DEVELOPMENT AND IMPLEMENTATION OF ALGORITHMS IN A POPULATION OF COOPERATIVE AUTONOMOUS MOBILE ROBOTS

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Abstract

An increase in the number of mobile robot users has lead to the design and implementation of cooperative autonomous mobile robots. Autonomous robots require the ability to build maps of an unknown environment while simultaneously using these maps for navigation. The main factor in multiple mobile robots is that a team of smaller and simpler mobile robots can outperform a single, large and complex robot.

The paper treats localization and map building as a joint probability, i.e. while robots navigate they localize and build local maps. These local maps from each robot in the team are fused into a global map at some instances during navigation. Cooperative simultaneous localization and map building (C-SLAM) implemented by Extended Kalman Filter (EKF) algorithms are proposed towards task manipulation in a multirobot set up.

The article entails modelling a multiple mobile robot system, in order to understand robot population communication and cooperation within an operational environment.

Key words: Multi mobile robots, cooperative SLAM, position estimates, Autonomous mobile robots, EKF, Localization

1. Introduction

The advantages brought by spatial coverage by multi-robot system have seen a number of research communities into looking development of cooperative autonomous systems. Multiple robot systems are lately investigated in several scenarios, e.g. cooperative transportation of goods in the industries [1], cooperative monitoring and surveillance in disaster areas, and also successful test have been carried out in a highly dynamic environments such as museums [2]. To achieve effective, flexible and robust mobile robot team, a framework, i.e. algorithm that meets the requirements of modularity to integrate different modules must be designed [3]. A robot team can frequently perform tasks and robustly than a single robot vehicle. However, accomplishing cooperation demands that each vehicle be aware of relative locations of collaborators in addition to the baseline environment knowledge, localization problem. Each member of robot team must possess absolute positioning capability by means of external sensors like differential global positioning system (DGPS). Unfortunately, the difficulty brought by multipathing errors makes this impossible to rely on this sensor alone. Cooperating robots must be able to share information as they autonomously traverse an unknown environment, implying that the platforms must build a map during exploration. Thus, it becomes imperative to develop an algorithm that treat localization and map building as a joint/ couple problem, i.e. cooperative simultaneous localization and map building (C-SLAM) problem [8].

To achieve the above requirements, an Extended Kalman Filter based C-SLAM algorithm has to be developed to localize a team of robots in an environment. Measurement from the odomentry sensors as well as those from the exteroceptive sensors are fused by EKF to localize the robots and concurrently landmark feature perceptions are used to build a local map of the environment by each robot. In most mobile robot applications two basic localization estimation methods are employed together: Absolute and relative localization. Relative positioning is based on dead-reckoning. Absolute positioning method relies on range measurement of landmarks existing in that environment.

The easiest approach to localization in a multirobot group is to solve the localization problem for each robot separately and independently. However, localization and map building can substantially benefit from the cooperative use of more than one robot. Hence, in this article localization and mapping by robot team are not decoupled. Mapping is done by merging multiple local maps obtained by each member of the robot team during specific motion segments into global map [13].

In recent years, more work has focused on the convergence of stochastic estimation techniques to build and maintain estimates of the vehicle and feature map positions in an EKF based SLAM algorithms. A number of researchers went further to solve issues of computational cost, Data association or loop closure problems associated with this type of estimation [20, 21].

When a team of robots is composed of different platforms carrying different proprioceptive and exteroceptive sensors and thus having different capabilities for localization, meaning the quality of the localization estimates will vary significantly across the individual members.

This paper present cooperative localization and map building algorithm of a heterogeneous team (where robot populations have different sensors, actuators and mechanical platforms) of robots during task manipulation. Section two summaries the related work to the problem looked at by this article. The next section, i.e. 3, introduces experimental platforms to be used. Section four illustrates cooperative modelling of multirobot system. The last sections cover expected results followed by conclusion respectively.

2. Related Work

An extensive amount of research has been carried out in the areas of localization, mapping, and exploration for single autonomous robots, [13, 16, 17, 18, 19], but only fairly recently has this been applied to multirobot teams. In addition, nearly all of this research has taken existing algorithm developed for single- robot mapping, localization, or exploration, and extended it to multiple robot systems [10]. An example of a system that is designed for cooperative localization is presented

in [4]. The authors introduce the concept of "portable landmarks", where group of robots are divided into two teams in order to perform cooperative positioning. This system is not robust, as mapping of the environment would be a slow process. [5] Presented a Kalman Filter-based distributed localization approach for cooperative localization. A centralised KF performs data associations from a group of mobile robots using both relative and absolute sensors. The standard KF prediction equations are decentralized and distributed among the robot team. They argue that the multirobot localization problem renders the state propagation equations of the centralised system to be decoupled with state coupling occurring only when relative pose observations become available. [6] Extended the previous work from considering a single robot SLAM using Kalman filtering to multiple robots. They formulate a consistent framework to include interrobot measurements, as well as measurements of fixed landmarks. There is no information exchange in this system hence cooperation is not fully realized.

While most of the work presented above discussed feasibility and implementation of different algorithms for cooperative localization and mapping, mobile robot team considered are of homogeneous (all robots equal) composition. Other researchers looked at this problem from the particle filter framework [9] and many built frameworks to emulate C-SLAM algorithms.

In this paper, C-SLAM is considered to be of stochastic nature [11,14, 15], because mobile robots are thought to be continuously and randomly moving in an environment while recording and sharing position perception and features perceptions of the environment. This article proposes EKF-SALM based cooperative localization algorithm that possess the following strengths:

- The environment in which the team operate is dynamic as robots change their positions all the time.
- Robots should communicate their position and information about the environment to one another, or a central control station to detect their relative position, share information about environment and to transmit it to individual robots.

 A modular design is needed so that each component of the system can be developed systematically.

3. Experimental platforms

The mobile robot team to be used for experiments are provided by different vendors. The robot group bring advantages and disadvantages. The positive being, some robots are equipped with high precision sensors, hence they could to help localize smaller robots, fitted with less expensive sensors improving cooperation [7]. The negative comes from the issue of compatibility, since platforms are provided are of heterogeneous mixture. The table 1 below shows two different robot systems to be used for experiments. The two platforms are a Robotino (from Festo) and ER1 [12] and a four wheeled mini vehicle. The challenge is to build modular control algorithms for these platforms to achieve cooperation during exploration and task manipulation. Simple tasks like exploration and object recognition can be cooperatively achieved with these platforms.



Table 1. Comparison of the two mobile robots to be used in the cooperative task manipulation experiment.

The figure 3.1 below shows the mechatronics set up of a robot. Mechatronics is the synergetic combination of precision mechanical engineering, electronic control and systems thinking in the design of products and processes [22]. These different entities making a robotino robot are modules which when put together form a robot being a Robotino.

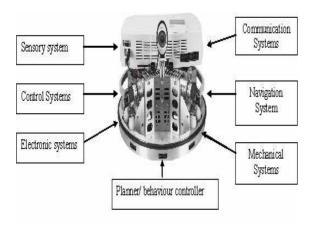


Figure 3.1 Sub –systems that forms a single composition, a Robotino robot.

4 Modelling

Given N number of mobile robots and M static features, the world state at time k (i.e. discrete time) is denoted as a single state vector as $x[k] = \begin{bmatrix} x_v[k]^T & x_f[k]^T \end{bmatrix}^T$, where $\mathcal{X}_v[k] = \begin{bmatrix} x^1_v[k]^T & x^2_v[k] & \dots & x^N_v[k]^T \end{bmatrix}^T$ represents the states estimation of mobile robot team at time step k. Similarly the combined states estimation of all the landmark features in the environment is given as $x_f[k] = \begin{bmatrix} x_{f_1}[k]^T & x_{f_2}[k]^T & \dots & x_{f_M}[k]^T \end{bmatrix}^T$ at time step k.

As the robots explore the environment, the pose (position and orientation) as well as the land mark position information must be shared amongst the cooperating robots. A simple example of cooperation is shown by the figure 4.1 where two robots are exploring the environment, with robot 1s' payload sensors being of high quality than those on robot 2. Robot 1 communicates its pose estimate to the robot 2, and this information is then processed by robot 2 confirming the orientation of robot 1. The solid/dashed lines represent the regions of confidence before/after the relative pose measurement exchange.

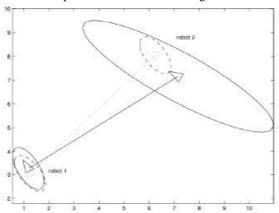


Figure 4.1: Illustration of cooperative localization (Source: [4])

Figure 4.2 shows intercommunication between some modules of a robot. This control structure exists in each robot member in a team. The world model/ the world states carry information about the robots positions, feature perception from exeteroceptive sensors and information from other robots in the team. Each robot avail its local map and behaviour decision to other robot by some communication channel. Decisions made by a particular robot are sent as control commands to the motion control to activate appropriate actuators.

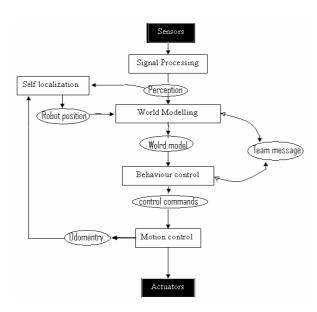


Figure.4.2. An overview of modules (rectangles) and exchanged messages (ovals) of a modular framework (reference).

4.1 Module overview

Self Localization is an algorithm that estimates the robot's current position and heading based on objects detected by the sensors and current motion information performed by the robot. World Modeling fuses any data generated by the localization and signal processing modules as well as information generated by the robot's team mates to estimate the current state of the system. Signal processing process signals from the exeteroceptive sensors to give an environment perception of features and landmarks that exist in the space. Behaviour control module reports the current decision taken by the robot like stopping, turn in place and object avoidance mode given the state of the world model and other team message. Motion control responds to behaviour control commands by sending correct signal to the actuators to carry out the stated command. This module strongly depends on the specific robot's kinematics, dynamics and hardware used for executing the motions.

Two control variables under motion control module are heading and speed which need to be controlled during target tracking. The measurement from the range finder gives heading reading with respect to the target that a robot to

need reach. If desired speed is set as one of the variables used to control motion in order to track a target, actual speed measurement is sensed by the accelerometer and feed back to the comparator. In cases where there is an object on the way, i.e. a landmark or another robot, the behaviour control will switch to obstacle avoidance mode, when its done, target tracking mode is switched on until a target is reached. Figure 4.2 illustrate motion control using speed as a control variable.

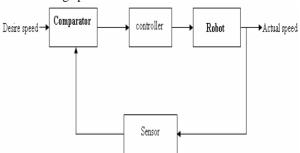


Figure 4.3 Speed used as a parameter for controlling motion

Information exchange between cooperating robots ensures that each robot knows the position of other robot in an operational environment hence it can decide its route while tracking the point of interest. In this set up robots would avoid exploring places where a team member has being hence quickening the exploration task. Target/point of interest could be a communicated point from one collaborator in a task of search and rescue mission, or work point where robots has to come together to cooperatively do a task.

5. Results

In cooperative task manipulation, robots need to move from where they are to the point of interest. The ability to reach a set point is of massive importance in cooperating robots, in transporting heavy substances, agents are required to properly position around the work piece. Figure 5.1 shows multi robot team of four tracking target while avoiding objects as well as each other. The environmental information from each robot enables team members to map their routes with prior knowledge of the existing obstacle/landmarks in the terrain.

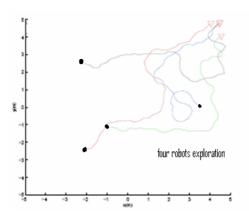


Figure 5.1 Cooperative target following mobile robots stating [dots] at different points and tracking the same end points [arrows] (reference).

The effect of pose communication is shown by a simulation results of three robots are shown in figures 5.2 and 5.3 respectively. Robot 2 in figure 5.2 receives absolute positioning information from its sensors and there is no communication with robot 1 or 3. The result shows that the position error is bounded for robot 2, while bounding lines around the positioning errors for robot1 and robot3 are growing. The lines represent regions of confidence for position error. This follows from an illustration shown by figure 4.1 that communication between robot team will improve the position estimates of the robots in the team.

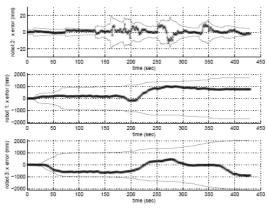


Figure 5.2 Position errors for robot 2, 1 and three. Robot 2 does not communicate its position.

If one robot is stopped, i.e. in the case of robot 2 shown by figure 5.3 below while robots 1 and 3

continuously measure their relative position and orientation with respect to robot 2, position uncertainty for the two robots decreases. Position error for robot 2 is constant while robot 1 and 3s' position errors are bounded because absolute position of robot 2 is available. The other two robots uses robot 2 as an active landmark.

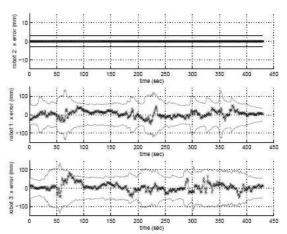


Figure 5.3 Position errors for robot 2, 1 and three. Robot 2 is used as an active landmark.

6. Conclusion and future research

This article presented a scheme for localization and map building for a team of heterogeneous robots in an unknown environment. A heterogeneous robot composition was shown to be of added value, since platforms vary in sensing ability. Information exchange between agents becomes imperative for robots to fully cooperate in an operational environment. Localization and mapping problem released by EKF algorithms is treated as a joint probability. Modular design of algorithms assures flexibility, scalability, and the overall robustness of the system.

Further work will involve the mathematical modelling of a population of mobile robots. Robots control structure will be drawn showing inter module and interaction and communication, i.e. information flow. Simulations of multi robot cooperation in an open source like player would be carried, whose finding are transferable to the platforms for experimental purposes.

7. Acknowledgement

This research paper is made possible by the collaboration between Tshwane University of

Technology and the Council of scientific and Industrial research (CSIR).

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