

# 3D Surface Matching from Range Images using Multiscale Local Features

By

Huy Tho Ho

B.E. (First Class Honours)

A thesis submitted in partial fulfillment of the  
requirements for the degree of  
**Master of Applied Science**

School of Electrical and Electronic Engineering  
The University of Adelaide  
Australia

December 2009

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## Abstract

Object recognition is one of the most important problems in computer vision. Traditional object recognition techniques are usually performed on optical images that are 2D projections of the 3D world. Information about the depth of objects in the scene is not provided explicitly in these images and thus, it makes 2D object recognition techniques sensitive to changes in illumination and shadowing. As surface acquisition methods such as LADAR or range scanners are becoming more popular, there is an increasing interest in the use of three-dimensional geometric data in object recognition to overcome these limitations.

However, the matching of 3D free-form surfaces is also a difficult problem due to the shape and topological complexity of 3D surfaces. In addition, the problem is further complicated by other issues such as variations in surface sampling resolution, occlusion, clutter and sensor noise. The huge amount of information required to describe a 3D surface is also another challenge that 3D surface matching techniques have to deal with.

This thesis investigates the problems of 3D surface matching that include 3D surface registration and object recognition from range images. It focuses on developing a novel and efficient framework for aligning 3D surfaces in different coordinate systems and from this, recognizing 3D models from scenes with high levels of occlusion and clutter using multi-scale local features.

The first part of the thesis presents two different schemes for extracting salient geometric features from 3D surfaces using surface curvature measures known as the curvedness and shape index. By deriving the scale-space representation of the input surface, surface positions with high local curvature or high local shape variations are selected as features at various degrees of scale. One advantage of the proposed approaches is their applicability to both 3D meshes with connectivity information and unstructured point clouds.



In the second part of the thesis, an application of the multi-scale feature extraction framework to 3D surface registration and object recognition is proposed. A Delaunay tetrahedrization is performed on the features extracted from each input range image to obtain a set of triangles. Possible correspondences are found by matching all possible pairs of triangles between the scene and model surfaces. From these correspondences, possible transformations between the two surfaces can be hypothesized and tested. In order to increase the accuracy and efficiency of the algorithm, various surface geometric and rigidity constraints are applied to prune unlikely correspondences. By finding the match that aligns the largest number of features between the two surfaces, the best transformation can be estimated. In the case of surface registration, this transformation can be used to coarse-align two different views of the same object. In the case of 3D object recognition, it provides information about the possible pose (location and orientation) of the model in the scene surface. Experimental results on a variety of 3D models and real scenes are shown to verify the effectiveness and robustness of the approach.

## Declaration

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 to Huy Tho Ho 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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Huy Tho Ho  
December 2009



## Acknowledgements

First and foremost, I would like to express my sincerest gratitude to my supervisors, Dr. Danny Gibbins and Prof. Douglas A. Gray, for their valuable guidance, support and encouragement throughout my Master research. Completion of the thesis would not have been possible without their encouragement and time.

I would also like to thank the School of Electrical & Electronic Engineering, Dr. Danny Gibbins and Prof. Douglas A. Gray for providing the Master scholarship as well as their support for my travel to conferences.

I am grateful to the institutions and people who made their data and code publicly available, including Dr. Ajmal Mian (3D data), Carnegie Mellon University (Mesh Toolbox), Stanford University (3D data), Universität Stuttgart (3D data). I would also like to thank the Defence Science and Technology Organisation (DSTO) for providing the vehicle simulation data used in the experiments.

Finally, I would like to thank my grandmother, my parents and my brother for their unconditional love and support. Last of all, thank you, Thanh, for always being there for me.



## List of Publications

The following papers have been written based on the materials presented in this thesis

1. H.T. Ho and D. Gibbins, “Multi-scale Feature Extraction from 3D Models with Applications to Surface Registration”, to appear in *IET Computer Vision Journal*, 2009.
2. H.T. Ho and D. Gibbins, “Multi-scale Feature Extraction from 3D Models using Local Surface Curvature”, *Proceedings of Digital Image Computing: Techniques and Applications (DICTA '08)*, Canberra, Australia, December 2008.
3. H.T. Ho and D. Gibbins, “Multi-scale Feature Extraction for 3D Surface Registration using Local Shape Variation”, *Proceedings of Image and Vision Computing New Zealand (IVCNZ'08)*, Christchurch, New Zealand, November 2008.



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