

Experimental Analysis of Area Localization Scheme for Sensor Networks

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Abstract—For large wireless sensor networks, identifying the exact location of every sensor may not be feasible or necessary. A coarse estimate of the sensors' locations is usually sufficient for many applications. An efficient Area Localization Scheme (ALS) has been proposed for large sensor networks. ALS is a range-free localization scheme that tries to estimate the position of a sensor within a certain area rather than its exact location. As the complex calculations are handled by the powerful sinks instead of the sensors, this reduces the energy consumed by the sensors and helps to extend the lifetime of the network. In this paper, we discuss the implementation of ALS using MICAz motes and the localization experiments carried out in both indoor and outdoor environments. We also propose algorithms and techniques to improve the accuracy of ALS in realistic deployment scenarios. We observed that the performance of ALS is comparable or better than other localization schemes that have been implemented while ALS has lower complexity and hardware requirements.

Keywords – area localization, wireless sensor networks

I. INTRODUCTION

Deployment of low cost wireless sensors is a promising technique for several applications such as early warning and alert systems, ecosystem monitoring, warehousing, logistics and surveillance. Sensor data is typically interpreted with reference to a sensor's location, e.g. reporting the occurrence of an event, tracking of a moving object or monitoring the physical conditions of a region. Localization, the process of determining the location of a sensor node in a wireless sensor network, is a challenging problem as reliance on technology like GPS [2] is infeasible due to cost and energy constraints.

II. RELATED WORK

A number of localization schemes have been proposed to date which take into account factors like network topology, device capabilities, signal propagation models and energy requirements. Most localization schemes require the location of some nodes in the network to be known, which are referred to as anchor nodes, reference nodes or beacon nodes in the literature. The localization schemes that use reference nodes can be broadly classified into three categories: Range-based schemes [1][2][3], Range-free schemes [4][5] and schemes that use signal processing or probabilistic techniques [6][7]. Among the many proposed schemes, some have been implemented [11][12][13].

III. ALS ALGORITHM

A preliminary design of the Area Localization Scheme (ALS)[8] has been reported, which in its current form, can only function in an ideal radio channel and not in a real environment with fading, shadowing and other forms of interference. In section IV, we propose algorithms and techniques that will enable ALS to be deployable in a real environment, both indoors and outdoors. ALS is a range-free scheme that provides an estimation of a sensor's location within a certain area, rather than the exact coordinates of the sensor. The granularity of the location estimate is determined by the size of areas which a sensor node falls within and this can be easily adjusted by varying the system parameters. The advantage of this scheme lies in its simplicity, as there is no need for Time of Arrival, signal strength or Angle of Arrival measurements by the sensors. In ALS, there are three types of nodes, categorized according to their different functions, namely, reference nodes, sensor nodes and sinks.

A. Reference nodes

The main responsibility of the reference nodes is to send out beacon signals at varying power levels to help the sensor nodes construct their signal coordinates. Reference nodes are either equipped with GPS to provide accurate location information or placed in pre-determined locations. For an ideal isotropic antenna, the received power at a distance d from the transmitter is given by

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi d} \right)^2 \quad (1)$$

while the two-ray ground reflection model considers both the direct path and a ground reflection path; the received power at a distance d is given by

$$P_r = \frac{h_r^2 h_t^2 G_r G_t P_t}{d^4} \quad \text{for} \quad d > \frac{4\pi h_t h_r}{\lambda} \quad (2)$$

where P_t is the transmitted power, d is the distance between the transmitter and receiver, λ is the wavelength and, h_t and h_r are the heights of the transmitter and receiver respectively. G_t and G_r represent the gains of the transmitter and receiver respectively in Eqns (1) and (2). If the received power is fixed at a certain value, the beacon signal with a higher transmitted power reaches a greater distance. Using

Eqn (1) or (2) and the threshold power that each sensor can receive, the reference node can calculate the power required to reach different distances. Each reference node then broadcast a set of beacon packets with increasing power levels. The beacon signal transmissions by the different reference nodes do not need to be synchronized but they have to be scheduled so as to avoid collisions. The transmitted set of power levels need not be the same for all the reference nodes. It is also not necessary for the reference nodes to know each other's position, nor the set of power levels transmitted by one another.

B. Sensor node

A sensor node is a device that monitors the environment. Sensors typically have limited processing capability, storage capacity, communication range and battery power. Therefore, it is not desirable for sensor nodes to perform complex calculations or send out information frequently. In ALS, the sensor nodes use a simple signal coordinate representation to indicate their location information to the sinks. Power contour lines can be drawn on a area based on the set of beacon signal power levels PS transmitted by each reference node as shown in Fig. 1. The contour lines represent the furthest distances that the beacon signals at each power level can travel.

For illustration, we assume there are n reference nodes referred to as R_1, R_2, \dots and R_n . For a sensor in the area, we let the lowest transmitted power levels it receives from the n reference nodes be S_1, S_2, \dots and S_n respectively. S_1, S_2, \dots and S_n are simple integer numbers associated with the different power levels rather than the actual signal strengths. The mappings between numbers and the actual power values are known to the reference nodes and sinks. The signal coordinate is defined as the n -tuple $\langle S_1, S_2, \dots, S_n \rangle$ such that each S_i , the i^{th} coordinate, is the lowest power level received from reference node i . For illustration, we consider a square area with reference nodes at the four corners as shown in Fig. 1. In this case, the set of power levels PS with three different power levels is the same for all the four reference nodes with the smallest power level represented by the integer 1 and the highest power level represented by the integer 3. Contour lines for beacon power levels 1 and 2 are drawn but the contour line for the power level 3 is not drawn as it covers the whole area. For the sensor node located in the shaded region, the lowest power level received from reference nodes 1, 2 and 3 is 3 while the lowest power level from reference node 4 is 2. As a result, the location of the sensor can be represented by the unique signal coordinate $\langle 3,3,3,2 \rangle$. Similarly, every other region in the square area can be represented by a unique signal coordinate which is marked in the figure.

Each reference node sends out beacon signals N_r times at all the power levels in the set PS . In real conditions, fading and shadowing can cause the power level to vary erratically about the expected signal strength predicted by the large-

scale path loss model. Hence, the lowest signal power level received by a sensor from a reference node need not be the same for all the rounds 1 to N_r . Hence, a threshold value $CONF_LVL$ (30% in our experiments) is used which represents the confidence level with which the values S_1, S_2, \dots, S_n can be estimated. If there is a power level L_x that occurs with frequency greater than $CONF_LVL$ in the set PS , then L_x is set to be the i^{th} co-ordinate in the node's signal coordinate.

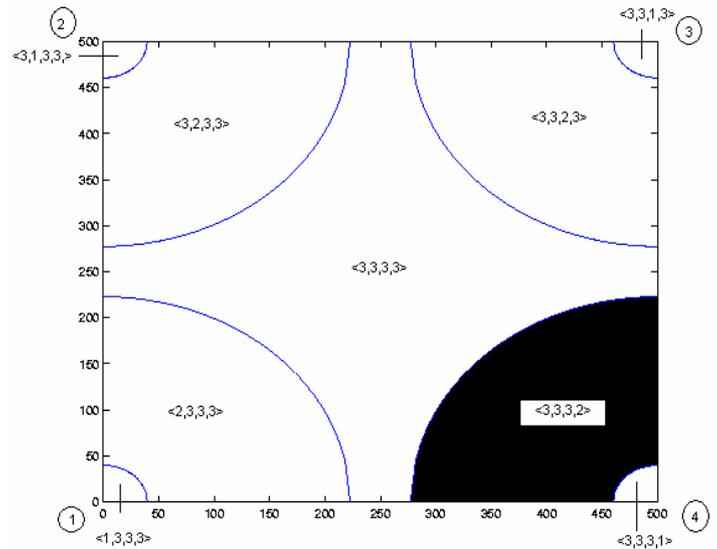


Fig. 1. Example of ALS under ideal isotropic conditions

C. Sink

A sink is in charge of collecting information from sensor nodes and then processing the information. From a hardware point of view, a sink usually has much higher computing and processing capabilities than a sensor node. Typically, the data acquired by a sensor needs to be associated with location information to be meaningful but the sensor itself need not know its own location. In this case, the sensor only knows its signal coordinate and attaches this to the data originating from it. The sink knows the locations of all the reference nodes and their respective transmitted power levels, whether by direct communication or from a priori knowledge shared during deployment. Therefore, with the knowledge of the physical layer model, signal propagation algorithms and the signal coordinates from the sensors, the sink can determine which region a sensor falls in. When a sink need to get information from sensors specific to a certain region, it includes the signal coordinate in its request and the sensors simply compare the incoming signal coordinate to their own to see if they lie in the relevant region.

Fig. 1 illustrates an example of the calculations made by the sink assuming ideal isotropic conditions. The sink divides the square target area into 9 smaller regions based on the information it has. A sink can then locate the region a sensor node lies in based on the signal coordinate

information from the sensor. A key advantage of ALS is that all the complex calculations are done by a powerful sink (or backend server) and not the power-constrained sensors. Therefore, the localization process consumes little power at the sensor nodes, helping to extend network lifetime.

IV. ENHANCEMENTS TO ALS

To improve the accuracy of ALS in practical deployment scenarios, we have made several enhancements to the original ALS design [8].

A. Propagation Model

The accuracy of ALS depends largely on the wireless physical layer. In practical deployment scenarios, the freespace or two-ray ground reflection propagation model may not apply. Therefore, we have used the empirical log-distance path loss model with log-normal shadowing [9] shown below:

$$PL(d)[dB] = PL(d_0) + 10n \log\left(\frac{d}{d_0}\right) + X_\sigma (dB) \quad (3)$$

where n is the path loss exponent which indicates the rate at which the path loss increases with distance, d_0 is the reference distance (typically set to 1 m), d is the distance between the transmitter and receiver, $PL(d_0)$ is the power loss at distance d_0 and X_σ is a zero-mean Gaussian distributed random variable (in dB) with standard deviation σ . X_σ describes the random shadowing effects which occur over a large number of measurements for the same transmitter-receiver separation. To estimate parameters n and X_σ , we can have a vehicle or robot move around the region in consideration and take RSSI measurements at different distances. The model in Eqn (3) can then be used to draw out the signal map.

The experiments were carried out in both indoor and outdoor environments. For the indoor environment, we use a large open indoor multi-purpose hall (MPH) located in our institute. For the outdoor environment, the experiment was first carried out in an open field with no obstacles and subsequently carried out in an open park with trees as the main obstacles. The path loss exponents for different environments are calculated using regression analysis on the range measurements in Table I. The path loss exponent was calculated to be 2.92 for MPH and 2.96 for the open field. Fig. 2 illustrates the regression analysis for the range measurements in open field.

We observed that the range measurements for each power level vary with the height at which the reference nodes are placed. Therefore, we fixed the height of the reference nodes for our experiments. The reference nodes are placed at a height of 12 cm above ground level for indoor environment and 190 cm above ground level for outdoor environment. All the sensors are placed 12 cm above ground level.

TABLE I
ESTIMATED AND MEASURED RANGE MEASUREMENTS FOR DIFFERENT MICAZ POWER LEVELS FOR INDOOR AND OUTDOOR ENVIRONMENTS

Power Level	Indoor (Path Loss Exponent = 2.92, Height of reference node = 12 cm)		Outdoor (Path Loss Exponent=2.96, Height of reference node=190 cm)	
	Estimated	Measure	Estimated	Measured
3	2.2	2.5	2.5	2.5
7	4.9	5.5	13.0	13.5
11	7.3	8.0	19.2	17.5
15	9.3	9.0	24.3	24.5
19	10.8	13.0	28.3	30.0
23	-	-	33.1	33.5
27	-	-	38.7	37.0
31	-	-	41.8	41.0

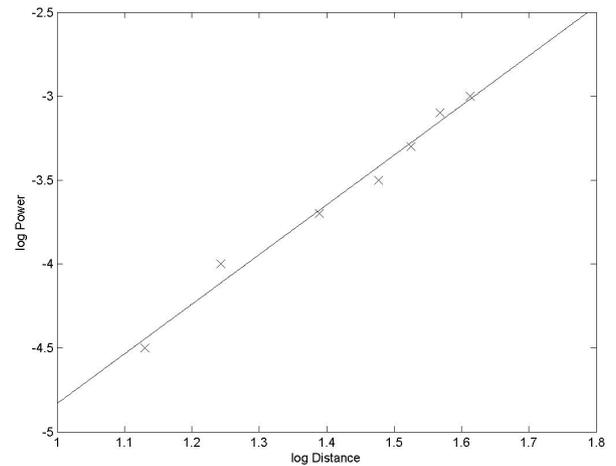


Fig. 2. Analysis of the path loss exponent in open field

B. Shadowing and Fading Effects

The original ALS did not consider shadowing and fading effects, therefore each power level has distinct boundaries in the signal map. To lessen the inaccuracy resulting from shadowing and fading effects, we use overlapping ranges to construct the signal map. For the indoor environment, we use 5dBm power difference to construct the shadowing region for higher power levels of 7 to 19. For the outdoor environment, we use 2dBm for all power levels. The ranges used are shown in Table II.

TABLE II
RANGES USED IN ALS FOR INDOOR AND OUTDOOR ENVIRONMENTS

Power Level	Range without shadowing		Range with shadowing	
	Indoor	Outdoor	Indoor	Outdoor
3	0-250	0-250	0-250	0-250
7	251-550	251-1350	251-550	150-1550
11	551-800	1351-1750	551-1250	1150-2050
15	801-900	1751-2450	551-1350	1450-2850
19	901-1300	2451-3000	600-1800	2100-3450
23	-	3001-3350	-	2600-3900
27	-	3351-3700	-	2850-4350
31	-	3701-4100	-	3150-4900

C. Rotation of Reference Nodes

We also observed that the range measurements depend on the relative orientation between the transmitter and receiver antennas as the radio patterns of the MICAz antennas are not circular [10]. Therefore, we run each ALS experiment four times with four different relative orientations between the transmitter and receiver antennas. This helps alleviate the problems caused by the irregularity in the radio patterns of the sensor antennas.

V. EXPERIMENTAL SETUP AND RESULTS

We used MICAz motes [14] for all the nodes in the testbed – reference nodes, sink and sensors. An area size of 10m by 10m is chosen for the indoor environment and an area size of 30m by 30m is selected for the outdoor environment. Up to 35 sensors are placed randomly in the area, while eight reference nodes are positioned at the four corners and the four mid-points of the sides of the area. We use the metrics described in TABLE III to evaluate ALS.

TABLE III
METRICS USED TO EVALUATE ALS

Metric	Explanation
Number of sensors in predicted area	This metric refers to the number of sensors that are correctly located in the predicted area after calculations by the sink.
Number of sensors within 1-hop area	This metric refers to the number of sensors that are not correctly located in the predicted area but lies within an adjacent region of the node. We let the average area size estimate of the sensor nodes be A . Circles with radius $\sqrt{A/\pi}$ and $2\sqrt{A/\pi}$ are drawn from the predicted point estimated location of the node. The circular ring between radii $\sqrt{A/\pi}$ and $2\sqrt{A/\pi}$ is defined as the 1-hop neighboring region of the node. This is illustrated with an example in Fig. 3.
Area Size Estimate	This metric refers to the average predicted area size compared to total area in percentage terms.
Error	This metric refers to the average distance between the actual locations of the sensors and the predicted point estimated locations of the sensors which is obtained by calculating the centroids from the areas estimated.

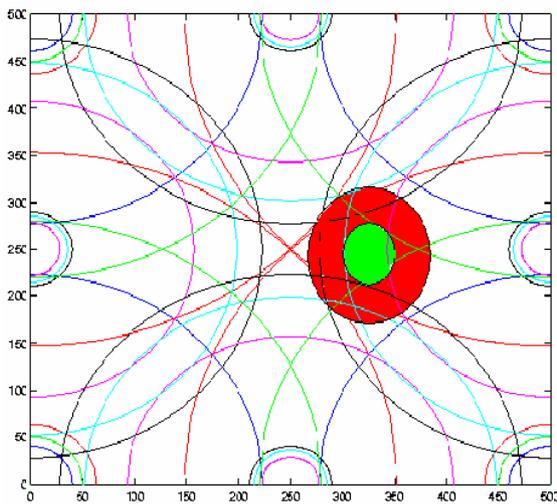


Fig. 3. Illustration of 1-hop region

The results we have obtained in the experiments are shown in Table IV. We plot the actual location versus point estimated locations for the sensors in Fig. 4 for MPH, Fig. 5 for open field and Fig. 6 for the park. The crosses are the actual locations of the sensors, the circles are the predicted point estimated location of the sensors (the approximate centre of the region) and the squares are the locations of the reference nodes.

TABLE IV
SUMMARY OF EXPERIMENTAL RESULTS

Environment	No of sensors in predicted area	No of sensors within 1-hop area	Area Size Estimate	Error (m)
MPH	21/35=60.0%	9/35=25.7%	3.48%	1.09
Open Field	17/30=56.7%	13/30=43.3%	2.76%	2.04
Park	16/30=53.3%	9/30=30.0%	2.58%	3.37

For all the scenarios, more than 80% of sensor nodes lie within their predicted area or within a 1-hop region of the predicted areas with the average area size estimate of less than 3.5%. This means that in real deployments, sensors can be located quickly once the predicted region is calculated. The performance of ALS becomes worse as we move from the open field to the park because multipath effects from obstacles cause fluctuations in signal strength resulting in sensor nodes receiving incorrect signal coordinates. The accuracy of localization also depends on many other factors, such as, the hardware used, environment, number of reference nodes utilized and the size of the deployment area.

TABLE V compares ALS with other localization schemes that utilize radio signals. We observed that our results obtained are comparable or better than these localization schemes which have been experimentally tested.

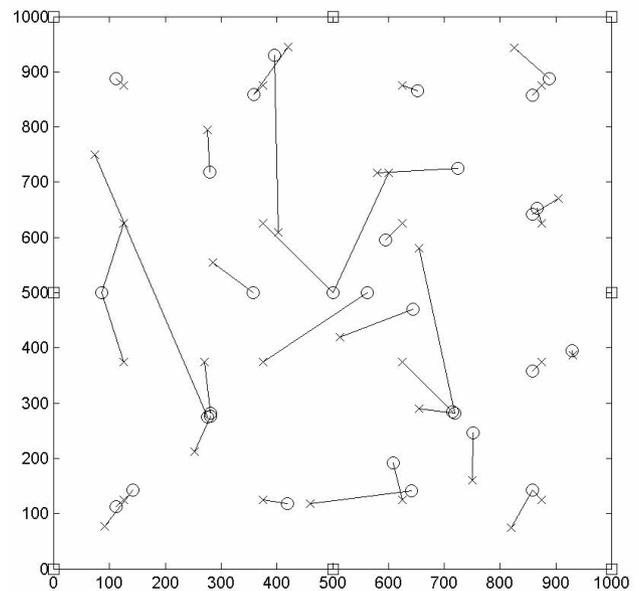


Fig. 4. Actual versus Estimated Locations of Sensors (MPH)

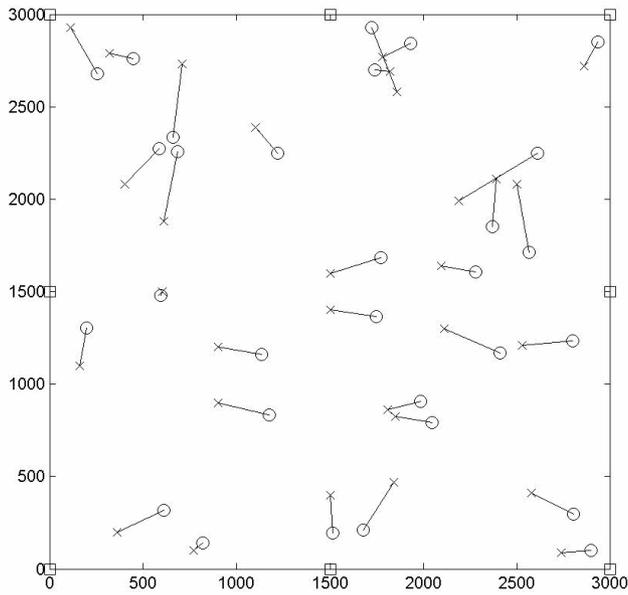


Fig. 5. Actual versus Estimated Locations of Sensors (Open Field)

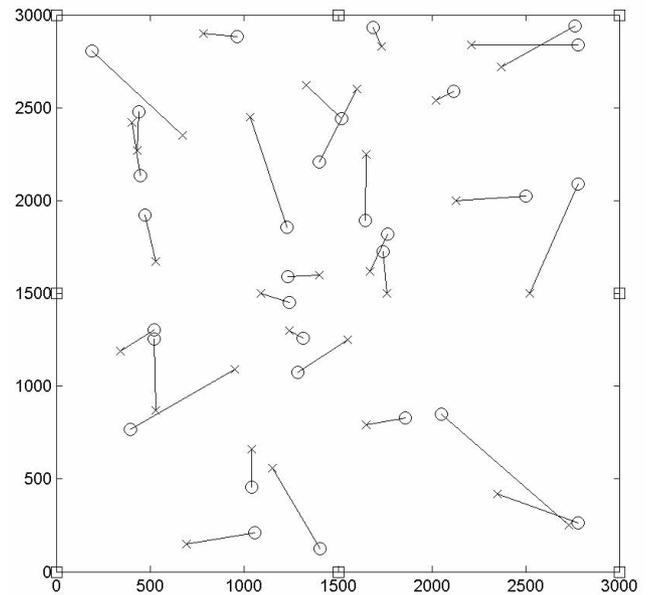


Fig. 6. Actual versus Estimated Locations of Sensors (Park with obstacles)

TABLE V
COMPARISON WITH OTHER IMPLEMENTED SENSOR NETWORK LOCALIZATION SCHEMES

Scheme	Hardware	Environment	No of reference nodes	Area	Error
ALS	MICAz	Indoor	8	10m x 10m	1.09m
ALS	MICAz	Outdoor (Open Field)	8	30m x 30m	2.04m
ALS	MICAz	Outdoor (Park)	8	30m x 30m	3.37m
MoteTrack [11]	MICA2	Indoor	20	1742 m ²	50 th percentile: 2m 90 th percentile: 3m
Ecolocation [12]	MICA2	Outdoor	10	12m x 12m	around 1m
Probability Grid [13]	MICA2	Outdoor	3	5x5 grid, approximately 12 meters apart	79% of radio range where radio range is about 15m

VI. CONCLUSION AND FUTURE WORK

ALS is a range free localization scheme that provides a coarse estimation of the location of a sensor within a certain area. While the sensors simply record the signal levels received from reference nodes, the sinks carry out most of the complicated computations to determine the locations of the sensors. We have modified ALS to enable it to be used in real indoor and outdoor environments, and implemented the ALS algorithm on a wireless sensor network for experimental study. Due to the enhancements introduced and the appropriate selection of parameter values, the results obtained are comparable or better than other localization schemes that have been implemented, and ALS has lower complexity. In our future work, we will incorporate routing protocols that run on top of the ALS algorithm. A sensor can estimate whether it is nearer or further away from the destination, compared to its previous hop, based on the signal coordinate information of its neighbor, the destination

and itself. This information can be used for developing fast and efficient routing protocols.

REFERENCES

- [1] S. Gezici, Z. Tian, G. Giannakis, H. Kobayashi, A. Molisch, V. Poor and Z. Sahinoglu, "Localization via Ultra Wide Band Radios", *IEEE Signal Processing Magazine*, Vol. 22, No. 4, July 2005, pp. 70-84.
- [2] Global Positioning System standard – Positioning Service Specification, 2nd Edition, June 2, 1995.
- [3] N. B. Priyantha, A. Chakraborty and H. Balakrishnan, "The Cricket Location-Support system", *Proceedings of the 6th ACM International Conference on Mobile Computing and Networking (Mobicom 2000)*, August 6-11, 2000, Boston, MA, USA.
- [4] D. Niculescu and B. Nath, "DV Based Positioning in Ad Hoc Networks", *Telecommunication Systems*, Vol. 22, No. 1-4, 2003, pp 268-280.
- [5] S.Y. Wong, J.G. Lim, S.V. Rao and Winston K.G. Seah, "Density-aware Hop-count Localization (DHL) in wireless

- sensor networks with variable density”, *Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC 2005)*, 13-17 March 2005, New Orleans, L.A., USA.
- [6] L. Doherty, K. Pister, and L. Ghaoui, “Convex Position Estimation in Wireless Sensor Networks”, *Proceedings of the 20th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM 2001)*, April 22-26, 2001, Anchorage, AK, USA.
- [7] S. Capkun, M. Hamdi and J. Hubaux, “GPS-free positioning in mobile ad-hoc networks”, *Proceedings of the 34th Annual Hawaii International conference on System Sciences*, Jan 3-6, 2001, Hawaii, USA.
- [8] Q. Yao, S.K. Tan, Y. Ge, B.S. Yeo, Q. Yin, “An Area Localization Scheme for Large Wireless Sensor Networks”, *Proceedings of the IEEE 61st Semiannual Vehicular Technology Conference (VTC2005-Spring)*, May 30 - Jun 1, 2005, Stockholm, Sweden.
- [9] Theodore S. Rappaport, *Wireless Communications: Principles and Practice*, 2nd Edition, Prentice Hall, Dec 2001.
- [10] D. Lymberopoulos, Q. Lindsey and A. Savvides, “An Empirical Analysis of Radio Signal Strength Variability in IEEE 802.15.4 Networks using Monopole Antennas”, *Proceedings of the Second European Workshop on Sensor Networks (EWSN 2006)*, Feb 13-15, 2006, ETH, Zurich, Switzerland.
- [11] Konrad Lorincz and Matt Welsh, “Motetrack: A Robust, Decentralized Approach to RF-Based Location Tracking”, *Proceedings of the International Workshop on Location- and Context-Awareness (LoCA2005)*, May 12-13, 2005, Munich, Germany, pp. 63-82.
- [12] K. Yedavalli, B. Krishnamachari, S. Ravula and B. Srinivasan, “Ecolocation: A Sequence Based Technique for RF Localization in Wireless Sensor Networks”, *Proceedings of Information Processing in Sensor Networks (IPSN2005)*, April 25-27, 2005, Los Angeles, CA, USA, pp 285-292.
- [13] R. Stoleru and J. A. Stankovic, “Probability Grid: A Location Estimation Scheme for Wireless Sensor Networks”, *Proceedings of Sensor and Ad Hoc Communications and Networks Conference (SECON2004)*, Oct 4-7, 2004, Santa Clara, CA, USA, pp. 430-438.
- [14] Crossbow Technology Inc. <http://www.xbow.com>