SIMULATION OF ROBOT-ASSISTED WSN LOCALIZATION USING REAL-LIFE DATA

Michał Marks*, Ewa Niewiadomska-Szynkiewicz*,**
* Research and Academic Computer Network (NASK)
Wawozowa 18, 02-796 Warsaw, Poland
and
** Institute of Control and Computation Engineering
Warsaw University of Technology
Nowowiejska 15/19, 00-665 Warsaw, Poland
Email: mmarks@nask.pl, ewan@nask.pl

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ABSTRACT

The paper concerns the problem of robot-assistance in localization of stationary nodes in Wireless Sensor Networks (WSN). In our work, we present a simulation of localization process based on real-life data obtained during experiments. The paper describes classical localization algorithm – multilateration, however this algorithm is run not only on raw distance estimates but also on distance estimates obtained after application of specialized filtering procedures. A provided case study demonstrates the localization accuracy obtained for a robot localizing three stationary nodes during it's movement along example path.

INTRODUCTION

Localization of moving objects is one of the fastest developing topics in the field of wireless communication. The domain which few years ago was a point of interest mostly researchers working in robotics, now becomes more and more popular in other fields. The idea of providing information about mobile user position especially in indoor environment attracts attention not only researchers, but first of all a huge number of companies. They hope this technology will open for them a new advertisement market. As a confirmation one can look at the well known localization contest organized in recent years by Microsoft co-located with IPSN conference (International Conference on Information Processing in Sensor Networks). The best solutions published last year provided means and algorithms allowing to locate user with localization error lower than half of meter (see Dewberry and Petroff (2015); Sánchez et al. (2015); Lazik et al. (2015)).

The obtained accuracy is impressing. However there is one disadvantage – each of this solutions require highly specialized devices and techniques to achieve such accuracy. For example Sanchez et al. propose to build a map of the environment. Their system employs a high definition point cloud generated by pair wise registration of laser scanner acquisitions, yielding accurate maps consisting of 3D points, normals and (optionally) colors. As a consequence this method can by applied only in environment where specialized mapping procedure was done earlier. Overcoming this drawback is difficult and usually influence worse accuracy, however the survey paper published by Liu et al. (2007) outlines at least few methods applying Received Signal Strength (RSS) measurements for localization of moving objects.

High localization quality obtained by our High Performance Localization System (HPLS) in case of static networks (see Marks et al. (2014)) encouraged us to validate by simulation the possibility of localizing moving object in WSN environments. The simulation is done numerically but is based on real-life data registered in existing network composed by set of Crossbow MicaZ nodes.

This paper is organized as follows. Section II explains all aspects of collecting and processing RSSI data from testbed networks. Section III introduces the localization task formulation. Next this task in solved using localization scheme described in Section IV. Section V presents some numerical results obtained in our test network. Finally, Section VI concludes the paper and gives possible future directions for research on robot-assisted wireless positioning.

REAL-LIFE RSSI DATA

Received Signal Strength Indicator (RSSI) is considered to be a simplest and cheapest method amongst the wireless distance estimation techniques, since it does not require additional hardware for distance measurements and is unlikely to significantly impact local power consumption, sensor size and thus cost. Main problem in application RSSI is low accuracy. According to well-known wireless channel models (described in next section) received power should be a function of distance. However, the RSSI values have a high variability and it's difficult to use them as a distance estimator (see Benkic et al. (2008); Ramadurai and Sichitiu (2003); Marks and Niewiadomska-Szynkiewicz (2011)).

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The radio signal propagation modeling

Propagation models are generally focused on predicting the average received signal strength at a given distance from the transmitter, as well as the variability of the signal strength in close spatial proximity to a particular location. Propagation models that predict the mean signal strength for an arbitrary transmitter-receiver separation distance are useful in estimating the radio coverage area of a transmitter and are called *large-scale* propagation models, since they characterize signal strength over large distances (hundreds or thousands of meters). On the other hand, propagation models that characterize the rapid fluctuations of the received signal strength over very short travel distances or short time durations are called *small-scale* models (see Rappapport (2002)).

In this paper we do not concentrate on small fluctuations of the signal strength in time. Hence the large-scale model is used further. Rappapport (2002) and many other authors claim that both theoretical and measurement based propagation models indicate that average received signal power decreases logarithmically with distance, whether in outdoor or indoor radio channels. The mean large-scale path loss can be expressed as a function of distance:

$$PL(d)[dB] = PL(d_0)[dB] + 10nlog\left(\frac{d}{d_0}\right), \qquad (1)$$

where d is the transmitter-receiver distance, d_0 is a reference distance (for IEEE 802.15.4 radio typically the value of d_0 is taken to be 1 m) and n is the path loss exponent (rate at which signal decays). The value of n depends on the specific propagation environment and should be obtained through curve fitting of empirical data. Many authors, including Gibson (1999), indicate an empirical experiment as the best way to select an appropriate path loss for the reference distance d_0.

The received signal strength P^r at a distance d is:

$$P^r(d)[dBm] = P^t[dBm] - PL(d)[dB], \qquad (2)$$

where P^t denotes the power of transmitter.

Data collection

The data collection procedure was done by Jarosław Śmietanka – Warsaw University of Technology student during his thesis preparation (see Śmietanka (2015)). All series of experiments were done outside, in the field 10m x 10m. The MicaZ nodes were placed on wooden sticks 1.8 m tall. Two types of experiments were carried out. The first series was dedicated to measure RSSI values characterizing signal propagation between one mobile node and each of stationary nodes. As a result signal characteristics for three pairs of nodes were collected – they are described in *Training stage: RSSI-distance relationship identification* subsection. The second series of experiments was done assuming scenario with one mobile node moving around the whole test area and exchanging messages with three stationary nodes. This series of experiment is described in subsection *Testing stage: Tests on a full grid*. Figure 1 demonstrates the testbed configuration.

Training stage: RSSI-distance relationship identification

As it was written in previous subsection, the first experiment was dedicated to measuring RSSI values characterizing signal propagation between one mobile node and each of stationary nodes. The aim of this experiment was identification of relationship between distance separating nodes and values of Received Signal Strength. At the beginning separation distance between nodes was equal 1 meter. Later it was extended one by one by 1 meter up to final separation distance equal 10 meters. The experiments confirmed the high variability of RSSI signal – what is illustrated in Figure 2. As it can be seen for mobile node and *stationary node #1* the registered values are not monotonous. For example the signal strength equal -75 dBm was observed both for distance equal 5 and 7 meters, while for 6 meters the signal was stronger (-73 dBm). Of course the presented values represents mean values for a series of 20-30 radio signal measurements.

Fig. 1. Testbed configuration for RSSI data acquisition.

Although the fluctuations of the signal strength make localization much more difficult, we decided to build the RSSI-distance relationship model and check how this fluctuations impose localization process. Similar results were observed by us earlier – Marks et al. (2014) and they didn't prevent us from obtaining high localization accuracy. The RSSI-distance modelling was done using OLS scheme (see Marks and Niewiadomska-Szynkiewicz (2011)).

Using (1) and (2) we can estimate the average distance between nodes i and j as a function of received signal strength P^r_{ij}:

$$\tilde{d}_{ij} = d_0 \cdot 10^{\frac{P^t - PL(d_0)}{10n}} \cdot 10^{-\frac{1}{10n}P^r_{ij}}, \qquad (3)$$

where d_0 denotes the reference distance, $PL(d_0)$ the path loss at the reference distance, n the path loss exponent and P^t output power of the transmitter. It should be pointed that the goal of the calibration procedure is only to predict a value of the distance d_{ij} for known value of P^r_{ij}, not to find the exact value of the parameters $n, P^t, d_0, PL(d_0)$. Hence, we can simplify the equation (3) introducing parameters η and θ:

$$\tilde{d}_{ij} = \eta \cdot 10^{\theta \cdot P^r_{ij}}, \qquad (4)$$

where $\eta = d_0 \cdot 10^{\frac{P^t - PL(d_0)}{10n}}$ and $\theta = -\frac{1}{10n}$. It seems to be reasonable to fit the RSSI-distance curve based on two parameters not four.

It is obvious that this average distance differs vastly from the true physical distance between selected nodes, but there is no chance to fit the curve describing signal propagation to all

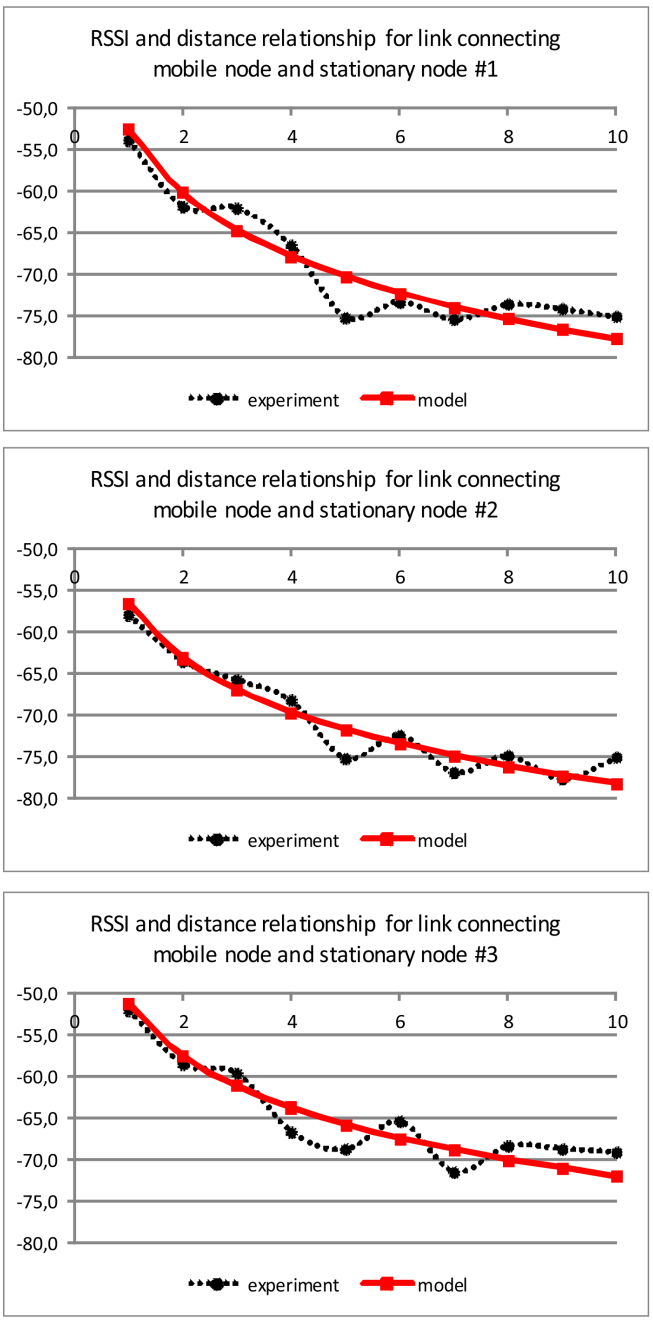

Fig. 2. Distance-RSSI relationship for Mobile node and particular anchors.

samples. An ordinary least square (OLS) method can be used to calculate values of parameters η and θ that minimize the error between the true physical and estimated distances:

$$\min_{\eta_{ols},\theta_{ols}} \sum_{(P^r_{ij},d_{ij})\in\Psi} \left(\eta_{ols}\cdot 10^{\theta_{ols}\cdot P^r_{ij}} - d_{ij}\right)^2. \tag{5}$$

Obtained RSSI-distance curves are illustrated in Figure 2 by red lines.

Testing stage: Tests on a full grid

Using nomenclature from Machine Learning field the aim of training stage is building models which are later validated in testing stage. In the considered experiment the situation is very similar. The propagation models achieved as a solution of optimization task (5) creates basis to estimate distances in more realistic scenario. The estimation is done separately for each pair (mobile – stationary node). In this scenario, as it was written earlier, mobile node moves around the whole test area and exchanges messages with three stationary nodes. To be precise, by moving around, we understand a set of measurements which are done on a grid 10m x 10m with cell equal 1m x 1m. As a result at the end of this stage there are 121 locations with known distances between them and every stationary node. The experiment configuration is very similar to the one described by Bulusu et al. (2000).

LOCALIZATION TASK FORMULATION

For the purpose of simulation the robot-assisted localization we assume that the location of robot is known in each point of its trajectory and locations of three stationary nodes are unknown. The aim of localization process is determining the positions of stationary nodes with the minimal displacement. Without any information about relationship between stationary nodes the localization of each node can be treated independently. Hence, the average localization error can serve as the localization quality indicator.

Let's define the robot trajectory (path) A as a set of K points:

$$A = a_1, a_2, ..., a_K, \tag{6}$$

where the distance between two neighbouring points is equal one meter:

$$\bigvee_{k=2,\dots,K} ||a_k - a_{k-1}|| = 1. \tag{7}$$

Therefore the localization task can be expressed as:

$$\min_{\hat{x}} J = \frac{1}{M}\sum_{i=1}^{M}\sum_{k=1}^{K}(||a_k - \hat{x}_i||_2 - \tilde{d}_{k,i})^2 \tag{8}$$

where M is the number of stationary nodes, $\hat{x}_i$ denotes estimated positions of node i and $\tilde{d}_{k,i}$ distance between pairs of nodes (k, i).

LOCALIZATION SCHEME

Classic Approach – Multilateration

The most intuitive approach to solve the task defined in (8) is to use collaborative multilateration algorithm described by Savvides et al. (2001). The idea of algorithm is very simple and it can be expressed as a minimization of differences between measured distances and distances resulting from estimated nodes locations:

$$\bigvee_{i=1,\dots,M} \min_{\hat{x}} \sum_{k=1}^{K}(||a_k - \hat{x}_i||_2 - \tilde{d}_{k,i})^2 \tag{9}$$

Real-data filtering

Multilateration is a widely used and popular algorithm in WSN localization, however it's accuracy is not impressive for noisy measurements. Unfortunately in case of localization problem defined in previous section there is no place for algorithms utilizing the information about all connections in the network, which are much more precise, as the one described by Marks et al. (2014).

Therefore the only factor influencing localization accuracy which can be improved is the measurements quality. To be precise, not exactly measurements quality as we cannot change the data which are already obtained from real-life deployment, but the measurements can be filtrated to form a smooth curve. This is the consequence of condition (7) which limits possible changes in distances between stationary node x_i and two point on the path a_k, a_{k+1} to 1 meter. Only if the mobile node is going straight in direction of node s_i the distance is equal 1 meter. The general condition can be express as:

$$\Big| ||d_{k,i} - d_{k+1,i}||_2 \Big| \leq 1 \tag{10}$$

In the proposed localization scheme the condition (10) is realized by application of two smoothing functions. The aim of the first one (peak-filter) is limitation local peaks in distances for subsequent a_k points. The second function applied after realization of (peak-filter) is (local-change-filter) which limits too big differences in subsequent distances values.

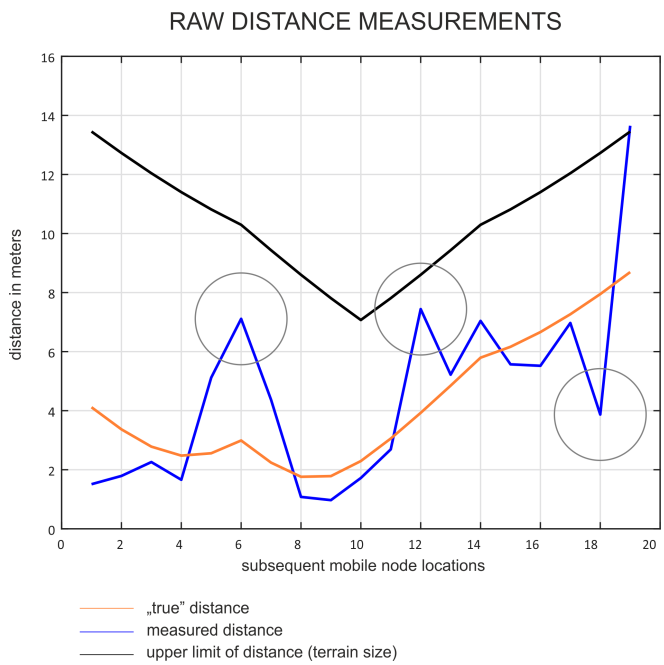

Fig. 3. Raw distance measurements obtained for subsequent mobile nodes positions.

To illustrate what is the distance filters purpose let's analyze the raw distance measurements obtained for subsequent mobile nodes positions and stationary node #1 – Figure 3. The grey circles denotes the highest peaks. The peak-filter identifies all peaks in the curve and limits them starting from the most significant one. By significance we mean the absolute difference between values of distances for current, previous and next mobile node positions. How strict is the peak-filter function depends on the tolerance parameter which determines which absolute differences of distances are acceptable and which values should be corrected. Additionally peak-filter function utilize information about upper limit of distance – which is determined by terrain size. The node which is localized must be inside the searching field. The Figure 4 presents how the distance curve looks like after applying peak-filter – in upper part and after applying both filters in lower one.

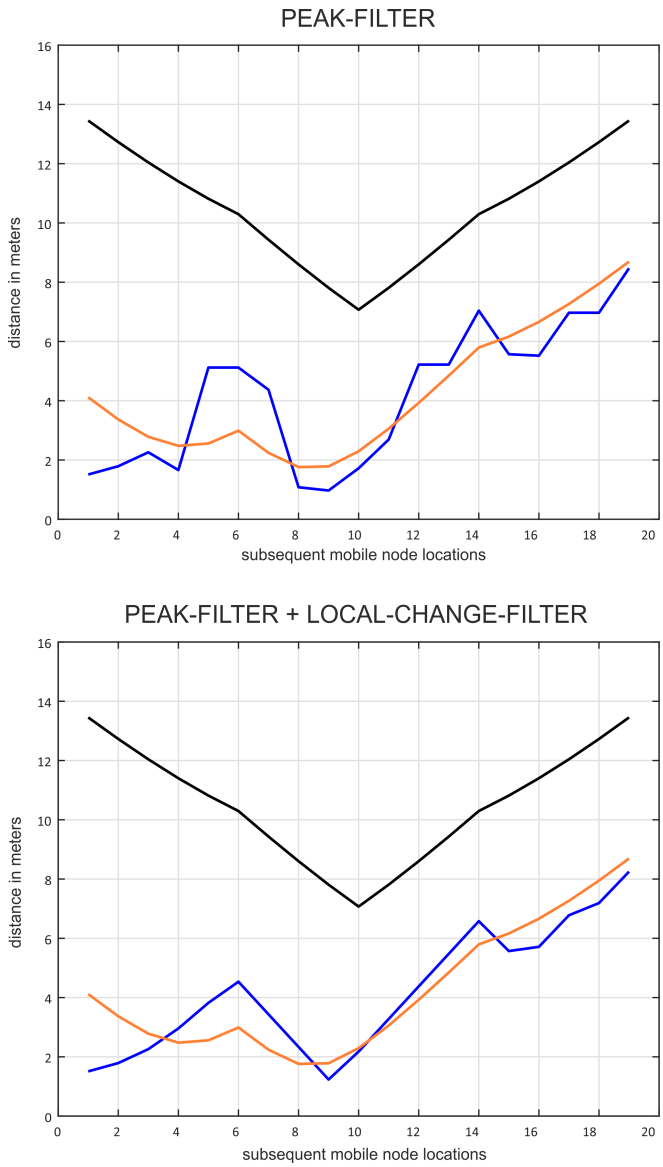

Fig. 4. Filtrated distance measurements obtained for subsequent mobile nodes positions.

The local-change-filter is used to determine and reduce changes in distances for subsequent mobile nodes positions occurring in monotonous function range. Similarly to peak-filter also local-change-filter behaviour depends on the tolerance parameter which determines what absolute differences of distances are acceptable and what values should be corrected.

NUMERICAL RESULTS

For the purpose of localization schemes evaluation the path composed of 19 locations was selected. The considered mobile node path is presented in figure 5. True locations of three stationary nodes are marked with blue (node #1), red (node #2) and green (node #3) triangles. The mobile node started in the bottom-left corner and moved to upper-right one. First attempt to localize stationary nodes was taken after visiting first four locations. Later the process was repeated until achieving the last location by mobile node. The final solution – after visiting all locations is presented in Figure 6. Figure 6a shows the locations obtained using raw distance measurements, while the Figures 6b and 6c illustrate locations found after localization method run on filtrated data – respectively after peak-filter and peak-filter + local-change-filter application. The shorter are lines connecting true locations (marked with triangle) and estimated locations (marked with squares) the better are location estimates. The quality of location estimates for different distance measurements (raw and filtrated) is presented in Table I. As it can be observed application of filtering process improves the localization quality, however for particular node the location error can be higher in comparison to RAW distance measurements – node #2. In general application of smoothing functions resulted in mean localization error reduction from 2.00 to 1.03 meter.

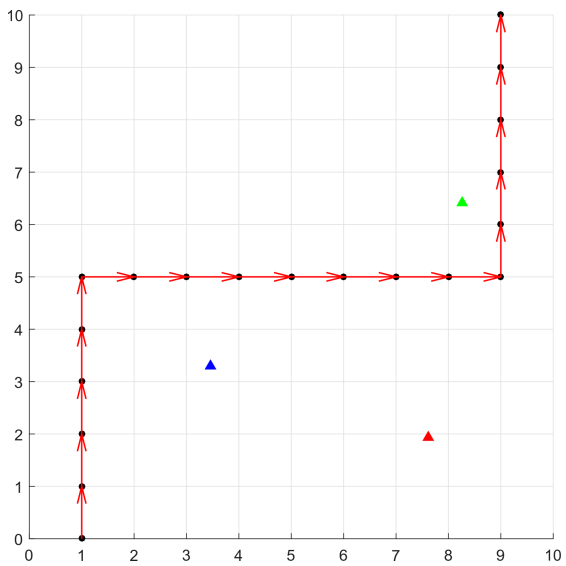

Fig. 5. Mobile node test path.

TABLE I. LOCALIZATION ERRORS FOR STATIONARY NODES 1-3 AND DIFFERENT DISTANCE MEASUREMENTS.

Localization Error	RAW distance measurements	Peak-filter	Peak-filter Intel + local-change-filter
Node #1	2.39	0.90	0.55
Node #2	1.90	2.09	2.38
Node #2	1.70	0.70	0.17
Mean	2.00	1.23	1.03

As it was mentioned earlier the localization process was repeated along the mobile node path. The values of localization errors as a function of travelled path length are presented in figure 7. The general rule is that the more measurements

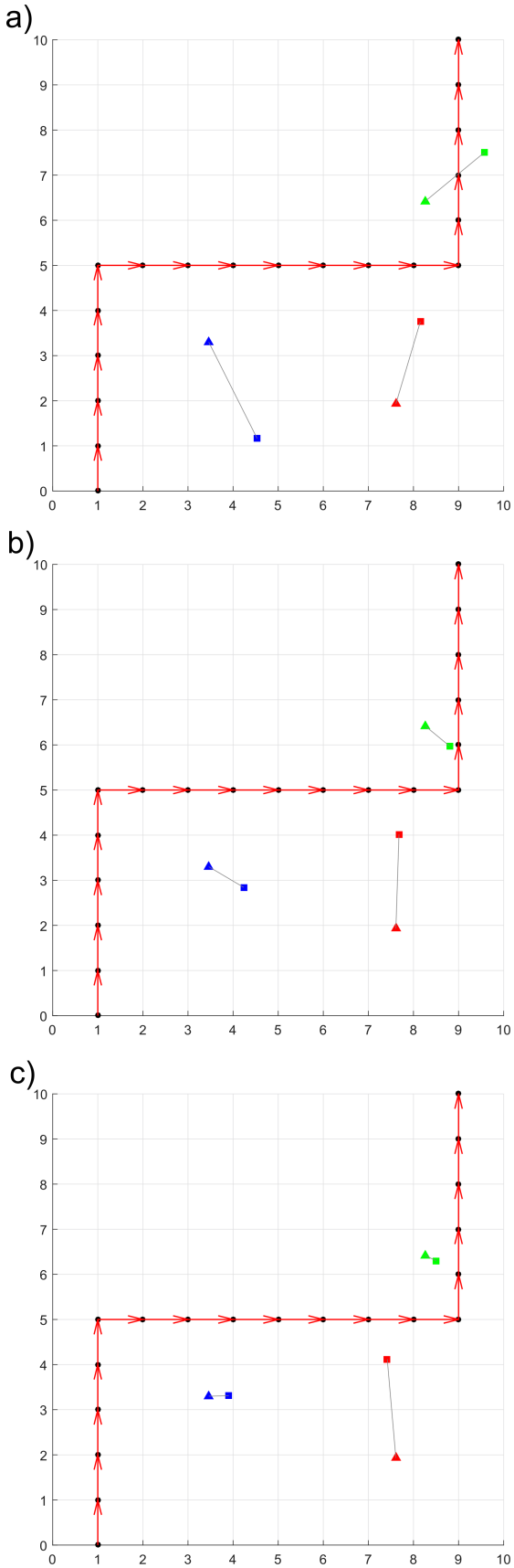

Fig. 6. Distance-RSSI relationship for Mobile node and particular anchors.

is available the more precise locations should be computed. However in some conditions the quality of localization can decrease after adding additional distance measurements which are disrupted by high measurement errors. Such situation can be observed for node #2 (red lines). The best position estimation was obtained after visiting 16 points along the mobile node path, not after 19 points. This is the result of significant underestimation of distances for the last 4 measurements – see row two in figure 8.

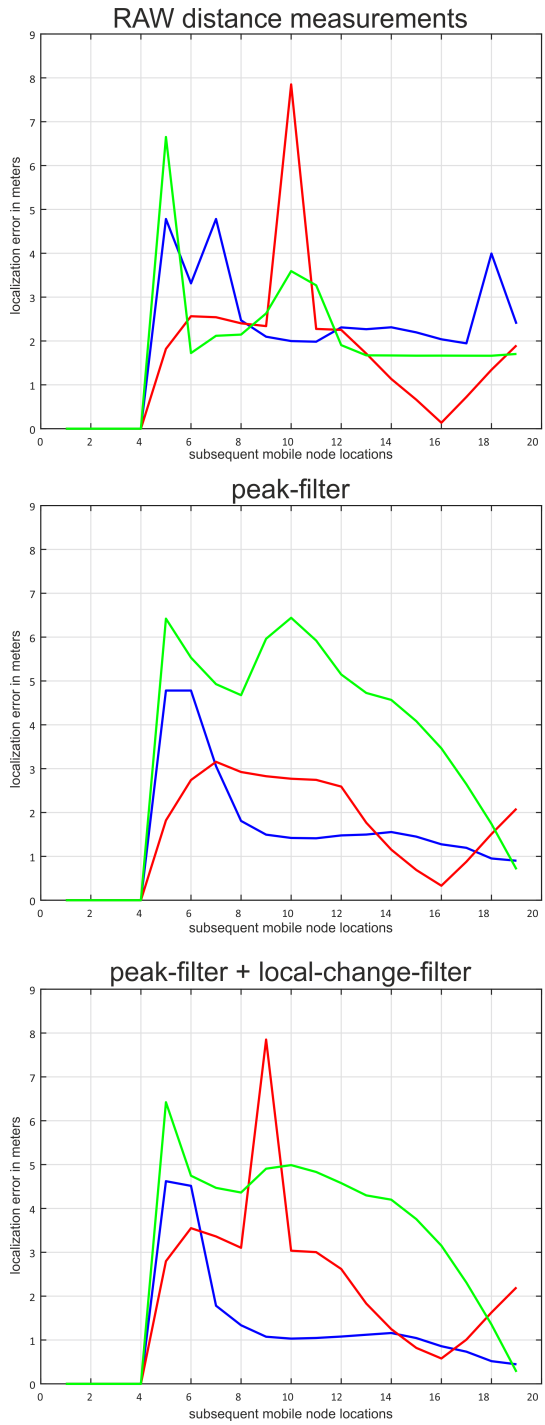

Fig. 7. Localization errors for different path length.

CONCLUSIONS

The aim of this study was simulation of robot-assisted localization in Wireless Sensor Network (WSN). For the purpose of simulation real-life data were collected and used to estimate inter-node distances exploited in further simulations. Such strategy guarantees that localization algorithms were validated in conditions not far from real-life deployments. In the same time it was possible to test localization methods for different mobile-robot paths without necessity of hardware paths realization. The main originality in our approach is incorporation of specialized smoothing filters. The proposed smoothing filters correcting distances measurements allowed on almost 50% localization error reduction in comparison to RAW distances measurements.

In the future we plan to prepare an extensive set of tests with different mobile node paths. These experiments should let us to use collected data to propose an optimal routes for mobile node, which allow us to minimize localization errors for stationary nodes.

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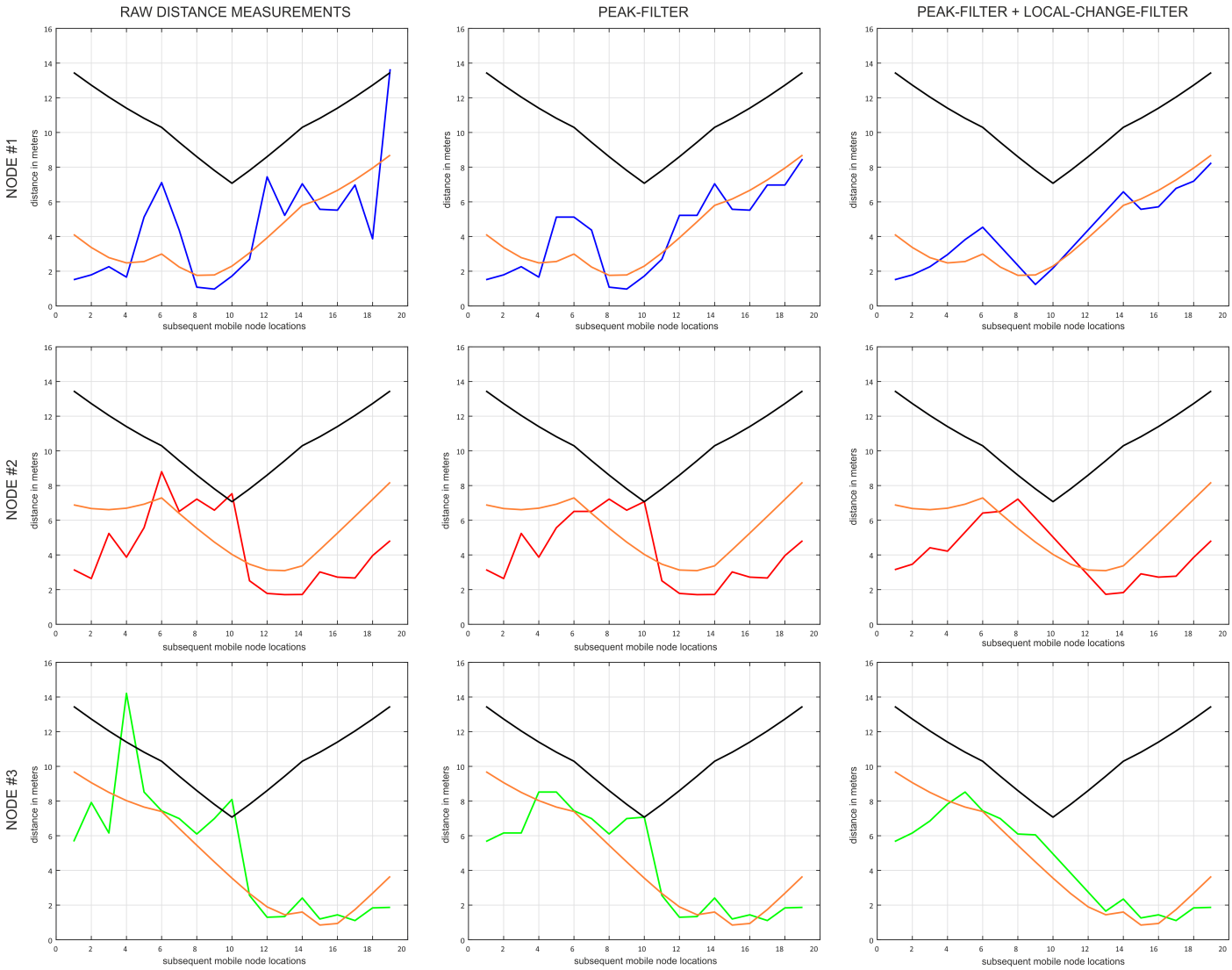

Fig. 8. Distance measurements obtained for subsequent mobile nodes positions. Each row represents distances for one stationary node. Different types of measurement – RAW and filtrated are presented in subsequent columns.

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AUTHOR BIOGRAPHIES

MICHAŁ MARKS received M.Sc. (2007) in computer science and Ph.D. (2015) in automation and robotics from the Warsaw University of Technology. Since 2007 with Research and Academic Computer Network (NASK). The author and co-author of over 30 journal and conference papers. His research area focuses on wireless sensor networks, global optimization, distributed computation in CPU and GPU clusters, decision support and machine learning. His e-mail is `mmarks@nask.pl`

EWA NIEWIADOMSKA-SZYNKIEWICZ DSc (2005), PhD (1995), professor of control and information engineering at the Warsaw University of Technology, head of the Complex Systems Group. She is also the Director for Research of Research and Academic Computer Network (NASK). The author and co-author of 3 books and over 140 papers. Her research interests focus on complex systems modeling, optimization, control and simulation, parallel computation and computer networks. Her email is `ewan@nask.pl`.