Localization of a Wireless Sensor Network with Unattended Ground Sensors and Some Mobile Robots

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Abstract— **A range-free approach for adaptive localization of un-localized sensor nodes employing a mobile robot with GPS is detailed. A mobile robot navigates through the sensor deployment area broadcasting its positional estimate and the uncertainty in its estimate. Distributed computationally-inexpensive, discrete-time Kalman Filters, implemented on each static sensor node, fuse information obtained over time from the robot to decrease the uncertainty in each node's location estimate. On the other hand, due to dead reckoning and other systematic errors, the robot loses positional accuracy over time. Updates from GPS and from the localized sensor nodes serve in improving the localization uncertainty of the robot. A Continuous-Discrete Extended Kalman Filter (CD EKF) running on the mobile robot fuses information from multiple distinct sources (GPS, various sensors nodes) for robot navigation. This two-part procedure achieves simultaneous localization of the sensor nodes and the mobile robot.**

Keywords— **Adaptive Localization, Continuous-Discrete Extended Kalman Filter (CD EKF), Simultaneous Localization, Sensor Networks.**

I. INTRODUCTION

Location information is imperative for applications in both wireless sensor networks and mobile robotics. Many sensor network applications, such as tracking targets, environmental monitoring, geo-spatial packet routing, require that the sensor nodes know their locations. The large scale of deployment in sensor networks makes careful placement or uniform distribution of sensor nodes impractical. The requirement of the sensors to be small, un-tethered, low energy consuming, cheap, etc., make the sensors resource-constrained [1]. Localization is a challenging problem and yet crucial for many applications.

Approaches to the problem of localization are varied. A detailed introduction to localization in sensor networks is presented in [2]. GPS [3] solves the problem trivially, but equipping the sensors with the required hardware may be impractical. A small section of active beacons can be placed in the sensor network and other sensors can derive their location from these anchor nodes [4], [5]. Cooperative localization methods have been developed for relative localization [6], [7]. Other approaches involve RSSI [8], TOA [9], [10], AOA [11], and Signal Pattern Matching [3].

For localization with no additional hardware on the sensor node, the geometric constraints of radio connectivity are exploited. Some authors suggest using a mobile robot (whose position is known) to localize the sensors. However, the position of the mobile robot may be hard to determine. LaSLAT [12] uses a Bayesian filter to localize the sensor network and track the mobile robot. In [13], a particle filter is employed to localize elements of the network based on observation of other elements of the network. In [14], a mobile robotic sensor localized the network based on simple intersections of bounding boxes. In [15], geometric constraints based on both radio connectivity and sensing of a moving beacon localize the sensor network. The Kalman filter has been used in dead-reckoning for mobile robots but its full potential in localization of WSN has not heretofore been fully explored. In [16], an extended Kalman filter is used for localization and tracking of a target. The Kalman filter was used in [17] for active beacon and mobile AUV localization and in [18] for scheduling of sensors for target tracking. SLAM [19] and CML [20] employ Kalman filters for concurrent mapping and mobile robot localization, which can be considered similar to our work wherein the geometric constraints introduced due to radio connectivity of the static sensors play the role of features. In this paper we use the full capabilities of the Kalman filter in the general WSN localization problem.

Our work exploits geometric constrains based on radio connectivity such that range information is not needed. A mobile robot initially sweeps the network, and broadcasts from the robot are used to localize the sensor nodes. Computationally inexpensive Kalman filters implemented on the sensors fuse the information. On the other hand, as time passes, the mobile robot gradually loses its own localization information. We present an algorithm that uses updates from the better localized sensors along with GPS updates, when they occur, to correct this problem. A continuous-discrete extended Kalman filter running on the robot estimates the robot state continuously and fuses the discrete measurement updates available from the more localized sensors and infrequent GPS.

II. SENSOR LOCALIZATION USING MOBILE ROBOT

In this section we provide an algorithm that runs on each Unattended Ground Sensor (UGS) node that allows it to update

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its position estimate, and the uncertainty in that estimate, as a mobile robot with known position moves through the network. The algorithm is range-free in that only the communication range need be known, not the range from the node to the mobile robot. It is assumed in this section that the mobile robot's position is exactly known.

A. Scenario

A deployed wireless sensor network comprised of static unattended ground sensors is to be absolutely localized by a mobile robot. The robot broadcasts consist of its own position and its position uncertainty estimates. Broadcasts can only be heard within the robot's communication range. The static sensors, on receiving these broadcasts, combine the new information to update their current location estimate. A simple discrete-time Kalman filter running on each static sensor node serves to fuse information and update its location and uncertainty estimates.

This is a formalized rigorous approach employing Kalman filters for localization, in contrast to bounding boxes [14], [15], which are harder to update and keep track of. The developed algorithm is simple and can efficiently be implemented on the sensor nodes with a small computing power. The Kalman filter is simply an optimal recursive data processing algorithm [21] and has been subject of extensive research and applications, particularly in the area of autonomous navigation.

B. Robot Control

A classical three-wheeled tricycle robot model is employed in all simulations. This configuration uses a controlled steering angle and drive speed to navigate to a desired position as illustrated in Fig. 1.

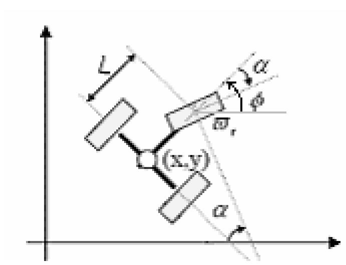

Figure 1. Tricycle Robot Configuration.

The states and kinematics of the robot are given by,

$$X = [x \quad y \quad \phi \quad \alpha]^T \tag{1}$$

$$\dot{X} = a(x,t) = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\phi} \\ \dot{\alpha} \end{bmatrix} = \begin{bmatrix} v_t \cos\alpha \cos\phi \\ v_t \cos\alpha \sin\phi \\ \frac{v_t}{L} \sin\alpha \\ \omega_\alpha \end{bmatrix} \tag{2}$$

with (x, y) the position of the robot, α the steering angle, and ϕ the heading angle. The control inputs are the speed v_t and the steering rate ω_α.

A simple Proportional-Derivative goal-based controller with a temporally varying goal is implemented to navigate the robot along a desired trajectory. For more details, see [22].

This dynamical setup allows more accurate simulations than the simple moving-point model usually assumed in sensor network localization papers.

C. Sensor Node Kalman Filter

Each static sensor node maintains its own position and uncertainty estimates. The mobile robot broadcasts contain the robot's position estimate and uncertainty estimate. The broadcasts can only be heard within the robot's communication range. A discrete-time Kalman filter running on each sensor node combines this information to optimally update the node's position estimate and its uncertainty. For more details on the derivation of the Kalman filter equations, interested readers are referred to [26].

The Kalman filter is a set of mathematical equations running in a software algorithm that provide an efficient computational means to estimate the state of a process. The state of sensor i at discrete time instant k is

$$x_k^i = [x^i \quad y^i]^T \tag{3}$$

The sensor state is governed by the linear stochastic difference equation

$$x_{k+1}^i = A_k^i x_k^i + B_k^i u_k^i + G_k^i w_k^i \tag{4}$$

with measurements given by

$$z_k^i = H_k^i x_k^i + v_k^i \tag{5}$$

The random variables w_k^i and v_k^i represent process and measurement noises given by

$$x_0^i = (\bar{x}_0^i, P_{x_0}^i),\ w_k^i = (0, Q_k^i),\ v_k^i = (0, R_k^i) \tag{6}$$

where (m, P) denotes a Gaussian noise process with mean m and covariance P.

For stationary nodes, the system matrices are given by

$$A_k^i = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, B_k^i = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, G_k^i = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, H_k^i = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{7}$$

The *a priori* position estimates prior to measurement updates at time $k+1$ are given by the time update equations, which give the effects of time on sensor localization:

$$P_{k+1}^{i}{}^{-} = P_k^i + Q_k^i \quad (8)$$

$$\hat{x}_{k+1}^{i}{}^{-} = \hat{x}_k^i \quad (9)$$

In these equations, $\hat{x}_k^i$ represents the position estimate of node i at time k, while the covariance matrix P_k^i gives the corresponding uncertainty in the position estimate.

The a posteriori estimates given a position measurement z_k are given by the measurement update equations, which gives the effect of the robot broadcast on sensor localization:

$$P_{k+1}^{i} = \left[P_{k+1}^{i}{}^{-^{-1}} + H_{k+1}^{i}{}^{T} R_{k+1}^{-1} H_{k+1}^{i} \right]^{-1} \quad (10)$$

$$\hat{x}_{k+1}^{i} = \hat{x}_{k+1}^{i}{}^{-} + P_{k+1}^{i} H_{k+1}^{i}{}^{T} R_{k+1}^{-1} \left(z_{k+1}^{i} - H_{k+1}^{i} \hat{x}_{k+1}^{i}{}^{-} \right) \quad (11)$$

The covariance matrices Q_k^i and R_k are design parameters chosen by the engineer. With a zero Q_k^i, the uncertainty in location of the sensor i remains constant with time. With an extremely small Q_k^i, the localization uncertainty slowly drifts with time. This means that the current measurements from the mobile robot are given more weight than the current node position estimate, which avoids the node's becoming too certain of a position that may be incorrect.

When the robot is in range and the sensor hears the broadcast position of the robot, the measurement update equation is used to combine the new information to improve sensor node position and uncertainty estimates. In this section, the robot is assumed to be perfectly localized. Thus when a sensor hears a broadcast, it could only be within the communication range of the robot whose position is broadcast. The measurement uncertainty matrix R_k reflects this, and is chosen as

$$R_k = \sigma^{Bot}, \sigma^{Bot} = \begin{bmatrix} \sigma_x^{Bot} & 0 \\ 0 & \sigma_y^{Bot} \end{bmatrix} \quad (12)$$

$$\sigma_x^{Bot} = \frac{Range_x^{Bot}}{\sigma_{const}}, \sigma_y^{Bot} = \frac{Range_y^{Bot}}{\sigma_{const}} \quad (13)$$

where σ^{Bot} is the uncertainty introduced due to $Range^{Bot}$, the communication range of the robot. We assume the design parameter $\sigma_{const} = 3$, to include 70% of the communication range, $Range^{Bot}$, of the robot. (Gaussian uncertainties are assumed.) Through this selection of R_k the Kalman filter automatically takes care of the range of the robot within which it hears broadcasts.

Table I shows the position update algorithm that runs on each node, which is very simple and easy to implement. It consists of four equations, two for the time update, and two for the measurement update. This algorithm automatically provides uncertainty estimates through the computation of the error covariance P_k^i, which is equivalent to the bounding box information provided by the algorithm in [14].

TABLE I. STATIC SENSOR NODE LOCALIZATION ALGORITHM

1. At each discrete time instant,
2. **if** robot broadcast received by sensor
3. **then**
4. Update sensor state and uncertainty estimates using KF measurement equations (10,11).
5. **else**
6. Propagate estimates using time update equations (8,9).
7. **end if**

D. *Simulation Results*

Extensive simulations have been performed to verify the effectiveness of the proposed algorithm. We also studied the effects of initial sweep paths and the robot broadcast interval on sensor localization. The mobile robot is navigated along the desired sweep path and periodic location information is broadcast. On receiving a broadcast, sensors update their location and uncertainty estimates. This is a range-free procedure that relies on the limited communication range of the robot, and as such, the sensor locations are updated based on the position of the robot. That is, the updated sensor position estimate is a weighted combination of its current location estimate and the current location of the robot. Thus sensors hearing only one broadcast will have an estimated location that is projected onto the path of the robot.

Fig. 2 shows the initial sinusoidal sweep path and the position and range of the broadcast with a broadcast interval of 5 discrete time instants. The 'x' represent the actual positions of the static sensors that are to be localized. The sensor nodes do not initially know their actual positions. The nodes all have initial position estimates being the centroid of the deployment area, and an initial uncertainty of infinity, corresponding to complete lack of knowledge of their positions.

Fig. 3 illustrates the localized sensors after the robot has made its sweep through the network. The '•' represent the final position estimates of the nodes. To remain consistent with earlier work involving bounding boxes (e.g. [14]), the uncertainty of the sensors in their position estimates has been depicted as rectangles representing 3σ of the uncertainty distribution, assuming Gaussian uncertainties. Note that the sensors always outside the communication range of the mobile robot do not become localized (i.e. they have no bounding box, which denotes infinite position uncertainty). The sensors that receive more than one broadcast from the mobile robot end up being better localized, since each position update reduces the position uncertainty.

The effectiveness of the algorithm is demonstrated by the fact that in every case, the actual location (marked by an ‘ *x* ’) is within the uncertainty bound of the estimated position (marked by a ‘ • ’).

The localization error of the sensors, computed as the Euclidean distance between true and estimated positions, is depicted in the vertical axis of Fig. 4. Sensors near the path of the mobile robot that have received multiple broadcasts have smaller errors.

The same simulation was rerun with different mobile robot broadcast intervals, and the effect of broadcast interval on the average localization error of the network is depicted in Fig. 5. Generally, as broadcast interval decreases, the average error decreases.

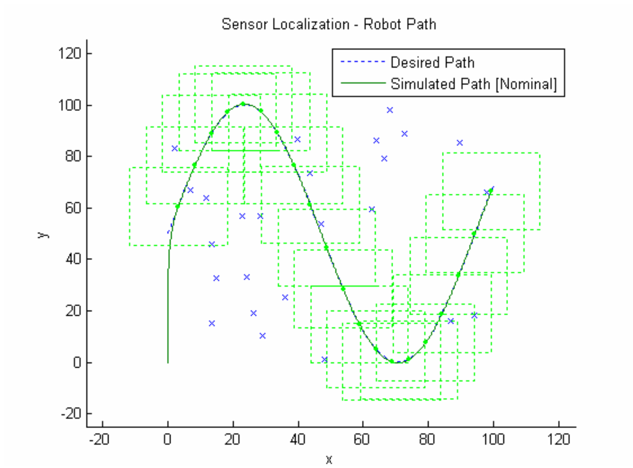

Figure 2. Initial sinusoidal sweep path with broadcast locations and range of broadcast.

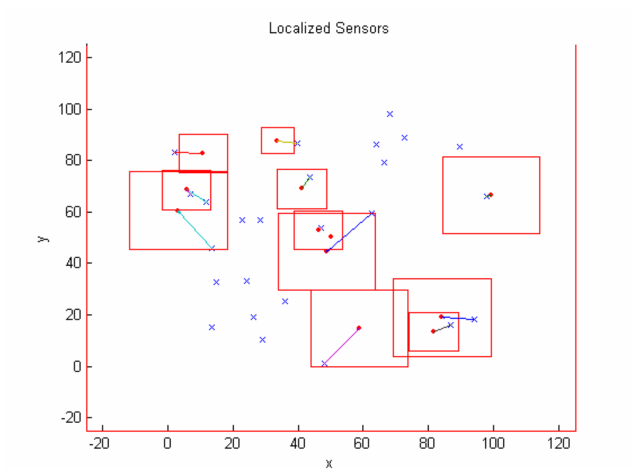

Figure 3. Localized sensors, real positions (denoted by ‘x’) and estimated positions (denoted by ‘ ● ’), are illustrated after initial mobile robot sweep of the deployment area. Uncertainty rectangles have been illustrated to depict the uncertainty of the sensor in its position estimate.

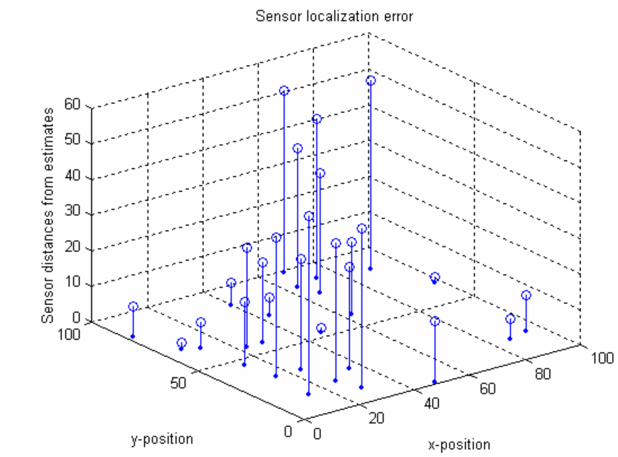

Figure 4. Localization error, computed as the Euclidean distance between real and estimated positions, of sensors after initial sweep of the deployment area.

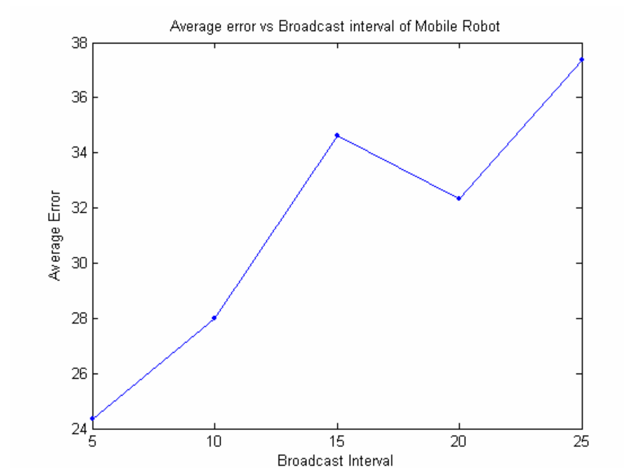

Figure 5. Effect of broadcast interval on average localization error.

III. Simultaneous Mobile Robot and Sensor Localization

In this section we consider the realistic case where the mobile robot’s position is not exactly known. We provide an algorithm which runs on the mobile robot that fuses position information from GPS, when it is available, and from the already-localized sensor nodes. This allows the robot to update its position estimate as well as the uncertainty estimate. When this algorithm is run simultaneously with the algorithm of the previous section running on each sensor node, the result is simultaneous mobile robot and sensor localization. A procedure is given to avoid detrimental recursive feedback between the two algorithms.

A. Mobile Robot Localization

When localizing the sensor nodes in the previous section, the robot was assumed to know its position exactly at all instants of time. However, as the robot navigates by dead reckoning, or due to steering inaccuracies, its localization increasingly deteriorates as time passes. Location updates from the GPS, when they occur, and from stationary sensor nodes that have already been localized can be used to improve the localization estimate of the robot.

Some sensor nodes are localized more finely due to more numerous updates they have previously received from the mobile robot. These sensors can be employed to localize the robot when its position information deteriorates. This is accomplished by having each sensor node make a transmission that contains the node's position estimate and uncertainty. This is received by the robot when it is in range. The sensors transmit at fixed intervals, with each sensor having a different random interval. This ensures that the updates between mobile robot and sensor nodes are staggered in time and that no recursive feedback occurs.

A continuous-discrete extended Kalman filter running on the mobile robot is used to simulate the robot and update the states using measurements from the GPS system and the better-localized UGSs. Extended Kalman filters have been used for local and infrequent global senor data fusion [23], for mobile robot localization [24], and in navigation of autonomous vehicles [25]. For information about the Extended Kalman filter see [26].

The continuous-time system model of the robot is given by (2) as

$$\dot{X} = a(X,u,t) + G(t)w \tag{14}$$

The sampled discrete-time measurement model of the robot is given by

$$\begin{aligned} Z_k^{gps} &= h^{gps}\left[X(t_k),k\right] + v_k^{gps} \\ Z_k^{ugs} &= h^{ugs}\left[X(t_k),k\right] + v_k^{ugs} \end{aligned} \tag{15}$$

where

$$X(0) = \left(\bar{X}_0, P_0\right), w(t) = (0,Q), v_k^{gps} = \left(0, R^{gps}\right), v_k^{ugs} = \left(0, R^{ugs}\right) \tag{16}$$

$$a(X,t) = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\phi} \\ \dot{\alpha} \end{bmatrix} = \begin{bmatrix} v_t \cos\alpha\cos\phi \\ v_t \cos\alpha \sin\phi \\ {v_t}/{L} \sin\alpha \\ \omega_\alpha \end{bmatrix}, G(t) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{17}$$

$$h^{gps}\left[X(t_k),k\right] = \begin{bmatrix} x \\ y \end{bmatrix}, h^{ugs}\left[X(t_k),k\right] = \begin{bmatrix} x \\ y \end{bmatrix} \tag{18}$$

In the extended Kalman filter, the effect of time on the robot states is given by the time update equation

$$\begin{aligned} \dot{\hat{X}} &= a\left(\hat{X},u,t\right) \\ \dot{P} &= A\left(\hat{X},t\right)P + PA^T\left(\hat{X},t\right) + GQG^T \end{aligned} \tag{19}$$

In [27], the deleterious effects of time passing are shown in terms of increasing position uncertainty and decreasing belief. These effects are formally captured in a rigorous manner by the time-update equations (18)-(19), which shows how uncertainty increases due to dead reckoning and steering uncertainties.

The effects of the GPS navigation updates, when they are received, are given by the measurement update equation

$$\begin{aligned} K_k &= P^-(t_k)H^{gps^T}\left(\hat{X}_k^-\right)\left[H^{gps}(\hat{X}_k^-)P^-(t_k)H^{gps^T}(\hat{X}_k^-) + R^{gps}\right]^{-1} \\ P(t_k) &= \left[I - K_k H^{gps}\left(\hat{X}_k^-\right)\right]P^-(t_k) \\ \hat{X}_k &= \hat{X}_k^- + K_k\left[Z_k^{gps} - h^{gps}\left(\hat{X}_k^-,k\right)\right] \end{aligned} \tag{20}$$

The effects of the updates based on localized sensor nodes, when they are received, are given by the UGS measurement update equation

$$\begin{aligned} K_k &= P^-(t_k)H^{ugs^T}\left(\hat{X}_k^-\right)\left[H^{ugs}(\hat{X}_k^-)P^-(t_k)H^{ugs^T}(\hat{X}_k^-) + R^{ugs}\right]^{-1} \\ P(t_k) &= \left[I - K_k H^{ugs}\left(\hat{X}_k^-\right)\right]P^-(t_k) \\ \hat{X}_k &= \hat{X}_k^- + K_k\left[Z_k^{ugs} - h^{ugs}\left(\hat{X}_k^-,k\right)\right] \end{aligned} \tag{21}$$

The measurement uncertainty matrices R^{gps} and R^{ugs} represent the uncertainty in the GPS and the uncertainty in the update offered by UGS i respectively. The uncertainty in the sensor update, R^{ugs}, is a combination of the uncertainty of the sensor position and the uncertainty due to the communication range of the sensor. These uncertainties combine in quadrature as

$$\begin{aligned} R_k^{ugs} &= \left[{P^i}^2 + {\sigma^i}^2\right], \sigma^i = \begin{bmatrix} \sigma_x^i & 0 \\ 0 & \sigma_y^i \end{bmatrix} \\ \sigma_x^i &= \frac{Range_x^i}{\sigma_{const}}, \sigma_y^i = \frac{Range_y^i}{\sigma_{const}} \end{aligned} \tag{22}$$

where σ^i is the uncertainty introduced due to $Range^i$, the communication range of sensor i.

Similarly, the measurement noise covariance of the sensor, (12), has to be modified to include the uncertainty in the robot's position. The robot is no longer absolutely localized with zero uncertainty. The uncertainty in robot localization and the uncertainty due to robot communication range combine in quadrature, modifying (12) as

$$R_k = \left[P_{XY}^{Bot\,2} + \sigma^{Bot\,2} \right] \qquad (23)$$

P_{XY}^{Bot} is the partial error covariance of the robot which effects only the position of the robot, and σ^{Bot} is as defined earlier.

The Jacobians of the nonlinear system, determined from (2), are given by the following system matrices:

$$A(X,t) = \frac{\partial a(X,t)}{\partial X} = \begin{bmatrix} 0 & 0 & -v_t \cos\alpha \sin\phi & -v_t \sin\alpha \cos\phi \\ 0 & 0 & v_t \cos\alpha \cos\phi & -v_t \sin\alpha \sin\phi \\ 0 & 0 & 0 & {v_t}/{L} \cos\alpha \\ 0 & 0 & 0 & 0 \end{bmatrix}$$
$$H^{gps}(X) = \frac{\partial h^{gps}(X,k)}{\partial X} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \qquad (24)$$
$$H^{ugs}(X) = \frac{\partial h^{ugs}(X,k)}{\partial X} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

With these equations in place and programmed as a software algorithm on the mobile robot, and the sensor nodes running the algorithm presented in the previous section, the mobile robot and the static sensors automatically mutually update their estimates with incoming updates. There is no additional decision-making logic to be implemented as in other range-free work discussed earlier. There is no need to compute bounding boxes, as the error covariance matrices are automatically updated as measurements are received.

The algorithm to be implemented on the mobile robot that updates its position estimate and uncertainty based on GPS measurements and on the localized sensor nodes is given as Table II. This algorithm is efficient to implement since the bulk of it is mathematical equations.

TABLE II. MOBILE ROBOT LOCALIZATION ALGORITHM

1. Navigate robot along desired path.
2. Broadcast location information at discrete intervals.
3. **if** broadcast from GPS received
4. Update robot state and uncertainty estimates using measurement equation (20).
5. **end if**
6. **if** broadcast from sensor received
7. Update robot state and uncertainty estimates using measurement equation (21).
8. **end if**

When algorithm II is run on the robot simultaneously along with algorithm I on each sensor node, simultaneous mobile robot and sensor localization occurs.

B. Simulation Results

The simulations described in Section II have been rerun with GPS updates and sensor updates implemented as Algorithm II on the mobile robot. Infrequent GPS updates and temporally staggered sensor updates help localize the robot. Fig. 6 shows the robot's sweep path with GPS and UGS updates disabled. A systematic dead reckoning error, [28], has been injected into the mobile robot to give gradually deteriorating position information. The localization of the robot deteriorates with time as can be seen in the deviation of the robot's estimated path (hyphenated green line) from the robot's true path (continuous green line.)

Fig. 7 illustrates the robot's sweep path which is corrected in time by GPS and UGS updates using Algorithm II. As is evident, the robot's localization has improved and the positions of where the robot thinks it is (the estimated position), and where the robot actually is (the true position) are much closer, since the estimates are continuously corrected using Algorithm II as position information arrives, either from GPS or from sensor node broadcasts.

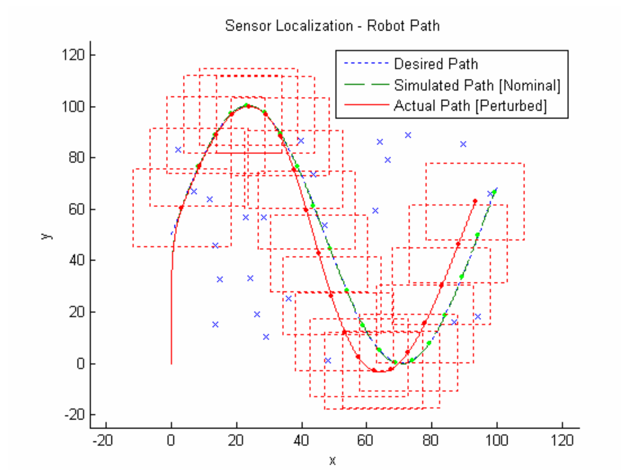

Figure 6. Initial sweep path of the robot with GPS and UGS updates disabled. Robot's localization deteriorates with time as evident in the deviation in the estimated path (hyphenated green line) and the true path (continuous red line.)

Robot broadcasts occur along the true path of the robot and consist of the robot's estimated position (slightly different from the robot's true position where the broadcast occurs) and uncertainty. Sensors within range receive the broadcast and update their positional information based on the robot's estimates.

Fig. 8 illustrates the localized sensors after the initial sweep. True sensor positions are indicated by an 'x' and estimated positions by a '•'. Now, some true sensor positions are outside the 3σ boxes due to the added uncertainty in the robot position, though they are generally close to these boxes. Fig. 9 depicts the final localization error of each sensor.

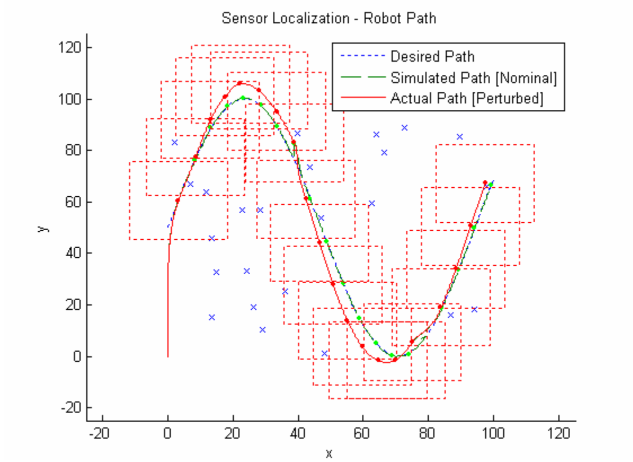

Figure 7. Initial sweep path of the mobile with GPS and UGS updates enabled as Algorithm II. The robot's localization has improved and the true position and the estimated position of the robot along the path are much closer.

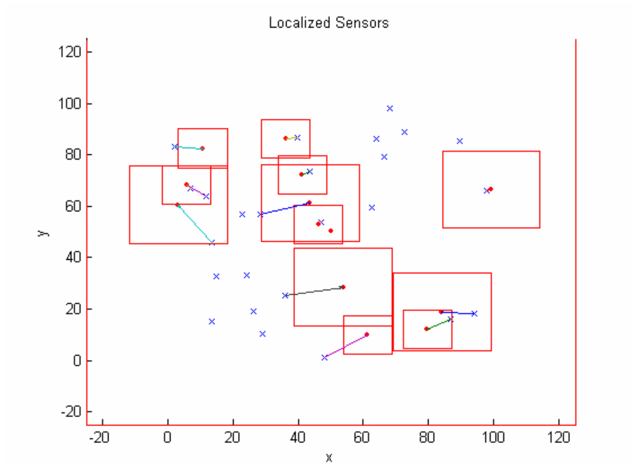

Figure 8. Localized sensors after initial sweep of the deployment area. True sensor positions are indicated by a 'x' and estimated positions by a '●'.

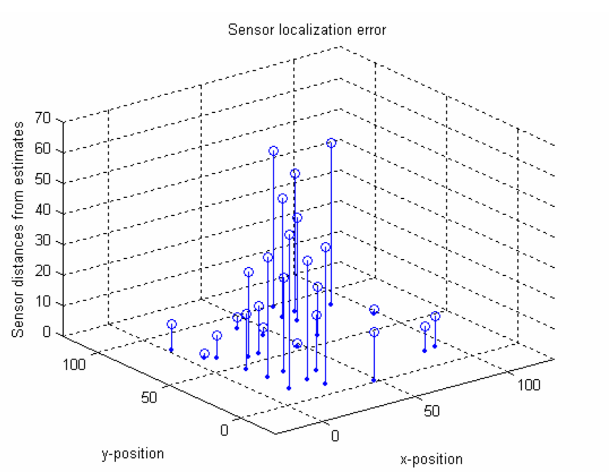

Figure 9. Localization error of sensors computed as the Euclidean distance between true and estimated positions.

IV. Conclusion

Rigorous mathematical algorithms for adaptive simultaneous localization of the static unattended ground sensors and the mobile robot have been demonstrated. The first algorithm localizes the static sensors and the second algorithm localizes the mobile robot. These algorithms together allow simultaneous localization of the static sensor and the mobile robot. A third adaptive localization algorithm ensures that the region of the deployment area with the largest uncertainty is localized with minimal robot movement.

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