

Faculty of Engineering and Information Technology
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**Cross-source point cloud matching by
exploring structure property**

A thesis submitted in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy

by

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CERTIFICATE OF AUTHORSHIP/ORIGINALITY

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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6.6 Comparable performance of our proposed registration methods in solving challenging indoor registration problems. The results show that CSGM is the highest accurate algorithm while PSTN achieves comparative accuracy. 150

List of Publications

Papers published

- **Xiaoshui Huang**, Lixin Fan, Qiang Wu, Jian Zhang, Chun Yuan (2017), A coarse-to-fine algorithm for matching and registration in 3D cross-sourced point clouds. *in* 'Transactions on Circuits and Systems for Video Technology (TCSVT)', full paper accepted.
- **Xiaoshui Huang**, Jian Zhang, Lixin Fan, Qiang Wu, Chun Yuan (2017), A Systematic Approach for Cross-Source Point Cloud Registration by Preserving Macro and Micro Structures. *in* 'IEEE Transactions on Image Processing (TIP)', vol. 26, no. 7, pp. 3261-3276, July 2017.
- **Xiaoshui Huang**, Jian Zhang, Qiang Wu, Lixin Fan, Chun Yuan (2016), A coarse-to-fine algorithm for registration in 3D street-view cross-source point clouds. *in* 'International Conference on Digital Image Computing: Techniques and Applications (DICTA)' (pp. 1-6). IEEE.
- **Xiaoshui Huang**, Lixin Fan, Jian Zhang, Qiang Wu, and Chun Yuan (2016), Real Time Complete Dense Depth Reconstruction for a Monocular Camera. *in* 'Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)' (pp. 32-37). IEEE.
- **Xiaoshui Huang**, Chun Yuan, and Jian Zhang (2015), Graph Cuts Stereo Matching Based on Patch-Match and Ground Control Points

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- **Xiaoshui Huang**, Jian Zhang, Qiang Wu, Chun Yuan, and Lixin Fan (2015), Dense Correspondence Using Non-local DAISY Forest. *in* 'International Conference on Digital Image Computing: Techniques and Applications (DICTA)' (pp. 1-8). IEEE.
- Shoujin Wang, Liang Hu, Longbing Cao, **Xiaoshui Huang**, Defu Lian, Wei Liu. (2018), Attention-based Transactional Context Embedding for Next-Item Recommendation. *in* 'The Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18)'.

Papers to be submitted

- **Xiaoshui Huang**, Jian Zhang, Lixin Fan, Qiang Wu, Chun Yuan (2017), Cross-source Point Cloud Registration by using weak regional affinity and pixel-wise refinement. To be submitted to 'IEEE Transactions on Multimedia (TMM)'.
- **Xiaoshui Huang**, Jian Zhang, Lixin Fan, Qiang Wu, Chun Yuan (2017), PSTN: learning a rotation-invariant descriptor for cross-source point cloud matching. To be submitted to 'IEEE Transactions on Multimedia (TMM)'.

Patents Granted

- Lixin Fan, **Xiaoshui Huang**, Qiang Wu, Jian Zhang. "Point cloud matching process". U.K. Patent: GB2550567. issued date: 2017-11-29.

Abstract

Cross-source point cloud are 3D data coming from heterogeneous sensors. The matching of cross-source point cloud is extremely difficult because they contain mixture of different variations, such as missing data, noise and outliers, different viewpoint, density and spatial transformation. In this thesis, cross-source point cloud matching is solved from three aspects, utilizing of structure information, statistical model and learning representation. Chapter 1 introduces the value of cross-source point cloud registration and summarizes the key challenges of cross-source point cloud registration problem. Chapter 2 reviews the existing registration methods and analyse their limitation in solving the cross-source point cloud registration problem. Chapter 3 proposes two algorithms to discuss how to utilize structure information to solve the cross-source point cloud registration problem. In the first part of this chapter, macro and micro structures are extracted based on 3D point cloud segmentation. Then, these macro and micro structure components are integrated into a graph. With novel descriptors generated, the registration problem is successfully converted into graph matching problem. In the second part, weak region affinity and pixel-wise refinement are proposed to solve the cross-source point cloud. These two components are unified represented into a tensor space and the registration problem is converted into tensor optimization problem. In this method, the tensor space is updated when the transformation matrix is updated to get feedback from the recent transformation estimation step. Chapter 4 discusses how to utilize the statistical distribution of cross-source point cloud to solve matching problem.

ABSTRACT

The goal is to find the potential matching region and estimate the accurate registration relationship. In this chapter, ensemble of shape functions (ESF) is utilized to select potential regions and a novel registration is proposed to solve the matching problem. For the registration, Gaussian mixture models (GMM) is selected as our mathematical tool. However, different to previous GMM-based registration methods, which assume a GMM for each point cloud, the proposed algorithm assumes a virtual GMM and the cross-source point clouds are samples from the virtual GMM. Then, the transformation is optimized to project the samples into a same virtual GMM. When the optimization is convergence, both the parameters of GMM and the transformation matrices are estimated. In Chapter 5, a deep learning method is proposed to represent the local structure information. Because of arbitrary rotation in cross-source point clouds, a rotation-invariant 3D representation method is proposed to robust represent the 3D point cloud although there are arbitrary rotation and translation. Also, there is no robust keypoints in these cross-source point cloud because of they come from heterogenous sensors, train the network is very difficult. A region-based method is proposed to generate regions for each point cloud and synthetic labelled dataset is constructed for training the network. All these algorithms are aimed to solve the cross-source point cloud registration problem. The performance of these algorithms is tested on many datasets, which shows the effective and correctness. These algorithms also provide insightful knowledge for 3D computer vision workers to process 3D point cloud.