Towards Reliability and Scalability in Feature Based Simultaneous Localization and Mapping

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Certificate

I, Gibson Hu, declare that this thesis entitled *Towards Reliability and Scalability in Feature Based Simultaneous Localization and Mapping* and the work presented in it are my own. I confirm that:

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Abstract

Simultaneous Localization and Mapping (SLAM) has always been an attractive topic in the vibrant field of robotics. Feature based representations of the problem can be seen as one of the most common definitions. In recent years, many SLAM researchers have realized some limitations of filtering based methods and started to focus more on optimization based SLAM techniques. However, this raises several questions surrounding convergence reliability and, similar to filtering, algorithm scalability.

In SLAM, sensor noise and non-linearity often causes the problem to become difficult. Converging towards the global minimum in a non-linear least squares formulation is by no means easy. Typically, one would need to start from a good initial estimate, preferably already inside the basin of attraction of the global minimum. In this thesis, we introduce a technique called Iterative Re-Weighted Least Squares bootstrapping to achieve a good initial estimate even when the noise is exceptionally large.

As a robot continues to traverse through its environment the complexity of SLAM tends to scale badly with the cumulative nature of graph nodes and edges. To solve large SLAM problems within a reasonable time scale one must also take into consideration elements of accuracy and consistency. In this thesis, we propose two alternative algorithms to handle complexity, Sparse Map Joining and Pose Graph Representation. Both of which contain unique advantages for handling the diverse scenarios within SLAM.

A series of quantitative analyses are performed on a number of challenging datasets, both real and simulated. In addition to this we perform a comprehensive case study on a specific type of feature based SLAM problem, RGB-D SLAM. This demonstrates how our technique is capable of avoiding inaccuracies and failure scenarios that is otherwise common in other RGB-D SLAM algorithms.

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Nomenclature

Formatting Style

$\hat{x}$	Measured
$\bar{x}$	Estimated
$\tilde{x}$	Actual

Subscript

m	features index	i, j	pose index
t	time index		

Superscript

$\mathcal{M}$	marginalized	P	pose set
F	feature set	O	odometry set
K	pose subset	L	local map
G	global map	S	sensor

Notations

$\sim\mathcal{N}$	normally distributed	$\underset{X}{\operatorname{argmin}}$	minimizer
$[.]$	vector elements	$\|\|.\|\|$	Euclidean norm
X^*	the optimum	$X^{(0)}$	initial estimate

Variables

$\mathcal{G}$	undirected graph	$\mathcal{V}$	graph vertices
$\mathcal{E}$	graph edges	E	essential matrix
Z	measurement vector	X	state vector
Σ	covariance matrix	Ω, Λ	information matrix
χ^2	chi squared value	ν	degree of freedom
$\mathcal{P}$	optimisation problem	w	weight scalar
F	fundamental matrix	S	scale
K	calibration matrix	T	transformation matrix

Functions

$g()$	pose to pose	$h()$	pose to feature
$b()$	generalized model function	$\rho()$	m-estimator
$Rot()$	rotation matrix	$Proj()$	projection matrix
$Horn()$	Horn's method	$\psi()$	influence function

Abbreviations

SLAM	Simultaneous Localisation and Mapping
ML	Maximum Likelihood
GN	Gauss-Newton
GD	Gradient Decent
PDL	Powell's Dog-Leg
LM	Levenberg-Marquardt
STD	Standard Deviation
SGD	Stochastic Gradient Descent
SBA	Sparse Bundle Adjustment
iSAM	Incremental Smoothing and Mapping
g^2o	General Graph Optimization
ParallaxBA	Parallax Angle Bundle Adjustment
Alg	Algorithm
RMSE	Root Mean Squared Error
NEES	Normalized Estimation Error Squared

IRLS	Iterative Re-weighted Least Squares
GT	Ground Truth
IMU	Inertial Measurement Unit
RPE	Relative Pose Error
ATE	Absolute Trajectory Error
SIFT	Scale Invariant Feature Transform
SURF	Speeded-Up Robust Features
I-SLSJF	Iterated Sparse Local Submap Joining Filter
EIF	Extended Information Filter
EKF	Extended Kalman Filter
SMJ	Sparse Map Joining
BO	Batch Optimization
SO	Sequential Optimization
DCO	Divide and Conquer Optimization
LAGO	Linear Approximation for Graph Optimization
TORO	Tree based netwORk Optimizer
MO	Multi Observation method
SO	Single Observation method
PGR	Pose Graph Representation
MAP	Maximum a Posteriori

DBN	Dynamic Bayesian Network
ICP	Iterative Closest Point
RE-RANSAC	Re-projection Error RANdom SAmpling Consensus
EM-RANSAC	Essential Matrix RANdom SAmpling Consensus
VO	Visual Odometry
FABMAP	Fast Appearance Based Mapping
IR	Infrared
M-Estimator	Maximum likelihood-type Estimator
GPS	Global Positioning System