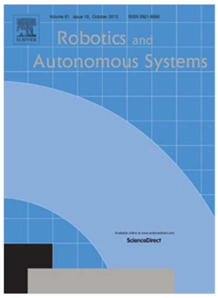
Accepted Manuscript



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PII: S0921-8890(18)30196-9
DOI: https://doi.org/10.1016/j.robot.2018.09.010
Reference: ROBOT 3088

To appear in: *Robotics and Autonomous Systems*

Received date : 7 March 2018
Revised date : 26 July 2018
Accepted date : 29 September 2018

Please cite this article as: N. Sullivan, et al., Analysis of cooperative localisation performance under varying sensor qualities and communication rates, *Robotics and Autonomous Systems* (2018), https://doi.org/10.1016/j.robot.2018.09.010

Analysis of Cooperative Localisation Performance Under Varying Sensor Qualities and Communication Rates

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Abstract

Cooperative Localisation (CL) is a robust technique used to improve localisation accuracy in multi-robot systems. However, there is a lack of research on how CL performs under different conditions. It is unclear *whether* CL is worthwhile, and *how* CL performance is affected if the system changes. This information is particularly important for systems with robots that have limited power and processing, which cannot afford to constantly perform CL. This paper investigates CL under varying sensor qualities (position accuracy, yaw accuracy, sample rate), communication rates, and number of robots for both homogeneous and heterogeneous multi-robot systems. Trends are found in MATLAB simulations using the UTIAS dataset, and then validated on Kobuki robots using an OptiTrack-based system. We find that yaw accuracy has a substantial effect on performance, a communication rate that is too fast can be detrimental, and heterogeneous systems are greater candidates for cooperative localisation than homogeneous systems.

Keywords: Cooperative Localization, Multi-Robot, Performance Analysis, Kalman Filter

1. Introduction

A fundamental challenge for mobile robotics is calculating the position and orientation (pose) of robots within their environment, known as *localisation*. This is necessary for robots to accurately interact with their environment, as well as for interacting with one another. In many industries, multiple robots operate within the same environment, known as *multi-robot systems*. Industries such as agriculture [1], warehouse automation [2], search and rescue [3], environment monitoring [4], healthcare assistance [5], mining [6], transport [7], and assembly [8], are beginning to use mobile robots in everyday operations. To address the localisation problem, robots are typically equipped with two types of sensors. The internal state of robots are measured by *interoceptive* sensors, such as gyroscopes, accelerometers, and wheel encoders. Interoceptive sensors reliably provide data, but have pose errors that accumulates over time. *Exteroceptive* sensors interact with the environment, such as GPS, cameras, and LIDARs. Exteroceptive sensors do not suffer from error accumulation, but they are sensitive to environment conditions. For example, localisation using GPS requires satellite signals, LIDARs require static terrain or recognisable features, and cameras require certain lighting conditions. There exists a lot of research in creating systems that are robust to exteroceptive sensor outages [9, 10]. In multi-robot systems, the environment can be measured by multiple robots. The robots can then share their information to improve localisation. This is known as *Cooperative Localisation* (CL).

There are two major areas of research for CL, one is known as *Cooperative Simultaneous Localisation and Mapping* (C-SLAM), where robots independently produce maps of the environment and then share and combine those maps. C-SLAM was a key contributor for the winning team of the MAGIC 2010 competition [11], where robots had to autonomously survey and map a 500m x 500m dynamic urban environment. Communication was not always available, so individual mapping and map fusion was necessary to continue surveillance during communication down-times. C-SLAM has also been used for tasks such as mapping a large area with aerial vehicles [12], localising underwater vehicles to reduce the need for surfacing [13], and to identify and track dynamic targets [14].

C-SLAM can be powerful, but it has requirements that make it unsuitable in certain systems. Firstly, each robot must have SLAM capabilities. This can inflate the cost of multi-robot systems, as effective SLAM often makes use of high quality sensors such as 3D LIDARs. Each robot must also be capable of processing data quickly, either through on-board processing or communication, and is therefore not suitable for systems with inexpensive processors or unreliable communication. Secondly, SLAM performance is dependent on the type and number of landmarks in the environment [15]. For example, SLAM does not operate well in open areas where there are few recognisable features.

The other major area for CL research involves measuring and communicating inter-robot observations. This differs from C-SLAM in that no map sharing occurs. Robots observe one another, estimate each others position, and communicate their estimates to the observed robots. There are no requirements for how robots localise and perform inter-robot measurements, allowing individual robots to have different sensors, processing capabilities, and internal representations of the environment. There is also less dependence on the environment, as it is able to operate provided robots are able to detect one another. This method is the focus of this paper.

Communicating and processing inter-robot measurements