Refinement of localization results in wireless networks using weighted Universal Improvement Schemes

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3 authors, including:

Oleksandr Artemenko

Robert Bosch GmbH

Andreas Mitschele-Thiel

Technische Universität Ilmenau

Refinement of Localization Results in Wireless Networks Using Weighted Universal Improvement Schemes

Oleksandr Artemenko, Andreas Mitschele-Thiel
Faculty of Computer Science and Automation
Technische Universität Ilmenau
98693 Ilmenau, Germany
Email: {Oleksandr.Artemenko, Mitsch}@tu-ilmenau.de

Mykola Kuznietsov
Institute of Computer Systems
Odessa National Polytechnic University
65044 Odessa, Ukraine
Email: kuznetsov@ics.opu.ua

***Abstract*—In this paper, we present an extension of our concept of the Universal Improvement Scheme (UnIS) investigated in our previous work. The main focus of UnIS is to improve the localization results of unknown wireless nodes, aka mobiles, in the network with prepositioned reference nodes, aka anchors. The UnIS algorithm uses some additional information known a priori about the network. This information is represented by distances, known before the experiment, between couples of mobile nodes being localized.**

In this work, the optimization of the UnIS algorithm is proposed. According to our previous observations, we introduce a novel weighted UnIS (W-UnIS) approach that uses different weighting criteria to achieve a higher improvement ratio. We compare the effectiveness of W-UnIS scheme to its predecessor using the data collected in a deployed wireless sensor network testbed. The obtained results indicate that the localization error can be reduced significantly using our new W-UnIS approach.

I. Introduction

A. Motivation

Wireless communications have already become a very important part of our everyday life. According to this, hundreds of new applications emerge every week defining higher and higher requirements on hardware and software. Localization is one of the most crucial issues for many such applications. To keep it simple and cheap, but nevertheless accurate and robust, is still a big challenge for thousands of researchers all over the world that try to improve the location estimation process.

According to the literature, there are schemes that can be applied for the refinement of the localization results. The majority of these schemes is based on the history collected during the location estimation process. Here, the amount of various filters can be listed: Kalman Filter [1], LaSLAT (Bayesian filter) [2], Particle Filter [3], Map-filtering [4], Rao-Blackwellized particle filter [5], Gaussian Mixture Filter [6], etc. The common problems of filters are that they need many continuously measured data sequences and appropriate results are given only after some time of operation (e.g., LaSLAT: 60 seconds of tracking [2]). In some situations, fast start-up time with only little available data is required (e.g., disaster scenarios). According to the requirements mentioned above, alternative systems or additional algorithms are essential for some ad-hoc network environments.

In our previous work, new possibilities to improve the localization results have been presented, implemented, simulated and evaluated on the real testbed. All proposed solutions use some additional information known a priori about the network. This information is represented by distances, known before the experiment, between couples of mobile nodes being localized.

From [7], a practical application example of this idea is the usage of known distances between nodes attached to an object being monitored or tracked (e.g., several wireless nodes attached to an automated robot that is used in some specific industrial process and needs to be localized). If the distances between pairs of these nodes are static, they can be measured a priori and used in the improvement process to enhance the accuracy of the localization results of each node. This idea has been investigated in our previous work [7]. In this work, we proposed an Universal Improvement Scheme (UnIS) that uses known distances between nodes and improves the localization results significantly.

To further increase the robustness and accuracy of our previous algorithm, we propose with this work an optimization of the improvement process. Based on our observations, we introduce a novel weighted UnIS (W-UnIS) scheme that uses different weighting criteria to achieve a higher improvement ratio. We compare the effectiveness of W-UnIS scheme to its predecessor using the data obtained in a deployed wireless sensor network testbed.

B. Paper Organization

The remainder of this paper is organized as follows. In section II, we briefly describe the basic Universal Improvement Scheme (UnIS) and its extensions derived from UnIS as a part of our previous work. Section III introduces new W-UnIS schemes and their mathematical models. Thereafter, section IV describes the developed testbed, received results and analysis of them. Finally, Section V concludes this paper.

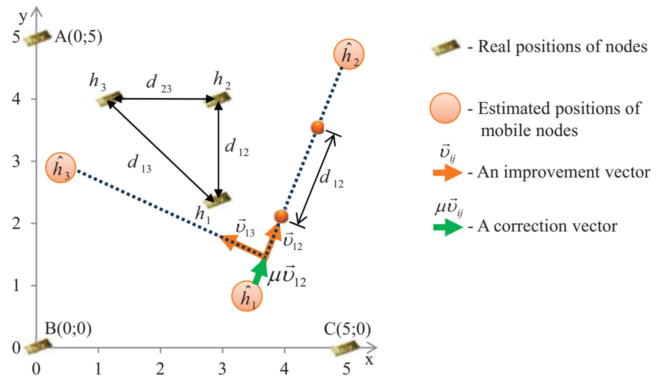

Fig. 1. P-UnIS improvement example for a network with three anchors and three mobiles

II. Previous Work

After the initial position calculation step of the localization process is complete and the first estimates of nodes' positions are available, the so called postimprovement step can be conducted to increase the accuracy of the location estimation. To do this, we apply UnIS refinement [7] that uses distances between mobiles, known a priori (e.g., d_{12}, d_{13}, d_{23} between mobile nodes h_1, h_2 and h_3 in Fig. 1).

The basic step in the improvement is represented by pairwise recalculations of position coordinates using the known distances between pairs of mobile nodes (e.g., reference distance d_{12} between real coordinates h_1 and h_2 in Fig. 1). At the beginning of the localization, each node estimates its distances to the given anchors separately and calculates its own virtual coordinates ($\hat{h}_1$, $\hat{h}_2$, $\hat{h}_3$ in Fig. 1) using one of the well-known calculation methods like trilateration. After the localization of each node, the refinement process is being conducted. One of the possible refinement methods could be the "shifting" of calculated coordinates of two mobile nodes to/from each other if the computed distance between them is bigger/smaller than the corresponding reference distance d known a priori.

Considering the simple pairwise refinement idea mentioned above, the following steps will be executed to improve the estimated virtual position of the node $\hat{h}_1$ in Fig. 1:

- According to the pair $\{\hat{h}_1, \hat{h}_2\}$, we move $\hat{h}_1$ along the improvement vector $\vec{v}_{12}$ so that
$\|(\hat{h}_1 + \vec{v}_{12}) - (\hat{h}_2 - \vec{v}_{12})\| = d_{12}$.
- Thereafter, the improvement vector $\vec{v}_{13}$ for the pair $\{(\hat{h}_1 + \vec{v}_{12}), \hat{h}_3\}$ will be calculated in the same way as $\vec{v}_{12}$ and will be applied as the next improvement step so that
$\|((\hat{h}_1 + \vec{v}_{12}) + \vec{v}_{13}) - (\hat{h}_3 - \vec{v}_{13})\| = d_{13}$.

In Fig. 1, vector $\vec{v}_{12}$ represents the movement of coordinates $\hat{h}_1$ and $\hat{h}_2$ until the distance between them is equal to the reference distance d_{12}. In such a way, the algorithm uses pairwise computations to refine the estimated coordinates of the mobile nodes and operates in a sequential way proceeding from one pair of mobiles to another.

To make system converge to some certain state, UnIS operates in an iterative way, i.e. each pair of mobile nodes goes through the improvement process many times. For this, it was essential to add a step size parameter μ to the mathematical model of the algorithm. A new movement vector, aka correction vector, is given then by $\mu\vec{v}_{ij}$ (e.g., $\mu\vec{v}_{12}$ in Fig. 1).

According to the idea above, the general description of the UnIS refinement is as follows. Let N represent all the mobile nodes in the network. Then, the first improvement step for the node $\hat{h}_i \in N$, with respect to its neighbor $\hat{h}_j \in N$, includes the calculation of the corresponding refinement vector $\vec{v}_{ij}$ and the estimation of new $\hat{h}_i[n+1]$ position:

$$\vec{v}_{ij} = \frac{\|\hat{h}_j - \hat{h}_i\| - d_{i,j}}{2\|\hat{h}_j - \hat{h}_i\|}(\hat{h}_j - \hat{h}_i), \tag{1}$$

$$\begin{aligned} \hat{h}_i[n+1] &= \hat{h}_i[n] + \mu\vec{v}_{ij} \\ &= \hat{h}_i[n] + \mu\frac{\|\hat{h}_j - \hat{h}_i\| - d_{i,j}}{2\|\hat{h}_j - \hat{h}_i\|}(\hat{h}_j - \hat{h}_i), \end{aligned} \tag{2}$$

where $d_{i,j}$ is a corresponding reference distance between nodes h_i and h_j, and μ is a step size parameter.

According to this basic idea, many new extensions from UnIS have been derived [7]. To evaluate different UnIS schemes, simulations and experiments have been conducted. The best improvement ratio was obtained by the scheme "P-UnIS Sequential Selective-DESC". We observed that sequential schemes are much more flexible than parallel ones and consider changes in the nodes' positions during the improvement process. Further flexibility is introduced by the selection feature. A correct criterion applied for organizing a nodes' sequence can result in a better improvement ratio (e.g., descending order in [7]).

Additionally, we observed in our experiments one weak aspect when one node with a very inaccurate position estimate "pulled" all the remaining nodes to a wrong place during the improvement. This happened because the step size parameter μ was considered to be static during the refinement process. However, it can be very profitable to modify the mathematical model correspondingly to make this parameter *adaptive* which can lead to even better improvements. Representing the main contribution of this paper, this phenomenon will be investigated in this work.

III. Optimization of UnIS

In this work, we introduce a weighted UnIS (W-UnIS) approach that uses adaptive step size parameter instead of static one

$$\mu_{adaptive} = \omega\mu, \tag{3}$$

where ω is a weighting function that reflects the accuracy level of the produced location estimate. The node, which position was estimated more accurately, has bigger weight (bigger mass inertia) during the refinement process and obtains, as a result, a smaller correction vector. To rate the accuracy level of the obtained localization result, one of the following aspects can be considered:

- From [7], the accuracy level A_i in location estimation of the node i is inversely proportional to a Mean Absolute Error ε in distance estimation between the i-th node and its neighbors according to reference distances known a priori:

$$A_i \propto \frac{1}{\varepsilon_i}. \tag{4}$$

- From [8], the accuracy level A_i in location estimation of the node i is inversely proportional to a quality of obtained reference signals:

$$A_i \propto \frac{1}{\text{signal quality}_i}. \tag{5}$$

Next, we describe every aspect in detail and present the weighting functions that have been derived.

A. Mean Absolute Distance Error (MADE)

To define a Mean Absolute Distance Error ε_i of the node i, we use initial estimates of the nodes positions $\hat{h}$ as well as the information, known a priori, about the reference distances d between these nodes:

$$\varepsilon_i = \frac{1}{|N_i|} \sum_{j \in N_i} |\|\hat{h}_j - \hat{h}_i\| - d_{i,j}|, \tag{6}$$

where $d_{i,j}$ is a reference distance between nodes i and j, and N_i represents all the neighbors of the mobile node i.

As mentioned above, the main idea of the W-UnIS approach is to increase the weight of those nodes which positions are likely to be more accurate and decrease the weight of the nodes which positions are likely to be less accurate. According to this idea, we developed several weighting functions that are given as follows:

$$\omega_1(\varepsilon_i) = \frac{\varepsilon_i}{\max\{\varepsilon_i, \varepsilon_1, \varepsilon_2, \dots, \varepsilon_{N_i}\}}, \tag{7}$$

$$\omega_2(\varepsilon_i) = \min\left\{\frac{\varepsilon_i}{\varepsilon_j}, 1\right\}, \tag{8}$$

$$\omega_3(\varepsilon_i) = 1 - \frac{\min\{\varepsilon_i, \varepsilon_1, \varepsilon_2, \dots, \varepsilon_{N_i}\}}{\varepsilon_i}, \tag{9}$$

where N_i represents all the neighbors of the mobile node i, ε_i is its MADE, and ε_j is a MADE of the neighbor node j.

B. Link Quality

According to [8], the quality of the signal affects the produced location estimation error significantly. If we assume that the nodes with stronger signals from anchors produce more accurate localization results than the ones with weaker signals, then giving these nodes bigger weights in the refinement process will positively affect the improvement ratio.

In our evaluation, we use Link Quality Indicator (LQI) to measure the quality of the obtained signals. In contrast to Signal Strength Indicator and according to the IEEE 802.15.4 specification [9] (E.2.3), "The LQI (see 6.7.8) measures the received energy and/or SNR (Signal to Noise Ratio) for each received packet." It is important to notice that smaller LQI values, unlike the signal strength, indicate a better quality of the signal and vice versa.

With respect to this, every node i during the initial localization process computes a mean Link Quality value l_i according to the obtained signals from reference nodes so that

$$l_i = \frac{1}{|K_i|} \sum_{j \in K_i} lqi_j,$$

where K_i represents all the reference nodes that are in communication range of the node i, and lqi are corresponding Link Quality values of signals from reference nodes that are estimated at the node i. According to this, we define a fitness function based on the Link Quality value l_i for the i-th node as follows:

$$f(l_i) = 1 - \frac{\min\{l_i, l_1, l_2, \dots, l_{N_i}\}}{l_i}, \tag{10}$$

where N_i represents all the neighbors of the node i.

Considering the fact that LQI-based optimization refers to statistic results only, it cannot be used as a standalone parameter. For this, it is essential to keep history of the estimated LQI data and conduct corresponding filtering. Since we try to avoid filters, we will combine two functions: $\omega_3(\varepsilon_i)$ that reflects the Mean Absolute Distance Error in (9) and $f(l_i)$ that considers the signal quality in (10).

Both of the functions are equally important for the improvement. Applying a Weighted Sums optimization technique, the new weighting function will be

$$\omega_4(\varepsilon_i, l_i) = \frac{1}{2}\omega_3(\varepsilon_i) + \frac{1}{2}f(l_i). \tag{11}$$

To evaluate all weighting functions introduced in (7)-(9) and (11), they were integrated in our emulation environment that will be introduced next.

IV. Evaluation

For the evaluation of the weighting functions, the data collected in our previous work has been used to emulate the real environment. To enable a fair comparison of different approaches, all algorithms had the same input.

A. Evaluation Environment

The core of the evaluation environment is represented by the data collected in our experimental testbed that will be described next.

1) Network deployment: The experimental testbed was deployed in one of the office rooms in the building #11 at the University of Applied Sciences in Erfurt, Germany. This room is equipped with standard furniture including chairs, bookshelves, and desks. It has two windows and represents a dynamic measurement environment where people may walk in and out of the room during the normal operation of the network, thus modifying the characteristics of the actual radio propagation channel.

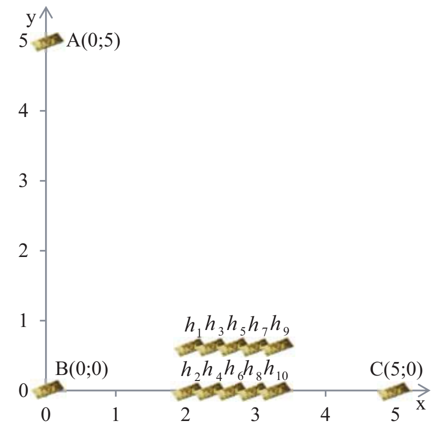

Fig. 2. Real positions of anchors A, B and C as well as ten unknown nodes from h_1 to h_{10}

The deployed localization system consists of the following main elements (Fig. 2): (i) three anchor nodes with known coordinates A [0;5], B [0;0] and C [5;0] used for the localization of unknown wireless sensor nodes; (ii) ten unknown nodes that need to be localized.

To obtain explicit results, the full information about the distances in meters between all mobile nodes was provided in the form of a matrix $D = [d_{i,j}]_{N \times N}$ presented in [7], where $N = 10$ is a total number of the unknown nodes and $d_{i,j}$ is a reference distance between the i-th and j-th node.

2) Hardware platform: For the measurement campaign, the wireless sensor nodes ZEBRA2411 from senTec Elektronik GmbH were used. These modules are based on the chip set ZRP1 developed by Freescale Semiconductor [10]. The nodes operate in the 2.4GHz ISM frequency band and allow wireless communication over a distance of more than 1000m (line-of-sight). ZEBRA contains a micro-controller, a High Frequency (HF) circuitry and a chip antenna with low noise amplifier (LNA) and power amplifier (PA) stages. An integrated Freescale HCS08 MCU serves as a base band controller and operates at 8MHz. A SMAC (Simple Media Access Control) protocol [11], which is based on the IEEE 802.15.4 standard, has been applied for communication between nodes. For the programming of nodes, we use the Metrowerks CodeWarrior development environment from Freescale.

3) Path loss model: According to the process of localization, we need to estimate distances from the observed LQI values and then use these distances for the position calculation step. There are a lot of studies which propose various models, even for indoor scenarios. The model which has been applied in this work was found in [12] and adapted to the LQI estimates produced with our hardware platform. So, the path loss L at distance d is

$$L(d) = L_{d_0} + L_p + 10\gamma \log_{10}\left(\frac{d}{d_0}\right) + \chi, \qquad d \geq d_0 \quad (12)$$

where $L_{d_0} = 72$ is the path loss at $d_0 = 0.1$ m, $\gamma \log_{10}\left(\frac{d}{d_0}\right)$ is the average path loss with reference to d_0, $\gamma = 3.1$ is the path loss exponent and $L_p = 2.4$ is the penetration loss and both are functions of the measured scenario and working environment; and $\chi = 3.6$ is the log-normal shadow fading. For the given scenario, the equation (12) and the corresponding parameters mentioned above produce the least-square error path loss log-distance model according to the collected LQI values.

The *trilateration* algorithm has been applied to calculate initial positions according to the estimated three distances from anchors.

4) Step size parameter: In our previous work, we observed that the P-UnIS algorithm produces the best improvement ratio with the step size in the range from 0.01 to 0.4 and performs best with the step size $\mu = 0.2$, which is common for all numbers of rounds.

In this work the step size $\mu_{adaptive}$ is designed to be variable (see (3)) and includes a weight value $\omega \in [0, 1]$. According to this and considering the basic value $\mu = 0.2$ in (3), we get $\mu_{adaptive} \in [0, 0.2]$.

According to this setup, we conducted a measurement campaign that took approximately 24 hours. The location estimation of each mobile node was performed every second according to newly observed LQI values. All the LQI data produced in the experiment was stored for the further emulation purposes.

Now, the picture of the evaluation platform is complete. Next, we present the evaluation results of different optimization functions presented above.

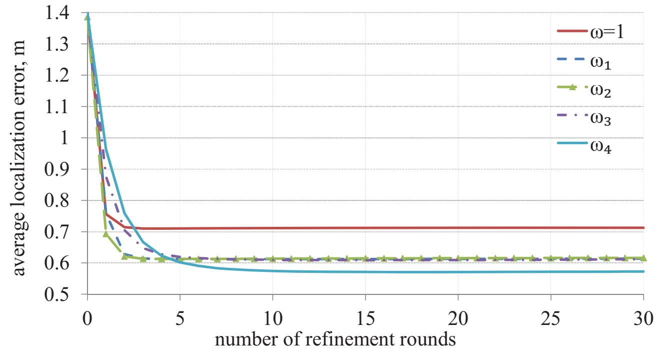

Fig. 3. Average localization error

B. Evaluation Results

Using the data obtained in the testbed, we evaluated weighting functions proposed above: ω_1 (7), ω_2 (8), ω_3 (9), ω_4 (11). To present the effectiveness of the methods, the standard P-UnIS improvement with static step size (i.e. $w = 1$) has been used as a benchmark (Fig. 3). 30 iteration steps were applied every time for the improvement of nodes positions.

The key observations can be stated as follows:

- As a part of the W-UnIS algorithm, all the introduced functions produce better results than the previous P-UnIS improvement with $\omega = 1$, according to the average localization error (Fig. 3). This supports the idea of using the Mean Absolute Distance Error (MADE) to weight the nodes positions.

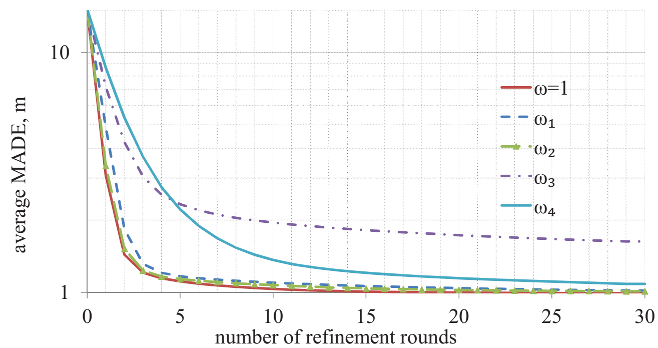

Fig. 4. Average Mean Absolute Distance Error (MADE)

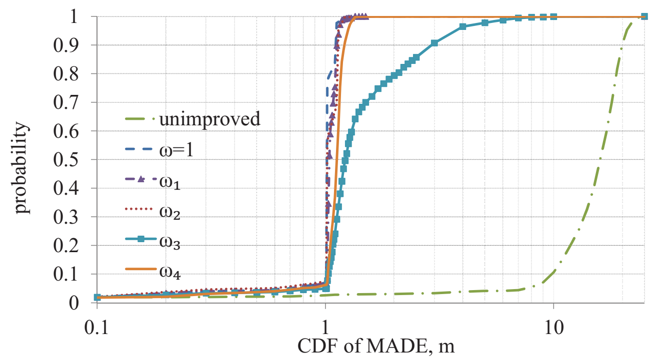

Fig. 5. Cumulative Distribution Function (CDF) of the MADE E_i according to (6)

- The best results are presented by ω_4 weighting function. ω_4 reflects the quality of the received signals from the anchors additionally to the information about MADE.
- Figure 4 shows how the MADE values change during the refinement according to different approaches. It is obvious that the best trend here is represented by static weight $\omega = 1$. Although this method does not reach the best accuracy in the location estimation, it minimizes the MADE value and, as a result, brings the nodes close to the original relative positioning.
- Figure 5 presents the comparison of the initial localization (unimproved results) and the proposed improvement schemes with respect to the accumulated MADE value of all mobiles in the network. Due to the big uncertainty in indoor signal propagation, unimproved location estimation presents more than ten times bigger distance error than the proposed improvement technique.
- The same as for P-UnIS, the major drawback of W-UnIS is represented by the need in the estimation of distances between unknown nodes, which is not always possible and depends on the working scenario.

V. Conclusion and Future Work

As the main contribution in this paper, we introduced the novel optimization strategy in improving the localization results for the networks with known distances between mobile nodes.

It was shown that adding weights to the estimated nodes positions yields 22% higher improvement ratio as compared to the previous refinement technique (0.573 m average localization error against 0.713 m, respectively).

In contrast to the existing improvement techniques that were discussed at the beginning of this paper, our algorithm does not require continuously measured data sequences and significant improvement is provided directly after first initial position estimations.

In our future work, we are going to continue investigation of different optimization techniques to gain even better localization results. Additionally, we are going to do a scalability analysis of our algorithm.

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