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COLLABORATIVE LOCALIZATION USING DYNAMIC NOISE COVARIANCE AND ROBOT MOTION MODEL FOR UNKNOWN AREA EXPLORATION

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Multi-robot systems are preferred in complex missions such as, unknown and unstructured area exploration, due to the scalability, robustness, efficiency and cost considerations. Accurate position estimation is a key problem that needs to be addressed for multi-robot systems in unknown indoor and outdoor environments. In this work, we propose a collaborative localization scheme for multi-robot systems. In this scheme, the robots operate without a static reference anchor infrastructure. Each robot localizes itself using individual sensors (such as, IMU and wheel odometry). Next, the robots share their own positions through communication and relative distances between them are measured using time-of-flight sensors (such as, ultra-wide band radio). Finally, we incorporate dynamic adaptive noise covariance in sensor fusion for further improving localization accuracy. The overall scheme is tested in simulation and we achieve high level (*cm* level) of localization accuracy. Detailed simulation results are presented to further demonstrate the scalability of the proposed scheme.

1. Introduction

Multi-robot systems have been receiving increased attention due to their distinct advantages compared to the single robot systems. Robustness to individual robot failure, capability to scale with a mission, time taken to complete a complex mission are some key advantages exhibited by multi-robot systems compared to single robot systems. In a complex mission such as search and rescue (especially, in an unknown/unstructured environment), efficient operation of such mobile-robot systems is a critical challenge. For instance, the operations of robots in cluttered *indoor* environments to explore multi-storied buildings and the operations in an unknown/unstructured *outdoor* environment with massive area exploration, require advanced sensors and compute capabilities. A sample exploration mission is shown in Fig.1a . Further, these robots must be capable of navigating safely and efficiently through unknown terrains and harsh environments while simultaneously carrying out their tasks towards accomplishment of a common mission. Accurate position estimation is a fundamental parameter for enabling efficient autonomous navigation of a mobile robot.

In an indoor environment (where GPS is inaccurate and unreliable), wheel odometry and IMU are traditionally used for localization. Wheel odometry accumulates errors overtime due to wheel slippage and encoder miscount. IMU has drift problem over time. Thus, it is very difficult to accurately localize the robot using wheel odometry and IMU in an indoor environment[1]. There are other existing approaches in literature, that can be used for precision position estimation, such as, time difference of arrival (TDOA), time of arrival (TOA), received signal strength (RSS), angle of arrival (AOA), and a combination of these techniques[2–4]. However, these techniques demand pre-installation of static anchor [19] infrastructure which are feasible only in known/well-structured environments and are not practical and hard to establish in unknown/unstructured environments.

For multi-robot systems, a technique called *Collaborative Localization* (CL) has been demonstrated for estimating the position of individual robots in a multi-robot setup providing significant improvements in the performance[5]. In CL, robots detect each other and communicate their estimates to correlate the estimates of their individual poses.

Traditionally, most of the CL approaches are based on range and bearing measurements. Existing approaches employ filter based solutions or geometry/model based solutions. The common filters used are extended Kalman filter (EKF)[6,7], particle filter[8] and unscented Kalman filter (UKF)[9]. Poor EKF initialization typically causes instability and suffers from bias problems associated with the measurement linearization.

Further, many CL approaches employ vision and acoustic based relative measurements[10,11]. In[12], the concept of "mobile landmark" is introduced, where, the exploration is carried out by using the robots themselves as landmarks. In[13], authors developed mobile robots which are equipped with required sensors to measure the range to landmarks. These robots then simultaneously localize themselves and also expand the range-only map by using odometry to increase the likelihood of obtaining a rigid graph. In[14], EKF-based fully decentralized CL has been introduced based on few static landmarks and limited communication between any two robots to obtain a relative measurement. In[15], distributed multi-robot localization is carried out based on acoustic pulses sent and received by the robots. This work applies concepts from Euclidean distance geometry to label each robot's measurements, constructing a set of relative distances and then a set of relative positions. Vision only solutions are extremely complex and generally demand higher computational power in order to extract the depth information, while acoustic only solutions require an array of acoustic sensors to establish a reasonably accurate bearing estimate.

To this end, we propose a novel approach where robots exploit the multi-robot system properties and communication for localization. In the proposed method, individual robot location information is estimated using wheel odometry, IMU and robot motion model with EKF. Next, the robots form a dynamic network, measure distances between each other through ranging and share their positions and velocities for accurate localization. Further, dynamic noise covariance concept [20] has been incorporated in EKF along with corresponding robot motion model for accurate localization without using any static anchors/landmarks.

The key contributions of this paper are outlined below:

(1) *Exploiting the availability and properties of multi-robot system* to localize individual robots
(2) *Decoupling the dependency on static anchor system* for robot localization
(3) *Error modeling and feedback* using dynamic error covariance for accurate localization

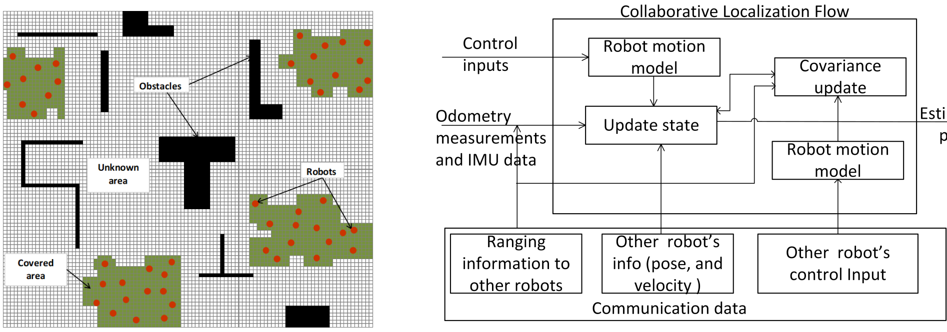
The remainder of the paper is organized as below. The proposed methodology for collaborative localization is described in Section 2. Experimental setup and results are discussed in Section 3. Conclusions are presented in Section 4.

2. Methodology

2.1. *Preliminaries*

In this work, each robot (*differential drive*) is equipped with various sensors such as, IMU, UWB transceiver and shaft encoder. The attitude and heading reference system (AHRS) algorithm is employed on IMU data using Kalman filter (KF) to measure the robot orientation[16]. A UWB transceiver is mounted on each robot for ranging (d) with others robots at anytime to measure the relative distance. The use of UWB transceiver is doubled as the communication radio for exchanging current pose (x, y, θ), velocity(v_x, v_y) and control input (u_t). A shaft encoder is attached on the robot wheel to assist in robot velocity estimation. A flow diagram of the proposed approach for multi-robot collaborative localization is presented in Fig. 1b.

We use the differential drive robot kinematics principle to estimate robot motion [18] in



(a) A sample multi-robot system in an area coverage mission

(b) Flow diagram of the proposed approach

Fig. 1. Proposed collaborative localization approach for a sample multi-robot system

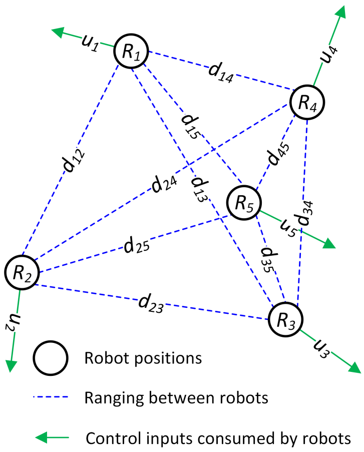


Fig. 2. Relative distance measurement and collaborative localization

EKF along with encoder data for robot wheel odometry estimation. The pose estimation model was developed by integrating kinematic model of robot in the prediction step of EKF technique, where the control input u_t for individual robot is represented as: $u_t = \begin{pmatrix} v_t \\ \omega_t \end{pmatrix}$. The estimated state $\bar{\mu}_t$ is represented as: $\bar{\mu}_t = \begin{pmatrix} x \\ y \\ \theta \\ v_x \\ v_y \\ \omega \end{pmatrix}$.

2.2. *Problem Formulation*

The main goal of the proposed scheme is to estimate the pose of each robot in a multi-robot system setting. In Fig. 2, the relative distance measurement for collaborative localization is depicted. Let us consider a team of N robots (R_i *where* $i \rightarrow 1$ *to* N). Let P_i be the pose of each robot (R_i) in a fixed reference frame. This is depicted in Fig. 3. For explanation purpose, in this paper, we consider the problem of localizing N robots navigating on a plane. However, the same approach can be employed for other scenarios as well. Under this

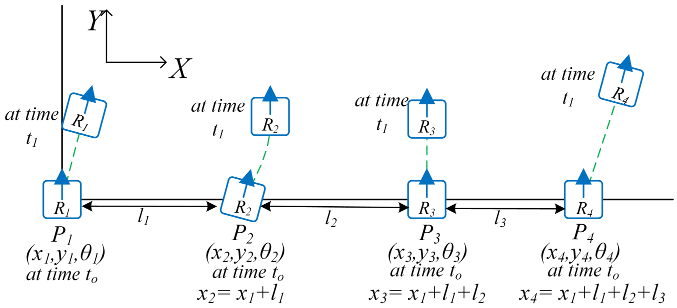


Fig. 3. Robot position initialization with a fixed reference frame

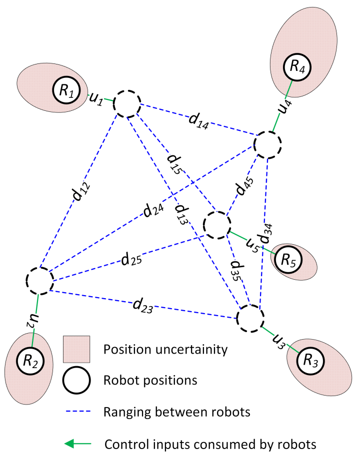


Fig. 4. Position estimation uncertainty for each moving robot

assumption, a robot pose is a triplet $P_i = (x_i, y_i, \theta_i)$ with Cartesian coordinates (x_i, y_i) and orientation θ_i. The number of robots in a team N can be changed dynamically depending on the communication availability and does not need to be known to the robots beforehand. For relative distance measurement, the minimum number of robots required is 3 ($N \geqslant 3$). Each robot is provided with an estimate of its own pose P_i and current velocity (v_{ix}, v_{iy}). At any given time, the relative distances between robots R_i and R_j are (d_{ij}). For instance, the relative distance matrix of robot (R_1) to other robots (R_j) is defined as $d_{1,j} = \begin{bmatrix} d_{12} \\ . \\ . \\ d_{1N-1} \end{bmatrix}$.

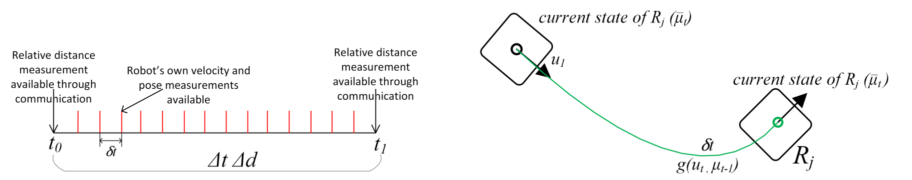
2.3. *Collaborative Localization*

The position uncertainty for each robot will increase over time as shown in Fig. 4. To reduce this position uncertainty, the collaborative localization scheme is proposed. In this scheme, we tightly couple the measured relative distances $d_{i,j}$ along with robot's own velocity (v_x, v_y) and orientation (θ) in EKF measurement vector (z_t). The measurement vector for (R_1) is

$$z_t = \begin{pmatrix} d_{12} \\ . \\ . \\ d_{1N} \\ \theta^{AHRS} \\ v_x^{odom} \\ v_y^{odom} \\ \omega^{IMU} \end{pmatrix} ; Q_t = \begin{pmatrix} \sigma_{d_{ij}} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & . & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{d_{NN}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{AHRS} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{v_x} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{v_y} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_\omega \end{pmatrix}$$

where (Q_t) is the measurement noise matrix and σ is the covariance matrix.

Note that, the availability of relative distance $d_{i,j}$ is limited by the communication speed. However, robot's own velocity (v_x, v_y) and orientation (θ) measurements are available in much finer time resolution (high frame-rate) as these are measured using on-board sensors. This is depicted in Fig 5a.



(a) Time difference between consecutive measurements

(b) Robot position estimation model based on current control input

Fig. 5. Robot pose estimation details based on control input

Difference in time and difference in distance between the availability of two consecutive relative distance measurements $(d_{i,j})$ are denoted by, (Δt) and (Δd), respectively (as shown in Fig 5a). The measurements (self) $(v_x, v_y$ and $\theta)$ on each robot are obtained every δt time instant. During each δt, other robot's (R_j) position (δd) is calculated based on corresponding velocity and control input obtained at time t_0 using the robot motion model as shown in Fig. 5b. Also, the relative distance error covariance $(\sigma_{d_{ij}})$ is dynamically updated in the measurement noise matrix (Q_t) at each δt. The relative distance error covariance $(\sigma_{d_{ij}})$ is computed as described in Algorithm 2.1 (Q_Update) based on the concept in [20].

Algorithm 2.1 Q_Update $(\mu_{t-1}, u_t, d_{1,j})$

$for\ j\ = 2\ to\ N$
$\bar{\mu}_{R_j} = g({u_t}^j, \mu_{t-1}^j)$
$\bar{d_{1,j}} = sqrt(\bar{\mu}_{R_1}, \bar{\mu}_{R_j})$
$\delta d = d_{1,j} - \bar{d}$
$\sigma_{d_{1,j}} = \sigma_{d_{1,j}} + cov(\delta d)$
$end\ for$
$Update\ Q$

3. Results & Discussion

The performance of the proposed scheme is tested using computer based simulations with ROS and mvsim environment[21]. We used Intel Core^{TM} i7 processor with 250GB storage and 8GB RAM. To validate the proposed scheme, two different scenarios are considered. Below is a short description of the same:

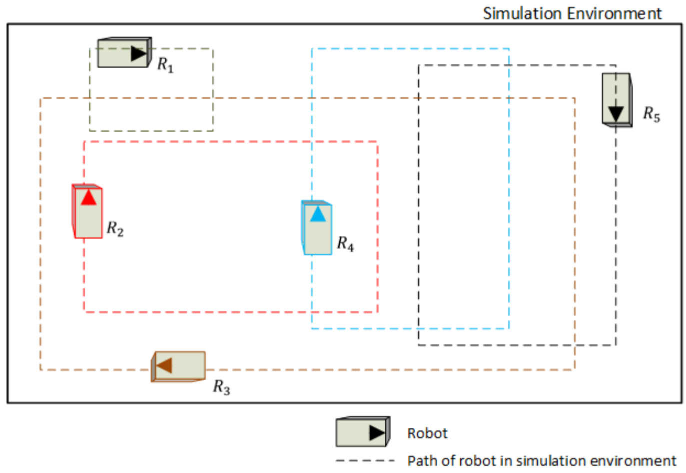


Fig. 6. A snapshot of simulation environment

- `Case 1`: Localization accuracy with minimum number of robots with varying speed and communication frequency.
- `Case 2`: Localization accuracy with higher number of robots considering scalability aspects.

In the simulation setup, the robots with differential drive kinematics are considered. Each robot is equipped with sensors such as, IMU and wheel odometry. Each robot provides a ground truth for localization. We incorporated ultra-wide band based ranging techniques for relative distance calculation with the measurement error margin of 50 cm. Further, we incorporate the wheel odometry error margin of 10 cm. Each robot explores a square area of 40 m x 40 m.

`Case 1`: In this experiment, we consider a team of four robots moving in rectangular paths as depicted in Fig. 6. Each robot receives information about the other robots every 1 *second* interval. We measure the localization accuracy by varying the robot speeds from 0.5 m/s to 3 m/s. Next, same experiment is carried out now with increased communication frequency (2 fps). The results obtained are shown in Fig. 7. In Fig. 7, the loop closure for robot R1 is demonstrated. The localization accuracy is compared with the ground truth. With the proposed approach, it is observed that the localization accuracy closely follows the ground truth.

In Fig.8a, the impact of varying robot speed on the localization accuracy (for a fixed communication speed) is presented. It is observed that, with increase in robot speed, the localization accuracy degrades. Finally, same experiment is repeated for increased communication speed. It is observed that, increased communication speed improves the overall localization accuracy. In TABLE 1, the minimum and maximum position errors for $comms\ fps = 1$ and $comms\ fps = 2$ are tabulated.

`Case 2`: In this experiment, we consider the scalability of the proposed scheme. To validate this, we tested the scheme with robot team size ranging from 4 to 50. The experimental setup for scalability analysis is as shown in Fig 8b. This figure also shows the connectivity between the robots in a team.

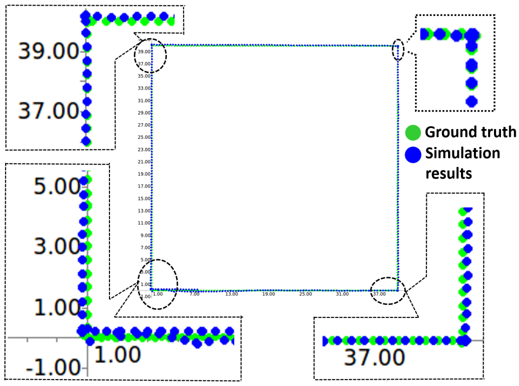
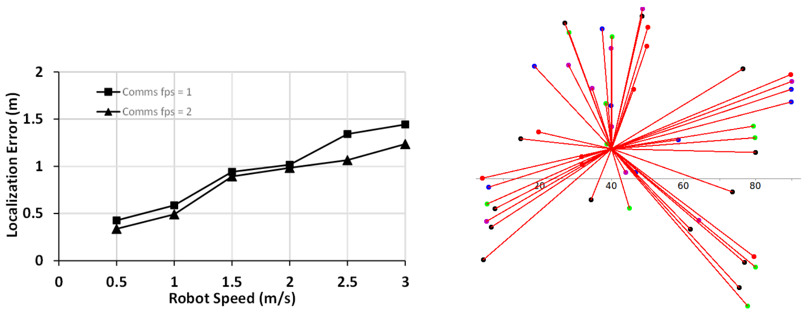


Fig. 7. Localization loop closure for R1 where green dots represent the ground truth and blue dots represent the results with the proposed scheme

Table 1. Minimum and maximum position errors for comms fps = 1 and comms fps = 2

Robot Velocity (m/s)	Min Error (m)		Max Error (m)	
	fps=1	fps=2	fps=1	fps=2
0.5	0.018	0.007	0.772	0.944
1	0.134	0.011	0.947	1.204
1.5	0.264	0.018	1.703	1.681
2	0.348	0.137	1.574	2.489
2.5	0.355	0.395	2.276	2.283
3	0.513	0.073	2.362	2.796



(a) Localization accuracy plot for varying robot speed

(b) The plot shows the connectivity of robot R1 with the other robots

Fig. 8. Simulation snapshot for scalability demonstration and localization accuracy

4. Conclusion

Accurate localization is a critical capability for efficient operation of multi-robot system. In this paper, a novel scheme for collaborative localization is presented which incorporates fusion of individual position information, relative distance between robots and dynamic adaptive noise covariance in sensor fusion. Simulations performed using ROS and mvsim demonstrate the high accuracy of the proposed scheme. It is observed that the localization accuracy is limited by the number of communication fps between different robots. With the increase in robot velocity, the communication fps should be increased to reduce the localization error. Finally, the increase in the number of robots from 4 to 50 resulted in similar localization accuracy demonstrating the scalability of the proposed approach.

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