

Maximum Consensus with Mixed Integer Linear Programming

by

Yang Heng KEE

A dissertation submitted to the School of Computer Science, The University of Adelaide for the degree of Master of Philosophy

August, 2016

Contents

\mathbf{C}	onter	nts			i
Li	st of	Figure	es		iii
Li	st of	Tables	5		\mathbf{v}
\mathbf{A}	bstra	act			vii
D	eclar	ation			ix
P	refac	e			xi
A	ckno	wledge	ments		xiii
1	Intr	oducti	on		1
	1.1	Param	eter Estimation		3
	1.2	Literat	ture Review		7
		1.2.1	Linear Regression		7
		1.2.2	Maximum Consensus		9
	1.3	Thesis	Contributions		10
	1.4		Organisation		10
2	Par	ameter	Estimation Methods		11
	2.1	Linear	Regression		11
		2.1.1	Linear Least Squares		12
		2.1.2	Smallest Maximum Error		13
		2.1.3	Least Absolute Error		13
		2.1.4	M-Estimation		14
		2.1.5	Least Median of Squares		15

	2.2	Maximum Consensus	16
		2.2.1 RANSAC	16
		2.2.2 Mixed Integer Linear Programming	21
3	Big	-M and M-bisection	23
	3.1	Feasibility and Maximum Consensus	23
	3.2	The Big-M Method	26
	3.3	M-bisection	29
	3.4	Main Algorithm	33
	3.5	Applications in Computer Vision	34
		3.5.1 Epipolar Geometry	35
	3.6	Experimental Results	38
		3.6.1 Synthetic Data	39
		3.6.2 Epipolar Geometry Estimation	40
	3.7	Summary	41
4	Gua	aranteed Outlier Removal	43
-	4.1	Overview of GORE	43
	4.2	MILP Formulation for GORE	45
		4.2.1 Lower Bound Calculation	48
	4.3	Main Algorithm	49
	4.4	GORE with Quasiconvex Residuals	50
		4.4.1 MILP Formulation	52
	4.5	Applications in Computer Vision	53
	1.0	4.5.1 Triangulation	53
		4.5.2 Image Matching	57
	4.6	Experimental Results	59
		4.6.1 Synthetic Data	59
		4.6.2 Image Matching	61
		4.6.3 Epipolar Geometry Estimation	62
		4.6.4 Triangulation	64
	4.7	Summary	65
5	Con	nclusion	67

List of Figures

1.2	Points for line fitting	3
1.3	A line drawn using two points can result in a bad fit	4
1.4	Line of best fit estimated using least squares	4
1.5	Least squares estimate skewed by a single (red) outlying point.	5
2.1	RANSAC in action	17
2.2	An illustration of the threshold "strip"	18
3.9	Affine epipolar geometry estimated using MILP	38
4.1	(a) Solving (2.17) exactly on \mathcal{X} with $N=100$ to robustly fit an affine plane $(d=3)$ using the Gurobi solver took 423.07s. (b) Removing 5 true outliers (points circled in red) using the proposed GORE algorithm (50s) and subjecting the remaining data \mathcal{X}' to Gurobi returns the same maximum consensus set	
4.10	in 32.5s, representing a reduction of 80% in the total runtime. Computational gain of GORE on synthetic data for dimensions $n = 3, \dots, 8$ and increasing number of rejection tests T	44
	as a ratio of problem size N . Time per test c is fixed at a	
	maximum of 15s	61

List of Tables

3.1	Results from 6 different sets of synthetic data. $ \mathcal{I} = \text{size of}$ optimised consensus set	40
3.2	Results of affine epipolar geometry estimation. $ \mathcal{I} = \text{size of optimised consensus set.}$	41
4.1	Results of affine image matching. $N = \text{size}$ of input data \mathcal{X} , $\epsilon = \text{inlier threshold (in pixels)}$ for maximum consensus, $ \mathcal{I} = \text{size}$ of optimised consensus set, $ \mathcal{X}' = \text{size}$ of reduced data by	
	GORE	62
4.2	Results of affine epipolar geometry estimation. $N = \text{size}$ of input data \mathcal{X} , $\epsilon = \text{inlier}$ threshold (in pixels) for maximum consensus, $ \mathcal{I} = \text{size}$ of optimised consensus set, $ \mathcal{X}' = \text{size}$	60
4.9	of reduced data by GORE	63
4.3	Results of triangulation. $N = \text{size of input data } \mathcal{X}, \epsilon = \text{inlier}$ threshold (in pixels) for maximum consensus, $ \mathcal{I} = \text{size of}$	
	optimised consensus set, $ \mathcal{X}' $ = size of reduced data by GORE.	64

Abstract

Maximum consensus is fundamentally important in computer vision as a criterion for robust estimation, where the goal is to estimate the parameters of a model of best fit. It is computationally demanding to solve such problems exactly. Instead, conventional methods employ randomised sample-and-test techniques to approximate a solution, which fail to guarantee the optimality of the result. This thesis makes several contributions towards solving the maximum consensus problem exactly in the context of Mixed Integer Linear Programming. In particular, two preprocessing techniques aimed at improving the speed and efficiency of exact methods are proposed.

Declaration

I, Yang Heng KEE, certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

I give consent to this copy of my thesis when deposited in the University Library, being made available for loan and photocopying, subject to the provisions of the Copyright Act 1968.

I also give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library Search and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

Signature	Date

Preface

During my studies at the University of Adelaide from 2014 to 2016, I have contributed to the production of one conference paper. Chapter 4 of this thesis is based on the content presented in the aforementioned paper, with details of the paper listed below:

Conference Publication

• T.-J. Chin, Y.H. Kee, A. Eriksson, and F. Neumann. Guaranteed outlier removal with mixed integer linear programs. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Acknowledgements

This study was an interesting experience for me, and the completion of this research would not have been possible without the support of many people.

First and foremost, I would like to express my deepest gratitude to my supervisor Dr. Tat-Jun Chin for his patience and his continued guidance and support. He was always at hand with his expertise and advice, and this journey would not have been possible without him.

It is also a pleasure to work with my co-supervisor Prof. David Suter, who held monthly research group meetings with students under his supervision to discuss and to throw around ideas regarding the current state of our research. I have benefitted greatly from those monthly sessions and enjoyed the group discussions with my peers.

Finally, I would like to thank my family and friends for providing their support and encouragement throughout my research for the past two years.