Collaborative Multi-Vehicle Localization and Mapping in Marine Environments

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Abstract—This paper explains an application scenario of collaborative multi-vehicle simultaneous localization and mapping algorithm (CSLAM) in a marine environment using autonomous surface crafts (ASCs) in order to validate its performance. The motivation behind this is that a team of ASCs can explore a marine environment more efficiently and reliably than a single ASC. However use of multiple ASCs poses additional scaling problems such as inter-vehicle map fusion, and data association which needs to be addressed in order to be viable for various types of missions. In this paper we first demonstrate the steps of extending the single vehicle extended kalman filter based simultaneous localization and mapping (EKF-SLAM) approach to the multi-vehicle case. Performance of the algorithm is first evaluated using simulations and then using real data extracted from actual sea trials conducted in the littoral waters of Singapore (Selat Puah) using two ASCs. GPS data is used to assess the accuracy of localization and feature estimations of CSLAM algorithm. The improvements that can be achieved by using multiple autonomous vehicles in oceanic environments are also discussed.

I. INTRODUCTION

Autonomous surface crafts (ASCs) are making a significant impact in ocean applications, including, search and rescue, port and harbor surveillance, hydrographic exploration etc. These tasks are not easily accomplished using single ASCs due to the sheer complexity and extent of the environment in addition to the problem itself. As such researchers are focusing more on using multiple ASCs to collaboratively achieve the complex missions. Having many ASCs may not only provide additional performance gains in terms of speed and accuracy, but also heterogeneity which can be exploited to achieve better results cost effectively.

For cost effective utilization of ASCs in various missions it's essential for ASCs to localize themselves in possibly unknown and unstructured marine environments in which they are deployed. For example if it's a hydrographic survey in shallow waters, multiple ASCs might be deployed to collaboratively scan a marine environment using multi-beam sonar scanners for extracting features and objects on the sea bed. The features that are extracted should be combined with accurate positional information in order to build accurate maps to be used for further examination. Even though GPS data

from surface vehicle can be used for localization, there is still a possibility that due to changing atmospheric and field conditions, GPS measurements are unavailable or inaccurate. We propose to overcome these problems through exploitation of artificial and/or naturally occurring features in the operating environment for collaborative mapping and localization of the vehicles. We use the well known simultaneous localization and mapping (SLAM) [1][2][3] framework as a basis for collaborative localization and mapping (CSLAM) of the ASCs. The approach involves each individual ASC, over small time/space scales, performing SLAM independently, and at specified times fusing these independent information (map and locations) to build an overall global map whilst improving each vehicle's position estimates. Combining information obtained from multiple ASCs is a challenging task due to the compounding positional errors of individual ASCs and the varying uncertainties and noise characteristics of the sensors.

This paper is organized as follows. In Section II we describe the related work that lead to multi-vehicle SLAM and basic building blocks of CSLAM. In Section III we briefly describe the probabilistic building blocks of CSLAM algorithm and how to extend those building blocks to solve multi-vehicle SLAM problem. In Section IV experimental results are presented and discussed with simulations and real data, while Section V concludes the paper.

II. RELATED WORK

In order to use autonomous robots in unknown environments for various exploration and other missions, there are two kinds of information that are most valuable - the map of the unknown environment and the position of the robot at any moment with respect to the map. These two types of information can be obtained concurrently by solving a single problem, commonly known as the simultaneous localization and mapping (SLAM) problem. In essence SLAM is the process in which the robots exploring the environment incrementally build a map while estimating its own position with respect to this map.

The first stochastic solution to SLAM problem was due to Smith et al. [4]. Since then, many developments have

taken place in SLAM. It has now come to a mature stage so that, practical implementations of SLAM are quite common place. But there are other issues of using SLAM in real world applications. For example most of the time, the robots may need to be operated in large environments. For example mapping a large marine environment using a single ASC is impractical. In such situations it is necessary to deploy teams of robots to accomplish the tasks in a collaborative manner.

Fenwick et al. presented one of the first algorithms on collaborative localization and mapping by extending the classical single vehicle SLAM implementation to multiple vehicles [5]. Although this methodology could exploit the heterogeneity of sensing capabilities and incorporate vehicle to vehicle observations for improved accuracy, it doesn't seem to be scalable and suitable for mapping larger areas with larger number of autonomous vehicles, due to higher network bandwidth requirements and rapidly increasing computational resource requirements. Thrun et al. presented a multi-robot SLAM algorithm based on the sparse extended information filters [6] which enables a team of robots to build a global map from local sub-maps of individual robots even if their relative starting locations are unknown and landmarks are ambiguous. Scalability was accomplished by alignment of the local maps into a single global map using a tree-based algorithm for searching "similar-looking" local landmark configurations, paired with a hill climbing algorithm. Howard et al. developed a multi-robot SLAM algorithm based on manifold representation [7], which has the key advantage of self-consistency meaning it doesn't suffer from "cross-over" exhibited in planar maps during loop closure. Howard et al. have also proposed a Rao-Blackwellized particle filter (RBPF) based multi-robot SLAM algorithm [8], which although has the advantage of faster mapping, doesn't take any advantage of overlapping features. Further it suffers from the curse of dimensionality, demanding higher memory requirements and computational time due to duplicate features. Moreover, it leads to filter divergence in the case of non-comparable speeds of robots.

Stefan et al. proposed a scalable and efficient solution to the multi-robot SLAM problem [9] by extending their original work on constrained local sub-map filter (CLSF) [10][11]. The key concept of CLSF is that the independent local sub-maps not only facilitated improved data association but also provided significant performance gains due to periodic map fusion. This made it an ideal approach to solve the multi-vehicle SLAM problem. In the CLSF approach, instead of fusing every feature observation directly into the global map, a vehicle relies on the local sub-map from features observed in its vicinity. These independently developed sub-maps are merged in to the global map periodically by appropriately formulating constraints between two maps by identifying common features from overlapped areas.

In this paper, we describe an application scenario of this CLSF based multi-vehicle CSLAM algorithm using ASCs in an ocean environment. Section III, provides the theoretical foundation for CLSF based multi-vehicle CSLAM.
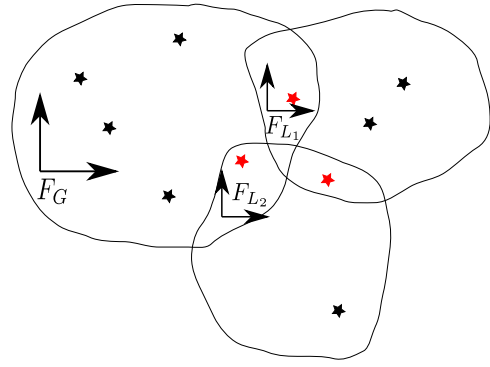

Fig. 1. Two robots start mapping independently, with respect to their local frames of reference. F_G refers to the global reference frame while F_{L_1} and F_{L_2} refers to the local reference frame of the two robots. Black stars in the local frames of reference correspond to the features mapped by each vehicle and the red ones correspond to the overlapping features.

III. MULTI-VEHICLE SLAM

Decorrelated nature of local sub-maps and delayed data association made CLSF an ideal methodology for Multi-Vehicle SLAM. The collaborating vehicles perform SLAM independent of each other and produce local sub-maps by using the features available in their vicinity. These sub-maps are fused into the existing global map and a consistent single global map is recovered at a later stage. Fig. 1 is a pictorial representation of this scenario.

In order to demonstrate this approach, lets consider the case of two robots collaboratively performing SLAM in an unknown environment (Fig. 1). Both of the robots, start from two arbitrary locations and continue to map with respect to their frame of reference. The origins of both robots with respect to the global reference frame are stored for later use. Once the decision is made to fuse the local maps into the global map, the local sub-maps are first transformed into the global frame of reference. Data association is then performed between features in the global map and local sub-maps to identify common (over lapping) features (red colored in Fig. 1). These common or duplicate features are used as constraints to obtain improved map and vehicle position estimates. After removing the duplicate features from these updated local sub-maps, they are fused into the global map, after which the robots can continue mapping again. The formulation of CLSF based Multi-Vehicle SLAM [9] approach is briefly discussed below.

Suppose the robots are at locatioin estimates, $^G\hat{x}_{v1}^+(k-1)$ and $^G\hat{x}_{v2}^+(k-1)$ and the map of the feature estimates is denoted by $^G\hat{x}_m^+(k-1)$ with respect to the global coordinate frame F_G. The superscript G indicates that the estimates are with respect to the global reference frame. The composite state vector is given by,

$$\hat{x}^+ = \begin{bmatrix} ^G\hat{x}_{v1}^+(k-1) \\ ^G\hat{x}_{v2}^+(k-1) \\ ^G\hat{x}_m^+(k-1) \end{bmatrix} \quad (1)$$

The covariance matrix of the state with respect to the frame

F_G is given by,

$$P^+ = \begin{bmatrix} {}^{G}P^+_{v1v1}(k-1) & {}^{G}P^+_{v1v2}(k-1) & {}^{G}P^+_{v1m}(k-1) \\ {}^{G}P^{+T}_{v1v2}(k-1) & {}^{G}P^+_{v2v2}(k-1) & {}^{G}P^+_{v2m}(k-1) \\ {}^{G}P^{+T}_{v1m}(k-1) & {}^{G}P^{+T}_{v2m}(k-1) & {}^{G}P^+_{mm}(k-1) \end{bmatrix} \tag{2}$$

At this point, the decision is made by both robots to build independent sub-maps and perform SLAM within their sensors' field of view. First, two new coordinates frames, F_{L_1} and F_{L_2}, are defined centered at the current vehicle estimates and then, each vehicle initializes a sub-map at the new origin, with no position uncertainty, and continue to perform SLAM. At some later time, both vehicles decide to combine the local sub-maps into the global map. Now the combined state vector is given by,

$$\hat{x}^+_{ism}(k) = \begin{bmatrix} {}^{G}\hat{x}^+(k) \\ {}^{L_1}\hat{x}^+(k) \\ {}^{L_2}\hat{x}^+(k) \end{bmatrix} \tag{3}$$

with,

$$^{G}\hat{x}^+(k) = \begin{bmatrix} {}^{G}\hat{x}^+_{L_1}(k) \\ {}^{G}\hat{x}^+_{L_2}(k) \\ {}^{G}\hat{x}^+_{m}(k) \end{bmatrix} \tag{4}$$

$$^{L_1}\hat{x}^+(k) = \begin{bmatrix} {}^{L_1}\hat{x}^+_{v_1}(k) \\ {}^{L_1}\hat{x}^+_{m}(k) \end{bmatrix} \tag{5}$$

$$^{L_2}\hat{x}^+(k) = \begin{bmatrix} {}^{L_2}\hat{x}^+_{v_2}(k) \\ {}^{L_2}\hat{x}^+_{m}(k) \end{bmatrix} \tag{6}$$

where the subscript 'ism' stands for independent sub-maps, which is an aggregated state vector that combines both composite state vector (which contains global vehicle position estimates and global feature estimates) and decorrelated local state vectors (vehicle position estimation and feature estimations) produced by individual vehicles performing SLAM. Vehicle state estimation and feature estimations are given by ${}^{L_i}\hat{x}^+_{v_i}(k)$ and ${}^{L_i}\hat{x}^+_{m}(k)$ with respect to the frame of reference F_{L_i}. The covariance matrix of the combined state vector is given by,

$$P^+_{ism}(k) = \begin{bmatrix} {}^{G}P^+(k) & 0 & 0 \\ 0 & {}^{L_1}P^+(k) & 0 \\ 0 & 0 & {}^{L_2}P^+(k) \end{bmatrix} \tag{7}$$

with,

$$^{G}P^+(k) = \begin{bmatrix} {}^{G}P^+_{L_1L_1}(k) & {}^{G}P^+_{L_1L_2}(k) & {}^{G}P^+_{L_1m}(k) \\ {}^{G}P^{+T}_{L_1L_2}(k) & {}^{G}P^+_{L_2L_2}(k) & {}^{G}P^+_{L_2m}(k) \\ {}^{G}P^{+T}_{L_1m}(k) & {}^{G}P^{+T}_{L_2m}(k) & {}^{G}P^+_{mm}(k) \end{bmatrix} \tag{8}$$

$$^{L_1}P^+(k) = \begin{bmatrix} {}^{L_1}P^+_{v_1v_1}(k) & {}^{L_1}P^+_{v_1m}(k) \\ {}^{L_1}P^{+T}_{v_1m}(k) & {}^{L_1}P^{+T}_{mm}(k) \end{bmatrix} \tag{9}$$

$$^{L_2}P^+(k) = \begin{bmatrix} {}^{L_2}P^+_{v_2v_2}(k) & {}^{L_2}P^+_{v_2m}(k) \\ {}^{L_2}P^{+T}_{v_2m}(k) & {}^{L_2}P^{+T}_{mm}(k) \end{bmatrix} \tag{10}$$

As can be observed, the covariance matrix of the combined state vector is block diagonal, due to the decorrelated sub-mapping approach. Now the combined state vector is transformed into the global reference frame, by a suitable transformation matrix.

$$^{G}\hat{x}^+_{ism}(k) = T_G(k).\hat{x}^+_{ism}(k) \tag{11}$$

The corresponding transformed covariance matrix is given by,

$$^{G}P^+_{ism}(k) = \nabla T_G(k).P^+_{ism}(k).\nabla T_G^T(k) \tag{12}$$

Now data association is performed in order to identify duplicate (overlapping) features present in local sub-maps and global map. These duplicate features are treated as constraints and a constraints minimization approach is used to recover a more robust estimates for combined state vector and covariance matrix. The constraints can be written in the form,

$$C.^{G}\hat{x}^+_{ism}(k) = b. \tag{13}$$

This is solved using linear constraint minimization approach [12] to obtain a better estimation of the combined state vector and covariance matrix. Now a suitable transformation is applied to remove duplicate features. Standard composite state vector and covariance matrix for Multi-Vehicle SLAM is recovered by applying another suitable transformation.

IV. RESULTS

A. Simulations

Simulations were conducted to verify the utility, feasibility and performance gains of the Multi-Vehicle SLAM algorithm. Two identical vehicles having same noise parameters and sensing capabilities were used in the simulations. The vehicles were driven on two overlapping trajectories while performing online Multi-Vehicle SLAM. The estimated trajectories of both vehicles are shown in Fig. 2, while Fig. 3 shows the vehicle position estimation error in X direction. The norms of vehicle position covariances are shown in Fig. 4. A saw tooth like covariance norm change can be observed due to the periodic fusion of local sub-maps into the global map.

For the purpose of comparison, another vehicle having identical noise parameters and sensing capabilities, were driven on the same trajectory as that of the first vehicle (Fig 5) performing EKF-SLAM without CLSF, and properties of the results were examined. It is evident from Fig. 6 that, due to the periodic map fusion, during Multi-Robot SLAM, it's covariance estimates are lower than that of a vehicle having identical noise parameters and sensing capabilities, performing mono-SLAM without CLSF. The feature estimations of Multi-Vehicle SLAM, seems to have better performance. Further, due to overlapped areas of both vehicles, feature estimates are much more robust.
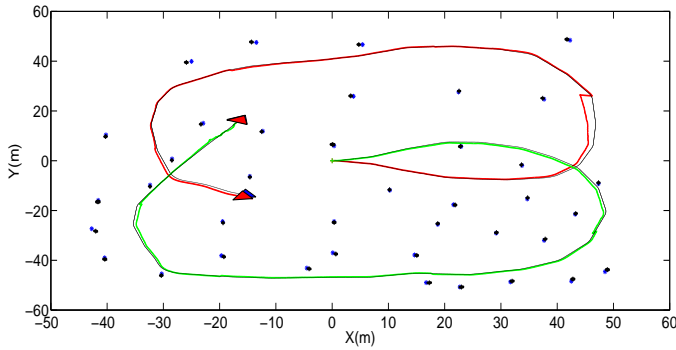
Fig. 2. Tracks of the two vehicles, after performing Multi-Vehicle SLAM. The estimated paths of two vehicles are shown in red and green respectively while actual paths are shown in black. Further, actual features are shown as blue stars while, estimated features are shown in black color, encircled in black by corresponding covariance ellipses.
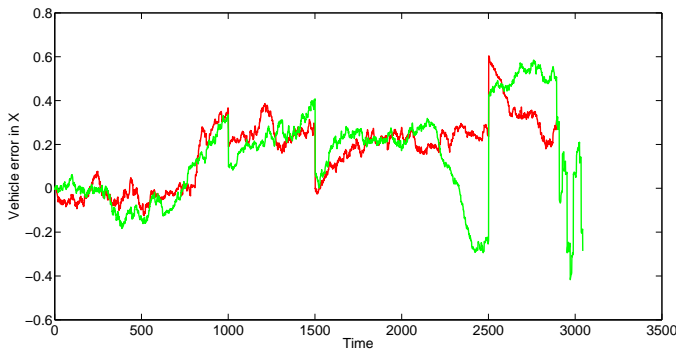

Fig. 3. The vehicle position estimation error in X direction. The red color corresponds to the first vehicle while green corresponds to the second vehicle.

B. Field Experiments

Field experiments were conducted using two ASCs in littoral waters of Singapore (Selat Pauh), in order to validate the performance practically. Each ASC was equipped with a DVL, a GPS unit and a fiber optic gyroscope (FOG) for collecting navigational and odometry information. For surface feature extraction, one of the ASC was equipped with a Velodyne 3D Laser scanner (Fig. 10), while a 2D SICK Laser were mounted on the second ASC (Fig. 11).

Two ASCs were driven arround the barge area by allowing them to detect the corners of the barge in order to consider the corners as features to be incorporated in the SLAM process. One of the safety boats was also used as a surface feature, which was kept stationary and is shown in the background of Fig. 10.The collected data was processed offline and applied to the developed Multi-Vehicle SLAM algorithm. Fig. 7 shows the resultant tracks by performing Multi-Vehicle SLAM. Corresponding position estimation error in X direction is shown in Fig. 8 while Fig. 9 shows the estimation errors in the Y direction.

V. CONCLUSION

In this paper, we have explained an application scenario of the CLSF based multi-robot SLAM [9] algorithm for evalu-
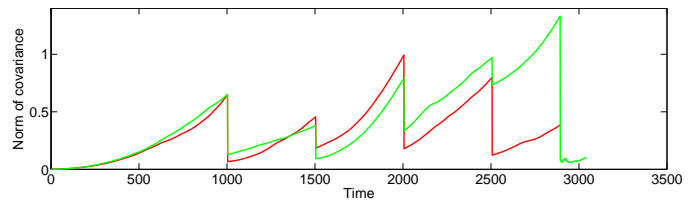

Fig. 4. Norm of the vehicle position covariances of both vehicles. It's clear that, when local sub-maps are merged into the global map, an improvement in position estimation can be obtained. The local sub-maps are merged at each 500th step.
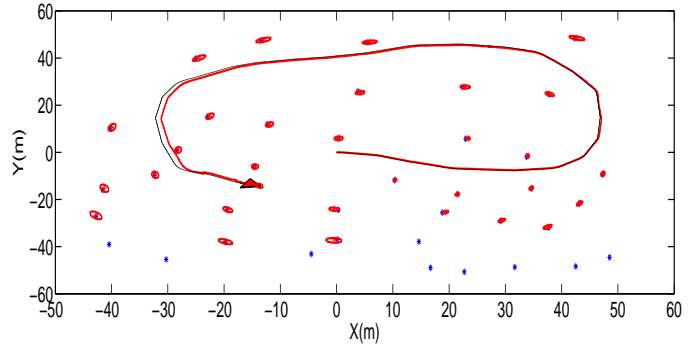

Fig. 5. Track of the first vehicle after performing EKF-SLAM without using CLSF process. The blue colored star marks correspond to the actual features, while red color ellipses correspond to covariances of observed feature estimations.
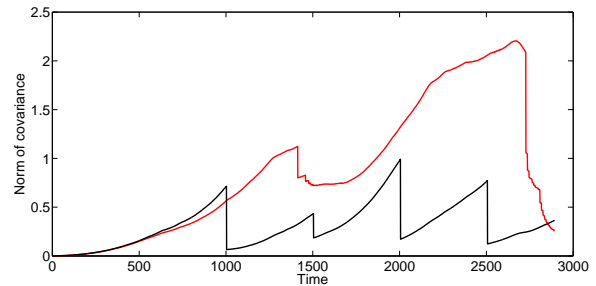

Fig. 6. The comparison of first vehicle's norm of position covariance in single vehicle SLAM case with Multi-Vehicle SLAM case. The red color graph corresponds to the single vehicle SLAM case while black corresponds to Multi-Vehicle SLAM case.
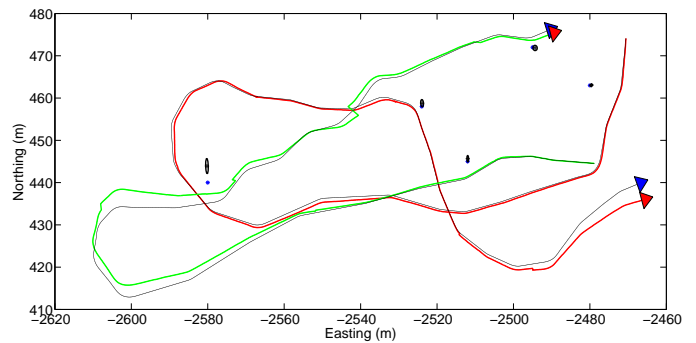

Fig. 7. Tracks of the two vehicles, after performing Multi-Vehicle SLAM during the field experiments in shallow waters of Singapore (Salat Pauh). The feature estimations shown with covariance ellipses (in black) corresponds to the four corners of the barge and the safety boat used during the experiment.
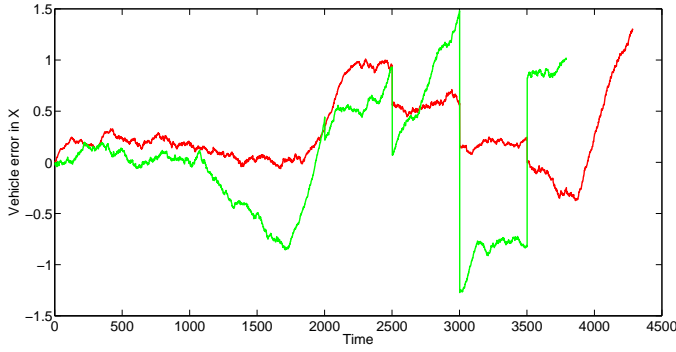
Fig. 8. The vehicle position estimation error in X direction during the field experiment. The red color corresponds to the first vehicle's error while green corresponds to the errors of second vehicle.
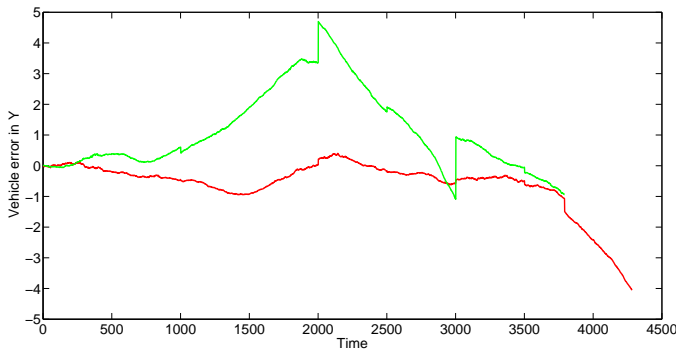

Fig. 9. The vehicle position estimation error in Y direction during the field experiment. The red color corresponds to the first vehicle's error while green corresponds to the errors of second vehicle.

Fig. 10. ASC with the Velodyne 3D Laser during the experiment. The safety boat seen in the background was also considered as a feature during the experiment.

Fig. 11. The ASC with the 2D Laser during the experiment.

ating its performance. We first demonstrated the formulation of CLSF based Multi-Vehicle SLAM algorithm, using the fact that, CSLAM problem can be solved as several mono-SLAM problems. The ability of delayed fusion of local sub-maps into the global map made CLSF an ideal and natural tool for solving the CSLAM problem.

The validity of the algorithm was first evaluated using simulations and then using real data from experiments conducted at the Sea. It is evident from the results that, in low clutter situations, CLSF based multi-robot SLAM algorithm performs quite well. We are currently working on CLSF based multi-robot SLAM algorithms suitable for applications in various field conditions such as in high clutter environments.

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