Simultaneous Localization and Mapping in Wireless Sensor Networks

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Abstract

Wireless sensors became smaller and cheaper in the recent years. Applications with thousands of nodes for tracking and monitoring are now feasible. Many of them require the knowledge about the locations of the sensors. The process of localization depends on estimating the position of the features within the environment. This paper proposes a novel algorithm to localize the sensors in any environment. Unlike any other technique like conventional SLAM, this new method does not require any architecture involving non-active beacons or mobile agents, such as robot. The new algorithm is presented that uses the sensors which act as active beacons themselves. The localization uses a least squares estimation (LSE), which processes the measured distances between the sensors. The distance measured was calculated based on received signal strength indicators (RSSI). Experiments were carried out in Mica2 Motes sensor networks. The estimated locations in the experiments were less then one meter away from the true locations which is an error of less than 10% of the transmission range from the sensors.

1. Introduction

Recent developments in integrated low-power sensing devices with wireless communication interfaces have opened a wide range of new applications. Two major key improvements are the miniaturization in size and the reduction in costs. The reduced costs enable applications with a large number of devices. Applications involve thousands of sensors, distributed in an area in order to measure parameters such as temperature, vibration, sound, humidity or magnetic fields, are emerging for monitoring and controlling events.

In many of these applications the knowledge about the location of the sensors is essential [1]. In small scale and wired networks the system can be supplied with the locations manually, while in large scale and mobile scenarios it is impossible. The network itself must have the capability to localize each node. In static networks, where the sensor locations are fixed, the localization takes place only once at the initialization phase. On the other hand, in dynamic networks, such as tracking of mobile objects, the localization is repeated a number of times depending on the system requirement.

Simultaneous Localization and Map Building (SLAM) is an efficient way to build map consistently and use this map to obtain the estimates of the system [2], the result of which can be seen in [3]-[9]. Conventional approach of SLAM requires a navigation system to build a map of the environment containing features using wide range of sensor types and use it simultaneously to localize itself for long periods of time in unknown environments, [4]-[10]. The modelling of the navigation system, such as robots, and the features are two essential requirements of the conventional approach. It uses Kalman Filter (KF) or Extended Kalman Filter (EKF) for localization which requires Gaussian state distribution.

The proposed approach does not require modelling of the navigation system as the entire map can be built based on feature localization. The features in this method are wireless sensors that communicate with each other. The unsupervised mutual communication among the sensors to build a map is the novel technique that diminishes the need of navigation system. Our approach uses Least Square Estimation (LSE) for localization which does not require Gaussian state distribution.

The rest of this paper is organized as follows. Section 2 provides an overview of the related work. In section 3, specific sensor network environment and constraints are described along with necessary hardware. Section 4 describes the algorithm of the localization. In section 5, the results of our experiments are shown. The interpretation and thoughts about future work are written in section 6. Finally our conclusion is in section 7.

2. Related Work

Many systems have been developed for localization. The most popular is GPS (Global Positioning System) which uses 24 geostationary satellites. Each of them is synchronized with three atomic clocks and periodically sends RF signal at exactly the same time. This includes the time and the location of the individual satellite. The GPS receiver must receive signals from at least four satellites. It measures the time difference of arrival (TDoA) from which the distance to the satellites can be calculated. The signal containing information about distance and the locations enables the receiver to determine its position. Although GPS has been successful, it has several constraints. Firstly, GPS requires presence of satellites which restricts its use in indoor applications. The clock speed of the sensors is another important issue. Localization with TDoA in combination with RF signals requires relatively faster clocks. For a 4 MHz processor, the electro magnetic wave propagates about 75 meters for each clock pulse. However, it is not possible to determine exact distance traveled by the wave or signal within one clock pulse duration. The resolution of the error in estimating the distance traveled by the wave depends on the processor speed. At least 300 MHz is required to get a resolution of less than one meter. But in a network with thousands of nodes this would cause significant costs.

Other localization systems have been developed, which use sound or ultrasonic waves. The waves propagate much slower and a low-cost sensor can capture arrival times easily. Related work described by Calamari [15], Cricket [16], Active Bat [19] and AHLoS [17] is as follows.

The principles of the Calamari and Cricket systems are the same. Several beacons with known positions are placed in the environment. They send periodic acoustic signals and RF signals at the same time. A receiver measures the TDoA for both signals. The RF signal propagation is much faster than the acoustic signal, so the arrival of the RF signal is almost same as the transmission start time of the acoustic signal. Thus the receiver can measure the time of flight (ToF) for the acoustic signal. Together with the knowledge of the speed for sound waves, it is possible to calculate the distance covered by the signal.

The Active Bat system works the opposite way. A sensor sends a signal to several pre-installed receivers which measure the ToF and thereby obtain the distances to the object. So the localization is done by the receivers and not by the sensor. Calamari, Cricket and Active Bat systems requires an infrastructure of receivers with known locations. In many scenarios, it is impossible to install receivers with known locations. For example, in a battlefield placement of receivers at known locations for using above methods is not possible.

In the AHLoS system, two types of sensors exist. One having a small number of sensors is equipped with a GPS, which can locate themselves after deployment and consequently act as beacons. The second type of sensors use acoustic ToF for the localization. This technique overcomes the limitations described in above methods where the placement of sensors at the known locations was necessary. Due to limitations of GPS explained earlier, this method is not feasible.

Localization system described by Moore, Leonard, Rus and Teller [23] use ultrasonic waves to measure the TDoA from signals of nearby sensors. Together with the known velocity of ultrasonic waves, the distances to these sensors are calculated. This network of sensors is then split into "robust" clusters, where the cluster itself calculates the relative coordinates of the sensors within the cluster. Finally, the clusters are merged by combining the graphs of overlapping sensors. The efficiency of this approach is low due to limitations of ultrasound waves. These include range limitations, vulnerability to noise, high costs and special hardware requirement. In the RADAR system explained in [22], pre-installed beacons with known locations transmit signals periodically. The distance is calculated from the strength of received RF signals. It is similar to GPS system, but it uses received signal strength indicator(RSSI) instead of TDoA. Several other localization algorithms using RSSI exists [24] [25]. But multifading and reflection can affect the RSSI significantly.

All techniques described above use distances between sensors or beacons for the localization. Also localization can be achieved using angle of arrival (AoA) measurements explained in [30] [26]. The position of sensors or beacons can be calculated from the angle to them. But special and expensive hardware is required to realize the AoA measurement which makes it impractical for large scale sensor networks.

3. Network Structure

A. Overview

We propose a novel technique for localization in an environment which does not require any special hardware. The network environment consists of a powerful computing device SNAP (sensor network access point) and wireless sensors. SNAP enables the localization process by sending required commands to the sensors. The sensors collect RSSI of radio signals from their neighboring sensors and send this data to the SNAP. The SNAP converts the RSSI to distances and uses a least squares estimation (LSE) to calculate the coordinates of the sensors.

Since the calculations of the LSE are very complex and low-cost sensor devices are not powerful, the calculations are performed by the SNAP. In an application where the end user is connected to the sensor network via the internet or a satellite connection, the data from the sensors is too large to send it to the user. Therefore, SNAP processes queries from user to retrieve the specific information from the sensors. Only the required data is send back to the user. In our approach, SNAP carries out the calculations for localization. There are three freedoms for localization results obtained in above methods. These are translation, rotation and reflection. Because the network has no anchors it is difficult to align the coordinates. The calculated locations can be shifted, rotated and mirrored. The locations of atleast three sensors must be known to transform the obtained results to absolute results. However in our approach, it is easy to obtain the locations of the sensors since the SNAP is installed close to the sensor

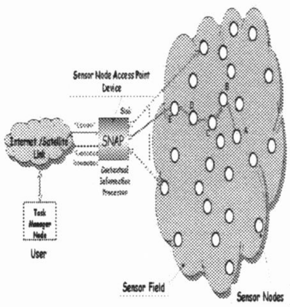


Fig. 1: Relation between end user, sensor network access point and sensor network.

network. The SNAP manages the sensors to gather the required data for localization. It also is responsible for estimating the locations of the sensors.

B. Sensors and SNAP

Figure 2 shows the proposed architecture which has two important components-sensors and SNAP. In terms of the localization, the sensors have two different modes which are *active* and *passive*. In the network, there should be one active sensor and the rest should be in passive mode. The active sensor polls the passive sensors multiple times. The passive sensor which was polled sends back a message to the active sensor. The active sensor measures the RSSI from the received signal and forwards the RSSI to the SNAP via the relay which forwards received data from active sensor to the SNAP and vice versa. One of the sensors in the network can act as a relay. The SNAP then sets the active sensor in passive mode and one of the passive sensors in active mode. This is done until every sensor goes through active mode. In Mica2 Motes sensor networks, ten commands between the sensors and the SNAP have been implemented.

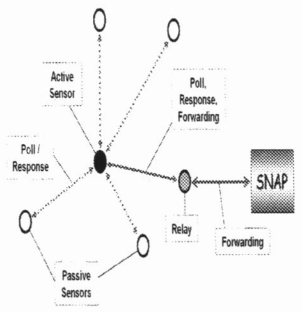


Fig. 2: Sensor modes. The sensor connected to the SNAP is called *relay*. One sensor is in *active* mode, while the remaining sensors are in *passive* mode.

4. Algorithm

This section describes the algorithm for localization. It is further divided into three sub-sections: RSSI to Distance Conversion, Trilateration and Least Squares Estimation (LSE).

Following assumptions are made in our approach. The sensors in our experiments have unique numeric continuous identifications starting with 1. The first rule says that sensor 1 is at position (0,0) in Cartesian coordinates eliminating the translation. Secondly, the sensor 2 must be on the positive x-axis which removes the rotation. The third rule specifies that sensor 3 must have a positive y coordinate and must be in quadrant one or two. Therefore, the reflection is also eliminated. With these rules the resulting networks are aligned uniformly.

The following section describes the three parts of the localization in detail.

A. RSSI to distance conversion

The conversion is done by a function which calculates the distance in meters from the RSSI. This function is specified in a calibration phase, before the localization takes place. In principle each environment requires a calibration, because electromagnetic waves propagate differently in varying surroundings. For the calibration, RSSI measurements and the true distances between the sensors are required. Since the transmission power is fixed for all sensors, RSSI is proportional to the power loss during the transmission, which is a function of distance. The sensors used in our experiments return the RSSI measurements as a 10-bit number from an analog-digital converter (ADC). The measurements however depend on the current battery power. This means that for each sensor, the function to map RSSI to distance is different. So each sensor has its own calibration function. Furthermore, the time between calibration and localization should not be too long. Otherwise the power level of the battery has changed and the conversion is biased. RSSI measurement can also be defined in dBm. For each sensor there exists an equation which calculates the RSSI in dBm from the ADC value of the signal strength and the battery power. This technique has the advantage that the conversion does not depend on the time difference between the calibration and localization. Also one calibration function for the entire network is sufficient as opposed to having different function for each sensor. Our experiments have shown that the ADC readings from the battery power were scattered and inconsistent and the localization results were not satisfactory. Therefore we used the RSSI ADC values for the localization which were relatively stable. Experiments have shown that the relation between RSSI and distance is logarithmic. The calibration function we are specifying in a parameter optimization has the form

$$s_i = a * log(b * d_i) + c \qquad (1)$$

where s_i is the signal strength, d_i is known distance and a, b, c are the parameters. It was our goal not to orientate on any physical model for the wave propagation. Instead we parameterize a function which fits the gathered data.

In some scenarios calibration is not possible. For example, if the network is in a remote site, it is difficult to measure the true distances between the sensors. For those scenarios, the sensors use a conversion function which is specific to the environment with similar characteristics. For example, if it is known that the network will be deployed in an open countryside, the sensors will use a function which was obtained from a calibration in an open countryside with the same structure.

B. Trilateration

Another key issue to make the localization accurate is to have sufficient initial conditions for the least squares estimation. Without good initial conditions a lot more sensor readings are required to get satisfactory results. This problem is solved by using the trilateration technique. The averages of the first five readings for each sensor are considered. With these values the locations are roughly estimated by using the trilateration described in [31]. The results of trileration need not be accurate.

Figure 3 displays an example for trilateration. First the coordinates of sensor 1 are set to (0,0). Then the measured distance to sensor 2, d_{12}, is used to set the location of sensor 2 to (d_{12},0). For sensor 3, the distances to sensor 1, d_{13}, and sensor 2, d_{23}, are taken and the coordinates are found using the following relation

$$x = \frac{d_{13}^2 - d_{23}^2 + d_{12}^2}{2d_{12}} \quad (2)$$

$$y = \sqrt{d_{13}^2 - x^2} \quad (3)$$

As required, the location of sensor 3 must be in the first or second quadrant. Therefore the positive result of the square root in the equation for y is location.

The coordinates for the other sensors are found using (2) and (3). However the y coordinate is uncertain at this stage. To remove the uncertainty, the distance to sensor 3 is calculated and compared to the measured distance. The coordinates, where the calculated distance is in acceptable range of the measured distance, is set to be the location of sensor.

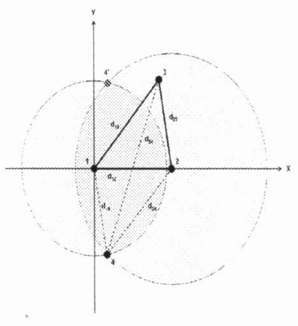


Fig. 3: Trilateration. Sensor 1 is at the center of coordinate system. Sensor 2 on the positive x-axis and Sensor 3 in quadrant one or two. The coordinates for the forth sensor are calculated with d_{14} and d_{24}. One of the two intersections of the circles is the location of Sensor 4. A comparison of the measured distance d_{34} to the estimated distance reveals the final location.

C. Least Squares Estimation

The localization uses a least squares estimation algorithm [28]. In an iterative process, the algorithm updates its estimates using multiple measurements. Firstly, we will explain the general non-linear least squares estimation, which leads to the recursive least squares estimation. The relation between the measured distances and coordinates is given by:

$$z = h(s) + v \quad (4)$$

where z is the measurement vector with the distances $(z_{12}, z_{13}, z_{14}, \ldots, z_{21}, z_{23}, z_{24}, \ldots, z_{n1}, z_{n2}, z_{n3}, \ldots)$, v is the noise in the form $(v_{12}, v_{13}, v_{14}, \ldots, v_{21}, v_{23}, v_{24}, \ldots, v_{n1}, v_{n2}, v_{n3}, \ldots)$ and $h(s)$ is the nonlinear relation between the measurements and estimate values:

$$h(t) = \begin{pmatrix} \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \\ \sqrt{(x_1 - x_3)^2 + (y_1 - y_3)^2} \\ \sqrt{(x_1 - x_4)^2 + (y_1 - y_4)^2} \\ \vdots \\ \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \\ \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2} \\ \sqrt{(x_2 - x_4)^2 + (y_2 - y_4)^2} \\ \vdots \\ \vdots \end{pmatrix} \quad (5)$$

x_n and y_n are the coordinates of the $n-th$ sensor. A first-order expansion is used to express the measurement residual, Δz, in terms of the error in the state estimate, Δt

$$\Delta z = H \Delta s + v \quad (6)$$

where H is the matrix derived from $\hat{s}$ according to the following differential equation

$$H = \left. \frac{\partial h}{\partial s} \right|_{\hat{s}} \quad (7)$$

The difference between the actual measurements and the expected measurements given the current state estimate is as follows

$$\Delta z = [z - h(\hat{s})] \quad (8)$$

This measurement residual can be used to obtain a correct state estimate, $\hat{s}_c$, through the relationship

$$\hat{t}_c = \hat{s} + \widehat{\Delta s} \quad (9)$$

where

$$\widehat{\Delta s} = (H' R^{-1} H)^{-1} H' R^{-1} \Delta z \quad (10)$$

For each step, the non linear least square estimation requires all the measurements acquired. This causes high computational power for large scale applications. The recursive least square estimation is a modification to reduce the effort. The state estimates are formed after each scan and stored, rather than storing all observation. Then the state estimates are updated sequentially after each scan as new observations are received.

As derived in [13], the updated state estimate becomes

$$\hat{s}(k+1) = \hat{s} + K(k+1)[z(k+1) - H(k+1)\hat{s}(k)] \quad (11)$$

where the gain matrix $K(k+1)$ is defined by

$$K(k+1) = P(k)H'(k+1)S^{-1}(k+1) \quad (12)$$

$$S(k+1) = H(k+1)P(k)H'(k+1) + R(k+1) \quad (13)$$

$$P(k+1) = [I - K(k+1)H(k+1)]P(k) \quad (14)$$

It can be noted that even though the distance between any two sensors are same, the measurements from one sensor to another sensor and vice versa are treated separately since the sensors produce different data due to the different noise characteristic of each sensor. In the experiment, it was also tested how the localization algorithm behaves when the data is averaged or both the measurements are considered for estimation. This is explained in detail in section 5.

5. Experiments

A. Methodology

The experiments have three stages.

- **Data collection:** In this phase the sensors deployed in the area, exchange messages to collect the RSSI as described in section 3-B.
- **Calibration:** The purpose of this stage is to optimize the parameters of a logarithmic function to fit the wave propagation in the specific environment. Once calibrated for a particular environment, the results can be reused for further experiments in the same environment.
- **Estimation:** The radio signal model obtained in the calibration is used to map the received signal strength to distances which are used by least squares algorithm to estimate the locations.

B. Experiment Setup

In the experiment, the sensor network consists of five Mica2 Motes sensors. The connectivity between all sensors is required to perform the data collection. For large scale application where total connectivity is not feasible, the algorithm can be modified to use the localization algorithm in sections of the network and later merge the data.

The sensors forward the data to the laptop via one of the sensors, where the Java application is collecting the data and storing them on the hard drive. The files can be processed by this computer or any other.

Two experiments were conducted in two separate locations within the university campus. In the first case, the area covered by the network was 6x7 meters and in the second case, the area was 7x14 meters.

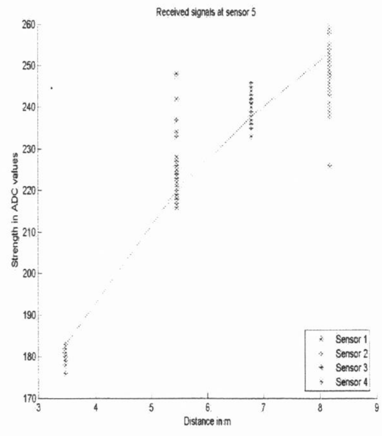
C. Calibration

The calibration was completed according to the procedure described in section 4-A. The calibration result was satisfactory. Figure 4 (a) shows the obtained calibration. The parameterized function fits the readings from the sensors very well.

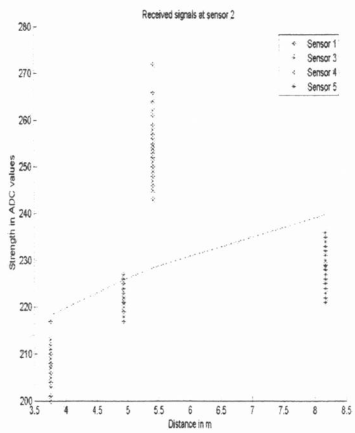
In Figure 4 (b) the parameterized function is not optimal. For one sensor the RSSI is higher than expected. Therefore the calibration function does not fit completely.

D. Results of Experiment 1

It is important how to handle the readings from sensor A to B and B to A. In theory they should be equal. But due to different noise and distraction they may be affected by varying noise. Three methods were used to handle that problem. The first is to take the average value of the two observations and combine them into one measured distance. The second is to treat them as two measurements which were merged later. So if 50 samples between each sensor were taken, it will be 100 in the calculations. The last method does not merge them and instead are considered separately. The above three mentioned methods to handle the bidirectional measurements produced very similar results. For the first experiment the merged values were the best. Figure 5 displays the results. Sensors 1, 2 and 4 were estimated very precise with less than one meter displacement. It may be mentioned, that the localization worked very good for sensor 4, even though the initial estimation was not good. Sensor 3 was incorrectly estimated about 1.5 meters in the x and y directions. Sensor 5 was estimated completely wrong. This will be addressed later in detail.



(a)



(b)

Fig. 4: Calibration examples. Figure (a) shows a good calibration. The function fits the measurements. In (b) the RSSI from one sensor are biased.

Figure 6 illustrates results for x coordinate of sensor 2. Although the initialization from the trilateration was incorrect by half a meter, the estimates of its location converged to the true value.

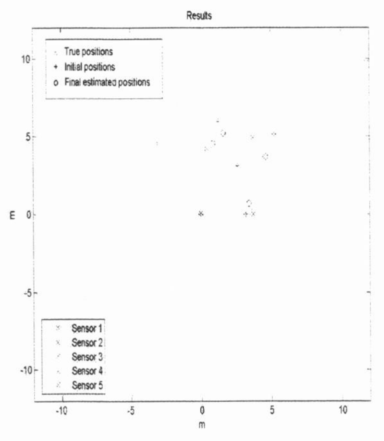


Fig. 5: Results of experiment 1

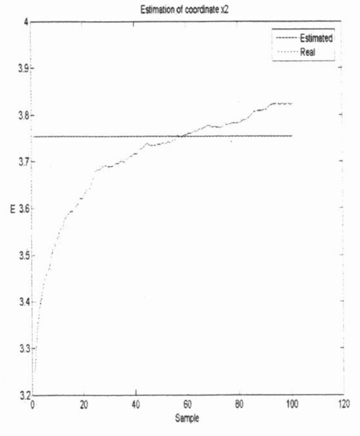


Fig. 6: Estimation of x coordinate for sensor 2

E. Results of Experiment 2

In the second experiment the different methods for handling the bidirectional measurements were nearly the same. Without fusing the results were slightly better than the others. Figure 7 displays the results.

Again the estimation of sensor positions was, in most cases, correct within one meter. Sensor 5 was estimated completely wrong in this experiment also.

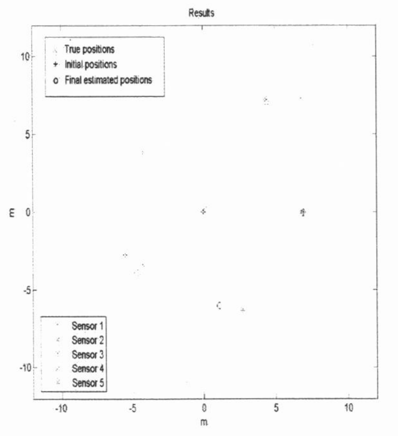


Fig. 7: Results of experiment 2

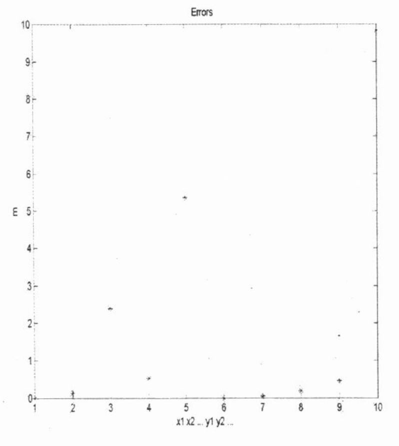


Fig. 8: Errors of experiment 2

F. Results Summary

The results of both experiments were encouraging and proved the validity of the proposed technique. The localization error was usually less than one meter which is within the acceptable range.

Only sensor 5 showed large deviation due to incorrect output level of this sensor. This incorrect output level was caused by the bias of some internal radio setting. This had the effect on the signal strength which led to incorrect distance mapping.

Except from sensor 5 it was only sensor 3 which was incorrectly estimated by more than a meter. The y coordinate converged to the true value while x coordinate did not. This was caused by reflection or distraction of the radio signals.

6. Discussion

The most prevalent problem for localization with RSSI is the erratic behavior of radio signals in different environments. The effects of changing environments on radio signals are common. In small rooms with many metal objects, the reflected signals cause difficulty in estimating the sensor location. Therefore such reflected signals are not suitable for the localization. Obstacles in between the line of sight may also weaken the signal due to which the sensors appear to be relatively far from actual position.

7. Conclusion

A wireless sensor localization algorithm was proposed and tested. The most important improvement to other localization algorithms is that it does not require special hardware like mobile agents and uses only RF signals. This approach is very suitable for environments, like hazardous areas, enemy territory etc, where access is limited. Even though the use of RF signal is influenced by environment, the experiment reveals that the method can still be useful for many scenarios.

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