Distributed Selection of References for Localization in Wireless Sensor Networks

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***Abstract*—The main purpose of wireless sensor networks is to provide information about an area of interest. In order to fulfill this task, physical parameters have to be measured by as many sensors as possible to improve the knowledge on the sensed area. In contrast, due to the resource-limited nature of sensor networks, the number of actively participating nodes should be kept to a minimum. This paper investigates the trade-off between the two conflicting requirements with special focus on localization of sensor nodes. A distributed algorithm to select subsets of sensor nodes for localization is analyzed regarding the accuracy of localization.**

I. Introduction

This paper considers localization in Wireless Sensor Networks (WSNs) using lateration, which is the most widely used approach in experimental and industrial localization systems [1], [2], [3]. Distances between nodes are estimated using Received Signal Strength (RSS) or Time of Arrival (ToA). Typically, it is assumed that beacons broadcast their absolute location information regularly during the first phase of localization. The second phase of localization involves all nodes with location information which form the superset of reference nodes consisting of both beacons and unknowns with estimated locations. In [4], [5], this approach is demonstrated to enable localization of unknowns not being in the neighborhood of at least 3 beacons (figure I). Because the number of references typically exceeds the number of unknowns during refinement, it is feasible to let the remaining unknowns request location information of neighboring references rather than having the references broadcast their location regularly.

From the information theoretic point of view, average accuracy of localization increases with the number of references used if their observations can be considered independent. On the one hand, it is common to involve as many references as possible to achieve maximum accuracy. On the other hand, limited resources of WSNs, such as bandwidth and energy capacity, suggest a more restrictive and selective use of references.

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II. Related Work

It has often been stated in the literature that relative locations of references and unknowns have strong impact on the accuracy of localization for both fine- and coarse-grained approaches. Therefore, best placement and optimal selection of beacons in terms of accuracy of localization has been spotted as an interesting field for investigations.

Since complexity of localization depends on the number of references used, it is desirable to select those references first which contribute most to high accuracy. In contrast, selecting a subset of references in order to optimize localization accuracy has intensively been studied in the literature. In [6], [7], [8], range measurements are weighted according to their variance and distance or references are selected based on the difference between distances and estimated locations [4]. Others apply tests to detect outliers in order to exclude them from calculations or just choose the nearest references for estimation of location [9], [10]. For coarse-grained localization, it has been reported in [11] that choosing the nearest three references increases localization accuracy when estimating distances with the DV-Hop method. Furthermore, in [12], localization errors are simulated at references to decide where additional references have to be placed to decrease errors efficiently. However, this leads to large computational overhead on references. In [13], geometry of the situation is considered. Here, the set of all references is divided into groups of three references. The references of one group form a triangle whose angles must meet a certain requirement for this group to be selected for localization. Drawbacks of this approach are high computational complexity as all possible groups of references are considered and the need for global knowledge to be available at references.

In [14], the authors suggest a distributed algorithm for selecting subsets of references which effectively reduces communication effort by excluding unsignificant nodes from participating in the localization process and, thus, prolongs the lifetime of WSNs. This paper extends the investigation of this algorithm by considering energy consumption and impact on accuracy of localization using a most likelihood estimator.

The remainder of this paper is organized as follows: Section III introduces the scenario and nomenclature. Section IV reviews the error model and the Cramer-Rao-Lower-Bound on localization error which is the criteria used for selecting subsets of references. In Section V the benefits of the approach are investigated regarding energy and communication and conclusions for the total energy consumption are drawn. Finally, Section VI reviews the algorithms used to select the subsets, Section VI-A presents simulation results and in Section VII

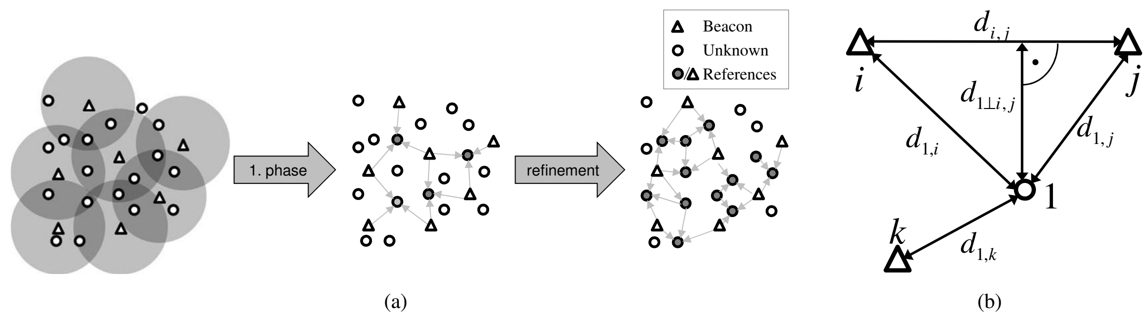


Figure 1. a) Iterative localization process. b) Distances used to calculate CRLB.

conclusions are drawn.

III. Scenario set-up and Variables

We consider random deployments of M sensor nodes where two different types of nodes exist: m_{b} beacon nodes with a priori known locations, and m_{u} unknowns to be localized. In the following, we use n_i to refer to a specific node. By considering a WSN in a later state of its lifetime, it is justified to assume that all unknowns in range of at least 3 beacon nodes have obtained an estimate of their location. The class of references is formed by all nodes with known locations and, therefore, contains all beacon nodes and unknowns with estimated locations. Consequently, in later states of the WSN, one node desiring to estimate its location or to improve the accuracy of its location estimate will have a relatively large number of references to choose from. This situation motivates the need for a resource-aware selection of the best subset of references in terms of localization accuracy.

First, we define the set of unknowns $U := \{n_i \mid i \in \{1, 2, \ldots, m_{\mathrm{u}}\}\}$, the set of beacons $B := \{n_i \mid i \in \{m_{\mathrm{u}}+1, m_{\mathrm{u}}+2, \ldots, m_{\mathrm{u}}+m_{\mathrm{b}}\}\}$ and the set of all nodes $N := B \cup U$ with $u_i \in U$, $b_i \in B$ referencing a specific unknown and beacon, respectively. Nodes are capable of wireless communication and thereby can estimate distances between communicating nodes. We assume that nodes are synchronized and use time division multiple access (TDMA). Assuming a 2D cartesian coordinate system, the true locations of nodes are $\mathbf{z}_i = (x_i\ y_i)^T$ with distances $d_{i,j} = ||\mathbf{z}_i - \mathbf{z}_j||$ between nodes n_i and n_j. Estimates of parameters are indicated by a hat, e.g. estimates of distance are $\hat{d}_{i,j}$. Since wireless communication has limited range r_{tx}, we further define the set of all beacons being within transmission range of the unknown u_i: $B_i := \{b_j \mid d_{i,j} \leq r_{\mathrm{tx}}\}$.

IV. Error of Localization

This Section states the error model which the further investigations build upon and reviews the Cramer-Rao-Lower-Bound (CRLB) on the error of localization which has been found by Patwari et al. [15].

Naturally, we seek to find estimates of location with smallest error $|\mathbf{e}_i|$, which is the distance between the true location and the estimate:

$$\mathbf{e}_i = \begin{pmatrix} x_i - \hat{x}_i \\ y_i - \hat{y}_i \end{pmatrix} \tag{1}$$

The average variance of unbiased estimates over x- and y-directions is:

$$\tilde{\sigma}_i^2 = E\left\{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2\right\} \tag{2}$$

A. Error Model

Lateration based localization relies on distances between reference nodes and unknowns. In order to determine its location, one unknown has to determine its distance to at least 3 references assuming coordinates are in 2D. Typically, these distances will be measured by use of radio signals, either by Time of Arrival (ToA) or by Received Signal Strength (RSS). Due to the nature of wireless communication, these metrics exhibit errors which, eventually, lead to erroneous results when used for localization. It has been shown in [15] that ToA and RSS (in decibels) can be modeled by gaussian distributions with sufficient accuracy for an office scenario. This approach assumes a shadowing model of the wireless channel which is characterized by obstacles randomly blocking the direct line of sight between nodes. In the following the model is shortly reviewed: Under the previously stated assumptions let σ^2_{rss} (σ^2_{toa}) and $\bar{P}_{i,j}$ ($\bar{T}_{i,j}$) denote the variance and mean of the RSS (ToA) measurements for nodes n_i and n_j:

$$\begin{aligned} P_{i,j} &\propto N\left(\bar{P}_{i,j}, \sigma^2_{\mathrm{rss}}\right) && (3)\\ \bar{P}_{i,j} &= P_0 - 10 n_{\mathrm{p}} \log_{10}(d_{i,j}/d_0) \\ T_{i,j} &\propto N\left(\bar{T}_{i,j}, \sigma^2_{\mathrm{toa}}\right) && (4)\\ \bar{T}_{i,j} &= d_{i,j}/v_{\mathrm{prop}} \end{aligned}$$

Where P_0 is the RSS at a reference distance d_0 and v_{prop} is the speed of propagation of radio waves.

B. Cramer-Rao-Lower-Bound on Localization Error

Based on the previous error model, a lower bound on the variance of location estimates can be derived employing the CRLB. Given a random variable x which follows an univariate distribution and an estimator $T(x)$ for the parameter ϑ of this distribution, the lower bound on the variance of estimates $Var\{T(x)\}$ is given by:

$$Var\{T(x)\} \geq \frac{\left(\frac{\partial}{\partial\vartheta} E\{T(x)\}\right)^2}{I(\vartheta)} \tag{5}$$

Where $I(\vartheta)$ denotes the Fisher-Information-Matrix. For the case of ToA and RSS[1] there exist solutions for the CRLB which will be reviewed briefly in the following. Without loss of generality we assume that node n_1 is an unknown trying to estimate its location and nodes $\{2, 3, \ldots, M\}$ are beacons. In this case, $\sigma^2_{1,\mathrm{rss}}$ ($\sigma^2_{1,\mathrm{toa}}$) is the lower bound on the variance of the location estimates of n_1 for RSS (ToA):

$$\sigma^2_{1,\mathrm{rss}} = \frac{1}{a} \frac{\sum_{i=2}^{M} d_{1,i}^{-2}}{\sum_{i=2}^{M-1} \sum_{j=i+1}^{M} \left(\frac{d_{1\perp i,j} d_{i,j}}{d_{1,i}^2 d_{1,j}^2} \right)^2} \tag{6}$$

$$a = \left(\frac{10 n_\mathrm{p}}{\sigma_\mathrm{db} \ln 10} \right)^2$$

$$\sigma^2_{1,\mathrm{toa}} = v^2_\mathrm{prop} \sigma^2_\mathrm{toa} (M-1) \left[\sum_{i=2}^{M-1} \sum_{j=i+1}^{M} \left(\frac{d_{1\perp i,j} d_{i,j}}{d_{1,i} d_{1,j}} \right)^2 \right]^{-1} \tag{7}$$

It is noted that $\sigma^2_{1,\mathrm{rss}} \propto \sigma^2_\mathrm{rss}/n^2_\mathrm{p}$ and $\sigma^2_{1,\mathrm{toa}} \propto \sigma^2_\mathrm{toa} v^2_\mathrm{prop}$. Therefore, parameters for simulations were chosen to yield $\sigma^2_\mathrm{rss}/n^2_\mathrm{p} = 1$ and $\sigma^2_\mathrm{toa} v^2_\mathrm{prop} = 1$.

Since the variance of estimates is connected to the mean error, the lower bound on variance is likewise an upper bound on accuracy. It is noted that the resulting error $||\mathbf{e}_1||$ of estimates relies on both bias and variance. However, since bias can sometimes not be avoided completely, reducing variance appears as a proper approach to increase accuracy. Consequently, the algorithm presented in [14] uses this bound as criteria to select subsets of references for localization.

C. Maximum Likelihood Estimator of Location

The following estimators are used for the performance evaluation in Section VI-A for RSS and ToA:

$$\mathbf{z}_1^{(\mathrm{rss})} = \arg\min_{\{\mathbf{z}_1\}} \sum_{j=2}^{M} \left(\ln \frac{\hat{d}^2_{1,j}}{d^2_{1,j}} \right)^2 \tag{8}$$

$$\mathbf{z}_1^{(\mathrm{toa})} = \arg\min_{\{\mathbf{z}_1\}} \sum_{j=2}^{M} \left(\hat{d}_{1,j} - d_{1,j} \right)^2 \tag{9}$$

Where $\hat{d}_{i,j}$ are estimated distances and $d_{1,j} = ||\mathbf{z}_1 - \mathbf{z}_j||$.

V. Benefits of Approach

As stated before, the more references are included the more accurately can the location of an unknown be estimated. This is intuitively understood since more information can be used for localization. But why does limiting the number of reference nodes has any benefit? Since WSN are resource-limited, only considering accuracy of localization does not reflect sufficiently the impact of localization since resources have to be spend for it which are not available for other tasks. Consequently, the efficiency has to be used as performance metric to analyze and compare algorithms for localization in WSNs. In this context, selecting the most important references is a suitable means to increase the efficiency of localization.

[1]In addition, in [2] the authors derive CRLB for hybrid RSS/ToA localization.

VI. Algorithms and Performance Evaluation

In this Section, the algorithms investigated are reviewed and results from simulations using Matlab are presented.

The algorithm, called ***R**eference **S**election using **L**ocal **CRLB*** (RS-LC), is based on Cramer-Rao-Lower-Bound (CRLB). The CRLB is used to quantify the potential increase of localization accuracy locally when adding references to the subset used for localization. RS-LC is compared with the conventional methods to select references which are based on distances only. For the simulations, the conventional methods are called ***R**eference **S**election using **L**ocal **D**istances* (RS-LD) and ***R**eference **S**election using **G**lobal **D**istances* (RS-GD). Table I lists all algorithms.

Starting point for all algorithms is the request for localization, which is broadcast by the unknown and allows its recipients to estimate their distance to the unknown either by using RSS or ToA. The considered algorithms can be divided into *Global* and *Local* algorithms indicating the degree of knowledge that is required for selecting. The global algorithm, RS-GD, requires that all references share the same knowledge. Hence, they are able to access the estimates of distance of other references. Therefore, RS-GD is likely to require more communication. In contrast, references running a local algorithm, namely RS-LC or RS-LD, can only access their own knowledge, i.e. their estimate of distance to the requesting unknown. In addition, RS-LC also utilizes information contained in the responses of other reference nodes, which are:

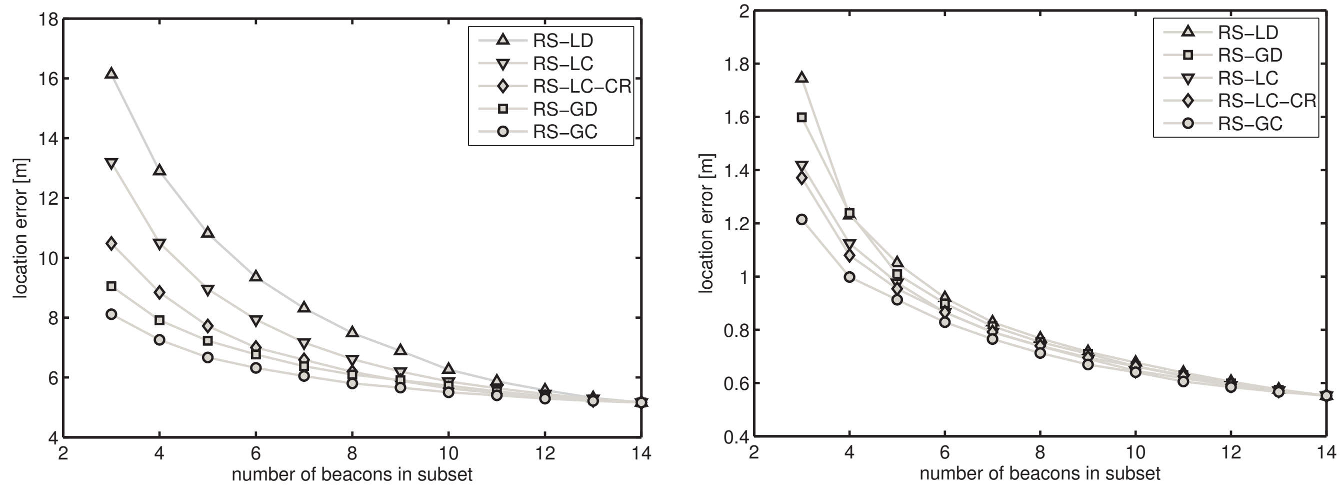
- estimated distance to requesting unknown,
- location of originator.

This way, the communication effort during RS-LC is kept as small as needed to enable localization of the unknown. The key to the distribution of the local algorithms is to assign probabilities of response based on the information being available at one reference node. For analyzis a Time Division Multiple Access (TDMA) scheme is assumed to avoid interference. This assumption can easily be relaxed to account for Carrier Sense Multiple Access schemes by substituting probabilities for back off times.

Algorithm	Degree of Knowledge	Metric used
RS-GD	global	Distance
RS-LD	local	Distance
RS-LC	local	Distance, CRLB
RS-LC-CR	local	Distance, CRLB, Circle-Rule

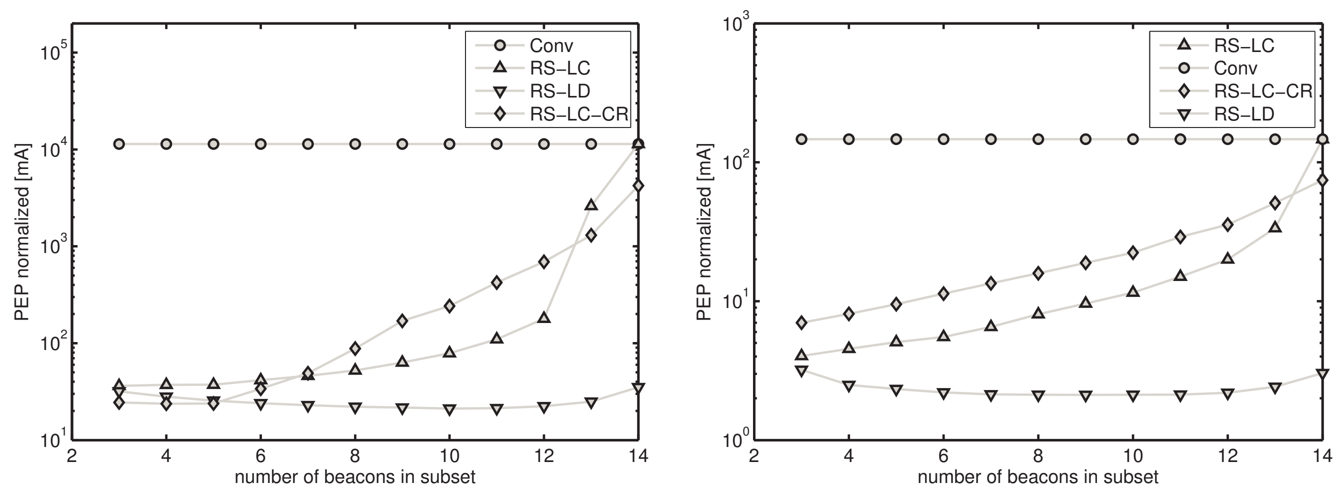
Table I
Overview of algorithms.

In some scenarios, references might know the location (estimates) of their adjacent reference nodes, for example, as a result of the first phase of localization. In this case, we propose to apply the so called *Circle-Rule* during the selection process, which, basically, allows reference nodes to respond immediately if they have no other references within the estimated distance to the requesting node (figure 2). The algorithm RS-LC-CR uses this rule.



(a) (b)

Figure 3. Simulation results: a) Lateration based on RSS. b) Lateration based on ToA.



(a) (b)

Figure 4. Power-Error-Product: a) Lateration based on RSS. b) Lateration based on ToA.

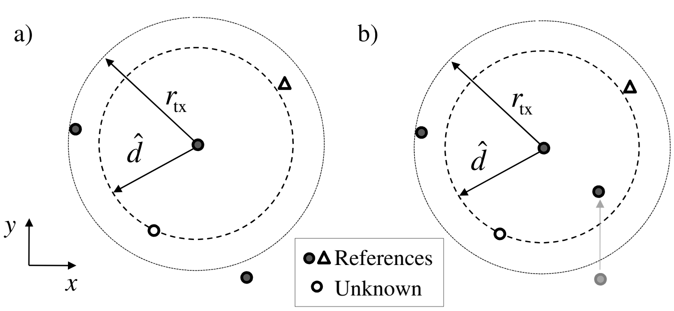


Figure 2. Circle Rule applies in a) but not in b); Tx range: r_{tx}, Estimated distance: $\hat{d}$.

The algorithms with local knowledge are described in table II. RS-LC is the same as RS-LC-CR if line 4 is left out during execution.

A. Simulation Results

We conducted simulations using Matlab to compare the performance of the algorithms in terms of MSE with the following parameters: number_of_nodes=169, number_of_unknowns=1, transmission range $r_{\text{tx}} = 150\ m$. Impact of borders is avoided by deploying all beacons in an area of size $3r_{\text{tx}} \times 3r_{\text{tx}}$ and placing the unknown randomly in the middle sector of size $r_{\text{tx}} \times r_{\text{tx}}$. Medium access is via TDMA. The average number of beacons within full transmission range of the unknown is 60. In order to avoid the hidden terminal problem, it is assumed that the requesting node broadcasts with half the transmission range while responding nodes use the full transmission range. As a result, 14 references receive the request for localization of the unknown. Distances are estimated using RSS or ToA, whereby a log-normal shadowing model is used for RSS and ToA is assumed to follow a Gaussian Distribution as stated in Section IV. To allow for comparison, the parameters of distributions have been chosen to yield $\sigma_{\text{rss}}^2/n_{\text{p}}^2 = 1$ and $\sigma_{\text{toa}}^2 v_{\text{prop}}^2 = 1$. Results are averaged over 500 independent de-

Table II
ALGORITHMS OF CLASS LOCAL-KNOWLEDGE. CODE IS EXECUTED AT b_i.

RS-LC-CR

```
procedure ProcessLocalizationRequest(d̂_{1,i},
    {d̂_{i,j} | b_j ∈ B_1})
  if no other beacon within distance d̂_{1,i} to
      unknown then
    % assign probability of responding
    P_i ← 1
  else
    % calculate probability of responding
    P_i ← 1 − (d̂_{1,i}/r_tx)^2
  end if
  H_i ← ∅
  for each tdma cycle
    % update set of beacons which have
        responded
    H_i ← H_i ∪ {beacons b_j whose response has been
        overheard by b_i}
    if card(H_i) = 1 then
      if σ̃_i(H_i ∪ {b_i}) > r_tx
        % quit current iteration without
            responding and try again next tdma
            cycle
        break
      end if
    elseif card(H_i) ≥ 2 then
      % update probability of responding
      P_i ← |1 − σ̃_i(H_i) / σ̃_i(H_i ∪ {b_i})|
    end if
    if randomNumber < P_i then
      % broadcast response
      respond(ownAddress, d̂_{1,i}, z_i)
      % exit procedure
      return
    end if
  end for
end procedure
```

RS-LD

```
procedure ProcessLocalizationRequest(d̂_{1,i})
  % calculate probability of responding
  P_i ← 1 − (d̂_{1,i}/r_tx)^2
  for each tdma cycle
    if randomNumber < P_i then
      % broadcast response
      respond(ownAddress, z_i)
      % exit procedure
      return
    end if
  end for
end procedure
```

ployments where for each deployment the location is estimated using the ML estimator of Section IV and the corresponding euclidean errors $||\mathbf{e}_1||$ are calculated (1). Results are depicted in figure 3. For the evaluation of the PEP, parameters of the popular mica2 mote have been used, i.e. $I_{\text{tx}} = 27\,mA$ in transmission and $I_{\text{rx}} = 10\,mA$ in receiving mode. Energy consumption ΔE has been normalized to source voltage and duration of one TDMA slot since these parameters are the same for all nodes and all algorithms [16]. Consequently, the normalized PEP has dimension of current.

Figure 3 shows the error of location $||\mathbf{e}_1||$ for the considered algorithms on the vertical axis and the number of beacons selected on the horizontal axis for both RSS. The algorithms can clearly be separated according to the achieved error. Among the algorithms with local knowledge, namely RS-LC-CR, RS-LC and RS-LD, RS-LC-CR performs best as it yields the smallest error of location for all sizes of the subset. As expected, the algorithms which are allowed to use global knowledge, RS-GD and RS-GC, achieve the smallest overall error. However, this is in exchange with higher energy consumption and communication effort. Figure 4 depicts the PEP for the algorithms with local knowledge and, as a reference, the PEP when all available beacons are used for localization which is denoted as *Conv*. Regarding PEP, RS-LC-CR performs best for subset size up to 4. For larger subsets, RS-LD achieves the smallest PEP and therefore the best ratio between error of localization and energy consumption. This is caused by the rapid convergence of the selection using RS-LD which, on average, completes the selection of a subset with 10 beacons after 21 TDMA slots. The rise of the PEP for RS-LC-CR for subsets larger than 5 is caused by the slow convergence of the algorithm. Here, 283 TDMA slots are needed on average to complete the selection of a subset with 10 beacons. The reason for this is that RS-LC-CR achieves a significantly lower average error than RS-LD for smaller subsets and, therefore, adding further beacons to the subset does not, on average, increase the achievable accuracy as much as for RS-LD.

Figure 3 shows the error of location $||\mathbf{e}_1||$ for ToA. The differences between the performance of the algorithms are relatively small compared with RSS whereby RS-GC achieves the smallest overall error and RS-LC-CR the smallest error among the algorithms with local knowledge. It is noted that the algorithms relying on distances only, namely RS-GD and RS-LD, achieve the largest error of localization. This is caused by the minor impact of distance between unknown and references on location estimates when ToA is used. However, when considering the efficiency using PEP (figure 4), RS-LD performs most efficient among all algorithms. This is again caused by the faster convergence of RS-LD compared with the other algorithms as explained for RSS.

VII. CONCLUSION

Distributed algorithms for selecting subsets of references for localization have been analyzed regarding error of location estimates, energy consumption and communication effort. Three algorithms, namely RS-GC, RS-LC and RS-LC-CR, use the Cramer-Rao-Lower-Bound on localization error for selecting and two algorithms, namely RS-GD and RS-LD, follow the conventional approach and rely on distances. For the case that reference nodes known the locations of adjacent reference nodes, RS-LC-CR is able to achieve the highest and RS-LD the lowest accuracy of location estimates if local knowledge is available only. However, taking into account the energy spend for localization using the Power-Error-Product reveals that RS-LD yields the best ratio between error and energy consumption due to its most rapidly convergence. However, all algorithms achieve a higher efficiency of localization compared with the conventional approach to use all available references for subsets of size up to 8 references when compared over equal periods of time.

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