Adaptive Distance Estimation and Localization in WSN using RSSI Measures

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***Abstract*—Localization is one of the most challenging and important issues in wireless sensor networks (WSNs), especially if cost-effective approaches are demanded. In this paper, we present intensively discuss and analyze approaches relying on the received signal strength indicator (RSSI). The advantage of employing the RSSI values is that no extra hardware (e.g. ultrasonic or infra-red) is needed for network-centric localization. We studied different factors that affect the measured RSSI values. Finally, we evaluate two methods to estimate the distance; the first approach is based on statistical methods. For the second one, we use an artificial neural network to estimate the distance.**

***Index Terms*—Wireless sensor network, distance measurement, network-centric localization, RSSI**

I. Introduction

ACCORDING to Moore's law, each year electronic devices become cheaper and smaller. Connecting huge numbers of small embedded systems, one is able to create powerful massively distributed systems. The best-known examples are wireless sensor networks (WSNs). Such sensor networks consist of a number of sensor nodes, possibly reaching hundreds or thousands of connected devices. Each node is a small computing device, which has the capability of sensing and computing in addition to the ability to communicate with other nodes. Wireless Sensor networks represent one of the emerging research domains. There are many applications for WSNs in military domains but also in civil applications such as habitat monitoring and emergency applications.

In this paper, we study and discuss short ranged RSSI based distance measurement and localization methods and possible improvements for a mobile robot. We introduce two methods for distance estimation based on the RSSI value; the first approach is a statistical method and the other one is based on a trained feed forward artificial neural network. For experimental tests, we developed a prototype using BTnode sensor nodes[1] and the mobile robot system Robertino.[2] One single BTnode is connected on top of the robot acting as a base station of the WSN. This has the main advantage that we can rotate and move the base station as well as changing the RF parameters during our measurements. Thus, we can investigate the influence of antenna orientation, signal strength, and local disturbances on the distance estimation in more detail as if we would use a static base station. Additionally, the robot is supplied with a database of fine-grained RSSI/distance pairs that have been gathered by performing many calibration runs.

II. Related Work

In the last few years, several approaches have been presented for indoor localization as well as for outdoor use. Maybe the most famous localization method is to measure the time of flight (ToF) of radio frequency (RF) signals, which is for example used in GPS systems. Usually, this method cannot be applied in WSN due to the short distance and the much too inaccurate time synchronization of the sensor nodes. Cricket motes exploit this fact and send RF and ultrasonic signals assuming the RF signal has no delay and measure the ToF for the ultrasonic signal [9]. RADAR is a user tracking system [2]. It uses empirical as well as mathematical models to determine the signal strength. Calamari uses RSSI and acoustic ToF to estimate the distance [11]. It uses an audible frequency to reduce the complexity of the system. SpotON is a RSSI based ad hoc localization system for WSNs [4]. It can be used for relative and absolute position determination. In this system, all the nodes need to be calibrated before being used. MoteTrack focuses on a robust, decentralized implementation [7] as the most localization systems need a base station for data processing. The majority of the nodes take over only a limited role in the localization process to support the case that one or more base stations are down. Additionally, the localization of mobile systems has been addressed [5, 10].

III. Considerations on RSSI based Distance Estimation

All signal strength-based localization systems, in particular indoor, must consider errors in the measured values, which result from multi-path propagation, reflection, and fading effects. At the execution time of the first measurements, there is limited relation between the RSSI value and the real distance. In addition, there is a set of influencing factors, which can be controlled and exploited for improved measurement results.

A. Antenna characteristics and orientation

The used antennas are regarded to forming sources with

[1] http://btnode.ethz.ch/
[2] http://www.openrobertino.org/

spherical radiation. Typically, signals are sent in the frequency range between 868 MHz and 915 MHz, thus, the antennas are about 8.3 cm ($\lambda/4$) long. Usually, it is assumed that the signals on their way from the transmitter to the receiver spread in all directions equally – otherwise, measurements of the mutual orientation would have to be admitted. Since we cannot determine mutual orientation but we do assume the fact that the orientation directly exerts influence on the RSSI, a method is needed to compensate the orientation effects.

B. Variation of the transmission power

The transmission power and the frequency determine the maximum range of the radio waves. While the maximum transmission power might be appropriate for long distance communication (disregarding energy requirements), differences in the RSSI are hardly visible for small distances between transmitters and receivers. However, the measurement of short distances for the localization in closed areas with small dimensions is important. Thus, the transmission power must be well-controlled for meaningful RSSI based distance measurements.

C. Variation of the Frequency

Small changes of the wavelength can lead to different developments of the fading effects caused by reflection. Thus, the dispersions caused by inappropriate frequency under the given basic conditions must be considered. Therefore, also the observation of the signal strength under different frequencies is a subject of the accomplished experiments.

D. Experimental Setup

Our lab is an area of 5x8m with desks, workstation computers and shelves (see Fig 1). In the middle there is a free area of about 3.5 x 5.0m. Our experiments take place here, since our main focus is to examine short range RSSI deviations under standard conditions for indoor localization (keeping the overall applicability in mind).

Fig 1. In the lab environment, a great number of objects may influence the radio transmission

In our lab, we are using BTnode sensor nodes, which employ a Bluetooth interface and a 433-915MHz low power radio chip CC1000. The nodes are equipped with an Atmel ATmega128L microcontroller running at 8MHz and 128Kbyte flash memory. For our measurements, we also used the mobile robot system Robertino. This robot carries a PC104 board running Linux. It is able to perform all the localization algorithms described in this paper. For communication with the sensor network, we attached a BTnode to the top of the Robertino.

IV. Distance Measurements

A. Statistical Aspects

First, we examined the characteristics of the RSSI. For the Chipcon CC1000, the RSSI is recorded with an analogue signal (0–1.2V) that is inversely proportional to the input signal level. Using a frequency of 868MHz, the readings from the AD converter can be converted to dBm:

$V_{RSSI}[V] = ADC \times 2.56V / 1024$

$P[dBm] = -50.0 \times V_{RSSI} - 45.5dBm$

We used the robot to request some data packets with arbitrary distance and saved the respective RSSI values. In this experiment, the distance between the robot and the sensor node was 2.2m. First, the RSSI values were observed for a time period of 120s.

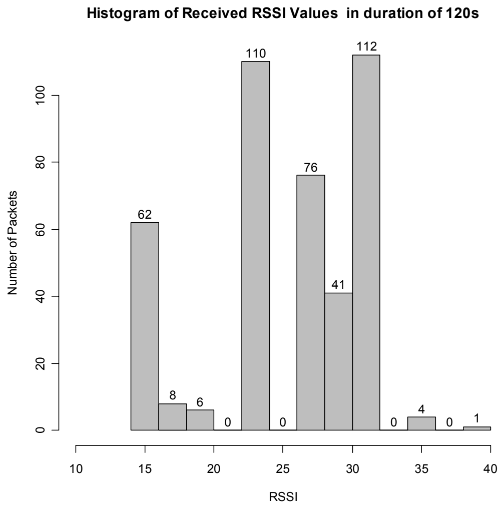

Fig 2. Variation of the RSSI values over 120s

In Fig 2, it is to be recognized that the measured values vary strongly under identical conditions. It is noticeable that from the range of RSSI values between 15 and 45 actually only 9 different values were measured. It is to be therefore assumed that the resolution of the RSSI does not cover the complete range of values. A further problem is that in two minutes only very few packets are sent. The bottle neck is the packet processing in the sensor node.

In another experiments it showed up that a transmitter can send between 170 and 180 packets in 30 seconds. The packet size (maximum 255 byte + 7 byte header) does not influence the speed. Therefore, it must be examined whether the evaluation of fewer RSSI values is statistically relevant. In a second attempt under identical conditions, we measures RSSI values over 20s (see Fig 3).

The comparison of both histograms shows differences in the distribution of the RSSI values. Nevertheless, the statistical properties need to be considered. A comparison of the statistical data shows that both measurements exhibit similar characteristics as depicted in Table I. For the localization system it is crucial that a small number of measurements supplies relevant results, since we need data from many different nodes.

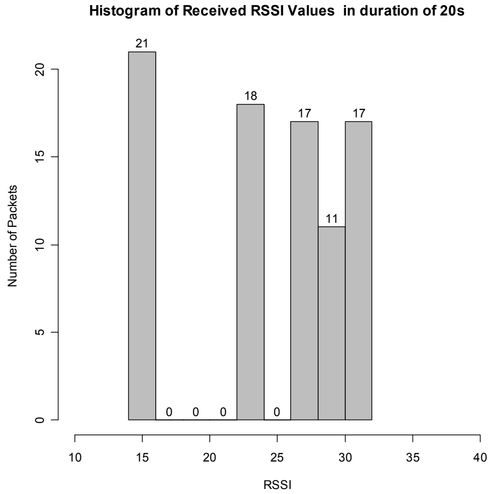

Fig 3. Variation of the RSSI values over 20s

Table I. STATISTICAL CHARACTERISTICS OF RSSI MEASURES

	RSSI (120s)	RSSI (20s)
Minimum	15	14
25%Quantile	24	21.75
Median	28	28
Mean	25.75	24.75
75%Quantile	31	30
Maximum	39	31
Standard div.	5.60	6.18

B. Distance dependency

In the next experiments, we examined how the RSSI values change with different distances. The past results suggest that small number packets can supply meaningful results. Therefore, in each experiment we used 60 packets to determine the RSSI values for distances of 1m and 3m. This range was selected to judge the relevance of indoors locations. The measurement environment was a hall in our sports center. A smaller range of the RSSI values is to be expected according to fewer reflection surfaces compared to our lab.

The expected decrease of the range of values did not appear in the changed environment (see Fig 4 and Fig 5). We assume that the quality of the used antennas caused this strong dispersion. One recognizes besides that the distance difference of 2m has little influence on the measured RSSI values. A comparison of the statistic data of both series of measurements confirms this impression. With 3m, a tendency is recognizable toward the higher RSSI values. However, this change is so small that inverse mapping of the RSSI on the distance would be connected with a large error.

C. Adjustment of the transmission power

Without modification, BTnode transceivers use a frequency of 868 MHz and a maximum power of 5 dBm. With a low quality antenna, they have an effective transmission range of

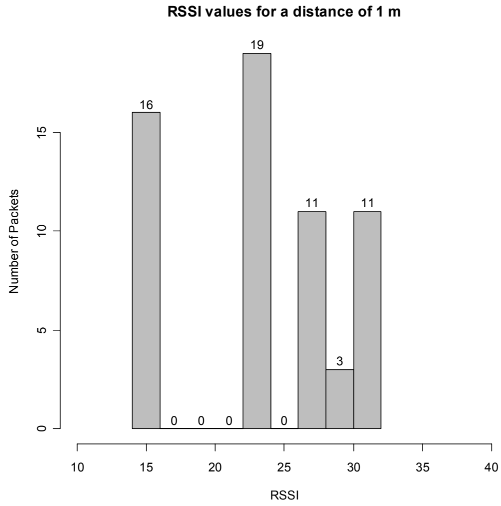

Fig 4. RSSI measurement for 1m

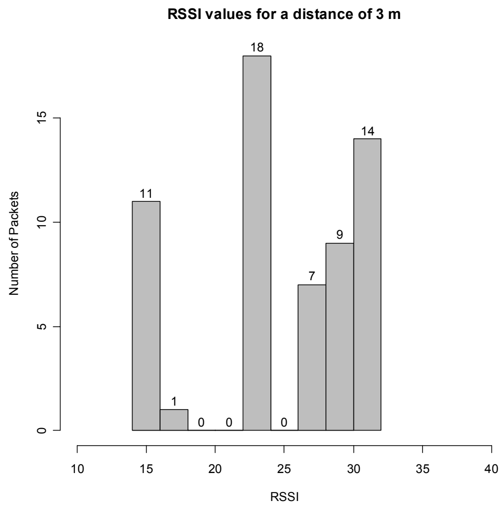

Fig 5. RSSI measurement for 3m

about 20m. For indoor localization, the transmission power should be adapted to cover the complete RSSI, so that one can expect sharp demarcations also between small distances. If the transmission power is regulated to the lowest value (-20 dBm), then the effective range lies below 1m, which is too small for distance measurement purposes. In an experiment, we compared a medium transmission power (-4 dBm) to the full transmission power as used before. Again, we measured distances of 1m and 3m.

From Fig 6 and Fig 7, it could be recognized that there is a clear shift of the range of values toward the higher RSSI. Especially for the 3m experiment, the desired effect occurred. The statistics show clear changes in the recorded values.

However, we will describe later that a simple interpolation between two reference values is not sufficient to reach an adequate illustration of the RSSI on the distance.

D. Adjustment of the frequency

In the next attempt, two different frequencies of 863.5MHz (λ 0.3474m) and 869.9MHz (λ 0.3449m) are compared regard-

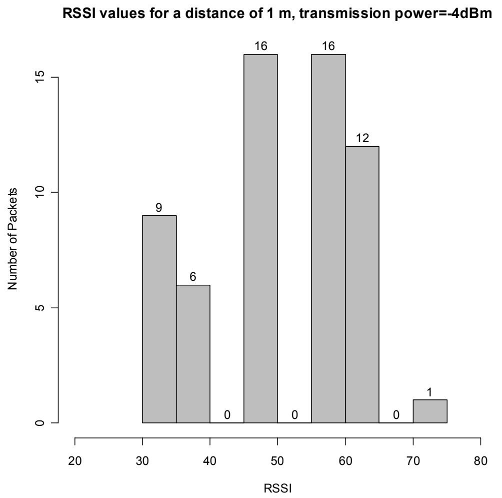

Fig 6. RSSI measurement for 1m, transmission power -4 dBm

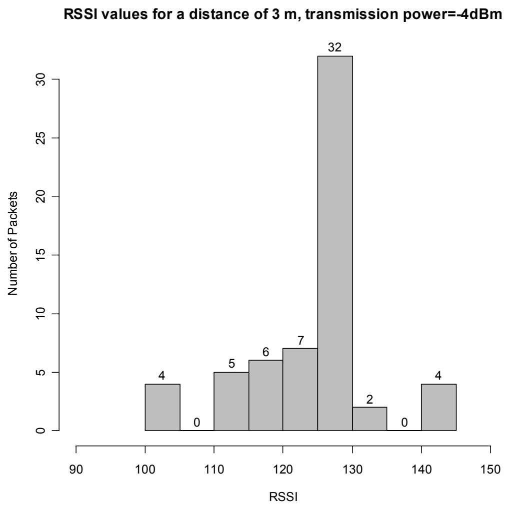

Fig 7. RSSI measurement for 3m, transmission power -4 dBm

ing the quality of distance approximations. In this experiment, a number of measurements were done automatically by the robot. It drove over a distance of 5m in steps of 50cm toward a sensor node. In each step, it requested 60 packets on the two frequencies and stored the RSSI values. The results are depicted in Fig 8 and Fig 9.

During this experiment, a high standard deviation is recognizable in the range between 2.0 and 3.0m for the lower frequency. Thus, the median is less meaningful regarding the distance, even if it rises almost straight-lined over a wide range with increasing distance. The minimum represents a much better distance indicator.

The RSSI values of the higher frequency exhibit a smaller difference between maximum and minimum for each individual step. The standard deviation of this series of measurements is small for all distances. With exception of the first and last hops minimum and median ascend with increasing the distance. Two further series of measurements, which were accomplished with higher transmission power however under the same conditions, exhibited a very similar pattern regarding the standard deviation. It is clear that the higher the standard deviation the more uncertainty during the distance estimation.

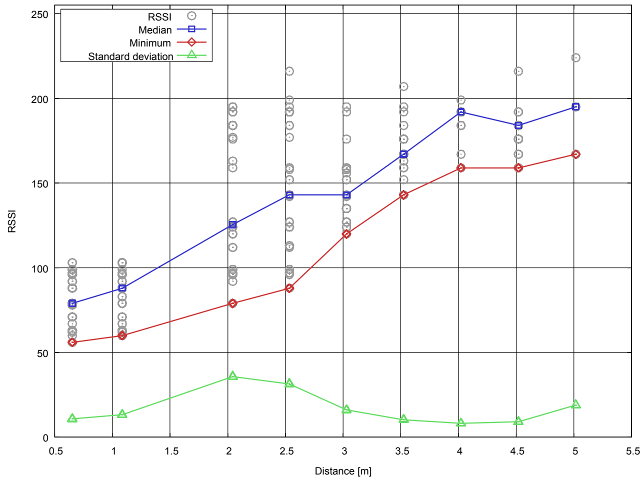

Fig 8. RSSI values measured at 863.5MHz

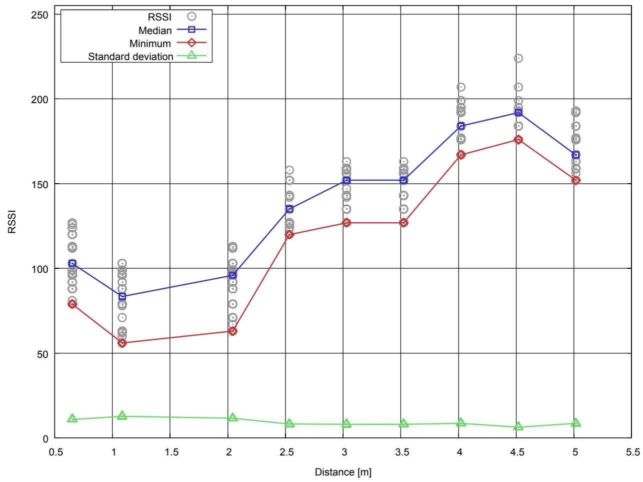

Fig 9. RSSI values measured at 869.9MHz

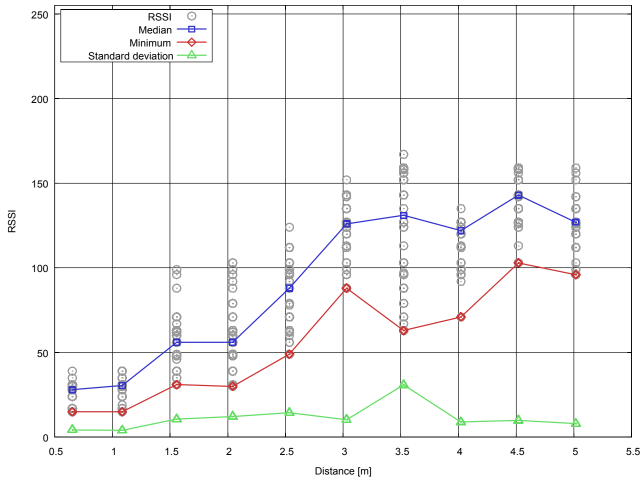

Fig 10. RSSI values measured during rotation

E. Change of Orientation

In the past experiments, the orientation of the robot and thus the alignment of the receiver node relative to the transmission node was always the same. Since a localization procedure needs data from many sensor nodes, which may stand in arbitrary alignment to the robot, we needed to examine whether the change in the orientation of the sensor node changes the RSSI values. It turned out that the standard deviation increased in the case of rotation. During each measurement, the robot rotated 180° to the left then 360° to the right; finally it goes back on the starting position. This rotation finally leads to a substantial advantage (Fig 10): using again the minimum of the RSSI measures, it is possible to overcome orientation effects – while the standard deviation of the measured values obviously increased. Thus, the experiment shows that a measurement without consideration of the orientation would be incomplete.

F. Smoothness of RSSI measurements

A further important aspect is the resolution of the RSSI. In order to evaluate the quality of the RSSI to distance mappings, measurements must be done in much smaller steps. In the following experiment, the distance increment of the robot is reduced to 10cm per step resulting in altogether 50 measurements, each one for 60 packets. Additionally, the robot rotated with each measurement around its axis.

The results as depicted in Fig 11 show that it needs about 0.5m to see somewhat higher RSSI values. In all measurement groups, a strong increase of the standard deviation and the maximum RSSI can be observed. These values should not be considered for the compensation calculation.

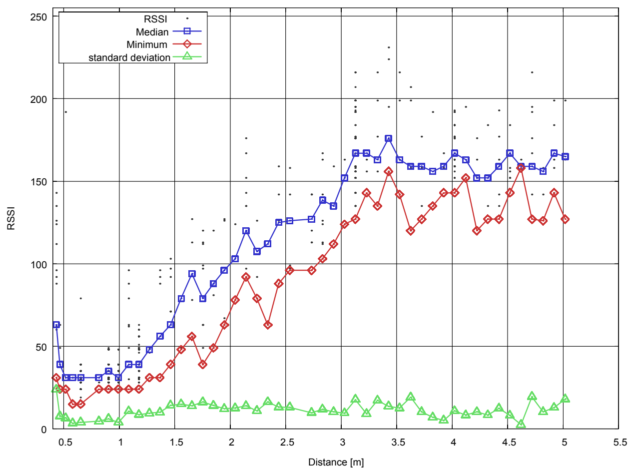

Fig 11. RSSI measures using 10cm step size

In the ranges between 0.5m and 1.0m as well as between 3.5m and 5.0m, the RSSI hardly contains information about the distance. The measured value stagnates or oscillates without a tendency. However, between 1.0m and 3.5m, the measured values seem to be meaningful.

V. Distance Approximation

In order to approximate the distance between two nodes, we compared two methods as discussed in the following.

A. Linear and exponential regression

The method for distance estimation is based on the comparison of the characteristics of descriptive data, e.g. the average, median, and quantiles. The average value appears however as less suitable, since only small packet quantities are regarded and, thus, arising peaks could distort the result. Therefore, we used only the minimum, the median, and the 25% quantile.

If we want to describe the measured RSSI values functionally, we need an illustration, which represents as exactly as possible the distances for measured RSSI values. For this function the statistic data of the RSSI form the input and the associated distance the output. In our experiments, we recognized that the data can be best described by a linear or exponential function as shown in Fig 12.

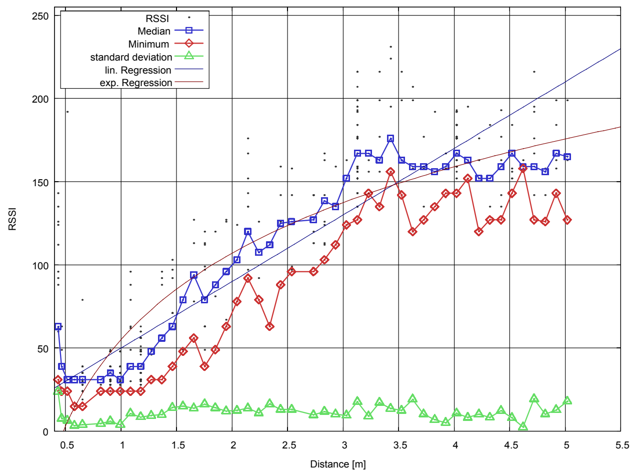

Fig 12. Linear and exponential regression based on the median of the measured RSSI values

B. Estimation using artificial neural networks (ANNs)

ANNs are biologically inspired classification algorithms. They try to simulate the human brain. Our brain consists of about 10 billion neurons; each neuron connected to about 10,000 other neurons through dendrites (inputs) and axons (output). At each neuron, the inputs are to be summed, if the summation of the inputs is greater than a threshold, then the neuron fires, and an output signal to the next neuron is generated. The inputs have different effects on the outputs depending on the synapse so some inputs have excitatory effects and others have inhibitory effects. The strengths of the inputs is determined by the weights in ANN. Feed forward artificial neural networks perform signal processing without possible feedback, thus, the signals flow from the inputs to the outputs of the network through several layers of neurons.

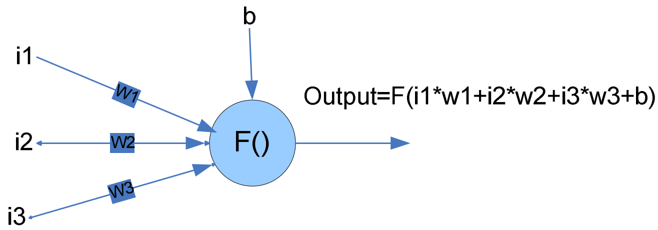

Fig 13. A single processing element in ANNs

The neuron is the basic processing element; the output of the neuron is a function of the inputs as shown in Fig 13. W_i is the weight, and b is a bias, which is corresponding to the threshold in the biological neural network. F() is called activation function.

The weights are to be determined in the learning process. This learning is either supervised or unsupervised. Samples with inputs and outputs are needed in the supervised leaning, while in the unsupervised are only the inputs needed. In this paper, we used supervised learning to train the network to estimate the distance based on the RSSI values, so the inputs are RSSI values and the output will be the estimated distance. Back propagation is the common used learning method in feed forward neural network. The error is to be back propagated to adjust the weights to reduce the error between the actual output and the estimated output.

Our neural network is implemented using MATLAB. We used an ANN with 60 inputs and one hidden layer with 20 neurons and one output. The sigmoid function is employed as activation function for hidden layer and liner activation function for output layer. The weights and biases are optimized using the Levenberg Marquardt optimization method.

VI. RSSI BASED LOCALIZATION

In this section, we show the applicability of the RSSI based distance measurement for localization. The basic localization method as used in our experiments is multilateration. Due to the limited space, we only describe the basics of trilateration, i.e. multilateration based on three measurements. Afterwards, a number of experimental results are provided.

A. *Trilateration*

If we need to estimate the location of a node based on known node, the position of this node is computed by the solution of a set of equations. The most common localization algorithm is the Trilateration as depicted in Fig 1.

If the distances are known to at least three reference objects, one can set up a system of circle equations. Given the positions of three known anchor nodes $M_i=(x_i,y_i)$, the following equation system must be solved to get the search position $P=(u_x,u_y)$:

$$(u_x - x_1)^2 + (u_y - y_1)^2 = r_1^2$$
$$(u_x - x_2)^2 + (u_y - y_2)^2 = r_2^2$$
$$(u_x - x_3)^2 + (u_y - y_3)^2 = r_3^2$$

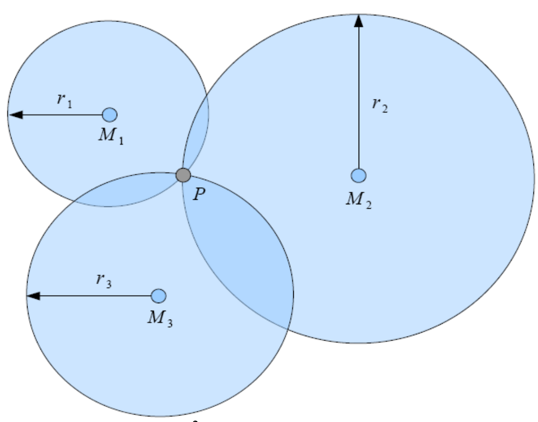

Fig 1. Trilateration in R^2

B. *Experimental results*

In our experiments, seven nodes (BTnode2 … BTnode9) are placed on the ground of our lab. We analyze the results of the localization system for six different positions (A … F). We tuned the system parameters to the values we tested in the past experiments. The robot requests 60 packets from each node. This setup is depicted in Fig 2.

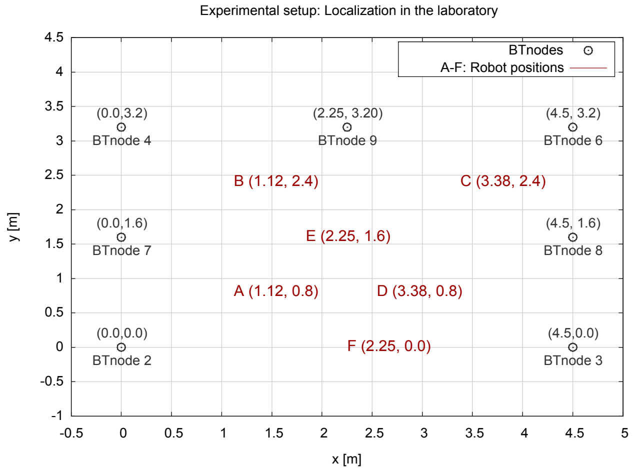

Fig 2. Experimental setup for localization including anchor nodes (BTnode2 … BTnode9) and searched positions (A … F)

1) *Typical results*

Table II contains a comparison between actual and estimated distances for position A for all considered regression curves. In particular, we evaluated linear and exponential regression using the minimum, the median, and the 20% quantile of the measured RSSI values. The table shows the real and the estimated distance to all sensor nodes. Additionally, the average estimation error is included in the table (last line). It is clear from this table that median based with linear regression has the smallest error compared to the other statistics and regression methods.

Table II. MEASUREMENT RESULTS FOR POSITION A

A Node	Dist. D(m)	Distance estimations with regression Min., Lin.	Min. Exp.	Med. Lin.	Med. Exp.	Qua. Lin.	Qua. Exp.
2	1.38	1.38	1.21	1.34	1.46	1.61	1.34
3	3.47	1.82	1.48	2.25	1.80	2.20	1.77
4	2.65	1.66	1.38	1.77	1.43	1.62	1.34
6	4.14	2.64	2.18	2.99	2.57	2.72	2.26
7	1.38	1.38	1.21	1.09	1.03	1.34	1.17
8	3.47	3.54	3.32	3.68	3.59	3.58	3.40
9	2.65	1.66	1.37	1.64	1.34	1.48	1.26
$\sum \Delta d/n$	0	0.74	0.99	0.69	0.90	0.75	0.94

After training the artificial neural network using the data of some calibration measures, the ANN was used to estimate the distances to the anchor nodes similar to the regression techniques. The estimated distances for node A are shown in Table III. Obviously, the estimation error of the ANN is comparable to the statistical methods.

Table III. DISTANCE MEASUREMENT FOR POSITION A USING THE ANN

A	Dist.	Distance estimation
Node	D(m)	ANN.
2	1.38	2.06
3	3.47	3.71
4	2.65	1.88
6	4.14	3.28
7	1.38	0.42
8	3.47	3.42
9	2.65	2.06
∑Δd/n	0	0.60

We finally used the multilateration technique to estimate the location of the particular node in the environment. We tested the impact of the number of anchor nodes for the quality of the position approximation by using between four and seven anchor nodes for the multilateration process.

Fig 3 shows the location information for position A using 4, 5, 6, or 7 anchor nodes, respectively. As can be seen, the localization quality is quite high. Actually, position A represents a typical example for the position quality. In the following, the best and worst cases are described.

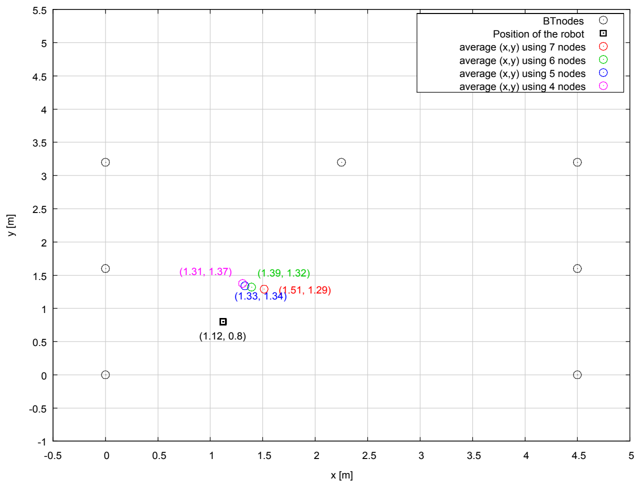

Fig 3. Position estimation for position A

2) *Worst case: position B*

The position computation for position B is based on a maximum of six instead of seven distance estimations. The localization process is completely automated and it may occur that any node is unavailable for the distance measurement process. We did not correct this consciously, since in the reality the occurrence of node failure is not rare. Table IV shows the distance estimation and Fig 4 depicts the corresponding average localization. Obviously, the quality of the distance measurement is comparably bad in this example. The average distance estimation error is about 0.8m resulting in high localization errors. Interestingly, the distance estimation using the ANN approach is much better in this example. Nevertheless, in average, both methods produce estimations with the same quality and error range.

Table IV. DISTANCE MEASUREMENT FOR POSITION B (WORST CASE)

B	Dist.	Distance estimation	
Node	D(m)	Med. Lin.	ANN
2	2.65	2.91	2.43
3	4.14	3.03	2.44
4	1.38	0.92	1.05
6	3.47	3.10	3.86
7	-	-	
8	3.47	2.94	3.45
9	1.38	2.41	1.58
∑Δd/n	0	0.80	0.48

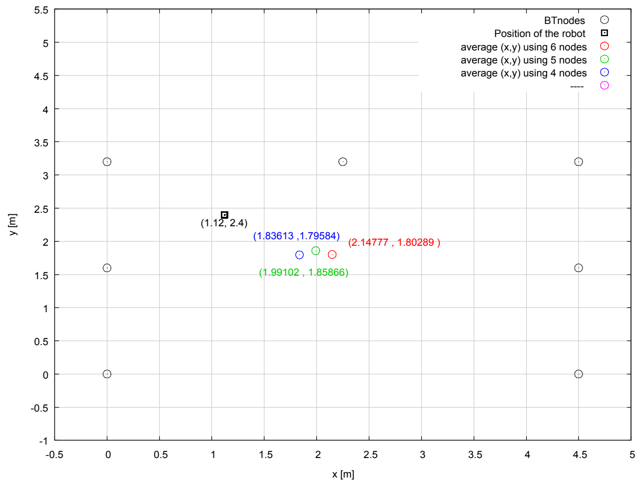

Fig 4. Position estimation for position B

3) *Best case: Position D*

Position D supplies the best results despite high dispersion over the averaged coordinates of all calculated positions. Table V shows the results for the distance estimations for position D. In this case, the regression method provides distance estimations with an average error of less than 0.5m. This result is quite encouraging compared to measures that can be found in the literature. In this specific case, the ANN was not able to produce high quality estimations as the average estimation error was about 1m. We need to further study possible combinations of the statistical regression methods with "fuzzy" approaches such as the ANN.

Finally, Fig 5 depicts the localization quality for the best case measurement, position D. Obviously, all the estimations perfectly approximated the right position.

Table V. DISTANCE MEASUREMENT FOR POSITION D (BEST CASE)

D	Dist.	Distance estimation	
Node	D(m)	Med. Lin.	ANN
2	3.47	4.15	5.0
3	1.38	1.04	0.51
4	4.14	3.15	3.55
6	2.65	1.48	0.71
7	3.47	3.16	3.44
8	1.38	1.14	1.73
9	2.65	2.67	4.31
∑Δd	0	0.54	0.99

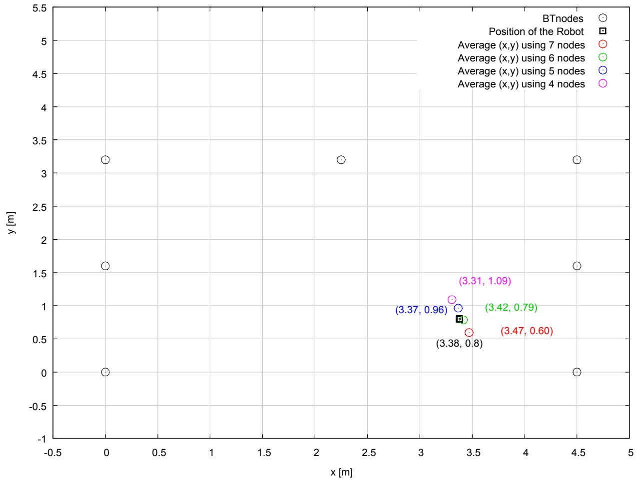

Fig 5. Position estimation for position D

VII. CONCLUSION

In conclusion, it can be said that a huge number of parameters must be considered for high quality distance estimation and, therefore, localization in wireless sensor networks using the received signal strength indicator. In particular, we identified the following parameters, which affected the distance measurement to a certain degree:

- The used transmission power
- The radio frequency
- The node orientation, i.e. antenna characteristics
- The localization algorithm
- The quality of the reference measurements

Based on these findings, we developed an adaptive testbed for distance measurements and localization experiments. In our opinion the most important factor for proper distance estimation is to choose a transmission power according to the relevant distances. If the power is too high the RSSI differences between different distances are not significant enough for a good interpretation – if it is chosen too small far-field effects take place for short distances already leading to calibration data containing only little distance information.

It is also important to take care of the chosen frequency for the localization setup. Our experiments have shown that some frequencies are more vulnerable to disturbances than others. But it can be assumed that this observation is individual for different orientations and positions of the robot in the test setup. Therefore it is desirable to compare the measurements of different frequencies not only prior but also during the localization to get the best possible results.

Depending on the quality of the antennas a RSSI based localization system must also take the bi-directional orientation of sensor-nodes into account.

On the other hand we made the experience that the localization algorithm itself and the preparation and interpretation of calibration data does not take much influence on the quality of position estimation. In additional experiments we also averaged the position results over all possible combinations of distance information (similar to GPS) which did not improve the results significantly.

The (well-known) major problem is that RSSI values do not necessarily contain any distance information. However we showed that even for noisy indoor environments an average positioning error of 50cm on an area of 3.5 x 4.5 m is possible by choosing the RF and algorithm parameters carefully based on empirical studies.

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