Paper Review of CHOMP
Gradient Optimization Techniques for Efficient Motion Planning

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October 6, 2021

1 Paper Summary

This paper proposed an optimization based method for efficiently planning collision free trajectories. This method explicitly defines the optimization objectives that considers both obstacles as well as dynamic requirements. The obstacle term is formulated as a potential function integrated through an SDF (signed distance field) representation, while the dynamical requirement is modeled with a quadratic function over the trajectory. The proposed regularized optimization method, like Gauss-Newton, converges much faster than naive Euclidean gradient, but does not require differentiability. They have also shown many successful implementations of their optimization planner on a variety of hardware platforms.

2 What I Learned

1. Signed distance field can be computed super efficiently with Euclidean Distance Transform, which takes linear time.
2. Finite differencing of the trajectory can be constructed with appropriate linear operators.

3 Opinions

3.1 Up Votes

- I like how obstacles are formulated into the optimization objective. The SDF is both efficient to compute as well as easy to be incorporated with objective functions. This eliminates the need for a sampling based planner that explicitly checks for collision.
- I also like their approach on using local linear approximation with regularized optimization objective. This not only results in a efficiently computable update rule, but also ensures smoothness across the trajectory update.

3.2 Down Votes

I don't really disagree much with this work. One slight shortcoming of CHOMP is that it might be hard to explicitly plan for tasks that requires close proximity or even contacts. The optimization results naturally repel the trajectory away from any occupied space. It might be hard to plan trajectories that aim to move towards some target object (obstacle).

4 Evaluations

The goal of this paper is to introduce a unified optimal control framework that is not only able to generate smooth trajectories, but also takes environment, more specifically obstacles, into account. It is a perfectly valid goal as previous work on motion planning considering obstacle avoidance mostly uses sampling based method, which can produce jerky and dynamically unfeasible trajectories. On the other hand, previous work on optimal control has not been successfully take obstacle avoidance into account with efficient computing. The significance of bridging the gap between optimal control and obstacle avoidance also lies in making the whole robotic control system easier to implement with such unified framework.

This paper is of very high quality in my opinion. The proposed methodology provides sound derivation of optimization theories that are both tractable and efficient to implement in practice. Their experimental results also suggests a huge success in a variety of sophisticated real world robotic system including the *LittleDog* from Boston Dynamic Inc. One slight unaddressed assumption they made is that CHOMP requires the knowledge of 3D environment around the manipulator. Accurate 3D reconstruction is in fact still a open and challenging problem to be solved.

5 Questions

1. Where does the metric M in Equation (3) comes from?
2. Is the computation still tractable if the manipulators are instead modeled with polygonal meshes?