

Minimal Transmission Power as Distance Estimation for Precise Localization in Sensor Networks

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ABSTRACT

Positioning sensor nodes requires distance information to reference points. Due to resource limitations in sensor networks, distance determination in low-cost sensor nodes without additional hardware is difficult. Known techniques such as distance estimation based on received signal strength (RSSI) are mostly inaccurate or have limitations. We propose a new method to measure the distance between a transmitting node and a receiving node using the minimal transmission power. The determined distance is more precise than RSSI, has a low variance and is therefore particularly suitable for positioning. Finally, we implemented a demonstrator application using weighted centroid localization to show the practical implementation.

Categories and Subject Descriptors

C.2.4 [Distributed Systems]: Distributed applications

General Terms

Measurement, Experimentation, Algorithms, Theory

Keywords

Localization, Distance Estimation, Transmission Power, Wireless Sensor Networks

1. INTRODUCTION

Miniaturization technologies and advances in communication technologies lead to development of extreme small, cheap, and smart embedded devices, so-called sensor nodes. Hundreds or thousands of these sensor nodes build a sensor network [1,10]. These sensor nodes are deployed randomly in mostly impenetrable target terrains to measure a specific set of conditions. Simple uncoordinated seeding of sensor nodes yields a stochastic distribution of nodes after deployment phase. This

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inhibits the assignment of measured data to its origin location. Due to this fact, a position determination of all sensor nodes is necessary.

Localization of sensor nodes is one of the most important research topics in wireless sensor networks. Currently, there are a lot of algorithms proposed. There are coarse grained methods which approximate node positions, e.g. centroid localization [5]. On the other side, there are fine grained algorithms proposed which calculate exact node position based on mathematical equations [16]. Independently of the algorithm's type, all of these algorithms require input data to determine the position more or less accurately. This input data may be received signal strength, neighboring node positions, time of flight from one node to another node, or others. Unfortunately, all measurements are faulty, dither and have a relatively high standard deviation caused by environmental influences such as obstacles, deviations of transceivers, flexion and interferences of waves, and other phenomena.

This paper presents a new technique to determine a distance between sensor nodes using transmission power of the transceiver. In Section 2, existing distance determinations and their characteristics are discussed. Then in Section 3, we explain the distance determination using transmission power. After theoretical considerations, we evidence the concept on a demonstrator using the localization algorithm "Weighted Centroid Localization" (WCL) in Section 4. Finally, the paper ends with a conclusion in Section 5.

2. DISTANCE DETERMINATIONS

Assuming a random distribution of nodes over the area of interest, inter-node distances are initially unknown. Since most positioning algorithms depend on this information, precise determination is essential. In sensor networks, a number of different techniques to determine distances are distinguished.

2.1 Neighboring nodes

Algorithms working with neighboring information use the knowledge of the existence of remote nodes being aware their own positions. These algorithms assume that known neighboring nodes are located close to the local node and determine the local position by estimating out of all neighboring positions. Hence,

distance d between two nodes is defined as a Boolean value. If $d=true$, the local sensor node is within transmission range of the remote sensor node. But a more precise information about the distance to the remote node is not possible. If no signal can be received, the local node is beyond the transmission range of the remote sensor node ($d=false$). Even though the entropy ($e=2$) is very small, because only binary values are distinguished, the precision of determined positions is more than acceptable [3]. It differs between 7% and 20% depending on the environment conditions and algorithm settings.

2.2 Distance Measurements

A more common method to determine a distance is based on measuring the received signal strength (RSSI) of the received messages. In theory, power relations between an idealized transmitting pole (antenna) and a receiving sensor node behaves quadratically to the distance (1), well known as Frii's transmission equation [12].

$$P_{RX} = P_{TX} \left(\frac{\lambda}{4\pi d} \right)^2 \quad (1)$$

- P_{TX} = Transmission power of sender
- P_{RX} = Remaining power of wave at receiver
- λ = Wave length
- d = Distance between sender and receiver

But in reality, ideal environment conditions are not met due to interferences, obstacles, flections, reflections, inhomogeneities of materials, and imprecise measurement methods. Systems relying on RSSI as input parameter tend to be quite accurate for short ranges if extensive post-processing is employed, but are imprecise beyond a few meters [13]. At short ranges, distance estimations with 2m averaged positioning error at a maximum range of about 20m are feasible [20].

An improvement is presented in [13] where radio interferometry techniques are used to achieve an average localization error of 3cm and a range of up to 160m with a largest error of approximately 6cm. The downside of this approach is that it requires special features of the radio chip and strict timing

accompanied by the high computational effort of the algorithm.

The measurement of the signal's time of flight (ToF) is a robust method to estimate distances which is used e.g. by GPS. A difficulty in conducting such measurements is that a tight time synchronisation of sender and receiver is required. Systems like Calamari [19] use a technique called "differential time of arrival" (DToA) to avoid the complex time synchronization. They send out two signals travelling at different propagation velocities and quantify the difference in time of arrival. If both signal propagation speeds are known, a distance can be determined from this difference measurement. The majority of the proposed schemes require acoustic or ultrasonic sound technologies to determine a distance. Additionally, all schemas are combined with radio frequency transmissions as signalling technology. The raw difference measurements tend to yield average estimation errors of about 74%. Yet, quite good accuracies are achieved if the raw measurement values are post-processed with elaborate techniques like noise cancelling, digital filtering, peak detection and calibration [19]. However, DToA systems inherently require an extra actuator and detector pair which increases cost, size, and energy consumption of the hardware platform.

2.3 Multihop Distance Estimation

Another method to determine a distance between sensor nodes is the hop count along the message's path [9,15,14]. If no distance estimates between adjacent nodes are available, the smallest number of traversed hops is counted. To determine the hop count, a flooding is initiated by a sensor node i to other nodes. Each sensor node knowing its own position replys the request with hop count 0 . If a sensor node receives a reply, it forwards the reply with an increased hop count. Sensor node i collects all hop counts from remote sensor nodes with known positions and stores the minimal hop count to this sensor node. This minimal hop count represents a distance. To determine the optimal hop count, the transmission range of sensor nodes must be adjusted such that each sensor node preferably reaches its direct neighbors only [4].

3. TRANSMISSION POWER AS DISTANCE

In our approach, the distance is determined out of the minimal transmission power which is required to send a message to

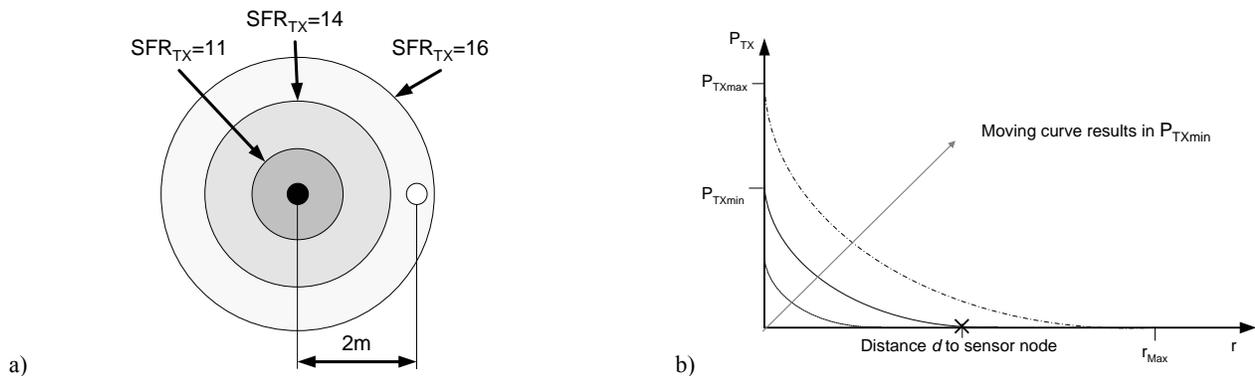


Figure 1. a) Determination of minimal transmission power by increasing the transmission power using SFR_{TX} successively. In this case, a message from the transmitting sensor node (solid circle) is received by the remote sensor node (blank circle) at a minimal transmission power of $SFR_{TX}=16$. b) Correlation between transmission power P_{TX} and distance d according to equation (1). The solid line represents the minimal transmission power P_{TXmin} required to receive a message at the remote sensor node.

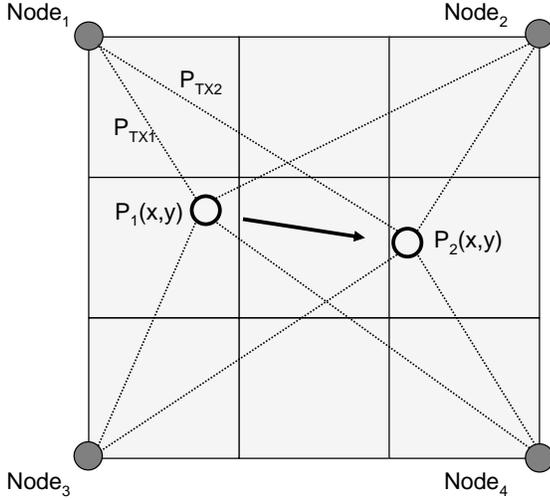


Figure 2. Moving sensor node (blank circle) from $P_1(x,y)$ to $P_2(x,y)$ in an array of 3x3 tiles

another sensor node. In microcontrollers, the transmission power P_{TX} cannot be adjusted directly. Instead, the transmission power is controlled via special function register (SFR_{TX}). Sensor nodes knowing their own position (we call them beacons in the remainder of this paper) transmit their position with a stepwise increasing transmission power in range $SFR_{TXmin} \cdot SFR_{TXmax}$. Figure 1a demonstrates a sensor node knowing its own position (solid circle). This node transmits a message containing its position and transmission power. In case of transmission power $SFR_{TX}=11$ and $SFR_{TX}=14$, the target sensor node (blank circle) is not able to receive the message. But if transmission power $SFR_{TX}=16$, the target node (blank circle) receives the message and stores the transmission power as distance. The sensor node only saves the smallest sufficient transmission power, messages with higher transmission powers are discarded.

As described in (1) and visualized in Figure 1b, transmission power P_R and d are quadratically related. To determine a linear distance, (1) must be rearranged. The relationship between P_{TX} and SFR_{TX} strongly depends on the hardware conditions and must be adapted respectively. The transfer function H_{TX} of a transmitter, according to the specifics of a npn-transistor, is

assumed as $H_{TX} = SFR_{TX}^4$. Thus, P_{TX} is approximately defined as:

$$P_{TX} \approx SFR_{TX}^4 \quad (2)$$

To finalize (1), we consider the transfer function of the transmitter H_{TX} and a constant scaling factor k representing the gain of the antennas. Inserting (2) into (1) results into (3) to determine a linear distance between two nodes.

$$P_{RX} = k \cdot SFR_{TX}^4 \left(\frac{\lambda}{4\pi d} \right)^2$$

$$\rightarrow d = SFR_{TX}^2 \sqrt{\frac{k}{P_{RX}} \left(\frac{\lambda}{4\pi} \right)^2} \quad (3)$$

$$d \sim SFR_{TX}^2$$

In dynamic systems with mobility as visualized in Figure 2, the position must be recalculated from time to time. Then, it is necessary to determine the new correct minimal distance. If the blank sensor node is moved from position $P_1(x,y)$ to $P_2(x,y)$, the minimal transmission power for the distance $Node_1, P(x,y)$ increases from P_{TX1} to P_{TX2} . Thus, the minimal transmission powers according to node 1 and 3 increase while they decrease for node 2 and 4.

To keep track of the periodically repeated distance estimation, we sum up all beacon transmissions of one sequence from $SFR_{TXmin} \cdot SFR_{TXmax}$ in rounds. To enable receiving sensor nodes to distinguish beacons from different rounds, a beacon message contains a round number that is increased from one round to another (Figure 3a). Thus, all sensor nodes consider the minimum of the perceived transmission power within one round in order to quantify the distance to the transmitting sensor node (Figure 3b). In each round, a new distance estimate is generated.

4. IMPLEMENTATION

Distance measurements based on RSSI are very unprecise. This is caused by the measuring principle at the receiver. First, measuring the signal strength is faulty. Second, all incoming bits are integrated over time to determine an averaged field strength.

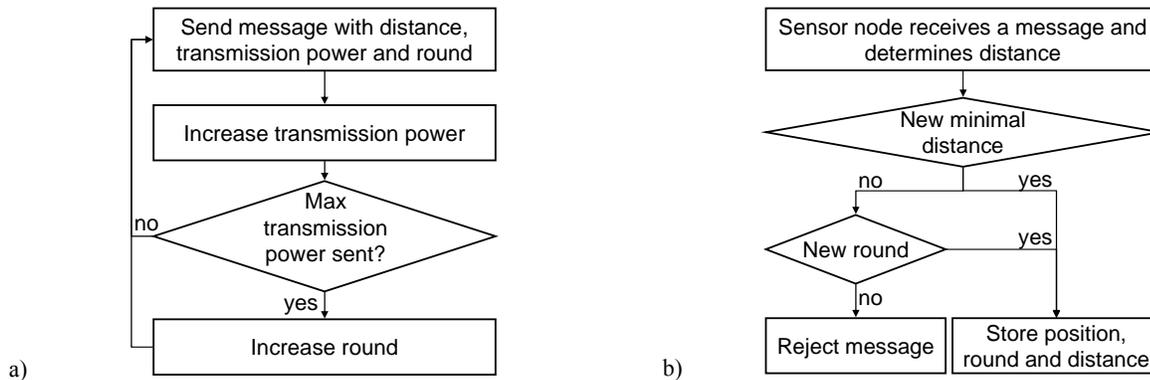


Figure 3. a) Flow diagram of a sensor node transmitting own known positions b) Flow diagram of sensor node receiving messages with positions from remote sensor nodes

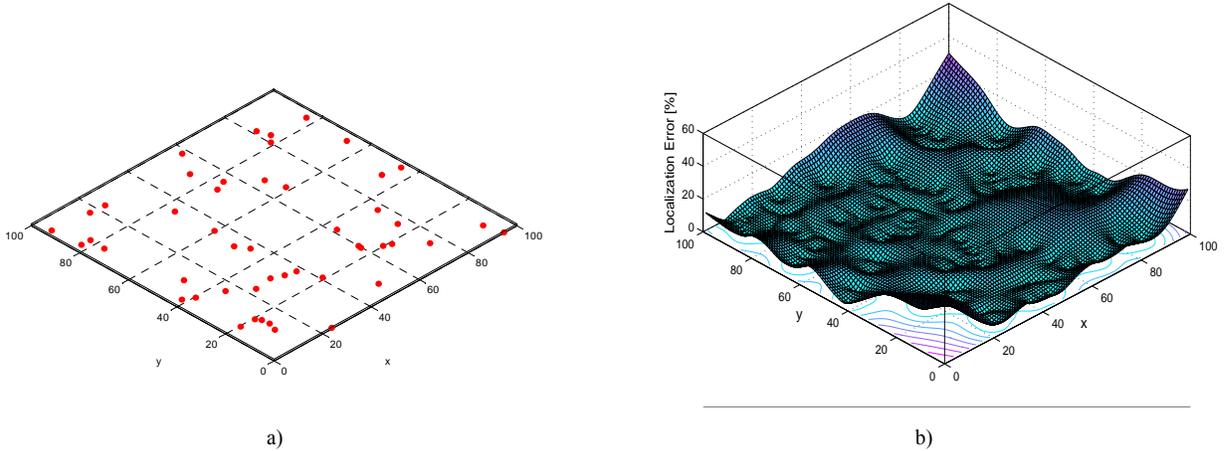


Figure 4. a) Sensor network with 60 uniformly distributed beacons (solid points), b) Localization error of the „Weighted Centroid Localization” algorithm (WCL) in a sensor network with 100x100 sensor nodes and the same beacon distribution as shown in a)

Thus, determined RSSI highly depends on the message content and on the transfer method (Manchester, Non-Return-to-Zero).

We implemented a demonstration application using embedded sensor boards (ESB) of the scatterweb project [17] to verify the distance determination based on minimal transmission power. Our application consists of beacons knowing their own position and sensor nodes. These sensor nodes do not know their own positions. Hence, they have to determine the position, e.g. with the algorithm “Weighted Centroid Localization” [4].

4.1 Weighted Centroid Localization

Weighted Centroid Localization (WCL) is a coarse grained localization algorithm which uses neighboring information and distance measurements. In WCL, a sensor network with a total number of k nodes consists of u sensor nodes and b beacons ($b \ll u$). Beacons are equipped with more efficient hardware and a localization system (e.g. GPS or Galileo [8]), whereby they are able to determine their own position. This position is assumed to be exact. In contrast to beacons, sensor nodes consist of resource-critical, low-cost hardware and do not know their own position. During deployment, sensor nodes and beacons are uniformly distributed over an area of interest (Figure 4a). After distribution, sensor nodes try to determine their own position. Weighted Centroid Localization (WCL) is divided into three phases.

In the first phase, all beacons broadcast their exact positions $B_j(x,y)$ together with information on the current transmission power and the current round. All sensor nodes in transmission range of a beacon store the received positions of these beacons.

In the second phase, WCL determines a distance to each beacon position. Currently, two methods of distance determination are successfully evaluated – distance measurement based on RSSI and hop count determination. Both methods provide valid distance information d_{ij} between a sensor node i and a beacon j . In our demonstration application, we implemented the proposed method of distance determination using distance measurements based on minimal power transmission.

Finally in the third phase, all sensor nodes calculate their approximative positions $P_i'(x,y)$ out of all n received beacon

positions in range based on a centroid localization (4). To increase the precision, WCL optimizes the accuracy of the position using the measured distances. But due to interferences, obstacles, and hardware restrictions, measured distances are inaccurate. Hence, distances are used only as additional input for the localization algorithm [18,7]. Thus, distances must not impact the position determination very excessive. During positioning, WCL considers beacons next to the sensor node more than remote beacons. In addition, the algorithm does not require very high precision of input values to converge. Therefore, WCL uses distance information only as a weight w_{ij} . Small distances to neighboring beacons lead to a higher weight than to remote beacons. Further, every coordinate of a beacon position obtains a weight depending on the distance $w_{ij}(d_{ij})$. Figure 4b briefly points out the localization error after weighted positioning in WCL.

$$P_i'(x, y) = \frac{\sum_{j=1}^n (w_{ij} \cdot B_j(x, y))}{\sum_{j=1}^n w_{ij}} \quad (4)$$

4.2 Distance Determination

The minimal transmission power scheme described in Section 3 is now used to determine the weight $w_{ij}(d_{ij})$. The weight $w_{ij}(d_{ij})$ requires a distance d_{ij} (5) and a degree g which defines the weighting of the distance and amounts to $g=3$ as proved in [4].

$$w_{ij}(d_{ij}) = \frac{1}{(d_{ij})^g} \quad (5)$$

Before programming the demonstration application, we measured the minimal transmission power from a beacon to a sensor node by stepwise increasing the distance between sensor node and beacon. Figure 5 visualizes the measured min. transmission power (y-axis) over the distance (x-axis). At each step, the empirical distances were measured forty times to determine the variance

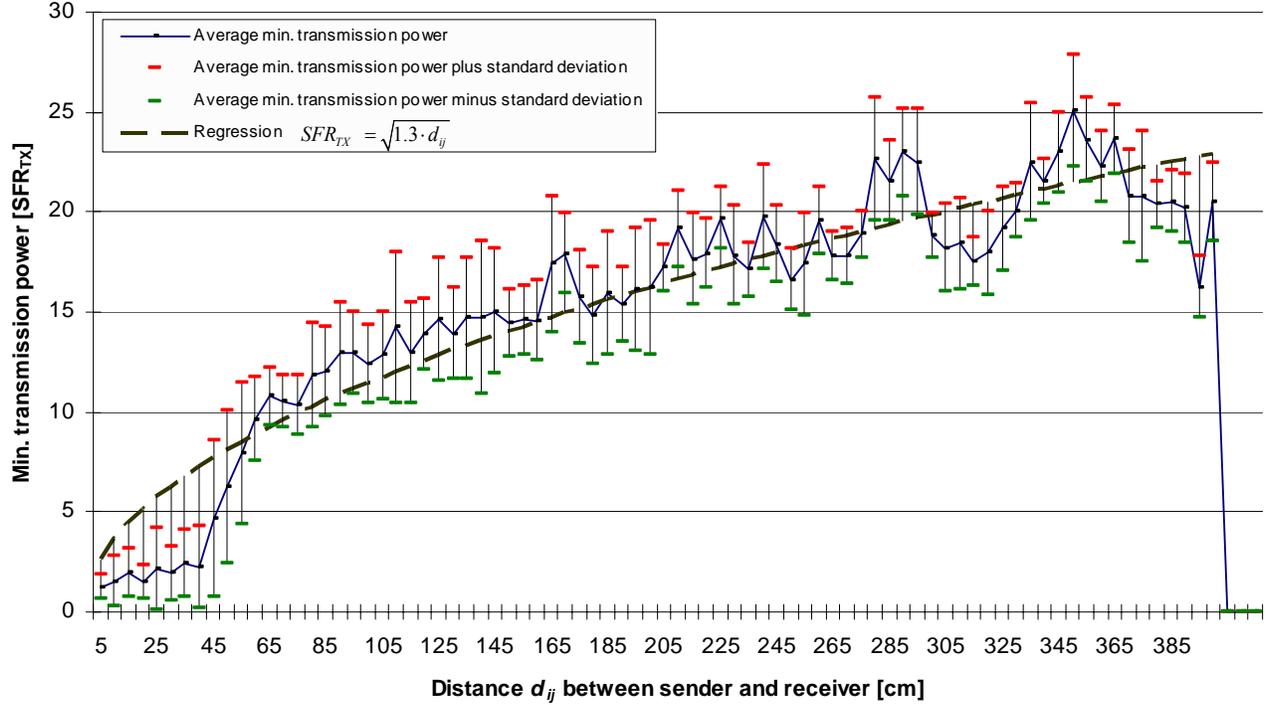


Figure 5. Minimal averaged transmission power SFR_{TX} over distance required to transmit messages between a beacon and a sensor node

besides a meaningful averaged distance. The graph shows that measuring minimal transmission power has a low variance and a high resolution.

After measuring, we squared the measured SFR_{TX} to get a linear equation (6) using (3). Now, we determined m by linear regression ($f(x)=mx+n$).

$$SFR_{TX}^2 = m \cdot d_{ij} \quad (6)$$

In our configuration, the scaling factor results in $m=1.3$ and $n=0$. Now, we rearrange (6) and obtain equation (7) which is similar to equation (3).

$$d_{ij} = \frac{SFR_{TX}^2}{1.3} \quad (7)$$

To determine the correct transmission power SFR_{TX} , equation (8) can be used for ESB sensor boards.

$$SFR_{TX} = \sqrt{m \cdot d_{ij}} \quad (8)$$

4.3 Demonstration Application

The demonstration application consists of 4 sensor nodes with pre-defined positions (beacons). Each beacon is located in one corner of an area of 2x2 meters. Any sensor node inside the area has to measure the temperature in its current tile in a set of 3x3 tiles (Figure 2).

To share temperature information, the nodes establish a *distributed virtual Shared Information Space* (dvSIS) [11]. The dvSIS may be seen as a semi-structured document and is described by a grammar. Every node holds a local instance of the dvSIS which may be incomplete, partially obsolete, or inconsistent with the local instances of other nodes, but converges against the dvSIS, which is looked upon as a virtual entity, since it exists as an abstraction only. To contribute to the dvSIS, every node broadcasts recently acquired information to its neighbors, while using a flooding control scheme. This scheme is based on meta information like time or location—e.g. acquired as discussed in this paper. To visualize the collected temperature readings, one node exports its local dvSIS instance to the graphical SpyGlass frontend [6].

All sensor nodes not knowing their own position calculate their position using WCL as described before. Depending on the environment conditions, the precision of the position oscillates between 10cm (5%) and 30cm (15%) as visualized in the video [2]. The video shows the described sensor network with two sensor nodes inside. Initially, these nodes calculate their own position as displayed in SpyGlass. Then, one of these sensor nodes is moved. An exponential weighted moving average over the last rounds is used to flatten the resulting sequence of distance estimates and to filter outliers. Thus, the new position is calculated with a little reaction time. Overall, the demonstration exemplifies that using min. transmission power results in a very precise positioning of randomly distributed sensor nodes.

5. CONCLUSION

In this paper, we presented a new approach to determine a distance between sensor nodes using minimal transmission power. The determined distance has a high resolution and a small variance compared with other distance determination techniques, e.g. RSSI. The distance determination process was empirically proved in a demonstration application. In this, the positioning error using an approximated position algorithm achieves a high precision between 5%-15%.

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7. REFERENCES

1. Akyildiz, Ian F., Su, W., Sankarasubramaniam, Y., and Cayirci, E. A survey on sensor networks, *IEEE Communications Magazine*, pp. 102- 114, August 2002.
2. Blumenthal, J., Buschmann, C., Koberstein, J. *Precise positioning in sensor networks using minimal transmission power*, <http://rtl.e-technik.uni-rostock.de/~bj/movies/PositionEstimationUsing-MinimalTransmissionPower.mpg>, Rostock, Germany, 2005.
3. Blumenthal, J., Reichenbach, F., Handy, M., and Timmermann, D. Optimal adjustment of the coarse grained localization-algorithm for wireless sensor networks, Invited Paper, *Proceedings of 1st Intl. Workshop on Positioning, Navigation, and Communication WPNC'2004*, Hanover, Germany, March 2004.
4. Blumenthal, J., Reichenbach, F., Timmermann, D.: Precise Positioning with a Low Complexity Algorithm in Ad hoc Wireless Sensor Networks, PIK - Praxis der Informationsverarbeitung und Kommunikation, Vol.28 (2005), Journal-Edition No. 2, S.80-85, ISBN: 3-598-01252-7, Saur Publishing, Germany, 2005.
5. Bulusu, N., Heidemann, J., and Estrin, D. GPS-less low cost outdoor localization for very small devices, *IEEE Personal Communications Magazine*, 7(5):28–34, October 2000.
6. Buschmann, C., Pfisterer, D., Fischer, S., Fekete, S. P. and Krölller, A. *SpyGlass: A Wireless Sensor Network Visualizer*, in *ACM SIGBED Review*, Vol. 2, No. 1, 2005.
7. Feldmann, S. An indoor Bluetooth-based positioning system: concept, implementation and experimental evaluation, *ICWN'03*, Las Vegas, USA, Institute of Communications Engineering, Hanover, June 23-26, 2003.
8. Gibson, J. The mobile communications handbook, 2. Edition, CRC Press, United States of America, 1996.
9. Gramlich, G. Numerical mathematics with matlab – An introduction for scientists and engineers, dpunkt.verlag, 2000.
10. Karl, H., Willig, A. A short survey of wireless sensor networks, *TKN Technical Report TKN-03-018*, Berlin, October 2003.
11. Koberstein, J., Reuter, F., Luttenberger, N. The XCast Approach for Content-based Flooding Control in Distributed Virtual Shared Information Spaces-Design and Evaluation”, 1st European Workshop on Wireless Sensor Networks (EWSN), Istanbul, Turkey, 2003.
12. Liu, C.H. and Fang, D.J. Propagation in *Antenna Handbook: Theory, Applications, and Design*, Y.T. Lo and S.W. Lee, Eds., Van Nostrand Reinhold, pp. 29.1–29.56, New York, 1988.
13. Maroti, M., Völgyesi, P., Dora, S., Kusy, B., Nadas, A., Ledeczki, A., Balogh, G., Molnar, K. Radio interferometric geolocation. In: *SenSys '05: Proceedings of the 3rd international conference on Embedded networked sensor systems*, 2005.
14. Niculescu, D., Nath, B.: Ad hoc positioning system (APS). In: *Ad hoc positioning system (APS)*, in *Proceedings of GLOBECOM*, San Antonio, November, 2001.
15. Savarese, C. Robust positioning algorithm for distributed ad-hoc wireless sensor networks, Technical Report, Delft University of Technology, 2001.
16. Savvides, A., Han, C. C., and Strivastava, M. B. Dynamic fine grained localization in ad-hoc networks of sensors, *Proceedings of the 5th International Conference on Mobile Computing and Networking*, Mobicom 2001, pp. 166-179, Rome, Italy, July 2001.
17. ScatterWeb GmbH *Embedded Sensor Board*, http://www.scatterweb.net/research_products/esb.en.html, Berlin, 2005.
18. Tschumi, S. Positioning in mobile ad hoc networks, *Semester Thesis*, ETH Zürich, Switzerland, 2002.
19. Whitehouse, K., Culler, D. Calibration as Parameter Estimation in Sensor Networks. In: *WSNA '02: Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications*, 2002.
20. Whitehouse, K., Karlof, C., Woo, A., Jiang, F., Culler, D. The Effects of Ranging Noise on Multihop Localization: an Empirical Study. In: *The Fourth International Conference on Information Processing in Sensor Networks (IPSN '05)*, 2005.