



A Preference Analysis Approach to Robust Geometric Model Fitting in Computer Vision

by

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*To my parents and my sister,
for their unconditional love and endless support.*

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Abstract

Robust model fitting is a crucial task in numerous computer vision applications, where the information of interest is often expressed as a mathematical model. The goal of model fitting is to estimate the model parameters that “best” explain the observed data. However, robust model fitting is a challenging problem in computer vision, since vision data are (1) unavoidably contaminated by outliers due to imperfections in data acquisition and preprocessing, and (2) often contain multiple instances (or structures) of a model.

Many robust fitting methods involve generating hypotheses using random sampling, and then (1) score the hypotheses using a robust criterion or (2) use a mode seeking or clustering method to elicit the potential structures in the data. Obtaining a good set of hypotheses is crucial for success, however this is often time-consuming, especially for heavily contaminated data. In addition, many irrelevant hypotheses are unavoidably generated during sampling process. This frequently becomes an obstacle for accurate estimation, and has been ignored in previous methods. In particular, mode seeking-based fitting methods are very sensitive to the proportion of good/bad hypotheses.

This thesis proposes several sampling methods for rapid and effective generation of good hypotheses, and hypothesis filtering methods to remove bad hypotheses for accurate estimation. The techniques developed here can be easily integrated into existing fitting methods to significantly improve fitting accuracy. We also propose a hierarchical fitting method, which recognizes that details in real-life data are organized hierarchically (i.e., large structures cascading down to finer structures). This can avoid excessive parameter tuning to obtain a particular fitting result, whereas existing fitting methods often fit data with a single number of structures and permit only one interpretation of the data.

The algorithms in this thesis are motivated by preference (or ranking) analysis, which has been widely used in areas such as information retrieval, artificial intelligence and marketing. Preference analysis provides a sophisticated non-parametric approach to analyzing the data and hypotheses in model fitting problems. The algorithms developed here are shown to be more reliable than previous methods, and to perform well in various vision tasks.

Declaration

I, Hoi Sim Wong, certify that this work contains no material which has been accepted for the award of any other degree or diploma 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.

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Date

Preface

During my PhD study at the University of Adelaide from 2009 to 2012, I have produced two conference papers and two journal articles. This thesis is based on the content presented in those papers, as listed in the following:

Conference Publications:

- H. S. Wong, T.-J. Chin, J. Yu, and D. Suter. Dynamic and Hierarchical Multi-Structure Geometric Model Fitting. In *Proceedings of International Conference on Computer Vision*, pages 1044–1051, 2011
- H. S. Wong, T.-J. Chin, J. Yu, and D. Suter. Efficient Multi-Structure Robust Fitting with Incremental Top-k Lists Comparison. In *Proceedings of Asian Conference on Computer Vision*, volume 6495, pages 553–564, 2010

Journal Publications:

- H. S. Wong, T.-J. Chin, J. Yu, and D. Suter. Mode Seeking Over Permutations for Rapid Geometric Model Fitting. *Pattern Recognition*, 46(1):257 – 271, 2013. Accepted in 2012
- H. S. Wong, T.-J. Chin, J. Yu, and D. Suter. A Simultaneous Sample-and-Filter Strategy for Robust Multi-Structure Model Fitting. *Computer Vision and Image Understanding*. Submitted in August 2011, currently under minor revision

I have also produced the following dataset, which has been made publicly available.

DataSet:

- AdelaideRMF is a dataset for robust model fitting. It contains a collection of image pairs for homography and fundamental matrix estimation on single and multi-structure data. AdelaideRMF can be downloaded from <http://cs.adelaide.edu.au/~hwong/doku.php?id=data>.

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