STEREO VISION BASED THREE DIMENSIONAL SIMULTANEOUS LOCALISATION AND MAPPING

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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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Damitha Chandana Herath

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Abstract

This thesis deals with the problem of stereo vision based three dimensional Simultaneous Localisation and Mapping in the context of autonomous robotic navigation. Simultaneous Localisation and Mapping (SLAM) refers to the problem of mapping landmarks in an environment by the navigating robot and concurrently using the mapped features in the localisation of the robot. This thesis concentrates on the issues that arise from using a short baseline stereo vision system as the primary sensor for observing the environment.

Initially, a stereo vision sensor is empirically studied in the context of SLAM. Several error sources that could potentially affect the performance of SLAM algorithms are identified. It is then shown that the observation model corresponding to the particular vision system is highly nonlinear and as a consequence, traditional filtering techniques such as the Extended Kalman Filter used in solving the SLAM problem generate inconsistent state estimates. This observation leads to the development of a novel nonlinear batch optimisation technique that is shown to produce consistent state estimates.

The next major contribution of this thesis arises from the development of a novel Multi Map (MM) framework for SLAM. The framework was inspired by observations of human navigation habits. The novel representation relies on two individual maps in the localisation and mapping process. The Global Map (GM) is a compact global representation of the robots environment and the Local Map (LM) is exclusively used for low-level navigation between local points in the robots navigation horizon. The LM in many aspects is similar to prevailing sub map methods and hence, has efficiencies of such representations. However, the combination of two map representations in the MM framework extends the capabilities of hitherto existent algorithms by not only in the way of improving consistency but also by way of increase in efficiency through the compact representation and the unique feature marginalisation strategy. In addition, it aids implementation of novel techniques for loop closure. The framework is highly suited for sensors like vision where map sizes tend to grow rapidly due to the very nature of the sensing techniques used.

Finally, the algorithms are validated with real experimental data collected using a mobile robot platform traversing in an indoor environment.