Characterizing the Energy Efficiency of Localization Algorithms in Wireless Sensor Networks

Dominik Lieckfeldt Jiaxi You Jakob Salzmann Ralf Behnke Dirk Timmermann
Institute of Applied Microelectronics and Computer Engineering
Richard-Wagner-Str. 31
18119 Rostock, Germany
firstname.lastname@uni-rostock.de

ABSTRACT

We propose a metric to characterize the energy efficiency of range-based localization algorithms in wireless sensor networks. The metric proposed differs from previous approaches in that it is bounded and supports objective comparison of localization algorithms using simulations. The goal of the current work is to show that our metric achieves expected results for well-known localization algorithms and, therefore, can be used to characterize and compare the energy efficiency.

Simulation results for energy efficiency show that maximizing the local likelihood yields highest energy efficiency whereas the linear least squares approach and the multi-dimensional scaling method exhibit a strong susceptibility when ranging errors are large.

Categories and Subject Descriptors

C.2.4 [**Computer-Communication Networks**]: Distributed Systems; C.4 [**Performance of Systems**]: Performance attributes

General Terms

Performance

Keywords

Sensor networks, energy efficiency, localization

1. INTRODUCTION

Sensor networks consist of a large number of electronic devices, called sensor nodes, which are deployed across a geographical area. Each sensor node is capable of sensing environmental parameters, wireless communication and is able to perform simple signal processing. Experimental deployments in the past years have shown that sensor networks can be used in a vast number of applications. The most prominent civil ones are habitat monitoring, environment observation and forecast applications [3][4].

The energy constraint nature of sensor networks makes energy-efficiency one of the major design goals. Sensor nodes are usually battery driven. Consequently, the research community has seen many works on energy-efficient MAC and routing protocols and topology control. Interestingly, not only many of the aforementioned tasks require a certain level of spatial awareness, but also a meaningful interpretation of the sensed data is typically only possible with the knowledge of where the data was sensed. As a consequence, localization of sensor nodes is a central task in sensor networks.

In general, efficiency is understood as the ratio of gain and cost. Consequently, a high efficiency is desirable especially when nodes are resource limited.

This work proposes LogarEEL, the *Logarithmic Energy Efficiency of Localization*, as a metric to characterize the energy-efficiency of localization algorithms. LogarEEL differs from earlier approaches in that it supports objective comparison which is achieved through normalization to the Cramer-Ráo-Bound of localization. Furthermore, it is consistent with the general understanding that a high value denotes high energy-efficiency. To depict the utility of LogarEEL, several well-known localization techniques are investigated in terms of energy-efficiency.

Due to space limitation, we focus on localization based on Received Signal Strength (RSS) measurements. However, the framework presented is also applicable to other methods of distance estimation for which a lower bound on the localization error can be formulated analytically.

2. RELATED WORK

This section reviews several approaches to characterize the energy-efficiency of localization in wireless sensor networks.

Feng et al. investigate localization based on distances estimated from RSS [2]. The authors use the *Utility* defined as the ratio of energy consumption and decrease of the Cramer-Ráo-Bound (CRB) on localization error to characterize the impact of a specific node on the overall energy efficiency. Specifically, an anchor node is more energy efficient the smaller its Utility is. Although Utility is lower bounded and based on the CRB it lacks objectivity since the energy consumption is not normalized and has unit W/m^2. In addition, the proportionality criteria is not met since low Utility denotes high efficiency.

Reichenbach et al. compare several algorithms for localization in terms of energy-efficiency regarding the *Power-Error-Product* (PEP) [7]. The PEP is the product of lo-

IWCMC '09, June 21–24, 2009, Leipzig, Germany

cation error and energy spent for localization. Therefore, a small PEP denotes high energy efficiency. However, the significance of the PEP is limited since it is not bounded, does not use a fixed reference and is anti-proportional to the general understanding of efficiency.

In many other works, efficiency is only used as a term and not defined explicitly. This work's contribution is the definition of *LogarEEL*, the *Logarithmic Energy Efficiency of Localization* as a metric to characterize the energy efficiency of localization. The distinctive features of LogarEEL are: It is normalized since it is based on the best achievable accuracy of an unbiased location estimator and the energy needed to (asymptotically) achieve this accuracy. Hence, it is bounded and corresponds to the general understanding that a high value denotes high efficiency.

The paper is organized as follows: Section 3 briefly introduces the models and symbols used and states the assumption about the wireless links. Section 3.2 reviews the CRB on localization accuracy which will be used for the normalization of LogarEEL. In Section 4, we introduce our metric of energy efficiency. Simulation results of LogarEEL for some well-known localization algorithms are presented in section 5. In section 6, we conclude and summarize the work.

3. MODELS AND ASSUMPTIONS

In the following, we introduce the models and symbols used in this work and elaborate on the assumptions made.

3.1 Model of Wireless Links

Wireless communication is obviously the most suitable way to exchange information between sensor nodes. We assume a time invariant, log normal fading channel, which is an accepted model in the research community.

This model assumes that the received signal strength $\mathcal{P}_{i,j}$ in dBm at receiver i from node j is given by:

$$\mathcal{P}_{i,j} = \mathcal{P}_0 - 10\epsilon \log_{10}(d_{i,j}/d_0) + X_{\mathrm{s}} \tag{1}$$

The parameter ϵ denotes the path loss exponent, which is usually in the range of 2 to 3 depending on the environment, $\mathcal{P}_0$ is the free-space RSS at a reference distance d_0 and $X_{\mathrm{s}} \propto N(0, \sigma^2_{\mathrm{rss}})$.

3.2 CRB on Localization Accuracy

Typically, nodes in a wireless sensor network require a certain degree of spatial awareness. The process of acquiring this knowledge is often referred to as localization. A common approach is to use so called *beacon nodes*, which are aware of their absolute geographical location, therefore, they serve other *blindfolded nodes* with no spatial awareness as anchor points. This work focuses on localization based on distances between blindfolded nodes and beacon nodes. However, the general idea also applies to other methods, such as angle-of-arrival or time-difference-of-arrival methods.

Naturally, one seeks to find estimates $\hat{\mathbf{z}} = [\hat{x}, \hat{y}]^{\mathrm{T}}$ of the true geographic location $\mathbf{z} = [x, y]^{\mathrm{T}}$ with smallest error. Since the measurements of RSS are typically noisy, the average deviation of the estimated from the true location are usually expressed by the *Mean Square Error* (MSE) $e^2 = E\left\{(\hat{\mathbf{z}} - \mathbf{z})(\hat{\mathbf{z}} - \mathbf{z})^{\mathrm{T}}\right\}$. $E\{\cdot\}$ denotes expectation.

For unbiased estimators given a description of the noise, an analytical bound found by Cramér and Ráo, the CRB, can be used to characterize the smallest possible MSE, hence, the highest possible accuracy of any such estimator.

To facilitate the following investigation, we define several variables. Let U be the set of sensor nodes that are not aware of their geographical location, B the set of beacon nodes, and S the set of all sensor nodes. The cardinality, i.e. the number of nodes in a set, is denoted by $|\cdot|$ and $m = |B|$, $n = |U|$ and $s = |S|$. To identify a specific node, we use the indices j and i where $B := \{i : 1 \le i \le m\}$ and $U := \{i : m < i \le m + n\}$.

The true geographical locations of the sensor nodes form the matrix $\boldsymbol{\theta} = [\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_{m+n}]^{\mathrm{T}}$ $\boldsymbol{\theta} \in \mathbb{R}^{(m+n)\times 2}$. Accordingly, the matrix of the estimated locations is $\hat{\boldsymbol{\theta}} = [\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_{m+n}]^{\mathrm{T}}$. Here, we included the known beacon node locations, which, of course, do not have to be estimated. However, this formulation facilitates later investigations.

Based on the previous error model, a lower bound on the variance of location estimates can be derived using the CRB. Given a random variable X with univariate probability density $p_\mu(X = x)$ and an unbiased estimator $T(X)$ for the parameter μ of p, the lower bound on the variance of estimates $Var\{T(x)\}$ is given by:

$$Var\{T(x)\} \ge \frac{1}{F(\mu)} = e^2_{\mathrm{crb},i} \tag{2}$$

$F(\mu)$ denotes the Fisher-Information-Matrix. Due to space limitations and as the CRB has been intensively studied in the literature, we restrict the discussion of CRB and refer the interested reader to the work of Patwari et al. [5] or Chan et al. [1].

4. ENERGY EFFICIENCY OF LOCALIZATION

In this section, we introduce the model for the energy consumption, classify the considered localization approaches and finally define LogarEEL.

4.1 Modeling Energy Consumption

During operation, sensor nodes typically draw energy from a battery. One major source of energy consumption are wireless communications [2]. We use a simple model for the energy consumption of sensor nodes which considers the energy spent for transmitting and receiving packets, respectively. For convenience, we leave unconsidered other sources of energy depletion, like energy consumption during idle times or during sensing activities. This does not reduce the significance of the investigations because the framework presented can easily be adapted to more complex energy models. In order to allow for an equal comparison, the results presented later use the same basis for all algorithms investigated.

$$\mathcal{E}_i = \sum_{j \in S} b^{\mathrm{tx}}_j \, \mathcal{E}_{\mathrm{tx}} + b^{\mathrm{rx}}_j \, \mathcal{E}_{\mathrm{rx}} \tag{3}$$

The set S contains all sensor nodes involved in the localization process, b^{tx}_j and b^{rx}_j are the number of bits transmitted and received by j, respectively and $\mathcal{E}_{\mathrm{tx}}$ ($\mathcal{E}_{\mathrm{rx}}$) denote the energy per transmitted (received) bit in [a.e.u./bit] where a.e.u. denotes an arbitrary energy unit. In the following, we regard the energy consumption during localization as its Cost and use these terms synonymously.

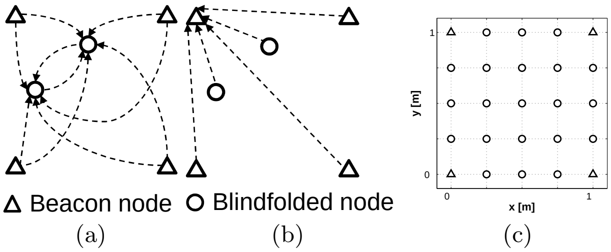

Figure 1: (a) Measurement phase: Each node determines distances to adjacent nodes by means of radio communication (using for example RSS). (b) Aggregation: Distances are transmitted to a central node. (c) Network configuration used for simulations.

4.2 Classification of Localization Algorithms

The algorithms, which will be explained in more detail in section 5, can be classified either centralized or decentralized regarding whether or not global information is required at one specific node. Since the centralized algorithms inherently estimate the locations of all involved blindfolded nodes, a fair comparison with decentralized approaches should consider two different situations: 1) Individual localization of a single blindfolded node, referred to as *individual localization* and 2) Localization of all blindfolded nodes, referred to as *total localization*. We realize that while being penalized in terms of Cost in the first situation, centralized approaches are expected to achieve improved efficiency for total localization.

Since knowledge about all distances is required for centralized localization, the localization process can be divided into a measurement phase, where nodes determine their distance to all neighbors, and an aggregation phase, where this information is transmitted to a central node (see figures 1a and 1b).

Specifically, in the measurement phase each node would broadcast a message to its neighbors. Having received such a broadcast, nodes would use the RSS of the transmission to infer the distance to the sender. Consequently, leaving unconsidered retransmissions, $m+n$ transmissions and $(m+n)\,(m+n-1)$ receptions are required to determine all distances in the considered network. In addition, communicating the distance information to a central station requires at least $m+n-1$ transmissions and receptions. Hence, using (3) the Cost of centralized, individual localization becomes $C_{\text{ind,cent}} = (2(m+n)-1)\mathcal{E}_{\text{tx}} + ((m+n)^2-1)\mathcal{E}_{\text{rx}}$. It is noted that for centralized, total localization all n blindfolded nodes are localized with the same Cost. Therefore, the per node Cost is $C_{\text{tot,cent}} = \frac{1}{n}\,C_{\text{ind,cent}}$.

In contrast, the decentralized approaches considered in this work rely solely on the distances to beacon nodes and, therefore, only require a total of m transmissions and, at each blindfolded node, m receptions. This yields $C_{\text{ind,decent}} = m\,\mathcal{E}_{\text{tx}} + m\,\mathcal{E}_{\text{rx}}$ for individual and $C_{\text{tot,decent}} = \frac{1}{n}(m\,\mathcal{E}_{\text{tx}} + n\,m\,\mathcal{E}_{\text{rx}})$ for total localization.

4.3 Definition of LogarEEL

In general, efficiency is the ratio between Gain (G) and Cost (C). Regarding localization in resource limited sensor networks, high efficiency denotes highly accurate location estimates for which to obtain only few resources had to be spent. In order to quantify this formulation more mathematically, we consider the relation between the MSE of location and the energy $\mathcal{E}_i$ spend to localize node i and define the the energy efficiency $\breve{\eta}_i$ of a localization algorithm:

$$\breve{\eta}_i = \frac{1/e_i^2}{\mathcal{E}_i} = \frac{G_i}{C_i} \tag{4}$$

However, this expression does not allow for statements like "the best" efficiency, since equation (4) has no upper bound. A reasonable way to improve the expressiveness of equation (4) is to normalize both Gain and Cost.

Concerning the error of localization, the CRB provides a means to assess the best possible performance of unbiased estimation of the location and can be calculated in closed-form [5]. Hence, the CRB is used to normalize the MSE and, therefore, limits the range of the normalized Gain $\tilde{G}$ to $0 \leq \tilde{G} \leq 1$: $\tilde{G}_i = \frac{1}{e_i^2/e_{\text{crb},i}^2}$.

Next we consider the Cost of localization, i.e. the energy consumption. In order to maintain the boundedness property, the Cost have to be normalized. We suggest to use the Cost associated with inferring the distances to adjacent beacon nodes for this purpose as this information is fundamental for the localization process. Consequently, the normalized Cost at node i become $\tilde{C}_i = \frac{C_i}{m(\mathcal{E}_{\text{rx}}+\mathcal{E}_{\text{tx}})}$.

Due to the possible range and the fact that most feasible estimators do not approach the CRB and have strongly varying efficiency, we propose to use the log scale on the original definition of the energy efficiency (4). Furthermore, since accuracy and energy consumption might have different importance to the overall system performance, we introduce a weighting factor α to account for this. Thus, the *Logarithmic Energy Efficiency of Localization* (LogarEEL) is

$$\eta_i = 10\,\alpha\,\log_{10}(\tilde{G}_i) - 10\,(1-\alpha)\,\log_{10}(\tilde{C}_i) \tag{5}$$

α has range $[0,1]$ and can be used to either emphasize Gain or Cost of localization. LogarEEL's upper bound is connected to the best possible accuracy given by the CRB and the least energy consumption needed to infer the required distance estimates. An increase of η by $1.5\,\text{dB}$ constitutes doubling the energy efficiency $\tilde{G}/\tilde{C}$ (assuming $\alpha = 0.5$).

5. EVALUATION

This section briefly reviews the localization algorithms which will be compared regarding energy efficiency using LogarEEL and outlines their associated Costs. After stating the parameters of the simulation, results are presented and discussed.

5.1 Maximum Likelihood Estimation (MLE)

Given the set of measured RSS $\{\mathcal{P}_{i,j} : 1 \leq i,j \leq m+n\}$, the locations $\mathbf{z}_i$ of the blindfolded nodes can be jointly estimated [5]

$$\hat{\mathbf{z}}_{\text{mle},i} = \arg \min_{\{\mathbf{z}_i \in \mathbb{R}^{2\times 1}\}} \sum_{i=m+1}^{m+n} \sum_{j=1}^{i-1} \left(\log \frac{\hat{d}_{i,j}^2}{||\mathbf{z}_i - \mathbf{z}_j||^2} \right)^2 \tag{6}$$

where the maximum likelihood estimate $\hat{d}_{i,j}$ of the distance between i and j is given by $\hat{d}_{i,j} = d_0 10^{(\mathcal{P}_0 - \mathcal{P}_{i,j})/(10\epsilon)}$. Although, this estimator is biased, its MSE closely approaches the CRB [5]. This algorithm is centralized since (6) has to be calculated at one node knowing all required distances and location of beacon nodes.

5.2 Local Maximum Likelihood Estimation (lMLE)

To reduce the complexity and to enable decentralized calculation of MLE, only the local likelihood is considered, meaning that (6) is calculated on each blindfolded node with the locally available estimated distances to adjacent beacon nodes. This leads to a slightly different form of (6) which we refer to as local MLE:

$$\hat{\mathbf{z}}_{\text{lmle},i} = \arg \min_{\{\mathbf{z}_i \in \mathbb{R}^{2\times 1}\}} \sum_{j=1}^{m} \left(\log \frac{\hat{d}^2_{i,j}}{||\mathbf{z}_i - \mathbf{z}_j||^2} \right)^2 \qquad (7)$$

Since this estimator utilizes fewer information than the MLE, it is expected that accuracy of estimates will tend to be lower than that of MLE.

5.3 Linear Least Squares Localization (LLS)

For decentralized Linear Least Squares localization, the received signal strength is used to estimate the distance between communicating sensor nodes. Based on the distances $\hat{d}_{i,j}$ to several beacon nodes, blindfolded node i can calculate its position by solving the following system of equations: $\hat{d}_{i,j} - \sqrt[2]{(x_i - x_j)^2 + (y_i - y_j)^2} \quad j \in B$.

This system of equations can be linearized by subtracting one of the equations from the others as shown, for example in [6]. We use the equation corresponding to the beacon node with the smallest estimated distance for linearization since we found empirically that this reduces the localization error. Without loss of generality, we consider the case that only one blindfolded node ($n = 1$) shall be localized in a fully meshed network and we employ the first beacon node, i.e. $j = 1$, for linearization.

$$\mathbf{z}_{\text{lls},m+1} = \frac{1}{2} (\mathbf{A}^{\text{T}} \mathbf{A})^{(-1)} \mathbf{A}^{\text{T}} (\hat{d}^2_{m+1,1} - \hat{\mathbf{d}} + \mathbf{d}) + \mathbf{z}_2 \qquad (8)$$

$$\mathbf{A} = \begin{bmatrix} x_2 - x_1 & y_2 - y_1 \\ \vdots & \vdots \\ x_m - x_1 & y_m - y_1 \end{bmatrix} \qquad (9)$$

Here, $\hat{\mathbf{d}} = [\hat{d}^2_{m+1,2}, ..., \hat{d}^2_{m+1,m}]^{\text{T}}$ and $\mathbf{d} = [d^2_{1,2}, ..., d^2_{1,m}]^{\text{T}}$.

Since the model assumptions indicate that distance estimates are biased, location estimates using LLS will also be biased. This estimator is based on minimizing the squared error using a linear approach. Consequently, this estimator applies a larger weight to the distance estimates with large errors which over emphasizes. In addition, large errors will render the linearization inappropriate which further contributes to the strong susceptibility of this estimator to errors.

5.4 Classical Metric Multidimensional Scaling (cmMDS)

Classical Metric Multidimensional Scaling is a set of statistical techniques originally developed to display the structure of distance-like data as a geometrical picture. Since cmMDS works on distance information between objects its applicability for localization of wireless devices has been discussed [8]. It is noted that cmMDS belongs to the class of centralized localization algorithms.

Table 1: Simulation parameters.

Parameter	Variable	Value
Deployment area	-	1 m × 1 m
Number of blindfolded nodes	n	21
Number of beacon nodes	m	4
Path loss exponent	ϵ	2
Tx,Rx energy cons.	$\mathcal{E}_{\text{tx}}, \mathcal{E}_{\text{rx}}$	1 a.e.u.
Gain-Cost weighting	α	0.5
Number of trials	-	5000

Starting with a square matrix $\mathbf{D}$ of pairwise distances between sensor nodes, cmMDS tries to find the relative arrangement of these points that best fits $\mathbf{D}$. Often the MSE between the measured and the resultant distances is used to define the goodness of a fit. Estimates of location following the MSE objective can be obtained in the following way where $\mathbf{I}$ is the identity matrix:

1. Double center $\mathbf{D}$: $\mathbf{D}_{\text{c}}$.
2. Compute Eigenvalues and -vectors: $\mathbf{D}_{\text{c}} = \mathbf{U}\,\mathbf{V}\,\mathbf{U}^{\text{T}}$.
3. Obtain intermediate coordinates $\check{\boldsymbol{\theta}}$ using the two[1] largest Eigenvalues v_1, v_2 and the corresponding Eigenvectors $\mathbf{u}_1, \mathbf{u}_2$: $\check{\boldsymbol{\theta}} = [\mathbf{u}_1, \mathbf{u}_2]\,\mathbf{I}\,[\sqrt{v_1}, \sqrt{v_2}]^{\text{T}}$.
4. Determine the similarity transform $\mathbf{T}$ that transforms the estimated locations of beacon nodes to their true locations and perform the same transform on all intermediate coordinates: $\hat{\boldsymbol{\theta}} = \mathbf{T}\,\check{\boldsymbol{\theta}}^{\text{T}}$

5.5 Simulation Results

For the simulations we consider a fully connected regular network of 25 nodes where the $m = 4$ beacon nodes are located at the corners (see fig.1c). During simulations the MSE of localization as given in Section 3.2 is calculated approximately on the basis of 5000 independent trials. Each trial consists of the estimation of distances based on noisy RSS measurements, whereas the measurement model of (1) is assumed. Based on this error, the normalized Gain and Cost are averaged over all blindfolded nodes and used to calculate the LogarEEL using (5). Regarding Cost, individual and total localization are considered independently. Table 1 states the simulation parameters.

Fig. 2 plots LogarEEL of MLE, lMLE, LLS and cmMDS versus the standard deviation of RSS measurements in the sample network of figure 1c. In general, the centralized approaches are advantageous for total localization since they inherently estimate all blindfolded node locations. Confidence intervals are omitted, as they are typically much smaller than 1 dB. Also, results of lMLE and LLS are omitted for individual localization since the graphs are just $5\,(\log_{10}(C_{tot,decent}) - \log_{10}(C_{ind,decent})) \approx 1.4\,\text{dB}$ below those of total localization in the considered scenario.

For localization of a single node (individual node localization) it is shown that with equally weighted Gain and

[1]For 2D (3D) coordinates the two (three) largest Eigenvalues should be used.

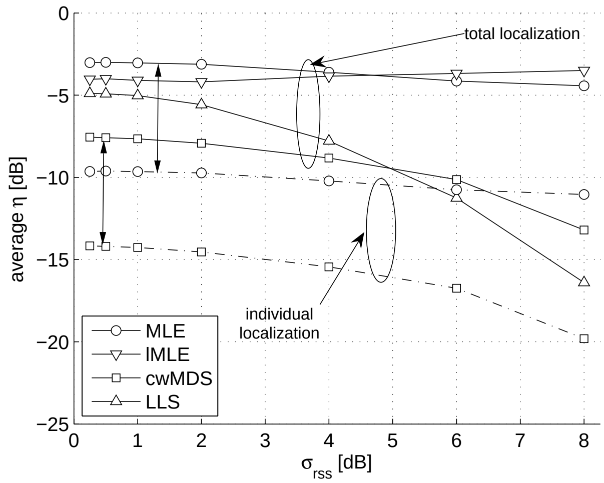

Figure 2: Average LogarEEL η of various localization algorithms versus fading standard deviation ($\alpha = 0.5$).

Cost (i.e. $\alpha = 0.5$), lMLE achieves the highest energy efficiency. This result stresses the point that the increase in accuracy of centralized MLE compared to decentralized lMLE does not outweigh the additional Cost for measuring and distributing the distance estimates during individual localization. For small values of σ_{rss}, LLS shows relatively high energy efficiency with regards to lMLE. However, LLS exhibits the highest degradation for growing σ_{rss}. This behavior is caused by the strong susceptibility of linear least squares based optimization to large errors and, yet slightly less pronounced, is also observed for cmMDS.

In the case of total localization, the centralized approaches have increased LogarEEL since their Cost is independent of the actual number of nodes to be localized and, therefore, the average Cost per node strongly decreases compared with individual localization. The decentralized approaches also have slightly increased efficiency, due to decreased Cost, but the improvement is smaller compared with that of the decentralized methods.

In general, LogarEEL of both MLE and lMLE are relatively insusceptible to changes of σ_{rss} which indicates that their performance is strongly connected to the CRB. This emphasizes the objectiveness of LogarEEL since the performance of MLE, which is able to approach the best possible accuracy as given by the CRB, is relatively unaffected by changes of a parameter of the wireless link, i.e. the standard deviation of RSS measurements.

6. CONCLUSION

We introduce LogarEEL, a metric to characterize the energy efficiency of localization algorithms in Wireless Sensor Networks. Since LogarEEL is upper bounded and normalized to the at most achievable accuracy, it constitutes an improvement over existing measures of energy efficiency of localization which are either unbounded or dependent on nuisance parameters. We further introduced a weighting factor which can be used to emphasize the impact of either accuracy of location estimates or the associated energy consumption.

As an example, we investigated with LogarEEL the energy efficiency of some well-known localization algorithms, namely Maximum Likelihood, Linear Least Squares estimation and a Multidimensional Scaling method. The intention of our investigations was to show that LogarEEL produces expected results for known localization algorithms and therefore to support its utility.

The results support the general understanding that centralized approaches have difficulties to cope with decentralized approaches in terms of energy efficiency. Furthermore, the susceptibility of mean square error based localization methods, namely Linear Least Squares and Multidimensional Scaling, to large errors is reflected by their decreasing energy efficiency. In contrast, MLE based approaches show little sensitivity. Summarizing, a decentralized local Maximum Likelihood method which optimizes only the local likelihood only yield the highest energy efficiency for single-node localization whereas the Multidimensional Scaling approach achieved the smallest.

Acknowledgment

This work was partially financed by the German Research Foundation (DFG) within the graduate school **Mu**lti modal **S**mart **A**ppliance ensembles for **M**obile **A**pplications (MuSAMA, GRK 1424).

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