

Energy Analysis of Received Signal Strength Localization in Wireless Sensor Networks

Patrik MORAVEK¹, Dan KOMOSNY¹, Milan SIMEK¹, David GIRBAU², Antonio LAZARO²

¹Department of Telecommunication, Brno University of Technology, Brno, Czech Republic

²Department of Electronic, Electric and Automatic Engineering, Rovira i Virgili University, Tarragona, Spain

moravek@phd.feec.vutbr.cz, komosny,simek@feec.vutbr.cz, david.girbau,antonioramon.lazaro@urv.cat

Abstract. *This paper presents an investigation of energy demands during localization of wireless nodes in ad-hoc networks. We focus on the method based on the received signal strength (RSS) to estimate the distances between the nodes. To deal with the uncertainty of this technique, statistical methods are used. It implies more measurement samples to be taken and consequently more energy to be spent. Therefore, we investigate the accuracy of localization and the consumed energy in the relation to the number of measurement samples. The experimental measurements were conducted with IRIS sensor nodes and their results related to the proposed energy model. The results show that the expended energy is not related linearly to the localization error. First, improvement of the accuracy rises fast with more measurement samples. Then, adding more samples, the accuracy increase is moderate, which means that the marginal energy cost of the additional improvement is higher.*

Keywords

Received signal strength, localization, localization error, energy consumption, RSS uncertainty, measurement, Wireless sensor network.

1. Introduction

Localization of nodes under different conditions in wireless sensor networks (WSN) is an attractive field of study. In certain applications, in which only several nodes form the whole network and the area of interest is easily accessible, it is not a problem to set the position of nodes manually. However, there are certain applications with tens or hundreds of nodes, where a manual setting of coordinates for each node would be a demanding and expensive process. Moreover, certain WSN applications require random nodes scattering over a particular area without manual placement [1]. Other applications include mobile nodes or aim to track mobile objects [2]. The topic of localization in mobile networks is addressed by several authors (e.i. [3], [4]).

Mobility, way of the deployment, and the number of nodes are the aspects that imply the necessity of autonomous

localization process. Moreover, localization in WSN has to be energy aware because of energy constraints [5]. Therefore, accurate and low-cost node localization process is a critical requirement after the deployment of wireless sensor nodes in a wide variety of applications. There are two categories of localization approaches: range-free and range-based. The former does not implement the distances for position estimation but rather the information about connectivity to the other nodes. The position is then expressed in relation to neighboring nodes. On the other hand, the latter approach needs to know the distances between nodes to calculate their position. The estimation of distances can be obtained by different localization techniques. Several of them have been proposed so far [6]-[11], based on the measurement of the time of arrival (TOA), the angle of arrival (AOA) or the received signal strength (RSS). From these measurements, the position of a node can be determined using different localization algorithms. Because of the broad use without additional hardware requirements we focus on the last localization method based on received signal strength. In practice, RSS is defined as a voltage measured by a receiver's received signal strength indicator (RSSI) circuit. Often, RSS is equivalently reported as a measured power. Wireless sensor nodes communicate with their neighboring sensors, so the RSS of the transmitted signals can be measured by each receiver during common communication without presenting additional bandwidth or energy requirements. RSS measurements are relatively inexpensive and simple to implement. To this end, RSS-based localization technique is attractive for a wide variety of applications.

Unfortunately, the RSS technique features significant estimation error mostly due to the several negative effects related to signal propagation. Those estimation errors are influenced by a few factors, such as manufacturing tolerances, antenna inadequacies and, most importantly, multipath effect. The multipath effect causing an existence of fading points is often difficult to predict or mitigate. Furthermore the multipath effect is expected to be significantly stronger indoor than outdoor. Most of the RSS-based methods require a relationship between the distance and the received power to estimate the position of unknown devices [7], [8]. This relationship is expressed using a radio channel model or using a database with recorded RSS maps [9]. Another phenomena

affecting the distance estimation is called RSS uncertainty. Random object movement in surrounding or coexistence of other wireless networks in the same frequency range entail random interference at the receiving node. That interference is unstable in time and features stochastic characteristic. To eliminate or minimize the effect of RSS uncertainty, statistical methods are implemented. That means a set of in-place measurements has to be gathered in order to process it and to determine the most probable value subsequently used for the distance estimation. However, with a higher number of measurements, more energy is consumed, and it is a significant issue in some applications where energy saving is critical.

Different applications require different accuracy of localization depending on the further use of the position knowledge. Location information used only for geographical routing, for example, does not have to be very accurate in comparison with application of storage management requiring more precise object localization. Therefore, it is desirable to have an option to specify the level of accuracy or a profile, which defines the compromise of the consumed energy and the level of localization accuracy. Considering the RSS based localization, the accuracy is influenced by the number of measurement samples to minimize the effect of RSS uncertainty. In mobile networks it can serve also for elimination of fading points influence on the distance estimation by repeating the measurements at several adjacent points of the node trajectory. Moreover, besides the accuracy-profile selection, an adaptable function is possible to implement. Knowing the possible coarse improvement of accuracy by an additional measurement sample and the energy cost of it, the measuring node can ask for more samples after the processing of an initial measurement set.

Nowadays, a big effort is being invested in the energy analysis and comparison of different localization algorithms. However, it is also important to know the energy requirements of the process preceding it. Most of the algorithms include the estimation of distance as an input parameter. Therefore, for the complex energy analysis of a localization process, the investigation of energy consumption during the distance estimation is crucial.

In this paper the relationship between the number of measurement samples (and, in consequence, localization error) and energy consumption is investigated. We performed outdoor measurements to investigate the influence of RSS uncertainty on the position estimation and we analyzed the energy consumption of IRIS sensor nodes. The results from the measurements were compared to the proposed energy model. The energy model has been used to calculate the energy consumption of IRIS motes during the localization process. Then, we related the consumed energy and the localization error for the different number of measurement samples in order to find the energy cost of each additional measurement sample and its contribution to accuracy improvement.

The known relationship can help during the design of an adaptable localization protocol, which considers both ac-

curacy and energy costs of localization. It means that, when just rough distance estimation is sufficient, the measurement includes less samples than in case that higher accuracy is needed and more RSS packets have to be transmitted to minimize the negative effect of RSS uncertainty. This adaptability helps to save energy during localization based on the distance estimation using RSS measurements.

In Section 2 the measurement technique used for node localization based on RSS is revised and in Section 3 an energy model for RSS-based localization is described. In Section 4, conducted measurements are presented; localization error as a function of the number of measurements at each point is obtained, which is related to energy consumption based on the model presented in Section 3. Finally, Section 5 draws the conclusions.

2. Related Work

The hyperbolic positioning algorithm [8] is one of the simplest algorithms how to determine the required position of a node. This algorithm reduces the position calculation to a linear least-square problem. Once the distances between the unknown and the anchor nodes with known position have been estimated by inverting the channel model (1)[12], the position of the unknown node can be calculated using the algorithm. In RSS based localization, the distances between nodes are inferred from the power of received signal. When considering the propagation phenomena (multipath fading, shadowing and large-scale effect of path losses), which is included in the variable called path loss exponent (PLE), the power in dBm at the distance d is typically modeled as

$$P_r(d) = P_0 - 10n_p \log\left(\frac{d}{d_0}\right) + X \tag{1}$$

where P_0 is reference power in dBm at the distance d_0 , n_p is a PLE and X (in dBm) refers to Gaussian random variable with log-normal distribution [9]. More detailed radio model description can be found in [12].

Let (x,y) be the position of an unknown node and (x_i,y_i) the position of an anchor node i . The sum-square error of the estimated position can be expressed as [7]:

$$F(x,y) = \frac{1}{2} \sum_{i=1}^N f_i^2 \tag{2}$$

where f_i is the deviation of the estimated distance (calculated from the estimated coordinates) from the measured distance (d_i - obtained from RSS measurement and the propagation model) for anchor i , given by:

$$f_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i \tag{3}$$

The purpose of the optimization is to minimize this objective function and, thus, produce the optimal position estimation. For notational simplicity, we define:

$$\mathbf{p} = (x,y)^T, \tag{4}$$

$$\mathbf{f}(\mathbf{p}) = (f_1, f_2, \dots, f_N)^T. \tag{5}$$

The Gauss-Newton algorithm is a method used to solve non-linear least square problems. It can be seen as a modification of Newton’s method for finding a minimum of a function. Unlike Newton’s method, the Gauss-Newton algorithm can only be used to minimize a sum of squared function values. However, it has the advantage that the second derivatives, which can be challenging to compute, are not required. Starting with an initial guess of \mathbf{p}_0 for the minimum, the method proceeds by the iterations defined in [13]:

$$\mathbf{p}_{k+1} = \mathbf{p}_k - (\mathbf{J}_k^T \mathbf{J}_k)^{-1} \mathbf{J}_k^T \mathbf{f}(\mathbf{p}_k) \tag{6}$$

where \mathbf{J}_k is the Jacobian matrix evaluated at iteration k , which can be analytically obtained from the differentiation of (5) as follows:

$$\mathbf{J}_k = \begin{bmatrix} \frac{x_k - x_i}{|\rho_{i,k}|} & \frac{y_k - y_i}{|\rho_{i,k}|} \end{bmatrix}, \tag{7}$$

$$|\rho_{i,k}| = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2}. \tag{8}$$

The assumption that $N \geq 3$ in the algorithm statement is necessary, because otherwise the matrix $\mathbf{J}_k^T \mathbf{J}_k$ cannot be inverted.

The power of received signal is influenced by several factors with deterministic and stochastic characteristic. The deterministic ones can be predicted, estimated and their influence included in the distance calculation.

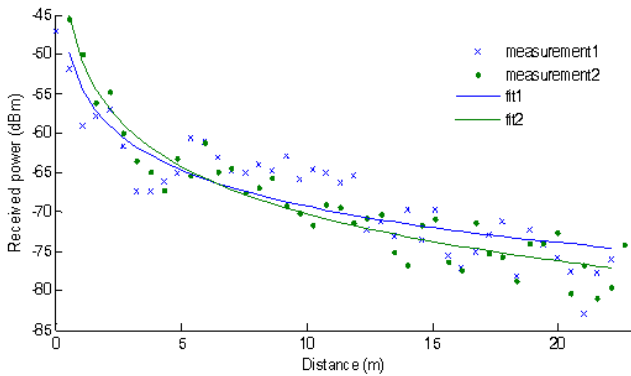


Fig. 1. Example of two measurements of the same channel with regression lines at 2.45 GHz.

Unlike these time stable factors, stochastic ones change in the time and, therefore, it is not possible to estimate them before the measurement. These random factors affect RSS measurement in an unpredictable way and cause so called RSS uncertainty. As an example, the effect of the uncertainty can be seen from results of our experiment (see Fig. 1), where the same channel has been measured twice and the derived radio propagation models considerably differs. For each distance twenty measurements were taken and the average value of the set was used for finding the fitting function.

Sources of RSS uncertainty include hardware imperfections, change in the channel due to the movement of persons or any other object in the surrounding of communicating nodes, random change of electromagnetic field or interference of other wireless networks in the same frequency band. These factors cannot be eliminated and their influence completely avoided. It is necessary to describe and characterize RSS uncertainty and involve procedures or methods, which are capable to eliminate its undesirable influence in order to obtain an RSS value without random variations. Then, for the localization purposes, it is important to find the signal distribution model and the deviation dependency of RSS uncertainty. The analysis of RSS uncertainty and its impact on RSS measurement is described in more detail in [14]. As confirmed in several papers (i.e. [15], [16]) when assuming a multipath channel and multiple signal effects, the RSS uncertainty features log-normal distribution.

Assuming that we have already estimated the distances between nodes using the propagation model, the calculation of the coordinates follows. Using trilateration for the calculation of node position in a 2D model, at least three anchor nodes with the known coordinates are necessary. To improve estimation accuracy, the fourth revising anchor node can be added. The situation is depicted in Fig. 2.

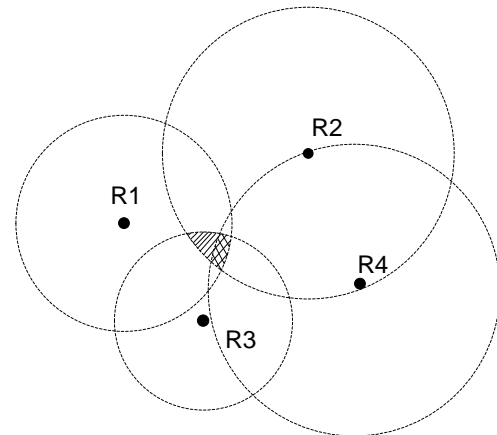


Fig. 2. Two dimensional lateration with four anchor nodes. The area of possible node occurrence is cross-hatched.

Energy consumption is a permanent critical topic of WSN and related technologies where network devices are equipped with limited energy sources, mostly with batteries. The battery capacity is the key parameter of device lifetime, however, it is not the only one. Beside the research on energy sources and storages, the lifetime of the network devices can be prolonged by optimization of their functions such as communication, management services, routing and data aggregation, localization and sensing. Moreover, the hardware energy requirements considerably determine the consumption during device operations.

The energy issue is relevant especially in the networks where the individual nodes are unattended and without the possibility to be powered from the main source. The authors of [17] studied the current consumption of commercial

chipsets for diverse wireless communication standards. The authors included Bluetooth, Ultrawideband (UWB), 802.11 (WiFi) and 802.15.4/Zigbee technologies and examined the current draw during packet transmission and reception. The study has shown that the 802.15.4 standard devices need much less energy (one tenth in comparison with UWB and 802.11 and half of the energy consumed by Bluetooth device).

Energy saving can have different approaches from individual sensor energy management to energy management of the entire network [17], [18]. The broad view is implemented, for instance, by [19], which addresses the problem of unbalanced energy consumption in the network. The authors propose the use of the ant algorithm to relieve the heavier communication load of the cluster heads in traditional cluster approach. A different approach is presented in [20]. The paper discusses the relation of applications with high throughput requirements to energy wastage. Generally, the energy consumption has larger importance than the throughput and performance and, thus, the current schemes cannot satisfy certain application requirements. In this paper authors focus on the medium access method, which should strictly control the medium access and, in this way, avoid or minimize collisions which extend the time of transmitter being in an active state. The authors propose a new medium access control method called SN-MAC that is based on CDMA protocol controlled either by transmitter or receiver side. In most cases, however, 802.15.4/Zigbee standard is used for WSN applications nowadays. Therefore, many studies refer that standard.

A new model of slotted (with beacon broadcasting) 802.15.4 MAC is proposed in [21]. The model is employed to predict the energy consumption per received data bit as a function of different parameters such as packet size, traffic load, number of nodes in a network and parameters of CSMA/CA algorithm. A mathematical formulation of energy consumption of Zigbee coordinators and end-devices is presented in [22]. The paper deals with the beacon broadcasting clusters connected in a tree topology. The consumption is examined on the basis of emitted traffic and beacon timing. The authors utilized the values of CC2420 radio transceiver and Microchip low-power microcontroller (PIC18LF8720) for the numeration of the proposed model. Subsequently, the model was evaluated by the proprietary simulation tool developed by the authors. Similarly, energy analysis with CC2420 chip was described in [23]. The analysis (supported by measurements) characterizes also the impact of packet losses on the energy consumption. The authors expressed the required energy per data bit as a function of the path losses considering the CSMA/CA algorithm. Empirical characterization of 802.15.4/Zigbee nodes with CC2480 radio chip can be found in [24] together with the characterization of some other 802.15.4 compliant devices (e.g. TI CC2520, MC1322x from Freescale). The authors performed the measurement of current drain during 802.15.4/Zigbee standard operations such as transceiver

initialization, channel scanning, association and binding, CSMA/CA method and packet transmission with acknowledgment reception.

3. Proposed Energy Model of Received Signal Strength Measurement

There are two different ways to obtain a node position depending on where the calculation process is executed. The first way is to measure signal strength from the anchor nodes at the unknown node and then calculate the position. This option assumes that anchor nodes transmit special RSS localization packets with their identification information, coordinates and the level of transmit power at least. The second way is to broadcast the RSS localization packet from the unknown node, estimate the distances at each individual anchor node and then, after exchanging the information among the anchors, calculate the position of the unknown node at the anchor node. Since we performed measurement based on the first principle, we focus on the energy analysis of that approach.

First, it is necessary to examine the energy consumption of radio communication and RSS measurement. As concluded in the previous analysis published in [25], energy consumption during radio communication consists basically of two parts: the energy transmitted to radio channel and the energy expended in electronic circuits of a node. Regardless different technical parameters of each type of sensor node, the energy consumption always increases with increasing length of the transmitted packet. For assuring the communication in a wireless unreliable channel, the acknowledgment packet is used for confirmation. Therefore, the affirmative packet transmission has to be considered in the RSS localization energy model as well.

Due to the RSS uncertainty, multiple RSS measurements have to be performed to minimize the estimation error. Multiple measurements naturally mean the repetition of RSS localization and acknowledgment packets. Based on the current drain analysis we proposed the following energy model of RSS measurement (see Fig. 3). The model follows the 802.15.4/Zigbee standard and considers the CSMA/CA method for medium access.

RSS measurement starts after channel scanning and association to the coordinator. It is a necessary procedure executed before any data can be transmitted. After that the node is in a sleep mode with transceiver turned off. In the first phase of measurements, transmitter circuits are activated (UP). Then, before transmission, the CSMA/CA algorithm requires listening and detection of any activity in the channel (MA-Medium Access interval). If no communication is detected, the node can start transmission (TX). The duration of the MA phase depends on the activity in the channel and its occupation. In the case the node detects some other transmission, it has to wait for a defined time interval be-

for the next attempt. When the channel is free for transmission the node starts to send data at the defined power level. Most commercial products offer several levels of transmitting power to save the energy and to decrease interference. The time of the transmission (t_{RSS}) depends on the length of the transmitted packet and the rate. The time interval needed for transmission of n bytes may be expressed as

$$t_{RSS}(n) = \frac{8 \cdot (MACoverhead + n)}{rate}. \quad (9)$$

$MACoverhead$ corresponds to the total overhead (preamble, frame delimiter, MAC header, CRC field) of the 802.15.4 frame, which can be up to 39 bytes including Auxiliary security header. Data rate can vary as well but we assume 250 kbps when operating in ISM 2.4 GHz band [26].

Acknowledgment of successful packet reception is optional according to the standard. When required (indicated by Ack Request bit in the Frame Control Field) the sending node listens and waits for the acknowledgment packet (ACK) after packet transmission. There is no contention after the packet transmission since all the nodes (except the one that received the packet) wait a certain interval to leave the channel free for the acknowledgment. The 802.15.4 MAC ACK frame has the minimal length of 5 bytes. When the ACK is received, the node transits in a sleep mode - turns off the transmitter circuit and in the case no other operation is required, the main processor transits into energy saving mode. If the ACK is not received during the defined interval, the waiting node considers the packet to be lost and retransmits it (not depicted in the figure).

In Fig. 3 the energy scheme of multiple measurements is depicted. When transmitting node receives the ACK it transmits immediately another packet up to a certain defined number of measurement samples in order to get the set of measurements for statistical assessment. When the last ACK is received, the node commutes to the sleep mode (D - Down).

A sensor node consists of three main energy consumers: sensor board, processing unit and RF transceiver. Localization process does not involve sensing; therefore energy consumption can be expressed by consumption of processing unit ($E_{\mu P}$) and RF transceiver (E_{Transc}):

$$E = E_{Transc} + E_{\mu P}. \quad (10)$$

Considering N RSS messages with bit duration t_{RSS} and N ACKs with bit duration t_{ACK} , energy consumption of RSS-based distance estimation for one node can be expressed as follows:

$$E_{anchor} = E_{UP_Transc} + N \cdot (t_{RSS} \cdot P_{tx} + t_{ACK} \cdot P_{rx}) + E_{UP_\mu P} + (t_{RSS} + t_{ACK}) \cdot P_{on_mu P}.$$

E_{UP_Transc} is energy needed for waking up a transceiver and $E_{UP_mu P}$ for waking up a microcontroller. P_{tx} stands for

the transmitter power and P_{rx} is the power of receiving circuits. $P_{on_mu P}$ is the power of microcontroller in the active state. Equation (11) expresses energy consumption of RSS localization for an anchor node. An unknown node expends energy (E_{unkn}) equal to:

$$E_{unkn} = E_{UP_Transc} + N \cdot (t_{ACK} \cdot P_{tx} + t_{RSS} \cdot P_{rx}) + E_{UP_mu P} + (t_{RSS} + t_{ACK}) \cdot P_{on_mu P}. \quad (12)$$

To summarize the energy consumption of RSS localization with multilateration for localizing one node using four anchors, the energy needed can be calculated as:

$$E_{RSS} = 4 \cdot (E_{anchor} + E_{unkn}) + E_{mlat} \quad (13)$$

where E_{mlat} is the energy that the microcontroller of the unknown node consumes during multilateration algorithm.

It is obvious from (11) and (12) that energy consumption depends considerably on the number of repetition of RSS measurements (N). Energy consumption increases linearly with the increasing number of measurements.

4. Measurements and Results

To examine the influence of RSS-based localization on energy consumption with relation to accuracy of localization, the following measurement scheme was proposed. All measurements were performed outdoor in a square area without obstacles. The presence of other wireless networks was significant. Therefore, to minimize their negative effect, the frequencies used during the experiments were selected at both edges of the 2.4 GHz ISM band.

The experimental setup was composed of a spectrum analyzer as a receiving mobile node. It was connected to a monopole antenna by means of a low-noise amplifier, in order to fix a low noise figure. Four signal generators were placed at the vertexes of the square and represented anchors. The measurement setup was proposed to be as general as possible in order to have results independent from particular commercial products. Because we used general signal generator and signal analyzer with monopole antennas, the measurement was not affected by individual transceiver characteristics of particular sensor nodes.

The link and environment characteristics with the path exponential loss were calculated from the initial measurements and the propagation model (see Section 2). Then, RSS measurement was performed at 25 points. At each point, 10 single values of received power were collected to calculate the mean, which is then used for distance estimation. The level of variance (expressed by standard deviation) at each point and for each anchor can be seen in Fig. 4. The deviation for majority of anchors is mostly less than 1 dBm. However, the radio channel for anchor 1 is worse and more prone to the effect of RSS uncertainty and that is why the level of variance is larger than in other cases.

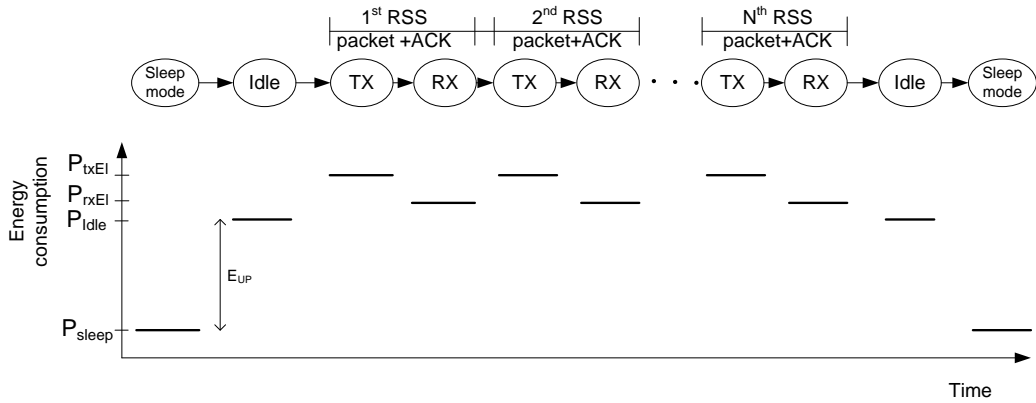


Fig. 3. The energy model of RSS measurement.

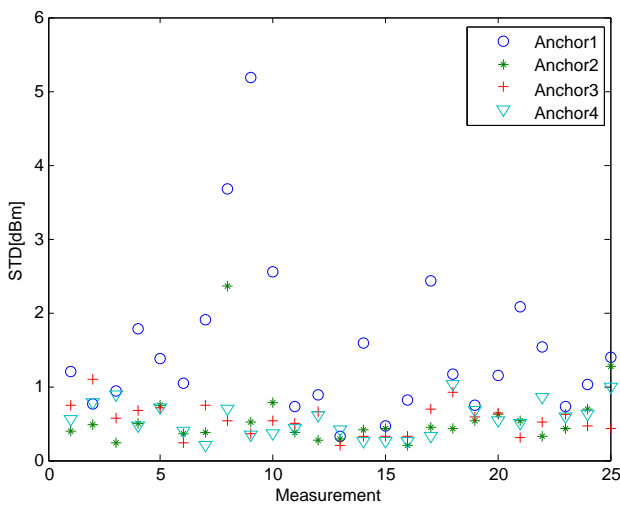


Fig. 4. Standard deviation of all 25 measurements at each anchor node.

Fig. 5 presents an example of three measurements performed at various points in the area. For the purposes of multilateration, distances between the receiver and the anchors were calculated from the mean of measured samples. Each point in the graph (+) represents the calculated position obtained from a different number of samples in the dataset (indicated by the adjacent digit). The dataset ranges from 2 to 10 samples. The coordinate system in the figure is set according to our experimental arrangement. The experimental testbed was placed in a field of 16x16m with the anchor nodes located in the vertices of the virtual square. All units in the figure are in meters. On the left side of the figure, there is the area of the experiment and circles representing the estimated distance in each measurement. The anchor nodes in the vertices are not pictured. On the right side, the calculated position with a larger scale can be seen. Each position is the result of multilateration using different number of measurement samples.

From the progress in position determination on the right side of Fig. 5 it is noticeable that with more samples the estimated position inclines to a certain position with decreasing steps. All three examples consider four anchors for

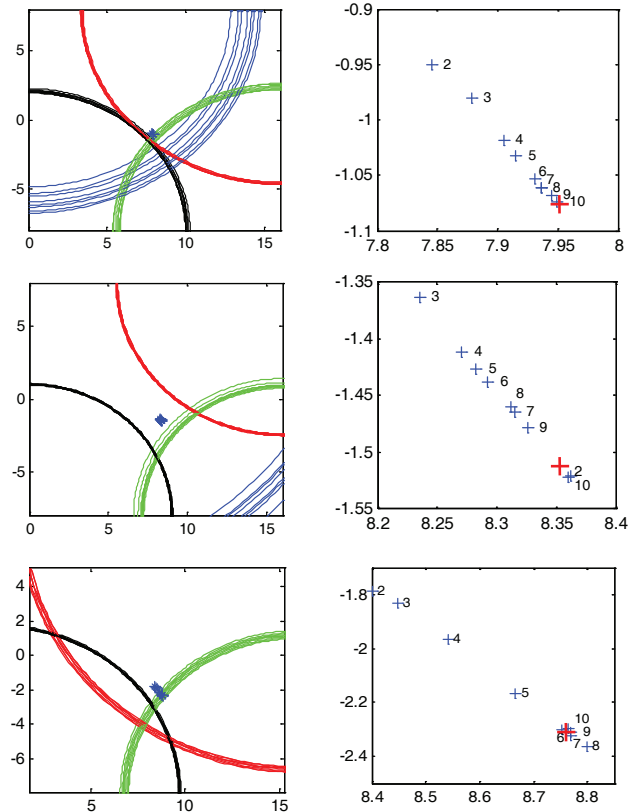


Fig. 5. Example of three measurements at three different points. In the left column, there are determining multilateration circles and the right side is focused on position calculation using a different number of samples. All units are in meters. The red cross shows the real position of the sensor.

multilateration. However, the signal power from one of the anchors suffers from big uncertainty and in the lowest example the power level circles are even out of the focused figure part.

Another performed experiment consists of 25 measurements at very close positions (only a few centimeters distant). Each measurement is composed of 10 samples. Fig. 6 combines all measurements and shows the position calcu-

lated using different number of samples (as in Fig. 5). As can be seen in Fig. 6, the calculated position converges in a smaller area with the increase in the number of samples considered (5-10). Positions determined with only two, three and four measurements are considerably far away from the position determined by measurements with more samples. Again, the figure represents a part of the experimental area.

To express the relation between measurements with different number of samples we stated the final estimated position as the most accurate and calculated the absolute error of each measurement in relation to the final position. The calculated absolute error is for measurements with different number of samples displayed in Fig. 7. The error is calculated for the mean value of performed measurements (N). It is obvious that the error is decreasing with the number of taken samples. First, the decrease is steeper and then the error differences are smaller.

To relate the error of localization and the energy consumption, we have performed the energy analysis with typical values. A Crossbow IRIS node [27] and RF 802.15.4 compliant RF transceiver CC2420 [28] are used as representatives for particular typical values. Further, we assumed 40B length of the RSS frame and 11B of the ACK frame.

Energy consumption for anchor and unknown nodes during distance estimation are calculated based on the energy model of communication (Fig. 3), equations (11), (12) and typical values for sensor nodes with 802.15.4 compliant RF transceiver. A one-to-one scheme is considered; it means one anchor and one unknown node with power supply 3 V and only one measurement. For wake-up current draw we assume 10 mA for transmitter (the minimum current draw) and 16 mA for receiver. The energy consumed by anchor node is 264 J and energy consumed by unknown node is 220 J. The energy expended by the microcontroller calculating the position was estimated from the time duration of the algorithm processing the information from four anchors. Using Gaussian elimination, the process took 2.49 ms in contrast to 1.083 ms when LU factorization was used. Therefore, employing the LU factorization, 25.992 J was consumed by position calculation.

It means that for multilateration with four anchor nodes we can derive energy consumption $E_{\text{triang1}}=1.961$ mJ for one measurement. For N RSS measurements (N measurement samples) $E_{\text{triang}}=N \cdot E_{\text{triang1}}$.

Fig. 7 relates energy consumption during the localization and the absolute error obtained from the measurements. The experimental test-bed consisted of 25 measurement points and the figure reflects the mean of those individual measurements with the same determined number of samples performed for the statistical data set. As can be seen, the energy obviously increases with the number of measurements. On the other hand, as the number of measurement rises, the error of position estimation decreases and con-

Microcontroller		
Parameter	Value	Unit
Wake-up time	1	ms
Current draw in active state	8	mA
Transceiver		
Wake-up time	1	ms
Current draw RX	16	mA
Current draw TX, 3dB	17	mA
Current draw TX, -17dB	10	mA
Bit rate	250	kbps

Tab. 1. Energy related parameters of microcontroller and transceiver.

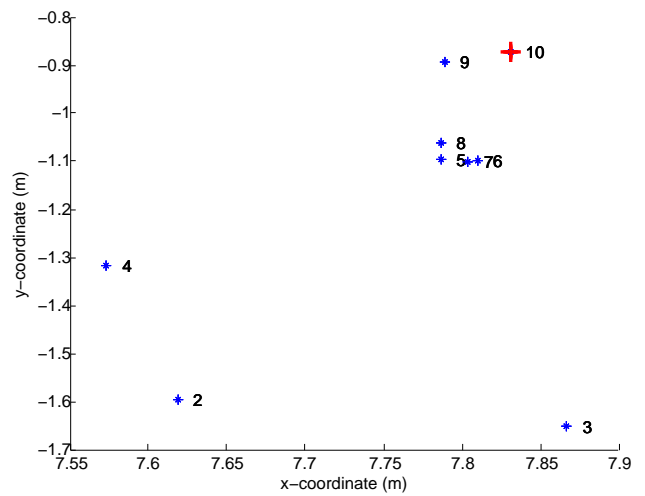


Fig. 6. Overall position estimation as a function of the number of samples taken at each point. The total number of measurement points was 25.

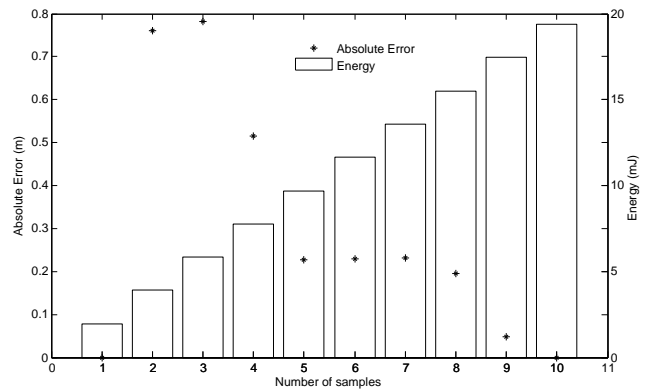


Fig. 7. Expended energy and mean of absolute error of estimated position under different number of samples.

verges to the final position. Up to five measurements samples, the convergence is faster in contrast to the measurement with five or more samples where the improvement is not so significant. In other words, the marginal energy costs increase (more energy is consumed for additional accuracy improvement).

5. Conclusion and Discussion

This work is devoted to the investigation of energy consumption during the RSS based localization using multilateration. Because of the uncertainty of signal strength measurements, multiple RSS measurements have to be carried out for received power determination. Based on a theoretical assumption, the minimization of the uncertainty can be achieved by sacrificing a certain amount of energy for multiple measurements. The more energy is depleted, the better results can be obtained. An energy model and time scheme for multilateration were proposed. The time scheme depicts the energy consumption during the distance estimation process and the model shows how the total energy is expended during multilateration. Since the power consumption of a microcontroller does not vary significantly when it is in an active state (the power analysis has been based on the commercial IRIS sensor mote), the dependence of expended energy and number of measurements is rather linear.

Measurements were performed in order to explore the dependence of the position determination accuracy on the number of measurements taken for RSS uncertainty elimination. Results show that with the increasing number of measurements the coordinate determination inclines to a certain position with smaller steps. It means that with a high number of measurement samples we can eliminate the influence of uncertainty. However, as our measurement implies, the convergence of position estimation is not linearly proportional to energy depletion. The first five measurement samples contribute to the position estimation more significantly. Concluding on the fact that position estimation can be improved with higher energy costs but not linearly, the mechanism of an adaptable RSS measurement protocol can be implemented. Based on the requirements of application and the certain number of obtained measurement samples (our recommendation is 5-6 samples), the receiving node can decide if more samples is necessary to improve the estimation and ask for them.

Acknowledgements

This paper was supported by the Spanish Government Project TEC2008-06758-C02-02.

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About Authors...

Patrik MORAVEK was born in 1984. He is a doctoral student at the Department of Telecommunications at the Brno University of Technology. He gained his Master's degree at the same university in 2008. His study specialization is TCP/IP stack and communication in ad-hoc networks. Nowadays, he is focused on wireless sensor network technologies and especially on the energy efficiency of radio communication and localization process.

Dan KOMOSNY was born in 1976. He is an associate professor at Department of Telecommunications, Brno University of Technology, Czech Republic. He received his Ph.D. degree in Teleinformatics in 2003. His research is focused on wireless sensor networks, IP networks and network operating systems. He gives lectures in courses dealing with Linux operating systems and communication in IP networks. He is an internal member of technical program committee of IEEE and IASTED conferences

Milan SIMEK was born in 1982. He received his Master's degree in Electrical Engineering in 2006 and Ph.D. in Localization for Wireless Sensor Networking in 2010. His doctoral thesis was focused on anchor-free localization and boundary detection in wireless sensor networks. Now he works as the assistant at the Department of Telecommunications of Brno University of Technology in Czech Republic. He is mainly interested in the research on the localization algorithms, investigation of the low-PAN energy consumption and 802.15.4 wireless channel measurements. He is a member of Communications and Telematics Group of Center for Informatics and Systems of the University of Coimbra in Portugal and European Committee for the 7th Framework Program.

David GIRBAU received the B.Sc. in Telecommunication Engineering, M.Sc. in Electronics Engineering and Ph.D. in Telecommunication from Universitat Politècnica de Catalunya (UPC), Barcelona, Spain, in 1998, 2002 and 2006, respectively. From February 2001 to September 2007 he was a Research Assistant with the UPC. From September 2005 to September 2007 he was a Part-Time Assistant Professor with the Universitat Autònoma de Barcelona (UAB). Since October 2007 he is a Full-Time Professor at Universitat Rovira i Virgili (URV). His research interests include microwave devices and systems, with emphasis on UWB, RFIDs and RF-MEMS.

Antonio LAZARO was born in Lleida, Spain, in 1971. He received the M.Sc. and Ph.D. degrees in telecommunication engineering from the Universitat Politècnica de Catalunya (UPC), Barcelona, Spain, in 1994 and 1998, respectively. He then joined the faculty of UPC, where he currently teaches a course on microwave circuits and antennas. In July 2004 he joined the Department of Electronic Engineering, Universitat Rovira i Virgili, Tarragona, Spain. His research interests are microwave device modeling, on-wafer noise measurements, monolithic microwave integrated circuits (MMICs), low phase noise oscillators, MEMS, and microwave systems.