SCHOOL OF COMPUTER SCIENCE AND INFORMATICS, CARDIFF UNIVERSITY

Initial plan: Enhancing the accuracy of rigid registration using a general and adaptive robust loss function

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1 DESCRIPTION

Rigid registration of two geometric data is vital for geometric applications in formulating the data. We see its wide usages including robot navigation, surface reconstruction and shape matching. Rigid registration is usually powered by a variant of Iterative Closest Point (ICP) algorithms [6, 4, 8] which alternate between closest point computations to establish correspondences between two data sets. ICP aims for optimal transformation that transfers the geometric correspondences into alignment. Nevertheless, we often observe the sensitivity to outliers and missing data in 3D scannings.

In this project, we consider improving a Sparse Iterative Closest Point approach [4] that employs sparsity inducting norms for optimizing the registration using a general and adaptive robust loss function. We expect the improved approach not only retains the simple structure of the ICP algorithm and achieving superior registration results when dealing with outliers and incomplete data but also more robust to noises and lowing the chance for mismatch caused by extreme values.

ICP algorithms formulate the local alignment problem as recovering a rigid transformation that maximises the number of zero distances between correspondences. Let P_i be a point in source geometric data, while D_i be the closet distance for P_i to reach the target geometric data. We want $min(\sum_i F(d_i))$, where in classical ICP algorithms $F(x) = x^2$, in sparse ICP $F(x) = x^p$ where $p \in [0,1]$. The goal can be achieved by minimising l_2 norm of the vector of error residuals in classical ICP while l_p norms in Sparse ICP, where $p \in [0,1]$.

We consider using a loss function taken from [3] to change this F(x). The simplest form of this loss function is:

$$f(x,\alpha,c) = \frac{|\alpha-2|}{\alpha}((\frac{(x/c)^2}{|\alpha-2|+1}^{\alpha/2})-1) \tag{1.1}$$

where α is a shape parameter that controls the robustness of the loss and $c > 0$ is a scale parameter that controls the size of the loss's quadratic bowl near $x = 0$.

Though this loss is undefined when $\alpha = 2$, it approaches L2 loss in the limit:

$$\lim_{\alpha->2} f(x,\alpha.c) = \frac{1}{2}x/c^2 \tag{1.2}$$

When $\alpha = 1$, this loss is a smoothed form of L1 loss:

$$f(x,1,c) = \sqrt{(x/c)^2+1}-1 \tag{1.3}$$

This loss's ability to express L2 and smoothed L1 losses is shared by the "generalized Charbonnier" loss [9], which has been used in flow and depth estimation tasks that require robustness [5, 7] and is commonly defined as

$$(x^2+\epsilon)^{\alpha/2} \tag{1.4}$$

This loss has significantly more expressive power than the generalized Charbonnier loss [3].

We expect to evaluate our approach by quantitative comparison to classical rigid registration methods as well as Sparse ICP and other recent robust variants.

2 ETHICS

We will use public data set [2] to evaluate the performance of the approach. Thus, we have decided that this project will not require ethical approval.

3 AIMS AND OBJECTIVES

The aims of the project are based around developing a Sparse Iterative Closest Point using a general and adaptive robust loss function. This ICP protocol should have a more accurate result for grid registration than other variants of ICP algorithms. The aims are outlined as follows:

3.1 AIMS

1. Develop and adapt a suitable loss function for replacing l_p norns.
2. Develop a Sparse ICP which use this loss function.

To tackle this project, We will be using different techniques and ideas used in standard Data Science-esque tasks. The following objectives how We will achieve the abovementioned aims of this project:

3.2 OBJECTIVES

1. Research classical ICP, Sparse ICP and test their performances with different kinds of input.
2. Research Robust Loss functions and who they can be embedded into Sparse ICP.
3. Test and compare the edited Sparse ICP with other varients.

4 WORK PLAN

4.1 DELIVERABLES

We endeavour to submit the following items by the deadline:

1. Final report
2. source code
3. Supporting documents related to our findings and analyses
4. The visualisation of the result of the project.

4.2 Research and Preparation

Before getting started with development, We need to read up materials relevant to the project. We will explore tutorials to understand how to properly use the existing frameworks that will be used for this project, e.g. the code of Sparse ICP. Once We have a feel for the frameworks, We can start to make early strides in developing a solution. Furthermore, We need to understand the used loss function and how it can be embedded in the framework for better results. We will use testing techniques to measure the loss function's performances concerning different parameters.

4.3 Implementation

After spending time researching and testing ideas, We will start to implementing ideas I have come across through our time researching. Such materials can be related to the parameters selected for the loss function. We will be going to be implementing a Sparse ICP, in which we will experiment it with different kinds of sparsity enforcement methods.

4.4 Supervisor Meetings

I have scheduled several weekly meetings with my supervisor, Bailing Deng. These meetings re an opportunity to share progress, raise issues, seek help from the supervisor.

4.5 Schedule

Taking into consideration commitments to my other modules in this semester, I have aimed to reach these weekly milestones by the end of the labelled weeks:

- **Week 1** 27/01/20-02/02/20:
  1. Initial Meeting with Supervisor to discuss the next steps to make with the project. Workshop with supervisor to obtain the test data set.
  2. Download all necessary software and code on my personal laptop. Including the code [1] and the dataset[2].
  3. Writing up an initial plan
- **Week 2** 03/02/20-09/02/20:
  1. Submit Initial Plan of the project. Initial Plan would have been discussed from the previous one to one meeting with the supervisor to properly understand what to write in the initial plan.
  2. Run and become familiar with the Sparse Iterative Closest Point using the code downloaded.
- **Week 3** 10/02/20-16/02/20: Program the loss function from the equations into C++ code.

- **Week 4** 17/02/20-23/02/20:Program the loss function from the equations into C++ code.
- **Week 5** 24/02/20-01/03/20: Complete programming the loss function from the equations into C++ code. (**Milestone one**)
- **week 6** 02/03/20-08/03/20: Combining the loss function to the Sparse ICP code.
- **week 7** 09/03/20-15/03/20:Combining the loss function to the Sparse ICP code.
- **week 8** 16/03/20-22/03/20: Complete Combining the loss function to the Sparse ICP code.(**Milestone two**)
- **week 9** 23/03/20-29/03/20: Test the performance of the edited Sparse ICP with the original one and other variants.(**Milestone three**)
- **week 10** 20/04/20-26/04/20: Write up the final project paper.
- **week 11** 27/04/20-03/05/20: Write up the final project paper.
- **week 12** 04/04/20-10/04/20: Submit the final project paper.

REFERENCES

[1] https://lgg.epfl.ch/sparseicp.

[2] https://projects.asl.ethz.ch/datasets/doku.php?id=laserregistration:laserregistration.

[3] J. T. Barron. A general and adaptive robust loss function. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4331–4339, 2019.

[4] S. Bouaziz, A. Tagliasacchi, and M. Pauly. Sparse iterative closest point. In *Computer graphics forum*, volume 32, pages 113–123. Wiley Online Library, 2013.

[5] Q. Chen and V. Koltun. Fast mrf optimization with application to depth reconstruction. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3914–3921, 2014.

[6] S. Kaneko, T. Kondo, and A. Miyamoto. Robust matching of 3d contours using iterative closest point algorithm improved by m-estimation. *Pattern recognition*, 36(9):2041–2047, 2003.

[7] P. Krähenbühl and V. Koltun. Efficient nonlocal regularization for optical flow. In *European Conference on Computer Vision*, pages 356–369. Springer, 2012.

[8] P. Mavridis, A. Andreadis, and G. Papaioannou. Efficient sparse icp. *Computer Aided Geometric Design*, 35:16–26, 2015.

[9] D. Sun, S. Roth, and M. J. Black. Secrets of optical flow estimation and their principles. In *2010 IEEE computer society conference on computer vision and pattern recognition*, pages 2432–2439. IEEE, 2010.