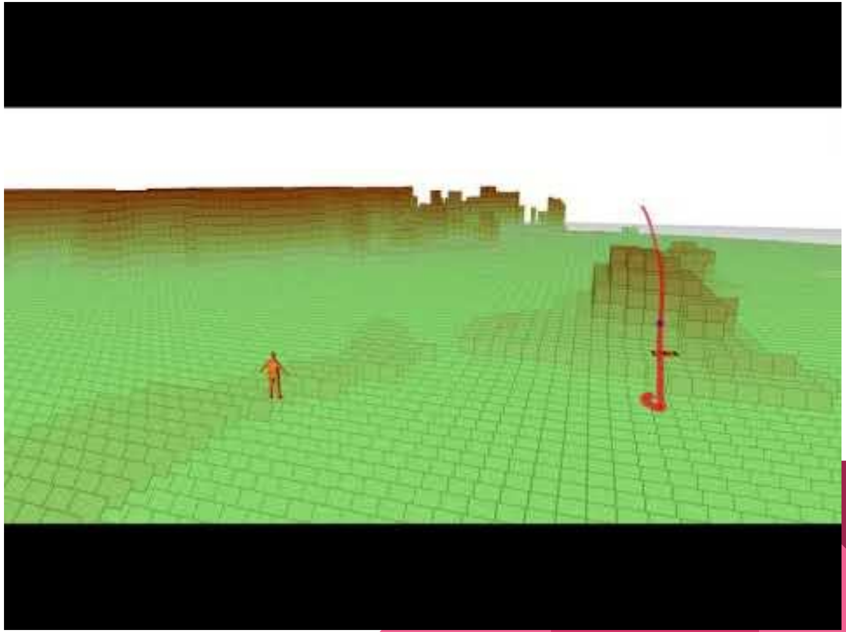
$$\xi = \begin{bmatrix} p_1 \\ p_2 \\ \cdots \\ p_{n-1} \end{bmatrix} = \begin{bmatrix} p_{1x} & p_{1y} & p_{1z} \\ p_{2x} & p_{2y} & p_{2z} \\ \vdots & \vdots & \vdots \\ p_{n-1\ x} & p_{n-1\ y} & p_{n-1\ z} \end{bmatrix}$$

$$\xi_{qk+1} = \xi_{qk} - \frac{1}{\lambda} M^{-1} g_k$$

Results: CHOMP

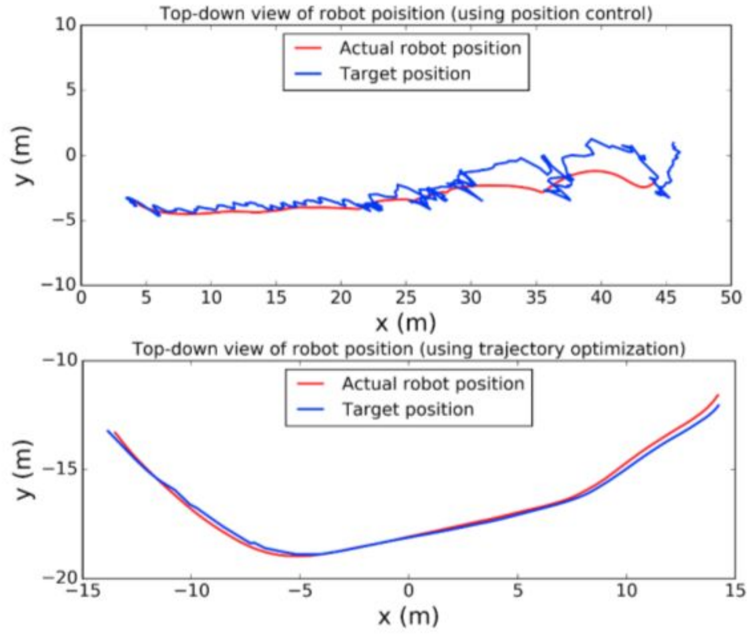
2D simulation results





Conclusion and Future Work

- CHOMP running online generates smooth, tractable trajectories
- GPMP is too parameter-dependant



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[1] C. J. Bowen and R. Thompson, Grammar of the Shot . Taylor & Francis, 2013.
[2] M. Mukadam, X. Yan, and B. Boots, “Gaussian process motion planning," in Robotics and Automation (ICRA), 2016 IEEE International Conference on , pp. 9{15, IEEE, 2016.
[3] J. Dong, M. Mukadam, F. Dellaert, and B. Boots, “Motion planning as probabilistic inference using gaussian processes and factor graphs.," in Robotics: Science and Systems , vol. 12, 2016.
[4] N. Ratli, M. Zucker, J. A. Bagnell, and S. Srinivasa, “Chomp: Gradient optimization techniques for ecient motion planning," in Robotics and Automation, 2009. ICRA'09. IEEE International Conference on , pp. 489{494, IEEE, 2009.
[5] J. Schulman, J. Ho, A. X. Lee, I. Awwal, H. Bradlow, and P. Abbeel, “Finding locally optimal, collision-free trajectories with sequential convex optimization.," in Robotics: science and systems , vol. 9, pp. 1{10, 2013.}
[6] Mustafa Mukadam, “Continuous-time Gaussian process motion planning via probabilistic inference”, 2017 IEEE Transactions on Robotics.