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NON-PROBABILISTIC APPROACH TO COOPERATIVE POSITION TRACKING IN LARGE SWARM OF SIMPLE MOBILE ROBOTS USING TRIANGULAR CROSS-OBSERVATION

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By

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Chair: Associate Professor Mohammad Hamiruce Marhaban, PhD

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Many applications in mobile robotics require that the accurate position of the mobile robots to be known. Dead reckoning (DR) is the simplest and the most cost effective method of keeping track of mobile robots' positions, but it is the most unreliable due to error accumulation problem. In multi-robot environment however, cooperative position tracking is a robust solution in the sense that the error in one robot will be compensated by the other group members. Unfortunately, many of the most popular approaches for cooperative localization in literature today are probabilistic, which are computationally complex and less tolerant to any deviation from their predetermined probabilistic motion and observation models. This research focuses on devising a computationally simpler non-probabilistic cooperative position tracking algorithm specifically for a large swarm of simple mobile robots with the purpose of reducing the error accumulation in the position estimates of an individual

robot due to noise in odometric measurement. This algorithm, which is term triangular cross-observation (TCO), involves three mobile robots simultaneously in every update decision making process, which provides two observation data for every robot. These two observation data are tested using their signs before one of them with the highest probability of giving a positive update is selected to be used for position update. The update process is done using a fixed update gain calculated that will give the best performance for the proposed algorithm, which keeps the complexity of the algorithm to a minimum of $O(1)$ as compared to $O(N^2)$ of an extended Kalman filter (EKF). In addition to that, this approach comes with the mechanism to validate the integrity of the observation data prior to the update process. The performance of the algorithm was validated and compared against that of the EKF through series of simulations using Stage multi-agent simulator. Simulation results have shown that despite the computational simplicity, the algorithm yields the percentage error of 0.033%, which is close to that of the EKF, which yields 0.028%, while the DR yields 0.125%. The simulation on the robot performance under the presence of outliers in position estimate among the group members yields an excellent result for the proposed approach with percentage error of 0.038% while the EKF has been badly affected with percentage error of 0.196%, higher than that of the dead reckoning, which is 0.131%. Similarly, corrupted measurement data introduced into the simulation have not affected the performance of the proposed approach as compared to that of the EKF. While the performance of the TCO was completely untouched with percentage error of 0.029% after 60 minutes of simulation, the performance of the EKF has been severely affected with percentage error of 0.115%, close to that of the DR with 0.122%. Overall, the theoretical analysis and simulations have shown that a computationally simpler non-probabilistic algorithm with a performance close to that of a probabilistic approach and robust against outliers can be devised by synthesizing information obtained from multiple simultaneous observations in cooperative position tracking.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

PENDEKATAN BUKAN BERASASKAN KEBARANGKALIAN KEPADA PENJEJAKAN LOKASI KERJASAMA DI DALAM KAWANAN BESAR ROBOT BERGERAK YANG RINGKAS MENGGUNAKAN CERAPAN SILANG TIGA PENJURU

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Kebanyakan aplikasi-aplikasi di dalam bidang robotik boleh gerak memerlukan kepada keupayaan penentuan lokasi yang tepat oleh robot-robot bergerak. Teknik andaian buta dilihat sebagai satu pilihan yang paling mudah dan murah bagi menjejaki lokasi-lokasi robot bergerak tersebut. Tetapi malangnya, teknik ini adalah paling tidak boleh dipercayai ketepatannya lantaran masalah pengumpulan ralat di dalam perkiraan lokasinya. Namun begitu, di dalam suasana di mana terdapat kawanan robot, teknik penjejakan lokasi yang berasaskan kerjasama mampu memberi ketepatan yang lebih baik. Tetapi malangnya, kebanyakan pendekatan-pendekatan yang sedia ada adalah berasaskan kebarangkalian dan memberi bebanan yang tinggi terhadap daya pemprosesan di samping kurang cekap dalam mengendalikan ralat-ralat yang tidak dapat dijangkau oleh model-model ralat asal yang telah ditentukan. Jesteru, kajian ini memfokuskan kepada penghasilan

pendekatan penjejakan lokasi berasaskan kerjasama yang lebih cekap tanpa melibatkan kebarangkalian, khusus untuk kawanan robot-robot bergerak yang besar bilangannya dengan tujuan untuk mengurangkan ralat terkumpul di dalam anggaran lokasi robot individu akibat daripada hingar di dalam bacaan odometri. Pendekatan yang digelar cerapan silang tiga penjuru ini, melibatkan tiga buah robot serentak setiap kali peroses penyelarasan terhadap anggaran lokasi dilakukan yang mana setiap robot akan memiliki dua data pemerhatian. Data-data pemerhatian ini kemudian diuji menggunakan tanda positif atau negatif data tersebut, dan salah satu data yang memberikan kebarangkalian penyelaran positif yang paling tinggi akan dipilih untuk digunakan dalam proses penyelarasan. Penyelarasan akan dibuat menggunakan nilai perolehan penyelarasan yang tetap yang memberikan pencapaian terbaik bagi pendekatan ini, menjadikan ia amat ringkas dengan nilai kerumitan pengiraan $O(1)$ berbanding dengan "extended Kalman filter" (EKF), iaitu $O(N^2)$. Tambahan pula, pendekatan ini dilengkapi dengan mekanisma untuk mengesahkan kewibawaan data pemerhatian sebelum sebarang penyelarasan dibuat. Pencapaian algoritma ini telah dinilai dan dibandingkan dengan pencapain teknik EKF secara simulasi menggunakan simulator multiejen Stage. Keputusan simulasi menunjukkan bahawa pendekatan ini mampu memberikan peratusan ralat sebanyak 0.033%, hampir dengan pencapaian oleh EKF iaitu sebanyak 0.028% sedangkan kaedah andaian buta memberikan peratusan ralat sebanyak 0.125%. Di samping itu juga, pendekatan ini telah terbukti cekap dalam mengendalikan ralat-ralat luar jangkaan yang besar di dalam perkiraan lokasi dikalangan ahli kawanan di mana pendekatan ini mencatatkan peratusan ralat sebanyak 0.038% sedangkan pendekatan EKF mencatatkan peratusan ralat sebanyak 0.196%, lebih teruk berbanding dengan teknik andaian buta yang mencatatkan sebanyak 0.131%. Demikian juga ralat besar dalam pengukuran posisi relatif mampu dikendalikan dengan baik oleh pendekatan yang dicadangkan dengan peratusan ralat hanya sebanyak 0.029% selepas 60 minit simulasi berbanding dengan teknik EKF dan andaian buta yang masing-masing mencatatkan peratusan ralat sebanyak 0.115% dan 0.122%. Secara keseluruhan, analisis teoritikal dan simulasi menunjukkan bahawa sebuah algorithma penjejakan lokasi yang lebih mudah dari segi kerumitan pengiraan yang mampu memberi pencapaian yang hampir setara dengan pendekatan EKF yang berasaskan kebarangkalian dan dalam masa yang sama mampu menangani ralat luar jangkaan di kalangan ahli kawanan. Ini dapat dicapai dengan mensintesis maklumat yang diperolehi melalui pemerhatian berbilang yang serentak di dalam kawan robot-robot semasa melakukan penjejakan lokasi.

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I certify that a Thesis Examination Committee has met on 18 June 2013 to conduct the final examination of Abdul Sattar bin Din on his thesis entitled "Non-Probabilistic Approach to Cooperative Position Tracking in Large Swarm of Simple Mobile Robots Using Triangular Cross-Observation" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Master of Science.

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DECLARATION

I declare that the thesis is my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously, and is not concurrently, submitted for any other degree at Universiti Putra Malaysia or at any other institution.

ABDUL SATTAR DIN

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LIST OF ABBREVIATIONS

GPS	Global Positioning System
DR	Dead Reckoning
IMU	Inertial Measurement Unit
CPT	Cooperative Position Tracking
KF	Kalman Filter
PF	Particle Filter
PDF	Probability Density Function
EKF	Extended Kalman Filter
UKF	Unscented Kalman Filter
MCL	Monte Carlo Localization
TCO	Triangular Cross-observation

CHAPTER 1

INTRODUCTION

1.1 Preface

Multi-robot systems [1] are becoming more popular nowadays and there are lots of researches in this particular area that have been and are being carried out targeting various potential applications. Multi-robot system as suggested in [2] consists of a group of simpler and cheaper individual robots such that the actual strength of the system can be derived from the cooperation among the group members. Multi-robot systems have advantages over their single robot counterparts in many aspects. As described in [2], [3], and [4], they have spatial advantage in the sense that they can cover larger areas, more fault-tolerant, more flexible, and more cost effective. Among the potential applications that can directly benefit from multi-robot systems are those that require large area coverage such as in surveillance [5], patrol [6], exploration [7], [8], localization and mapping [9], and search and rescue [10], [11]. In addition to those, several other applications that require the segregation and parallel execution of tasks such as in cooperative object transport [12], [13], [14], [15] and object pushing [16], [17] can equally benefit from the multi-robot systems. Many of these applications require the robots to be able to keep accurate position information and this ability often calls for some accurate absolute positioning devices such as a Global Positioning System (GPS) and maps. The nature of the environments in which the mobile robots are operating can sometimes prohibits the use of such devices.

One simple solution to this problem is to track the mobile robot's position from a known starting point, which is known in the literature as *dead reckoning (DR)*. This can be achieved through wide range of devices from something as simple as a wheel-shaft encoder to something as sophisticated as an Inertial Measurement Unit (IMU). Unfortunately, the dead reckoning method suffers from incremental error which renders the robot positioning unreliable over long distances. Furthermore, in DR, once the position tracking fails, the recovery is impossible without intervention from human operators. In multi-robot environment however, error in the estimated position in one mobile robot can be compensated by the other mobile robots through what is termed *cooperative position tracking (CPT)*. Cooperative position tracking or localization in multi-robot environment is gaining popularity among researchers [18]. Like the other previously-mentioned tasks, CPT task can derive great benefits from using multiple robots [19]. Two most popular approaches for CPT are based on the *Kalman filter* [20] [21] [22] and *particle filter* [23] [24] which, probabilistically model the states of the mobile robot to include the uncertainties inherent in sensor measurements. Both of these approaches in multi-robot system are the adaptations of their original single robot versions tailored for a more advanced robot, which makes them computationally complex. Even though particle filter-based approaches are flexible to adapt to various computational resource availability [25], the computational efficiency can be attained in the expense of the accuracy of the position tracking. Furthermore, the probabilistic approaches operate based on the predetermined motion and measurement models and therefore are less tolerant of the deviations resulting from unexpected events such as tracking failures or relative measurement failures.

1.2 Problem Statements

In this thesis, two major problems related to the current CPT approaches will be addressed. The first problem is concerning the complexity of the CPT approaches where many of the current sophisticated approaches are probabilistic and therefore tend to be computationally complex. Also, many works on these probabilistic approaches to improve some of the limitations have added even more computational complexity to them. In view of the promising future of multi-robot system that comprises simplified and miniaturised individual robots, there is a need to devise a computationally simpler CPT algorithm that offers a comparable performance with the more computationally complex algorithm, taking advantage of the multitude of observational data and the highly cooperative environment.

The second problem to be addressed is related to the robustness of the CPT approach in handling problems associated with the large swarm of simple mobile robots. Tracking failures among group members are highly probable in a large swarm of simple mobile robots and erroneous measurements from exteroceptive sensors are highly likely. In this situation, large errors need to be properly contained so as not to be spread to the other group members. Many of the most popular probabilistic approaches rely heavily on predetermined motion and observation models such that any deviations or abnormalities in the position estimation will go undetected. This leaves the estimated positions among the group members vulnerable to corruption.

To address the first problem, the proposed approach involves three mobile robots simultaneously instead of two in the estimated position update step to increase the probability of making positive updates without using probability in any form to model the uncertainty in the estimated position of the robot. The decisions arrived in this approach are solely based on the current actual and estimated state of the mobile robots. Many of the current sophisticated probabilistic approaches in cooperative position tracking have been adapted from the single robot system and experimented on small group of mobile robots.

As for the second problem, the proposed approach can detect and avoid mobile robots from making update based on the one with the potentially highest estimated position error within three robots locality. In addition to that, multiple observations used in this approach have enabled the algorithm to check the integrity of the observation data and detect the potential erroneous measurements. This approach, while helping the robot with tracking failure to recover, prevents the large error from affecting the other members which in turn, increases the quality of recovery.

1.3 Aims and Objectives

This research aims at formulating a CPT algorithm specifically for a large swarm of simple mobile robots with the main focus of reducing the computational burden borne by individual robots and capitalizing on the multitude of cooperative opportunities present within the group so as to give a comparable performance to its more complex counterparts. In addition to that, the formulated algorithm needs to be robust against large errors from the robot's positions and observations, which are highly probable in large swarm of mobile robots.

The specific objectives to be fulfilled in order to achieve the aims are outlined as follows:

1. To ascertain that extra information relevant to mobile robot's positioning can be obtained by involving more mobile robots simultaneously during update.
2. To analyse and compare the computational complexity between the proposed algorithm with a probabilistic extended Kalman Filter algorithm.
3. To ascertain that the derived algorithm is robust against unexpected events both in position tracking and robot's relative position measurements.

1.4 Scopes of Research

In this research, the method has been proposed and simulated based on the following assumptions:

1) The cooperative mobile robot's position tracking is carried out on two-dimensional plane (i.e. x and y coordinate).
2) Each mobile robot is equipped with a noisy odometry that can track the robot's position as it moves from a known starting point.
3) Every mobile robot is also capable of at least measuring its distance and bearing relative to other robots using an exteroceptive sensor.
4) Since the orientation of each mobile robot will not be cooperatively tracked, the mobile robot is equipped with some means to measure the orientation directly.
5) In this research also, one of the requirements is that each mobile robot can communicate with each other through at least a short range communication device via message broadcasting or one-to-one communication in order for them to share some required information.
6) The swarm size is assumed to be large enough such that each mobile robot in the group can simultaneously observe and communicate with at least two other members most of the time.

The method proposed and the results presented are also bounded by the following limitations:

1) This method does not include the robot's orientation in the tracking process since it can be directly measured even in GPS-denied environments and therefore is not subject to error accumulation.
2) The simulation does not include the potential delay in relative position measurements which might be the important factor in real implementation of the algorithm. The current simulation program used in this research has a limitation for such feature.
3) The simulations assume a passive form of relative position measurements through communication device. Therefore, the result does not reflect the full potential performance if active form of relative position measurements are employed.

1.5 Thesis Outline

The subsequent chapters start with reviewing several popular representatives of CPT approaches from the literature, pointing out some of their advantages and weaknesses. Next will be a methodology chapter in which, some basic theories behind the CPT will be introduced in the first section, followed by comprehensive explanations on the proposed method in terms of the concepts, mathematical formulations, and implementation. The proposed method of simulation and tools involved will also be described in the later part of this chapter. In the following chapter, all the results will be presented that will reveal some of the characteristics of the proposed approach and that will highlight the main advantages of this approach. The performance of the proposed approach will also be compared against one of the most popular representatives from the probabilistic approach. This chapter ends with discussions and summary of the findings from the results. Finally the whole thesis will be concluded in the last chapter and some suggestions for future works will be presented.

REFERENCES

[1] Y.U Cao, A.S. Fukunaga, A.B. Kahng, and F. Meng, "Cooperative mobile robotics: antecedents and directions, "*Proceedings International Conference on Intelligent Robots and Systems,* vol. 1, pp. 226-234, 1995.

[2] G. Dudek, M. Jenkin, E.E. Milios, and D. Wilkes, "A taxonomy for multi-agent robotics," *Autonomous Robots*, vol. 3, pp. 375-397, 1996.

[3] L.E. Parker, "Current state of the art in distributed autonomous mobile robotics," *Proceeding 5th International Symposium in Distributed Autonomous Robotic Systems,* pp. 3–12, 2000.

[4] S. Verret, "Current state of the art in multirobot systems," Defence Research and Development Canada - Suffield, Ralston ALTA, Technical Memorandum, 2005.

[5] L. Doitsidis, S. Weiss, A. Renzaglia, M. Achtelik, E. Kosmatopoulos, R. Siegwart, and D. Scaramuzza, "Optimal surveillance coverage for teams of micro aerial vehicles in GPS-denied environments using onboard vision," *Autonomous Robots*, vol. 33, pp. 173-188, 2012.

[6] L. Iocchi, L. Marchetti, and D. Nardi, "Multi-robot patrolling with coordinated behaviours in realistic environments," *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 2796-2801, 2011.

[7] R. Sawhney, K.M. Krishna, and K. Srinathan, "On fast exploration in 2D and 3D terrains with multiple robots," *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems,* pp. 73-80, 2009.

[8] W. Burgard, M. Moors, D. Fox, R. Simmons, and S. Thrun, "Collaborative multi-robot exploration," *Proceedings of IEEE International Conference on Robotics and Automation,* vol. 1, pp. 476-481, 2000.

[9] A. Howard, "Multi-robot Simultaneous Localization and Mapping using Particle Filters," *International Journal of Robotics Research*, vol. 25, pp. 1243-1256, 2006.

[10] K. Nagatani, Y. Okada, N. Tokunaga, K. Yoshida, S. Kiribayashi, K. Ohno, E. Takeuchi, S. Tadokoro, H. Akiyama, I. Noda, T. Yoshida, and E. Koyanagi, "Multi-robot exploration for search and rescue missions: A report of map building in RoboCupRescue 2009," *IEEE International Workshop on Safety, Security & Rescue Robotics*, pp. 1-6, 2009.

[11] C. Luo, A.P. Espinosa, D. Pranantha, and A. De Gloria, “Multi-robot search and rescue team,” *IEEE International Symposium on Safety, Security, and Rescue Robotics*, pp. 296-301, 2011.

[12] G.C. Pettinaro, L.M Gambardella, and A. Ramirez-Serrano, “Adaptive distributed fetching and retrieval of goods by a swarm-bot,” *Proceedings of 12th International Conference on Advanced Robotics,* pp. 825-832, 2005.

[13] J. Shao, L. Wang, and J. Yu, “Development of an artificial fish-like robot and its application in cooperative transportation,” *Control Engineering Practice*, vol. 16, pp. 569-584, 2008.

[14] N. Michael, J. Fink, and V. Kumar, “Cooperative manipulation and transportation with aerial robots,” *Autonomous Robots*, vol. 30, pp. 73-86, 2011.

[15] G. Eoh, J.D. Jeon, J.S. Choi, and B.H. Lee, “Multi-robot cooperative formation for overweight object transportation,” *IEEE/SICE International Symposium on System Integration*, pp. 726-731, 2011.

[16] J. Chen and R. Groß, “Cooperative multi-robot box pushing inspired by human behaviour,” *Proceedings of the 12th Annual conference on: Towards autonomous robotic systems*, pp. 380-381, 2011.

[17] P. Rakshit, A.K. Sadhu, P. Bhattacharjee, A. Konar, and R. Janarthanan, “Multi-Robot box-pushing using non-dominated sorting bee colony optimization algorithm,” *Proceedings of the Second International Conference on Swarm, Evolutionary, and Memetic Computing*, pp. 601-609, 2011.

[18] T. Arai, E. Pagello, and L.E. Parker, “Guest editorial: advances in multirobot systems,” *IEEE Transactions on Robotics and Automation,* vol. 18, pp. 655-661, 2002.

[19] F.E. Schneider, and D. Wildermuth, “Influences of the robot group size on cooperative multi-robot localisation—Analysis and experimental validation,” Robotics and Autonomous Systems, vol. 60, pp. 1421-1428, 2012.

[20] A.C. Sanderson, “A distributed algorithm for cooperative navigation among multiple mobile robots,” Advanced Robotics, vol. 12, pp. 335-349, 1998.

[21] S.I. Roumeliotis and G.A. Bekey, “Distributed multirobot localization,” *IEEE Transactions on Robotics and Automation*, vol.18, no.5, pp. 781- 795, Oct 2002.

[22] G. Welch, and G. Bishop, "An introduction to the Kalman filter," Department of Computer Science, University of North Carolina at Chapel Hill, 1995.

[23] D. Fox, W. Burgard, H. Kruppa, and S. Thrun, "A probabilistic approach to collaborative multi-robot localization," *Autonomous Robots*, vol. 8, pp. 325–344, 2000.

[24] S. Thrun, D. Fox, W. Burgard, and F. Dellaert, "Robust Monte Carlo localization for mobile robots," Artificial Intelligence, vol. 128, pp. 99-141, 2001.

[25] S. Thrun, W. Burgard, and D. Fox, Probabilistic Robotics. The MIT Press, September 2005.

[26] D. Hyun, H.S. Yang, G.H. Yuk, and H.S. Park, "A dead reckoning sensor system and a tracking algorithm for mobile robots," *IEEE International Conference on Mechatronics,* pp. 1-6, 2009.

[27] B. Cho, W. Moon, W. Seo and K. Baek, "A dead reckoning localization system for mobile robots using inertial sensors and wheel revolution encoding," *Journal of Mechanical Science and Technology*, vol. 25, pp. 2907-2917, 2011.

[28] Kelly, "Fast and easy systematic and stochastic odometry calibration," *Proceeding IEEE/RSJ International Conference on Intelligent Robots and Systems,* vol.4, pp. 3188- 3194, 2004.

[29] J. Borenstein and L. Feng, "Measurement and correction of systematic odometry errors in mobile robots," *IEEE Transactions on Robotics and Automation*, vol.12, pp. 869-880, 1996.

[30] S. Maeyama, N. Ishikawa, and S. Yuta, "Rule based filtering and fusion of odometry and gyroscope for a fail safe dead reckoning system of a mobile robot," *IEEE/SICE/RSJ International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pp. 541-548, 1996.

[31] M. Hashimoto, H. Kawashima, and F. Oba, "A multi-model based fault detection and diagnosis of internal sensors for mobile robot," *Proceedings International Conference on Intelligent Robots and Systems*, vol.4, pp. 3787- 3792, 2003.

[32] Z. Yan, D. Chi, Z. Zhao, and C. Deng, "Dead reckoning error compensation algorithm of AUV based on SVM," *OCEANS 2011*, pp. 1-7, 2011.

[33] R. Kurazume, S. Nagata, and S. Hirose, "Cooperative positioning with multiple robots," *in Proceedings IEEE International Conference in Robotics and Automation*, vol. 2, pp. 1250–1257, 1994.

[34] R. Kurazume, S. Hirose, S. Nagata, and N. Sashida, "Study on cooperative positioning system (basic principle and measurement experiment)," *Proceedings IEEE International Conference in Robotics and Automation*, vol. 2, pp. 1421–1426, 1996.

[35] R. Kurazume and S. Hirose, "Study on cooperative positioning system: Optimum moving strategies for CPS-III," *Proceedings IEEE International Conference in Robotics and Automation*, vol. 4, pp. 2896–2903, 1998.

[36] R. Kurazume and S. Hirose, "Development of a cleaning robot system with cooperative positioning system," Autonomous Robots, vol. 9, pp. 237-246, 2000.

[37] Y. Elor and A.M. Bruckstein, "A "thermodynamic" approach to multi-robot cooperative localization," Theoretical Computer Science, vol. 457, pp. 59-75, 2012.

[38] V. Amiranashvili and G. Lakemeyer, "Distributed multi-robot localization based on mutual path detection," Lecture Notes in Computer Science, vol. 3698, pp. 279-290, 2005.

[39] Z. Chen, "Bayesian filtering: From kalman filters to particle filters, and beyond," Technical report, McMaster University, 2003.

[40] S.I. Roumeliotis and G.A Bekey, "Bayesian estimation and Kalman filtering: a unified framework for mobile robot localization," *Proceedings IEEE International Conference on Robotics and Automation,* vol. 3, pp. 2985-2992, 2000.

[41] F.E. Schneider and D. Wildermuth, "Using an extended Kalman filter for relative localisation in a moving robot formation," *Proceedings of the Fourth International Workshop on Robot Motion and Control,* pp. 85-90, 2004.

[42] E.A. Wan and R. Van Der Merwe, "The unscented Kalman filter for nonlinear estimation," *The IEEE Adaptive Systems for Signal Processing, Communications, and Control Symposium,* pp.153-158, 2000.

[43] A. Prorok, A. Bahr, and A. Martinoli, "Low-cost collaborative localization for large-scale multi-robot systems," *IEEE International Conference on Robotics and Automation,* pp. 4236-4241, 2012.

[44] Wikipedia contributors, "Big O notation," *Wikipedia, The Free Encyclopedia*, http://en.wikipedia.org/w/index.php?title=Big_O_notation&oldid=56014773117.

[45] K.X. Zhou and S.I. Roumeliotis, “A sparsity-aware QR decomposition algorithm for efficient cooperative localization,” *IEEE International Conference on Robotics and Automation,* pp.799-806, 2012.

[46] G. Pillonetto, G.Erinc, and S. Carpin, “Online Estimation of Covariance Parameters using Extended Kalman Filtering and Application to Robot Localization,” Advanced Robotics, vol. 26, pp. 2169-2188, 2012.

[47] A. Martinelli, F. Pont, and R. Siegwart, “Multi-Robot Localization Using Relative Observations,” *Proceedings IEEE International Conference on Robotics and Automation,* pp. 2797- 2802, 2005.

[48] J. Derenick, J. Fink, and V. Kumar, “Localization using ambiguous bearings from radio signal strength,” *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 3248-3253, 2011.

[49] R.T. Vaughan, “Massively multi-robot simulations in Stage,” *Swarm Intelligence*, vol. 2, pp. 189-208, 2008.

[50] B. Gerkey, R.T. Vaughan, and A. Howard, “The Player/Stage Project: Tools for Multi-Robot and Distributed Sensor Systems,” *11th International Conference on Advanced Robotics*, pp. 317-323, 2003.

[51] B. Lee, J. Ji, and G. Woo, “A Case Study on Programming Intelligent Swarm Robots Using Pyro Environment and Player/Stage Simulator,” *International Conference on Convergence and Hybrid Information Technology,* pp. 3-6, 2008.

[52] Z. Shi, J. Tu, J. Wei, Q. Zhang, and X. Zhang, “The simulation scenario for swarm robots based on open-source software Player/Stage,” *International Workshop on Open-Source Software for Scientific Computation,* pp. 107-113, 2011.

[53] A. Staranowicz, and G. L. Mariottini, “A survey and comparison of commercial and open-source robotic simulator software,” *Proceedings of the 4th International Conference on Pervasive Technologies Related to Assistive Environments*, pp. 1-8, 2011.

[54] A. Harris, and J.M Conrad, “Survey of popular robotics simulators, frameworks, and toolkits,” *Proceedings of IEEE Southeastcon,* pp. 243-249, 2011.

[55] P. Castillo-Pizarro, T.V. Arredondo, and M. Torres-Torriti, “Introductory Survey to Open-Source Mobile Robot Simulation Software,” *Latin American Robotics Symposium and Intelligent Robotic,* pp. 150-155, 2010.

[56] Arafa and G. G. Messier, “A Gaussian Model for Dead-Reckoning Mobile Sensor Position Error,” *IEEE 72nd Vehicular Technology Conference Fall,* pp. 1-5, 2010.

[57] E. Sahin, and A. Winfield, “Special issue: swarm robotics,” *Swarm Intelligence,* pp. 69–72, 2008.

[58] S. Dawson, B. Wellman, and M. Anderson, “Identification of Issues in Predicting Multi-Robot Performance through Model-Based Simulations,” Intelligent Control and Automation, vol. 2, pp. 133-143, 2011.

[59] J. Owen, “How to Use Player/Stage, 2nd Edition,” Published online on http://www-users.cs.york.ac.uk/~jowen/playerstage-manual.html, 2010.