Leader-Follower Localization and Mapping using Range-Only Measurements

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***Abstract*—A major part of the autonomous mobile robotics research is to address the localization and mapping problem of mobile robots using external sensory measurements. Extensive research has been conducted in the literature to solve this problem. However, a cost-effective and modular solution to the mapping and localization problem of a mobile robot operating in an indoor environment remains open. Addressing such a problem is even more challenging when the robot has to solve the leader-follower problem where neither leader nor follower robot states are known *a priori.* This work pertains to address this problem using range-only measurements from a set of networked wireless (radio) sensors placed in the robot's operating space (two-dimensional). A customized radio sensor is equipped with the follower robot. Since the locations/states of both robots (leader and follower) are unknown a priori, a conventional Extended Kalman Filter Simultaneous Localization and Mapping (EKF–SLAM) technique is employed for the follower robot to estimate its position and orientation, the position of the leader, and the positions of the radio sensors (*i.e.,* building the map) placed in the robots' operating environment using range-only measurements from radio sensors. The proposed range-based approach for solving the leader-follower localization and mapping problem is validated using a commercially available robot simulator, V-REP (Virtual Robot Experimentation Platform).**

***Index Terms*—Leader-follower, mobile robots, simultaneous localization and mapping, extended Kalman filter, wireless sensor network**

I. Introduction

The task of localization and mapping in the context of leader-follower problems is very challenging. Such a task is becoming a ubiquitous facet of modern life due to its promising application in addressing not only the leader-follower problem but also applicable in industry industry with heavy equipment trucks, in agriculture with autonomous crop maintenance, in home life with the autonomous vacuuming robot, along with research and design as seen in [1], [2], [3], [4]. In most leader-follower problem addressed in the literature to date, it is assumed that leader/target's position/state is known *a priori*, which may not be the case in many applications such as tracking a mobile point source [5]. Furthermore, the localization and mapping task is of a paramount importance in addressing the problem of mobile target tracking, which has a number of promising applications, such as robotic navigation, search and rescue mission, wildlife monitoring, autonomous surveillance, to name a few. A large body of research has been conducted in the literature to address the localization and mapping problem. Relatively few papers have addressed the localization and mapping problem in the context of leader-follower tasks, where either (i) a static leader/target is used [6], (ii) the leader/target's location is predetermined, or (iii) expensive hardware platforms are used to implement the mobile target tracking strategy (see the work presented in [7], for example).

The work done in this paper addresses some of the aforementioned issues by carrying out a cost-effective and easy-to-implement localization and mapping algorithm in the context of a leader–follower problem, a wheeled mobile robot is employed as a follower and a target moving on a two-dimensional (2D) plane is used as a leader. We emphasize that the position of the leader is unknown to the follower robot *a priori.* Therefore, the position and orientation of the follower robot and the position of the leader are to be simultaneously estimated while building the map of the environment of the robot using a set of networked wireless radio sensors placed on the ground. It is assumed that a radio sensor is mounted on the leader. The follower robot receives range measurements [herein the received signal strength indicator (RSSI) from radio sensors] from all radio sensors in its operating range. These measurements are then used to estimate the position and orientation of the follower robot, the 2D position of the leader, and the 2D positions of radio sensors placed in the robot's environment. Once the follower robot estimates its states (position and orientation) and the position of the leader, it moves towards the leader using the motion controller running onboard the follower robot. The design and implementation of the current work are based on the preliminary work of the robot navigation and mapping strategy conducted by the authors in [4], [8], [9]. Therefore, the main objective is to advance the work in [4], [8], [9] for a more general case, where a mobile robot is to follow a leader whose position is unknown *a priori.*

The paper is organized as follows. Section II presents the problem setting using a bicycle-drive mobile robot that acts as a follower robot followed by the mathematical formulation of the localization and mapping problem in the context of a leader-follower robot framework. Modeling the wireless radio sensor network, which is the cornerstone of this paper, is

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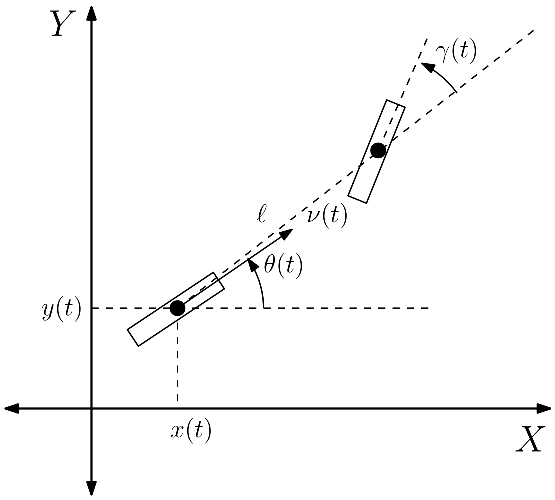


Fig. 1. Follower robot kinematic model used in this work.

given in section III. Section IV illustrates how to use range-only measurements from the customized radio sensors in determining the location and map of the robot's operating environment for addressing the leader–follower problem. A set of computer experiments using a commercial robot simulator is illustrated in section V followed by a conclusion and future work under investigation are given in section VI.

II. Problem Setting

This section briefly illustrates the (follower) robot's model and the performance metrics of localization and mapping in the context of a leader–follower problem. Without loss of generality, consider a rear-wheel bicycle-drive mobile robot (follower) model shown in Fig. 1. Assume that $\mathbf{q}^{[r]}(t) = [x(t), y(t), \theta(t)]^T$ denotes the pose (position and orientation) vector of the robot's rear-wheel at time $t \geq 0$ with $(x(t), y(t))$ being its two-dimensional position with respect to the global coordinate frame X-Y, $\theta(t)$ is its orientation with respect to the positive X-axis, ℓ is the distance between front and rear wheels, $\gamma(t)$ is the steering angle of the robot's front wheel. Suppose the actuator inputs of the robot at time $t \geq 0$ are its linear speed $\nu(t)$ and steering angle $\gamma(t)$ that define its trajectory. Following [10, Ch. 2], its kinematic model can be derived by a set of ordinary differential equations given in compact form:

$$\dot{\mathbf{q}}^{[r]}(t) = \mathbf{G}[\mathbf{q}^{[r]}(t)]\mathbf{u}(t), \tag{1}$$

$$\text{where} \quad \mathbf{G}[\mathbf{q}^{[r]}(t)] = \begin{bmatrix} \sin\theta(t) & 0 \\ \cos\theta(t) & 0 \\ 0 & 1 \end{bmatrix} \quad \text{and} \quad \mathbf{u}(t) = \begin{bmatrix} \nu(t) \\ \omega(t) \end{bmatrix},$$

with $\nu(t)$ and $\omega(t) = [\nu(t)/\ell]\tan[\gamma(t)]$ being the linear and angular velocities with respect to the rear-wheel's center of mass, respectively. Suppose that the follower robot modeled by (1) is supposed to follow leader whose trajectory is a time-varying 2D position vector $\mathbf{p}^{[L]}(t) = [x^{[L]}(t), y^{[L]}(t)]$, for $t \geq 0$. Without additional technical challenge, the leader is modeled as a point-mass described by an integrator:

$$\dot{\mathbf{p}}^{[L]}(t) = \mathbf{u}^{[L]}, \tag{2}$$

where $\mathbf{u}^{[L]}(t) \in \mathbb{R}^2$ is the leader's velocity vector with its linear speed given by $\nu^{[L]}(t) = \|\mathbf{u}^{[L]}(t)\|$. The pose (position and orientation) estimation of the follower robot relies on sensory measurements (range only RSSI measurements) from a set of networked radio sensors located in the environment. Suppose that the ideal locations (unknown to the follower robot) of the sensors are given by the set $\mathcal{B}^{'} = \{\mathbf{b}^{[1]}, \ldots, \mathbf{b}^{[s^{'}]}\}$ where $\mathbf{b}^{[j]} = [x^{[j]}, y^{[j]}]^T$, $j = 1, 2, \ldots, s^{'}$, and $s^{'}$ is the total number of radio sensors. The estimated pose of the follower robot at time t is denoted by the vector $\hat{\mathbf{q}}^{[r]}(t) = [\hat{x}(t), \hat{y}(t), \hat{\theta}(t)]^T$. Here, the map of the robot's workpsace is determined by estimating the positions of the radio sensors. The estimated position of the jth, $j = 1, \ldots, s^{'}$, radio sensor at time t is denoted by the coordinates $(\hat{x}^{[j]}(t), \hat{y}^{[j]}(t))$. The position and orientation estimation errors of the follower robot are $e_p(t) = \sqrt{[x(t) - \hat{x}(t)]^2 + [y(t) - \hat{y}(t)]^2}$ and $e_\theta(t) = \theta(t) - \hat{\theta}(t)$, respectively. The position estimation errors of the leader and the jth, $j = 1, 2, \ldots, s^{'}$, radio sensors are given by $e^{[L]}(t) = \sqrt{[x^L(t) - \hat{x}^{[L]}(t)]^2 + [y^{[L]}(t) - \hat{y}^{[L]}(t)]^2}$ and $e^{[j]}(t) = \sqrt{[x^{[j]} - \hat{x}^{[j]}(t)]^2 + [y^{[j]} - \hat{y}^{[j]}(t)]^2}$, respectively. The root-mean squared errors of the robot's position, orientation, leader's position, and jth radio sensor position estimation errors are defined as:

$$\mathrm{RMSE}_p^{[r]} = \lim_{t_f \to \infty} \sqrt{\frac{1}{t_f} \int_0^{t_f} [e_p(t)]^2}, \tag{3a}$$

$$\mathrm{RMSE}_\theta^{[r]} = \lim_{t_f \to \infty} \sqrt{\frac{1}{t_f} \int_0^{t_f} [e_\theta(t)]^2}, \tag{3b}$$

$$\mathrm{RMSE}^{[L]} = \lim_{t_f \to \infty} \sqrt{\frac{1}{t_f} \int_0^{t_f} \left[e^{[L]}(t)\right]^2}, \text{ and} \tag{3c}$$

$$\mathrm{RMSE}^{[j]} = \lim_{t_f \to \infty} \sqrt{\frac{1}{t_f} \int_0^{t_f} \left[e^{[j]}(t)\right]^2}, \tag{3d}$$

for $j = 1, 2, \ldots, s^{'}$. The problem is to minimize the RMSE quantities, $\mathrm{RMSE}_p^{[r]}$, $\mathrm{RMSE}_\theta^{[r]}$, $\mathrm{RMSE}^{[L]}$, and $\mathrm{RMSE}^{[j]}$, based on the range-only measurements from radio sensors while the follower robot follows the leader operating in a 2D environment.

III. Modeling Wireless Sensor Network

Note that the pose of the follower robot, the 2D position of the leader, and the map of the robot's operating environment is unknown *a priori*. Therefore, the solution of the leader-follower localization and mapping problem considered in this work substantially relies on the external sensory measurements. This work considers that a set of wireless RF (Radio Frequency) sensors are placed in the robot's operating environment (indoor). Each radio sensor is assumed to be uniquely identified with a digital ID stored in its memory and is able to receive a query signal from the follower robot. The

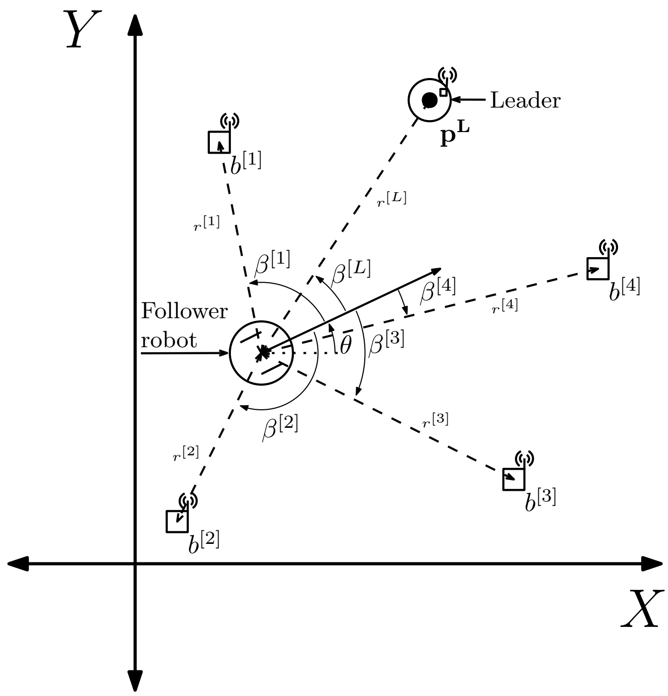


Fig. 2. Radio sensor network for leader-follower mapping and localization.

radio sensor is then able to respond to the (follower) robot with its own ID and the received signal strength indicator (RSSI), which is sensitive to the distance (range) between the robot and the leader/radio sensors, back to the follower robot. Since the follower robot is supposed to receive RSSI information from each radio sensor, it is mounted with a customized radio transceiver. The follower robot broadcasts a query signal through the customized radio transceiver to all radio sensors and receives ID and RSSI information from each individual radio sensor placed in its workspace. A radio sensor is mounted on the leader. This is illustrated in Fig. 2, where $r^{[j]}$ and $\beta^{[j]}$, for $j = 1, 2 \ldots, 4$, in this case, are the range [line-of-sight (LoS) distance between the robot and the jth radio sensor] and bearing, and $r^{[L]}$ and $\beta^{[L]}$ are the range and bearing of the leader. A mathematical model for the range-only RSSI data that the follower robot receives is necessary for it to determine the range and bearing of all radio sensors. Due to noisy RSSI and multipath effect in an indoor environment, determining an accurate mathematical model is almost impossible. However, an experimental study has been conducted to approximate the range based on RSSI measurements (see [11], [9], for more details). An approximate mathematical relation that relates RSSI measurements and the LoS distance (range) between the robot and the jth, $j = 1, \ldots, s'$, radio sensor at time $t \geq 0$ is given by

$$z^{[j]}(t) \approx P_{\text{ref}} + 10\eta \log_{10} r^{[j]}(t), \tag{4}$$

where $r^{[j]}(t) = \sqrt{[x(t) - x^{[j]}(t))^2 + (y(t) - y^{[j]}(t)]^2}$ is the ideal LoS distance between the robot and the jth radio sensor, P_{ref} is the power level (in this work, $P_{\text{ref}} = -29$ dBm) at a reference distance of 1 m, η is the signal propagation constant (here, $\eta = 2$), and $z^{[j]}(t) < 0$ is the RSSI that the robot receives from the jth radio sensor. The follower robot scans RSSI (range) measurements by turning its customized radio transceiver $360°$ and the bearing $\beta^{[j]}$ corresponds to the maximum RSSI when the transceiver is in the line-of-sight with the jth radio sensor. Suppose that $\mathcal{R}^{[j]}$ is the set of RSSI measurements recorded by a $360°$ scan by the follower robot's transceiver at time $t \geq 0$. The noisy bearing of the jth radio sensor is given by:

$$\beta^{[j]}(t) = \underset{[-\pi,\pi)}{\operatorname{argmax}} \, \mathcal{R}^{[j]}. \tag{5}$$

The measurement model of the follower robot consists of the noisy range determined by the inverse model of (4) and the bearing computed by (5), which is given in the form:

$$\mathbf{y}^{[j]}(t) = \left[r^{[j]}(t), \beta^{[j]}(t)\right]^T + \boldsymbol{\xi}(t) = \mathbf{h}(\mathbf{q}^{[r]}, \mathbf{b}^{[j]}, \boldsymbol{\xi}), \tag{6}$$

with $\boldsymbol{\xi} \in \mathbb{R}^2$ being the noise associated with the range and bearing measurements at time $t \geq 0$ and $\mathbf{h} : \mathbb{R}^2 \times [-\pi, \pi) \times \mathbb{R}^2 \times \mathbb{R}^2 \to \mathbb{R}^2$. The measurement model (6) will be used in the proposed leader–follower localization and mapping algorithm illustrated in the next section.

IV. Leader–Follower Localization and Mapping

Since the leader's position is unknown to the follower robot, it is important that the (follower) robot simultaneously estimates its own pose and the position of the leader to address the leader-follower problem. Among the major solution paradigms, such as Kalman filter, particle filter SLAM (aka. Monte-Carlo SLAM), and graphSLAM [12], for solving the simultaneous localization and mapping problem of a mobile robot, a conventional extended Kalman filter simultaneous localization and mapping (EKF-SLAM) algorithm is employed due to its simplicity of implementation in the current work. Despite major drawbacks of the EKF-SLAM algorithm, such as the assumption of Gaussian noise statistics, the computational complexity, and data association issues, it is the method of choice due to the customized hardware architecture of the transceiver mounted on the follower robot.

The current work exploits the customized sensor architecture for the EKF-SLAM algorithm to estimate the pose of the follower robot, 2D position of the leader, the map by estimating the positions of the radio sensors placed in the workspace. For that, the kinematic models of the follower robot and the leader given, respectively, by (1) and (2) are written in discrete form using Euler integration and evaluated at discrete time instant $t = kT$, for $k = 0, 1, 2, \ldots$ and $T > 0$ being the discrete sampling time with

$$\mathbf{q}_{k+1}^{[r]} = \mathbf{q}_k^{[r]} + \mathbf{G}^{[r]}(\mathbf{q}_k^{[r]}, \mathbf{u}_k, \boldsymbol{\zeta}_k) \equiv \mathbf{f}^{[r]}(\mathbf{q}_k^{[r]}, \mathbf{u}_k, \boldsymbol{\zeta}_k) \tag{7}$$

where $\boldsymbol{\zeta}_k \in \mathbb{R}^2$ is the additive Gaussian noise (*i.e.,* process noise) associated with the follower robot's linear speed ν_k and the steering angle γ_k and the subscript k indicates the value of the quantity $(\cdot)$ at time instant k. Let σ_ν^2 and σ_γ^2 denote the variances of the noise associated with ν_k and γ_k, respectively. Therefore, the noise vector $\boldsymbol{\zeta}_k$ takes the values from the Gaussian distribution of mean $\mathbf{0}$ and covariance matrix $\mathbf{Q} = \mathrm{diag}(\sigma_\nu^2, \sigma_\gamma^2)$, *i.e.,* $\zeta_k \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$. At time instant $k = 0$, the follower robot's estimation error is represented by the covariance matrix $\mathbf{P}_0^{[rr]} = \mathrm{diag}[(\mathbf{q}_0^{[r]} - \hat{\mathbf{q}}_0^{[r]}) \odot (\mathbf{q}_0^{[r]} - \hat{\mathbf{q}}_0^{[r]})]$. The technical details of the EKF-SLAM algorithm using the proposed customized radio sensor architecture can be sought in [8] and are omitted here for conciseness. However, the high-level steps of the EKF-SLAM algorithm for estimating the pose of the follower robot, the position of the leader robot, and the positions of the radio sensors representing the map of the environment are given in Algorithm 1.

Algorithm 1: Localization and mapping algorithm using customized radio sensors.

Input: Range-only data (RSSI data from leader and radio sensors)
Output: Estimated pose, position, and map of the follower robot, leader, and the environment.

```
begin
    • Initialize process and measurement noise
      covariance matrices
    repeat
        • Choose linear velocity ν_k and steering angle
          γ_k at time instant k ∈ {0, 1, 2 ...}
        • Compute follower robot's angular speed ω_k
        • Apply follower robot's actuating speeds for
          T seconds
        • Predict robot's pose, leader's position, and
          positions of radio sensors using EKF-SLAM's
          prediction equations as in [8]
        • Record, decode, and perform data association
          of RSSI measurements from radio sensors and
          the leader
        • Update the follower robot's pose, leader's
          position, and the positions of the radio sensors
          using the EKF-SLAM update equations
        • Record estimated (updated) robot's pose,
          leader's position, and the positions of the
          radio sensors
    until Time t → ∞
```

V. Virtual Experiments using V-REP

This section illustrates the performance of the leader-follower localization and mapping strategy using range-only RSSI measurements. A set of virtual experiments is conducted using the commercially available robot simulator, Virtual Robot Experimentation Platform (V-REP[1]) in cooperation with MATLAB[2] software in a desktop computer running Windows 10 operating system. V-REP is an industry standard robot simulator that takes into account dynamic properties of robots. Therefore, the performance of the current leader-follower localization and mapping strategy based on virtual experiments using V-REP is as realistic as what would happen in real scenarios. The setup of the virtual experiments is shown Fig. 3, where radio sensors, the leader, and the follower robot are annotated. Since a bicycle-drive robot modeled by (1) is unavailable in V-REP, a Pioneer 3-DX robot, which is a circular shaped differential-drive mobile robot, is chosen as the follower robot. The kinematic model of the Pioneer 3-DX robot is a special case of the bicycle-drive robot [13]. A sphere-shaped 3D object in V-REP is chosen as the leader. Two experiments are conducted. The performance metrics of each experiment are the follower robot's pose estimation errors, leader's position estimation errors, and the position estimation errors of radio sensors placed in a 2D environment of dimension 9 [m] $\times$ 9 [m]. The sampling time for running the experiments in a laptop computer is $T = 0.1$ [s]. In both experiments, four radio sensors are used, whose ideal (reference) positions on the ground are: $\mathbf{b}^{[1]} = [0.0, 3.5]^T$ [m], $\mathbf{b}^{[2]} = [6.5, 2.5]^T$ [m], $\mathbf{b}^{[3]} = [4.0, 7.25]^T$ [m], and $\mathbf{b}^{[4]} = [0.0, 8.0]^T$ [m].

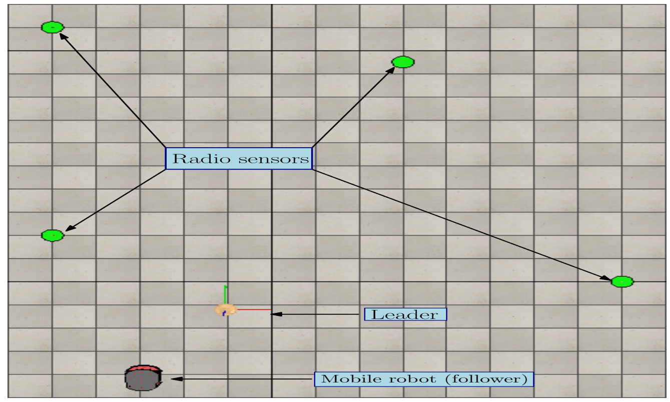


Fig. 3. Setup of virtual experiments in VREP.

In the first experiment, the leader is placed at a fixed position (reference) at $(x^{[L]}, y^{[L]}) = (5.0 \text{ [m]}, 4.0 \text{ [m]})$. The reference pose of the follower robot at time $t = 0$ is $\mathbf{q}^{[r]}(0) = [x(0), y(0), \theta(0)]^T = [1.0 \text{ [m]}, 0.5 \text{ [m]}, 90°]$. The follower robot is navigated towards the leader using a conventional proportional plus integral controller. The robot stops at the close proximity (distance between the leader and the follower) of the leader. The follower robot is navigated for time $t = 30$ [s] and its pose trajectory is shown in Fig. 4(a). The estimated robot's pose converges to the reference pose as the navigation time increases. This is natural since the follower robot obtains more RSSI measurements as it moves towards the leader. Fig. 4(b) shows how accurately the follower robot is able to estimate the leader's position as it has to reach within the close proximity of the leader. At time $t = 0$, the leader's position estimation error is about 70 [cm]. As the follower robot moves towards the leader, the leader's position estimation error converges to about 10 [cm]. Similar to the follower robot, the leader's position estimation converges to its reference position as time increases. The mapping performance

[1] See http://www.coppeliarobotics.com/ for details.
[2] www.mathworks.com

of the proposed localization and mapping strategy with the static leader is reported in Fig. 4(c), where the position estimation errors of four radio sensors are shown with different line styles. The initial position estimation error for all radio sensor was in the range from about 0.1 $[\mathrm{cm}]$ to 65 $[\mathrm{cm}]$. However, the position estimation errors for all radio sensors converge in the range of 5 $[\mathrm{cm}]$ to 30 cm as expected. The RMSEs defined in (3) are computed from time $t = 0$ to $t = 30$ [s], where $\mathrm{RMSE}_p^{[r]} = 0.42$ [m], $\mathrm{RMSE}_\theta^{[r]} = 0.10$ [rad], $\mathrm{RMSE}^{[L]} = 0.13$ [m], $\mathrm{RMSE}^{[1]} = 0.24$ [m], $\mathrm{RMSE}^{[2]} = 0.16$ [m], $\mathrm{RMSE}^{[3]} = 0.17$ [m], and $\mathrm{RMSE}^{[4]} = 0.46$ [m].

The purpose of the second experiment is to sustain the performance of the proposed leader-follower localization and mapping strategy when the leader's position is time-varying (mobile leader) and the follower robot has to follow the leader while maintaining a safe (predefined) distance. In this case, the leader is set to navigate through random path with a variable linear speed in the range from 0.1 $[\mathrm{m \cdot s^{-1}}]$ to 0.2 $[\mathrm{m \cdot s^{-1}}]$. The results are summarized in Fig. 5. The trajectories of both the follower robot [solid (dashed) line indicates ideal (estimated) positions] and the leader (diamond and solid green dot indicate ideal and estimated positions, respectively) shown in Fig. 5(a). The follower robot is supposed to follow the leader while maintaining a predefined safe distance of 1.5 $[\mathrm{m}]$. The follower robot is able to follow the leader with a safe distance of about 1.5 $[\mathrm{m}]$, as expected. The position estimation errors of the leader and the radio sensors are shown in Figs. 5(b) and 5(c). As it can be noticed, the position estimation errors of the leader converges to about 10 $[\mathrm{cm}]$. The position estimation errors of all radio sensors gradually decrease as it is clear from Fig. 5(c). The RMSEs recorded for this experiment are $\mathrm{RMSE}_p^{[r]} = 0.43$ [m], $\mathrm{RMSE}_\theta^{[r]} = 0.10$ [rad], and $\mathrm{RMSE}^{[L]} = 0.20$ [m]. The RMSEs for radio sensor estimation errors are $\mathrm{RMSE}^{[1]} = 0.18$ [m], $\mathrm{RMSE}^{[2]} = 0.21$ [m], $\mathrm{RMSE}^{[3]} = 0.32$ [m], and $\mathrm{RMSE}^{[4]} = 0.44$ [m], which are satisfactory considering the noise level considered for RSSI measurements in the measurement model (5).

VI. Conclusion

In this paper, a customized radio sensor network architecture is presented for addressing the localization and mapping problem in the context of a leader-follower robotic application, where a differential drive mobile robot is used as a follower and a moving particle (point mass) is employed as a leader. Since the leader's position is unknown, a customized radio sensor is mounted on the leader so that it is able to send RSSI measurement to the follower robot. The follower robot relies on RSSI measurements received from a set of networked radio sensors in an indoor environment for estimating its pose. The conventional EKF-SLAM algorithm is employed for estimating the pose of the follower robot, the position of the leader, and the positions of the radio sensors. Despite the limitations of EKF-SLAM method, satisfactory estimation errors are achieved due to customized sensor architecture incorporated in

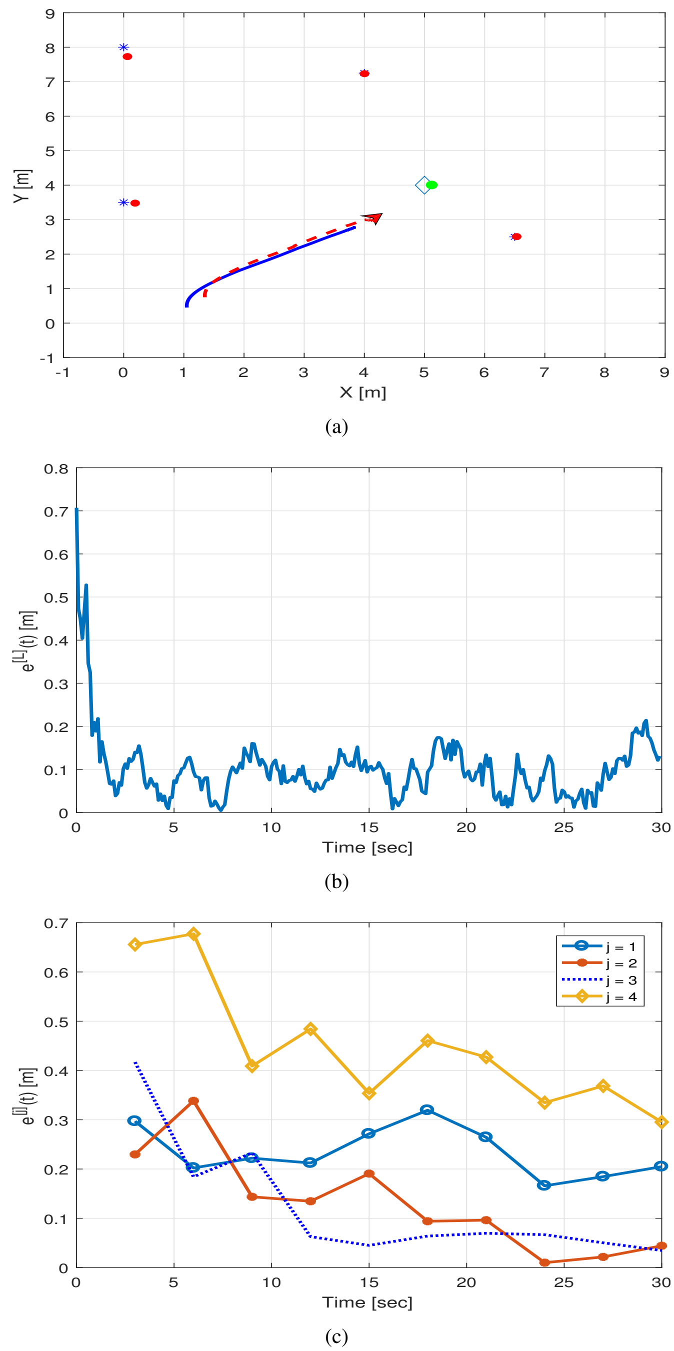
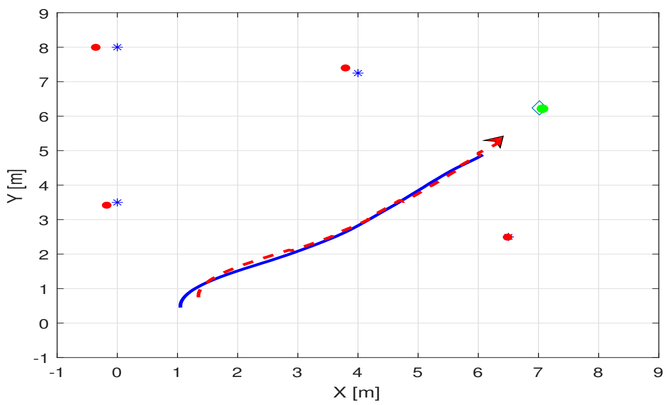
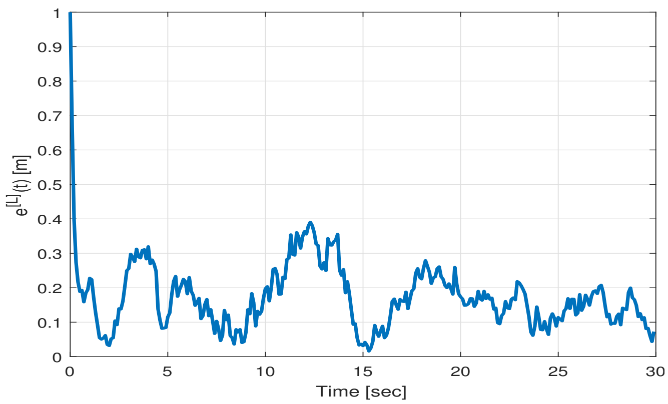


Fig. 4. Localization and mapping performance (a) robot's estimated and reference poses , (b) leader's position estimation errors, and (c) mapping (radio sensor position) errors.

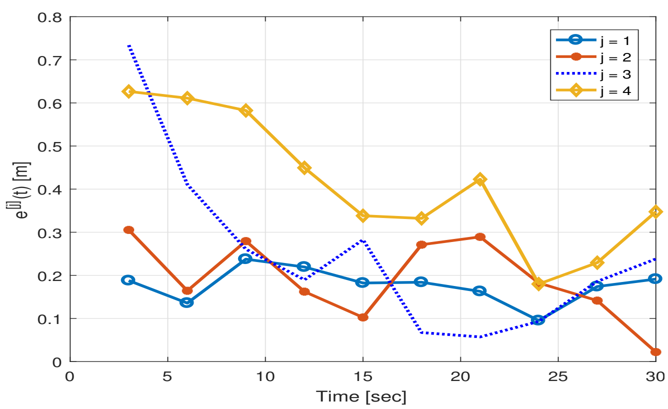
this work. Computer experiments using the commercial robot simulator, V-REP, demonstrated the satisfactory performance of the customized radio sensor network in localizing and mapping the environment, which is of a paramount importance in many robotic applications. Experiments using a commercial robot (follower) robot, a leader (mobile) robot, and a set of radio frequency sensors as radio sensors are currently being conducted in a laboratory setting.



(a)



(b)



(c)

Fig. 5. Performance of the leader–follower navigation (a) trajectories of both the leader and the follower robots, (b) leader's position estimation error versus time, and (c) mapping (radio sensor position) errors.

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