HAAG Weekly Report

Nikita Angarski – 3D Modeling

Week 7

Time-Log

- What did you do this week?
  - Met with both computational experts to explain math behind algorithm optimization
  - Edited the algorithm code to make a registration with the PCA kernel.
  - Met with seminar program team members to check in and accelerate program process
- What are you going to do next week
  - Test new PCA kernel registration on mouse dataset
  - Compare with vanilla and optimize testing suite to reflect testing changes.
  - Replicate method for testing accuracy using manual point datasets to compare with our transformation
- Blockers, things you want to flag, problems, etc.
  - Not currently

Abstracts:

A Bayesian Formulation of Coherent Point Drift

Abstract: Coherent point drift is a well-known algorithm for solving point set registration problems, i.e., finding corresponding points between shapes represented as point sets. Despite its advantages over other state-of-the-art algorithms, theoretical and practical issues remain. Among theoretical issues, (1) it is unknown whether the algorithm always converges, and (2) the meaning of the parameters concerning motion coherence is unclear. Among practical issues, (3) the algorithm is relatively sensitive to target shape rotation, and (4) acceleration of the algorithm is restricted to the use of the Gaussian kernel. To overcome these issues and provide a different and more general perspective to

the algorithm, we formulate coherent point drift in a Bayesian setting. The formulation brings the following consequences and advances to the field: convergence of the algorithm is guaranteed by variational Bayesian inference; the definition of motion coherence as a prior distribution provides a basis for interpretation of the parameters; rigid and non-rigid registration can be performed in a single algorithm, enhancing robustness against target rotation. We also propose an acceleration scheme for the algorithm that can be applied to non-Gaussian kernels and that provides greater efficiency than coherent point drift.

We also experiment the use of multi-kernels for PCA and show its comparison with classical PCA using circle, moons, classification, swiss roll and iris datasets.

Summary: The paper addresses the point set registration problem, specifically improving the Coherent Point Drift (CPD) algorithm. It introduces a Bayesian formulation of CPD, called BCPD, to address theoretical issues like convergence and parameter interpretation, along with practical issues like sensitivity to rotation. The Bayesian approach uses prior distributions to define motion coherence, ensuring algorithm convergence and enhancing robustness. The paper presents an accelerated version of BCPD applicable to various kernel functions and shows how CPD can be seen as a special case of BCPD. Experimental results demonstrate BCPD's improved registration accuracy and efficiency compared to existing methods on both artificial and real datasets.

What did you do and prove it

This week had some big progress made across the team, with all members contributing to the code. My contribution is listed in the below commit, where I introduce a PCA Kernel creation method, and then subsequently use it to replicate a registration method, but replacing the Gaussian kernel with the PCA one.

Link to meeting with Seminar Team: https://gtvault-my.sharepoint.com/:v:/g/personal/nangarski3_gatech_edu/EZhUeUQHgBdJscR21KzWKKkB3BmIHB-zug6a72TRvMjQPQ?e=vT7v7T&nav=eyJyZWZlcnJhbEluZm8iOnsicmVmZXJyYWxBcHAiOiJTdHJlYW1XZWJBcHAiLCJyZWZlcnJhbFZpZXciOiJTaGFyZURpYWxvZy1MaW5rIiwicmVmZXJyYWxBcHBQbGF0Zm9ybSI6IldlYiIsInJlZmVycmFsTW9kZSI6InZpZXcifX0%3D

Link to commit: https://github.com/Nikitos1865/pycpd-Porto/commit/46a16421b6cdcc4df5252e1f576ffbb66b33177c