Using signal propagation models to improve distance estimations for localisation in wireless geosensor networks

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***Abstract*—The determination of a precise position in wireless geosensor networks requires the use of e.g. distance measurements. These distance observations derived by Received Signal Strength (RSS) measurements are inherently inaccurate. Furthermore, in general, the distance observations using RSS do not take obstacles into account. In this paper we present a new approach to correct erroneous RSS measurements affected by obstacles. This technique is combined with the known "Anomaly Correction in Localization" (ACL) algorithm where sensor measurements are used to improve the determined sensor node positions and to detect and eliminate outliers.**

Keywords: wireless sensor networks, geosensor, localisation, raytracing, received signal strength, precise positioning

I. Introduction

The increasing miniaturization in the semiconductor field is leading to the development of very small and low-cost measurement devices. Due to their small size they are strongly limited with respect to processor capacity, memory size and energy resources. These measurement devices may be deployed as sensor nodes, able to sense different environmental parameters and communicate wirelessly with each other. Several hundreds or thousands of such geosensor nodes form a wireless geosensor network (GSN). The gathered data may be aggregated and transmitted over neighboring nodes to a high performance data sink where the data is processed. GSNs are evolving as a promising technique for industry, modern life science applications or natural disaster warning systems. One of the challenging issues in GSNs is the localisation of each sensor node using distance or angle measurements to the neighboring sensor nodes, as the resulting data is only useful if combined with the geographical position where it was measured. Due to the large errors caused by distance or angle measurements the positional accuracy is insufficient for most applications. Here, obstacles and multipath effects have a large influence on distance estimation.

In our new approach we take advantage of *a priori* knowledge about the area of interest and therefore about the future geosensor network. We have developed a tool, the "Anomaly Correction in Distance Measurements" (ACD), which simulates signal propagation in a defined area, taking obstacles and material characteristics into account to correct the erroneous distance measurement. Moreover, we propose an extension of the known "Anomaly Correction in Localization" algorithm (ACL) by the use of signal propagation models based on ACD.

This paper is structured as follows. In Section II the fundamentals of localisation in geosensor networks and distance estimation based on RSS measurements are summarized. Section III explains the basic concept of our proposed method and Section IV describes the new "Anomaly Correction in Distance Measurements" technique in detail. Section V then presents some first simulation results before Section VI summarizes the paper and discusses future work.

II. Background

A. Fundamentals of Localisation in geosensor networks

As mentioned before, the capability to self-determine the position of every sensor node is an important and essential feature of the nodes. A conceivable method would be the use of the Global System for Mobile Communication (GSM) or Global Navigation Satellite Systems (GNSS) (Gibson, 1996). Because of additional hardware and energy requirements, these techniques are only feasible for use on a small number of more powerful sensor nodes, further called beacons. These beacons determine their position with such methods. After the localisation process, the beacons make their position information available to all other nodes within the GSN. The sensor nodes measure angles or distances to the beacons and thus determine their position. For this, different methods are available and can be categorised as fine-grained or coarse-grained methods. An overview can be found in Reichenbach (2007a) and Stefanidis et al. (2004).

Simple fine-grained methods are the well known trilateration or triangulation, using distance or angle measurements respectively. Angle measurement requires additional hardware on the sensor nodes which makes it infeasible for use in geosensor networks. We therefore concentrate on localisation based on distance measurements only as it is the favored technique in literature. In the case of 2D-localisation, a system of at least three equations may be constructed using Euclidian distances (Bulusu, 2001). This system of equations has to be resolved by subtracting one equation from the other two. Then inserting one of the remaining unknowns produces a quadratic equation which may be uniquely resolved. This method requires a low calculation and memory effort. Because the distance measurements contain systematic and stochastic errors, the trilateration accuracy will be decreased by the lack of robustness of the position determination. In the worst case, the localisation process can fail.

B. Anomaly Correction in Localization (ACL)

In Reichenbach et al. the "Anomaly Correction in Localization" algorithm (ACL) has been proposed (Reichenbach et al. 2008). This algorithm uses spatial information inherent in sensor measurements. The principal idea used is as follows: Usually a sensor network contains redundant beacons. Using simple trilateration, different positions can be estimated followed by the determination and elimination of outliers. Therefore, the object of interest will be subdivided into sensor intervals where these intervals represent the physical parameter to be monitored. The expected sensor values will be modeled based on *a priori* information on the basis of e.g. surface models for outdoor scenarios or floor plans indoors and stored as a footprint map on the sensor nodes. During the localisation process, the determined position will be adopted one to one into the footprint map. The sensor then measures the physical parameter and compares the measured value with the expected one on the footprint map for the calculated position. If the position on the map matches the sensor measurement it will be marked as valid and used for the final localisation. If not it will be marked and deleted as an outlier. Here, only raw distances are used. In our approach this algorithm will be extended by a method which corrects deviations caused by obstacles in the signal path in distance observations.

C. Distance determination based on RSS Measurements

The commonly used technique for distance estimation in wireless geosensor networks is the use of the received signal strength. Some simplified fundamentals on distance estimation based on RSS will therefore be described next. Assume two sensor nodes K_1 and K_2 with distance d between them where K_1 is the emitting and K_2 the receiving node. Both nodes have visual contact and are located within the same medium, e.g. air. The transmitted signal propagates spherically with transmission power P_{TX} and decreases with the square of the distance d. In other words, the received signal strength is directly correlated to the distance between the sending node K_1 and receiving node K_2. This relation can be used to estimate distances. The major advantage is that RSS does not require additional hardware and resources and is therefore highly suitable for use in wireless geosensor networks. On the other hand, distance estimations based on RSS are highly imprecise and error-prone.

D. Signal propagation model and error sources

There are many factors affecting the distance estimation. One of the major problems is the signal propagation through the medium between the emitting and the receiving node and accordingly the fading of the signal. Several models exist in literature to take these problems into account (Rappaport, 2002). For our approach we make use of the "Attenuation Factor Model" (1) which is mainly based on the "Shadowing Model" (Shen et al. 2006). Common models are based on deterministic functions and presume an ideal transmission range. The "Attenuation Factor Model" takes signal fading caused by obstacles into account and is therefore more realistic. Here, the calculation consists of two parts (1). Firstly, the path-loss-exponent η is determined which represents the signal attenuation in different environments.

$$PL(d)_{dB} = PL(d_0)_{dB} + 10\eta \log\left(\frac{d}{d_0}\right) + \sum PAF \tag{1}$$

$PL(d)$ is determined relative to $PL(d_0)$ where d_0 is a small reference distance, usually 1m. The second part consists of a random variable X_{dB} which follows a Gaussian distribution with expectation μ=0 and standard deviation σ_{dB}. *PAF* describes the path attenuation due to obstacles and depends on the material the obstacle consists of. Using the received power on the sensor node, the distance can be estimated. Inserting (1) in (2), where P_{Rx} denotes the power of the received and P_{Tx} the power of the transmitted signal, and resolving for d this leads to (3).

$$P_{Rx} = P_{Tx} - PL \tag{2}$$

$$d = d_0 \cdot 10^{\frac{P_{Tx} - P_{Rx} - PL(d_0) - \sum PAF}{10\eta}} \tag{3}$$

This can be used to estimate the distance between the unknown and the beacon. A simple trilateration follows to determine the unknown's position $P(x,y)$. In randomly deployed wireless sensor networks, an initial position is not available. The parameter *PAF* can therefore not be determined, as no information about obstacles is available. This information gap may be closed by adopting ACL. This idea will be described in the next section.

III. BASIC CONCEPT

In the last section we presented some problems affecting distance measurements in wireless geosensor networks. In literature, various efforts to reduce these influences using better localisation algorithms can be found. However, these algorithms are all based on the same kind of data such as distance observations and beacon positions. As shown before, distance measurements in geosensor networks based on RSS are inaccurate and prone to errors due to obstacles in the signal path or multipath effects. Here we will use the *a priori* information from ACL to model these influences and to take signal propagation effects into account.

For a better understanding we will present an application example for indoor positioning. To localize lab samples within a lab environment GSNs can be used (Reichenbach et al. 2007b). As discussed in the previous section, each material has its own attenuation factor. In other words, each material decreases the signal strength differently. If the signal path is obstructed by e.g. walls, attenuation effects will occur which leads to a lower received signal strength at the receiving sensor node. Using this erroneous measurement will result in a false distance estimation and therefore in an inaccurate position. As mentioned for the ACL algorithm, different positions will be calculated using trilateration. However, before eliminating possible outliers using ACL, corresponding distances will be corrected taking obstacles in the signal path into account. The goal is to decrease the number of outliers and therefore the localisation error. However, applying the "Shadowing Model" for distance estimation is highly complex and therefore energy consuming. Testing distances should be reduced to single estimates where obstructed signal paths are highly probable.

IV. ANOMALY CORRECTIO IN DISTANCE MEASUREMENTS (ACD)

In this section we describe the "Anomaly Correction in Distance Measurements" method (ACD). Fig. 1 illustrates how erroneous distance measurements may affect the calculated position. The receiving sensor node is placed behind the obstructing wall. Due to the signal attenuation by the obstacle, the sensor node detects a signal strength which would occur for a longer distance without the obstacle.

If the sensor node is able to recognise erroneous RSS readings, it may be corrected by taking the obstructing obstacle into account. For this, the footprint map defined in Section II.B for ACL can be extended by including obstacles such as e.g. walls. Possible outliers may then be tested for obstacles in the line of sight to the beacons. Using an intersection test, ACD determines whether the corresponding signal may be attenuated by an obstacle. If it does, the received power will be corrected by the characteristic *PAF* for the material the obstacle consist of. With this newly determined distance, the localisation will be repeated and again checked by ACL. This implies certain prerequisites which have to be formulated before applying ACD successfully. It must be possible to clearly define the environment in which the geosensor network has to be deployed in order to set up a footprint map including all obstacles. Moreover, it must be possible to clearly define the spatial relation of the phenomenon being used using discrete

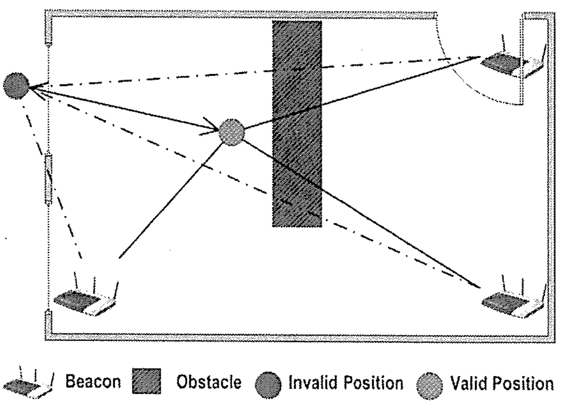

Figure 1. Position estimation with erroneous and with corrected distance observations

(or potentially, with an extension of the model, fuzzy) zones linked to expected observation values which can be determined independently of the current sensor network. Furthermore, it is essential to have an estimate for the attenuation factor of any obstacle within the sensor field.

The expected *PAF* then has to be defined by calibration measurements for the sensor field. For this, a rectangular measurement area is defined in which the sensor node is placed. The area is subdivided using an arbitrarily scalable raster, which may be represented using a square matrix. This allows both a very flexible configuration and a fast computation. *PAF*'s have to be pre-assigned and linked with the corresponding obstacles. These enclosed areas may be formed by a set of adjacent cells, whereby each cell is represented by the corresponding *PAF* in the relevant position in the matrix. If the determined positions have to be tested, the sensor node evaluates whether an obstacle lies within the direct line to the beacon. If it does then the corresponding distance will be recalculated.

V. SIMULATION AND RESULTS

Here we focus on indoor localisation only, but this approach can easily be modified for outdoor scenarios. For the simulations we used Matlab.

A. Simulation setup

As we performed only simulations without real measurements, we have chosen for the parameters η, *PAF*, and σ_{dB} the values determined in extensive measurements and published in (Rappaport, 2002). Table 1 gives an overview for the values used.

TABLE I. USED PARAMETERS FOR THE "ATTENUATION FACTOR MODEL"

Material	*PAF[dB]*	η	σ*[dB]*	*Frequency [MHz]*
Concrete Wall	15	3.0	7.0	1300
Concrete Block Wall 1	20	2.4	9.6	1300
Concrete Block Wall 2	20	3.0	7.0	1300
Wooden wall	6	3.0	5.0	1300
Brick	10	3.0	7.0	1300

The simulation setup was as follows. A part of a floor was defined including two rooms and one corridor with the following dimensions: Room 1 had dimensions of (4m x 6m), Room 2 (6m x 6m) and (10m x 4m) for the corridor respectively. Furthermore, three intervals have been defined which represent the physical parameter to be measured. In our simulation we have chosen temperature. Consequently, the temperature for Room 1 has been defined as 20°C, Room 2 23°C and the corridor 17°C. We assume constant temperature without any fluctuations to fulfil the prerequisites formulated in Section IV. Five beacons have been placed, one in each room and three in the corridor, which leads to 10 possible trilaterations. Each of these has been repeated 10.000 times to take empirical aspects into account.

B. *Simulation results*

Due to space limitations in this paper we only show the simulation for one scenario graphically. Fig. 2 illustrates the simulation result for concrete block wall 2.

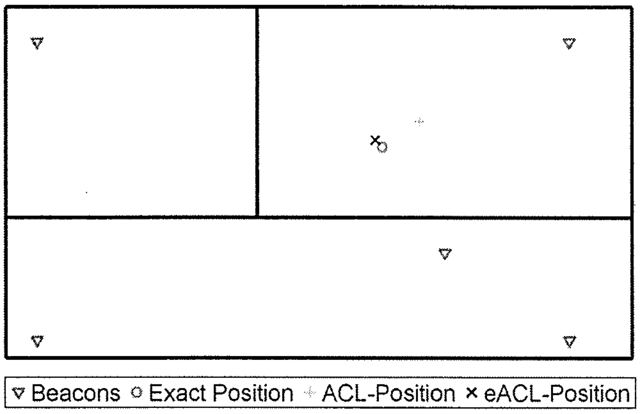

Figure 2. Simulation results

Here the beacons are depicted as magenta triangles, the exact position of the unknown sensor node as a green circle, and the determined positions as crosses. The simulation results for different materials can be seen in Table 2.

TABLE II. SIMULATION RESULTS

Material	*Valid after ACL[%]*	*Valid after eACL[%]*	*Deviation in Position ACL [m]*	*Deviation in Position eACL [m]*
Concrete Wall	2.18	10.76	0.78	0.25
Concrete Block Wall 1	1.07	8.51	0.87	0.28
Concrete Block Wall 2	1.11	10.14	1.10	0.19
Wooden wall	6.04	11.40	0.57	0.53
Brick wall	3.96	10.93	0.67	0.35

The simulations show that the material of an obstacle has a large impact on the received signal strength. RSS measurement is highly inaccurate by itself. Due to the log-normal distribution, small errors have large influences when determining distances from RSS. By using ACL it was possible to detect and to eliminate nearly all outliers. However, since it does not take obstacles into account, ACL falsely detects valid measurements as outliers. This also has an impact on the remaining observations used for trilateration. By applying eACL the falsely determined observations could be largely corrected. Here, the material has a large impact on the number of outliers. Depending on the material, eACL improved the number of valid points by factor 10. For the scenario where attenuation caused by the walls is lower, the improvement was only of factor 2. This has also an influence on the achieved accuracy. For more damping material, the precision of eACL increases also by factor 10 whereas the accuracy for the other material stays in the same ranges.

VI. CONCLUSION AND FUTURE WORK

In this paper we presented the "extended Anomaly Correction in Localization" algorithm (eACL) in which we have extended the existing ACL by a radio propagation model for distances derived by RSS measurements. Valid points falsely marked as outliers have been detected and distances corrected for the following trilateration. In first simulations it was possible to increase the number of valid positions by about factor 10 depending on the material. The resulting localisation error was reduced by factor 3 to 10 in some scenarios. The ACL algorithm can be considered as an efficient additional method for localisation. Even with relatively few preconditions it is possible to improve the localisation. In particular in combination with approximate algorithms it is possible to obtain good results, but also with exact positioning where large distance errors are present then the ACL is of benefit.

The presented approach only uses damping factors of different materials to model the path loss of the transmitted signal while passing an obstacle in the line of sight. Future work will be the implementation of reflection models and multipath effects. Furthermore the application of eACL in a sensor network to test real measurements is planned.

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REFERENCES

Gibson, J. (1996). *The mobile communications handbook*. Boca Raton: CRC Press.

Reichenbach, F. (2007a). *Resource-aware algorithms for exact localization in wireless sensor networks*. PhD thesis, University of Rostock

Stefanidis, A. and Nittel, S. (2004). *GeoSensor networks*. Boca Raton: CRC Press.

Bulusu, N., Heidemann, J., and Estrin, D. (2001). Adaptive beacon placement. In *Proceedings of the 21st International Conference on Distributed Computing Systems* (pp. 489-498).

Bulusu, N. (2000). GPS-less low cost outdoor localization for very small devices. *IEEE Personal Communications Magazine*. 7, 28–34.

Reichenbach, F., Born, A., Nash, E., Strehlow, C., Timmermann, D., and Bill, R. (2008). Improving localization in geosensor networks through use of sensor measurement data. In: Cova, T.J.; Miller, H.J.; Beard, K.; Frank, A.U.; Goodchild, M.F. (Eds) *Geographic Information Science : 5th International Conference*, (pp. 261-273).

Rappaport, T.S. (2002). *Wireless communications: principles and practice* (2nd Edition). New York: Prentice Hall.

Shen, X., Wang, Z., Jiang, P., Lin, R., and Sun, Y. (2006). Connectivity and rssi based localization scheme for wireless sensor networks. In *Proceedings of the International Conference on Intelligent Computing*, (pp. 578–587).

Reichenbach, F., Keil, C., and Timmermann, D. (2007). Reducing the localization error in wireless sensor networks by considering the measurements spatial relationship. In: *Proceedings of the 5th International Forum Life Science Automation*.