Paper

Multiobjective Approach to Localization in Wireless Sensor Networks

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Abstract— Wireless sensor network localization is a complex problem that can be solved using different types of methods and algorithms. Nowadays, it is a popular research topic. What becomes obvious is that there are several criteria which are essential when we consider wireless sensor networks. Our objective is to determine accurate estimates of nodes location under the constraints for hardware cost, energy consumption and computation capabilities. In this paper the application of stochastic optimization for performing localization of nodes is discussed. We describe two phase scheme that uses a combination of the trilateration method, along with the simulated annealing optimization algorithm. We investigate two variants of our technique, i.e., centralized and distributed. The attention is paid to the convergence of our algorithm for different network topologies and trade-off between its efficiency and localization accuracy.

Keywords— ad hoc network, localization, simulated annealing, stochastic optimization, wireless sensor network.

1. Introduction to Localization Techniques

Recent advances in wireless communications and electronics have enabled the development of low-cost, low-power and multi-functional sensors that are small in size and communicate in short distances. Cheap, smart sensors, networked through wireless links are deployed in various environments and are used in large number of practical applications, such as environmental information (light, pollution, temperature, etc.), traffic or health monitoring, intrusion detection, etc., [1], [2]. Typical sensor network consists of a large number of nodes – densely deployed sensor devices.

A sensor node by itself is strongly constrained by a low battery power, limited signal processing, limited computation and communication capabilities, and a small amount of memory; hence it can sense only a limited portion of the environment. However, when a group of sensor nodes collaborate with each other, they can accomplish a much bigger task efficiently. In order to do that nodes networked through wireless must gather local data and communicate with other nodes. The information sent by a given sensor is relevant only if we know what location it refers to. Location estimation allows applying the geographic-aware routing, multicasting and energy conservation algorithms. It makes self-organization and localization capabilities one of the most important requirement in sensor networks.

The simplest way to determine a node location is to equip this node with a global positioning system (GPS) or install it at a point with known coordinates. Because of the cost, size of sensors and constraints on energy consumption most sensors usually do not know their locations, only a few nodes, called anchors are equipped with GPS adapters. Location of other nodes, called non-anchors, are unknown. In such model the techniques that estimate the locations of non-anchors based on information about positions of anchors are utilized.

In this paper we define the mathematical model of the distance-based localization, and propose a two phase localization algorithm that uses a combination of the trilateration method, along with the stochastic optimization. We consider two possible implementations: centralized and distributed ones. The efficiency of proposed method strongly depends on the values of control parameters specific to the optimization algorithm. We report the results of numerical tests performed for various values of these parameters. We discuss the results obtained both for centralized and distributed scheme in terms of accuracy and energy efficiency. Finally, we model the localization task as a multiobjective optimization problem, maximizing the localization accuracy while minimizing the localization time.

2. Localization Problem Formulation

Let us formulate the mathematical model of the localization problem for distance-based approaches. There is a network of N nodes (sensors) in $\Re^k$ with bidirectional communication constraints as the edges. Positions of M nodes (anchors) are known. The Euclidean physical distance d_{ij} between the ith and jth nodes can be measured if $(i,j) \in N_i$, where $N_i = \{(i,j) : ||x_i - x_j|| = d_{ij} \le r\}$ denotes a set of neighbors of node i, $x_i \in \Re^k$ and $x_j \in \Re^k$ true locations of nodes i and j, r is a fixed parameter called transmission range (radio range). Assuming that we have the measurements of distances between all pairs of nodes we can formulate the model of the localization problem that minimizes the sum of squares of errors in sensor positions for fitting the distance measurements:

$$\min_{\hat{x}} \Big\{ J(\hat{x}) = \sum_{i=M+1}^{N} \sum_{j \in N_i} (\hat{d}_{ij} - \tilde{d}_{ij})^2 \Big\}, \tag{1}$$

where

$$\hat{d}_{ij} = ||\hat{x}_i - \hat{x}_j||, \quad \hat{x}_i \in \Re^k, \quad \hat{x}_j \in \Re^k. \tag{2}$$

The $\hat{d}_{ij}$ denotes an estimated distance between nodes i and j, $\hat{x}_i$ an estimated position of node i and $\hat{x}_j$ an estimated position of a neighbor of node i, $\tilde{d}_{ij}$ a measured distance between nodes i and j.

3. Properties of Localization Techniques

Let us now turn to focus on the properties of localization procedures. Even if we restrict the localization task to distance-based localization with anchors, there is still a number of facets that should be taken into account in design process.

3.1. Centralized versus Distributed Computation

First of all it is necessary to determine if any required computations should be performed locally, by the participants, on the basis of some locally available measurements or all measurements should be reported to a central station that computes positions of nodes in the network and distributes them back to the participants? There are two main issues that should be considered: scaling and efficiency.

Centralized algorithms are designed to run on a central machine with plenty of computational power. Each sensor node gathers the measurements of distances between its and all the neighbors and passes them to the central station where the positions of nodes are calculated. The computed positions are transmitted back into the network. Centralized algorithms overcome the problem of nodes computational limitations by accepting the communication cost of moving data back to the central station. This trade-off becomes less effective as the network grows larger, because it unduly stresses nodes near the base station. Furthermore, the data transmission to the central station involves time delays, so the centralized techniques can not be acceptable in many applications (e.g., mobile nodes).

In contrast, distributed algorithms are designed to run in the network where computation takes place at every node. Each node is responsible for determining its position using information about neighbors. It offers a significant reduction in computation requirements because the number of neighbors is usually not very big (between ten and twenty), so the number of connections is usually a few orders of magnitude less. The use of a distributed computation model is also tolerant to node failures, and distributes the communication cost evenly across the sensor nodes. On the other hand, distributed algorithms implementation is often connected with the loss of information and because of that the results which can be obtained are usually less accurate.

3.2. Speed versus Accuracy

The most important figure of merit for a localization system is the accuracy of its results. Of course the obtained accuracy depends on the selected method, range estimation error, the number of anchors, etc. In case of many methods, especially based on optimization techniques, the accuracy is also dependent on computation time. The open question is when the computation should be stopped and how to decrease the calculation effort?

3.3. Complexity of the Algorithm versus Energy Conservation

In our analysis we consider localization algorithms based on the stochastic optimization. It is obvious they are more complicated than one-hop localization techniques or simple multi-hop localization techniques based only on connectivity described in [3]. Intuitively, the more complex localization algorithm is the better accuracy can be obtained. It is true if we consider only the localization accuracy. However, we have to realize that more complex algorithm is connected with higher energy consumption for data processing and data transmission.

4. Criteria for Distance-Based Localization

Multiple criteria can be formulated for distance-based localization. In our analysis we decided to stress the importance of four criteria which are essential for wireless sensor nodes. The majority of them are connected with economical or technical constraints such as hardware cost, low battery power and limited computation capabilities.

4.1. Localization Accuracy

To evaluate the performance of tested algorithms we used the mean error between the estimated and the true location of the non-anchor nodes in the network, defined as follows:

$$LE = \frac{1}{N-M} \cdot \frac{\sum_{i=M+1}^{N}(||\hat{x}_i - x_i||)^2}{r^2} \cdot 100\%, \qquad (3)$$

where x_i denotes the true position of the sensor node i in the network, $\hat{x}_i$ estimated location of the sensor node i and r the radio transmission range. The location error LE is expressed as a percentage error. It is normalized with respect to the radio range to allow comparison of results obtained for different size and range networks.

4.2. Hardware Cost

Each sensor node is equipped with radio. It is necessary to communicate with other nodes. For example CC2420 radio module, which is very popular, allows the programmer to measure the received signal strength (RSS) that can be used to calculate inter-nodes distances $\tilde{d}_{ij}$ used in the performance function defined in Eq. (1). But many authors says, that this measure is inaccurate [4]. We can obtain more accurate results if we decide to use additional hardware, for example, a sensor board equipped with light, temperature, acoustic signals sensors. Acoustic signals in conjunction with the standard radio module allows to use time difference of arrival (TDoA) technique, which is assumed to be more accurate than RSS. However, additional hardware can significantly increase the sensor node cost (typical sensor board costs approximately the same as a simple node).

4.3. Energy Consumption

In our analysis we consider only the energy consumed at sensor nodes, and we do not take into account the energy consumption for the base station, which is assumed not to be energy constrained. At each sensor node energy is consumed for data processing and data transmission. Energy consumed for data processing depends on the quantity of processed data and the complexity of the performed operations.

4.4. Localization Time

The same as energy also localization time is related to data processing and data transmission. The communication time depends on a network size, efficiency of multi-hop transmission, complexity of the localization technique, and computational power. It is not the aim of our work to improve communication algorithms, but we would like to show how localization algorithms can be improved in order to achieve satisfying accuracy in a short time.

5. The TSA Scheme Description

5.1. Centralized TSA Method

In [5] we proposed the localization technique that uses a combination of the geometry of triangles (trilateration), along with the stochastic optimization. This algorithm operates in two phases.

In the first phase the initial localization is provided. Trilateration uses the known locations of a few anchor nodes, and the measured distance between a given non-anchor and each anchor node. To accurately and uniquely determine the relative location of a non-anchor on a 2D plane using trilateration alone, generally at least three neighbors with known positions are needed. Hence, all nodes are divided into two groups: group A containing nodes with known location (in the beginning only the anchor nodes) and group B of nodes with unknown location. In each step of the algorithm node i, where $i = M+1, \ldots, N$ from the group B is chosen. Next, three nodes from the group A that are within node i radio range are randomly selected. If such nodes exist the location of node i is calculated based on inter-nodes distances between three nodes selected from the group A and the measured distances between node i and these three nodes. The localized node i is moved to the group A. Otherwise, another node from the group B is selected and the operation is repeated. The first phase stops when there are no more nodes that can be localized based on the available information about all nodes location. It switches to the second phase.

Due to the distance measurement uncertainty the coordinates calculated in the first phase are estimated with non-zero errors. Hence, the solution of the first phase is modified by applying stochastic optimization methods. Two techniques, i.e., simulated annealing and genetic algorithm were considered. The numerical results obtained for simulated annealing (SA) were much more promising (see [5], [6]) w.r.t. calculated location accuracy and speed of convergence. So, we decided to focus on this approach. We called our method TSA (trilateration and simulated annealing). The structure of the SA algorithm used in the second phase of TSA is presented in Algorithm 1.

Algorithm 1: Simulated annealing algorithm used in TSA

$T = T_0$, T_0 – initial temperature
$\Delta d = \Delta d_0$, Δd_0 – initial move distance
while $T > t_f$ **do**
  for $i = 1$ to $P \cdot (N-M)$ **do**
    select a node to perturb
    generate a random direction and move a node at distance Δd
    evaluate the change in the cost function, ΔJ
    if $(\Delta J \leq 0)$ **then**
      //downhill move $\Rightarrow$ accept it
      accept this perturbation and update the solution
    else
      //uphill move $\Rightarrow$ accept with probability
      pick a random probability rp = uniform(0,1)
      if $(rp \leq exp(-\Delta J/T))$ **then**
        accept this perturbation and update the solution
      else
        reject this perturbation and keep the old solution
      end if
    end if
  end for
  change the temperature: $T_{new} = \alpha \cdot T$, $T = T_{new}$
  change the distance $\Delta d_{new} = \beta \cdot \Delta d$, $\Delta d = \Delta d_{new}$
end while

From the numerical experiments it was observed that the increased value of the location error is usually driven by incorrect location estimates calculated for a few nodes. The additional functionality (correction) was introduced to the second phase to remove incorrect solutions involved by the distances measurement errors. The detailed description of the correction algorithm can be found in [5].

5.2. Distributed TSA Method

From the numerical experiments performed for the centralized TSA method it was observed that centralized TSA provides quite accurate location estimates even in the case of unevenly distributed nodes with known positions.

However, in this approach we have to gather the measurements of distances between all pairs of network nodes in a single computer to solve the optimization problem Eq. (1). The data transmission to the central station involves time delays and it can not be used in some application, e.g., mobile networks. In contrast to the centralized method we proposed a fully distributed method where computations take place at every node. In this implementation each node is responsible for determining its position using local information about its neighbors.

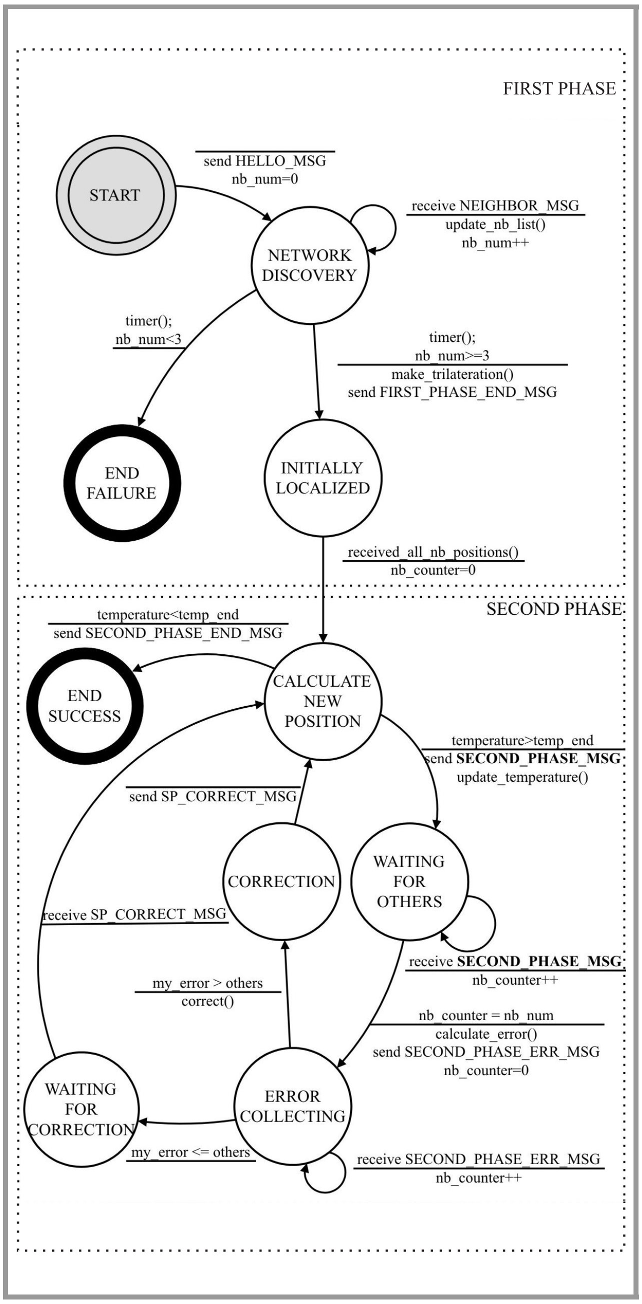

Fig. 1. The state diagram for distributed TSA method.

The state diagram for distributed TSA algorithm is presented in Fig. 1. The estimated position of each node is calculated in parallel. Every P iterations of SA algorithm the neighboring nodes exchange the messages with the current results of calculations.

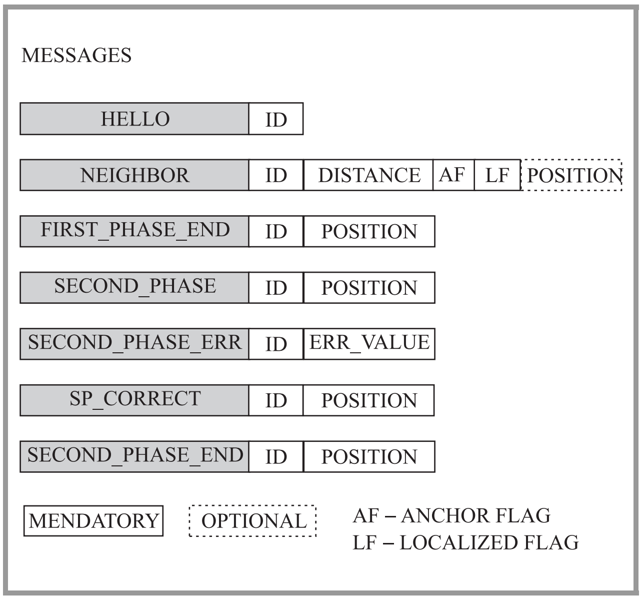

Fig. 2. The scheme of exchanged messages.

The messages structure is illustrated in Fig. 2. Next, the nodes update their location estimates. Many transmissions are needed to obtain a reasonable solution.

6. TSA Scheme Evaluation

We performed many numerical tests to cover a wide range of network system configurations including size of the network (200 – 10000 nodes) and anchor nodes deployment. Especially the anchor nodes deployment seems to be important to evaluate the proposed approaches to sensor network localization. Therefore we prepared a few test problems. Figure 3 depicts four network topologies: a, b with evenly distributed anchor nodes (a – random distribution, b – anchor nodes placed near the edges of a sensor field) and c, d with anchor nodes deployed only in a part of the region to be covered by sensors.

To solve the localization problem Eq. (1) we needed the values of the measured distances between pairs of nodes. In real applications the measured distance $\tilde{d}_{ij}$ between two neighbor nodes is produced by measurement methods described in literature [7], [8]. These methods involve measurement uncertainty; each distance value $\tilde{d}_{ij}$ represents the true physical distance d_{ij} corrupted with a noise describing the uncertainty of the distance measurement. For the purpose of numerical experiments we supposed that this disturbance is described by introducing Gaussian noise with a mean of 0 and a standard deviation of 1 added to the true physical distance d_{ij}:

$$\tilde{d}_{ij} = d_{ij}(1.0 + randn() \cdot nf), \qquad (4)$$

where nf denotes a noise factor.

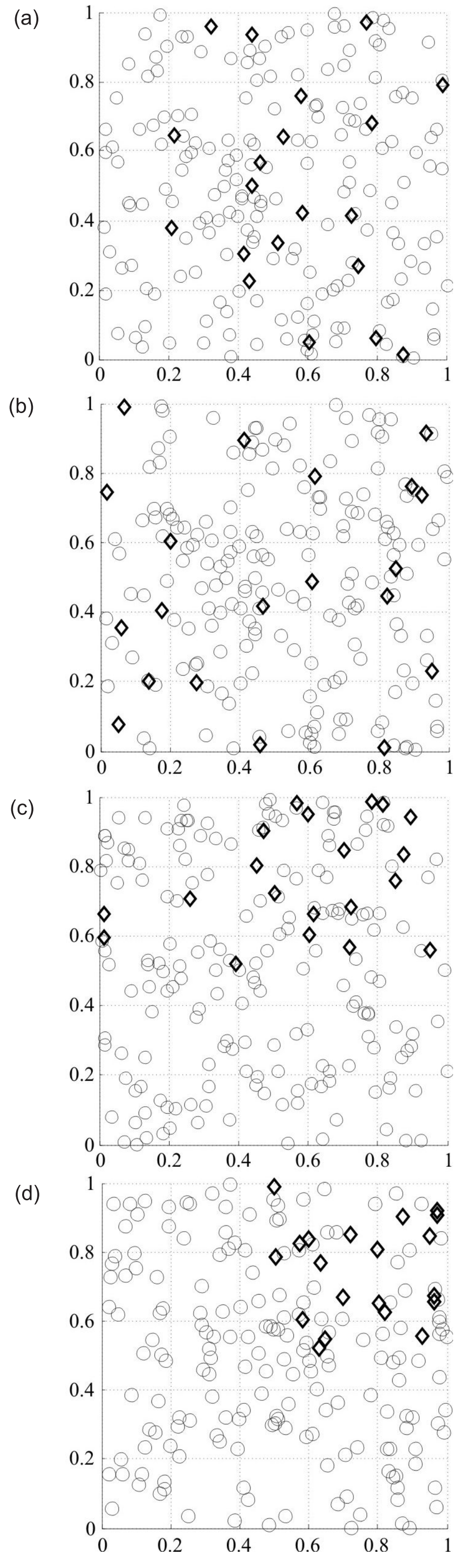

Fig. 3. Test problems four network topologies: a, b with evenly distributed anchor nodes (a – random distribution, b – anchor nodes placed near the edges of a sensor field) and c, d with anchor nodes deployed only in a part of the region to be covered by sensors.

6.1. Centralized versus Distributed TSA Methods

Figure 4 presents the solution quality difference between centralized and distributed algorithms for two test networks (b) and (c) depicted in Fig. 3. The obtained results confirm that from the perspective of location estimation accuracy, centralized algorithm provides more accurate location estimates than distributed one. As a final result we can say that for evenly distributed anchors we obtain quite accurate solution using both methods, otherwise the results of location estimation are much worse in case of distributed version of our scheme.

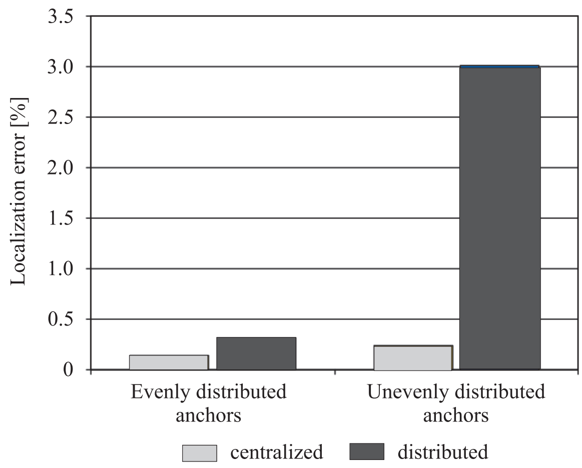

Fig. 4. Localization error for centralized and distributed scheme; test problems b and c.

Distributed version of localization algorithm has many advantages that were discussed in Subsection 3.1. However, distributed algorithm performance is often connected with the loss of information, which was confirmed in simulations (see Fig. 4). There are two reasons of that: loss of information due to parallel computation and loss of information due to the incomplete network map.

6.2. Complexity of the Algorithm versus Energy Use

Let us now turn to the structure of our algorithm. It operates in two phases. In the first phase the auxiliary solution (initial localization) is provided. The solution of the first phase is modified by applying stochastic optimization method in the second phase. Two aspects are worth considering here. First of all what does it mean that auxiliary solution is provided, and how far this solution can be improved in the second phase? The second question is, how the stochastic optimization implies the energy consumption?

The results obtained for centralized algorithm after the first phase and the second phase (final result) are collected in Table 1. The simulations were performed for four test networks depicted in Fig. 3.

From this table we can see that stochastic optimization greatly improves the solution quality. It is obvious that the TSA algorithm needs many iterations to achieve a stable solution. The cost of each iteration, in energy terms, is different for centralized and distributed TSA scheme. Centralized algorithm in large networks requires each sensors measurements to be sent over multiple hops to a central processor, while distributed algorithm requires only local information exchange between neighboring nodes but many such local exchanges may be required, depending on the number of iterations needed to arrive at a stable solution.

Table 1
Localization accuracy for different tasks

Test problem	Localization error (LE) [%]	
	I phase	II phase
a	6.3544	0.1447
b	8.8331	0.1414
c	25.0953	0.1961
d	57.0212	0.3248

In case of centralized implementation energy consumption for localization is asymmetric, because the multi-hop transmission stresses nodes near the central station more than any others. Fortunately this is not a problem because localization task generates only one packet per node which must be transmitted to the base station. In most cases this packet can be transmitted without fragmentation, because of the small amount of data.

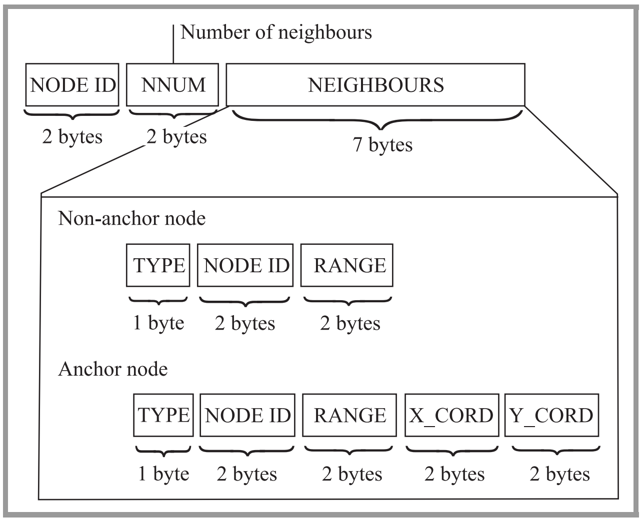

Fig. 5. Localization packet.

Figure 5 presents the localization packet structure. From this figure we can see that even for a node with 10 neighbors the packet size doesn't exceed the fragmentation boundary (approximately 100 bytes) – more detailed information can be found in [9].

Energy consumption becomes a bigger problem for distributed algorithms which require many local information exchanges between neighboring nodes. In the second phase many iterations is needed and each iteration is connected with "SECOND_PHASE_MSG" sending. The problem is depicted by the loop in Fig. 1. The critical message is marked in bold.

6.3. TSA Parameters Tuning

Robustness for anchor nodes deployment. In the paper [6] we have reported the comparison of the results obtained for the TSA method and some other methods. Our scheme seems to be very promising. However, its efficiency and robustness strongly depend on control parameters $\alpha, \beta, \Delta d_0, t_f$ specific to the simulated annealing algorithm used in the second phase of TSA, and depicted in Algorithm 1. All these parameters influence the speed of convergence and accuracy of the solution. To obtain the general purpose algorithm the values of them should be tuned for various network topologies.

We performed the experiments for four test problems presented in Fig. 3. Our aim was to calculate the values of SA parameters: $\alpha, \beta, \Delta d_0, t_f$, depicted in Algorithm 1, which minimize the localization error Eq. (3) for all considered tasks. We solved a decision problem defined as an optimization problem with four criteria (localization errors for tasks a, b, c and d), where all criteria are minimized:

$$\min_{\mathbf{z}} (LE_a(\mathbf{z}), LE_b(\mathbf{z}), LE_c(\mathbf{z}), LE_d(\mathbf{z})), \tag{5}$$

where $\mathbf{z} = [\alpha, \beta, \Delta d_0, t_f]$ denotes a vector of decision variables to be selected within the feasible set, which consists of 48000 elements. Model Eq. (5) specifies that we are interested in minimization of all objective functions and allows us to eliminate insufficient solutions leading to a dominated outcome vectors. After the elimination the Pareto frontier consists of 196 undominated solutions.

In order to select the preferred solution we used a quasi-satisfying approach to multiple criteria optimization – the reference point method [10]–[12]. The model of preferences was created by introducing the reference levels.

Table 2
Aspiration and reservation levels

Reference vector	LE_a	LE_b	LE_c	LE_d
Aspiration levels $\mathbf{r}^a$	0.10	0.10	0.25	0.50
Reservation levels $\mathbf{r}^r$	1.00	1.00	2.00	4.00

We considered two reference vectors: vector of aspiration levels $\mathbf{r}^a$ and vector of reservation levels $\mathbf{r}^r$, which specified acceptable and required values for the localization error (see Table 2).

Depending on the specified reference levels, the partial achievement function s_i can be built and interpreted as a measure of the decision maker satisfaction with the current value of outcome the ith criterion. It is a strictly increasing function of outcome LE_i with value $s_i = 1$ if $LE_i = r_i^a$, and $s_i = 0$ for $LE_i = r_i^r$. We used the piece-wise linear partial achievement function with strong dissatisfaction connected with outcomes worse than the reservation level and s_i value slightly greater than 1 for outcomes better than the aspiration level.

Having all the outcomes transformed into a uniform scale of individual achievements they can be aggregated to form a scalarizing achievement function Eq. (6). Maximization of the scalarizing achievement function generates an efficient solution to the multiple criteria problem:

$$\max_{\mathbf{z}} \left[\min_{i=a,b,c,d} s_i(LE_i) + \varepsilon \cdot \sum_{i=a,b,c,d} s_i(LE_i) \right]. \qquad (6)$$

The solution obtained by solving the problem Eq. (6) was equal:

$$\mathbf{z} = \begin{bmatrix} \alpha \\ \beta \\ \Delta d_0 \\ t_f \end{bmatrix} = \begin{bmatrix} 0.94 \\ 0.98 \\ 0.26 \\ 10^{-13} \end{bmatrix}.$$

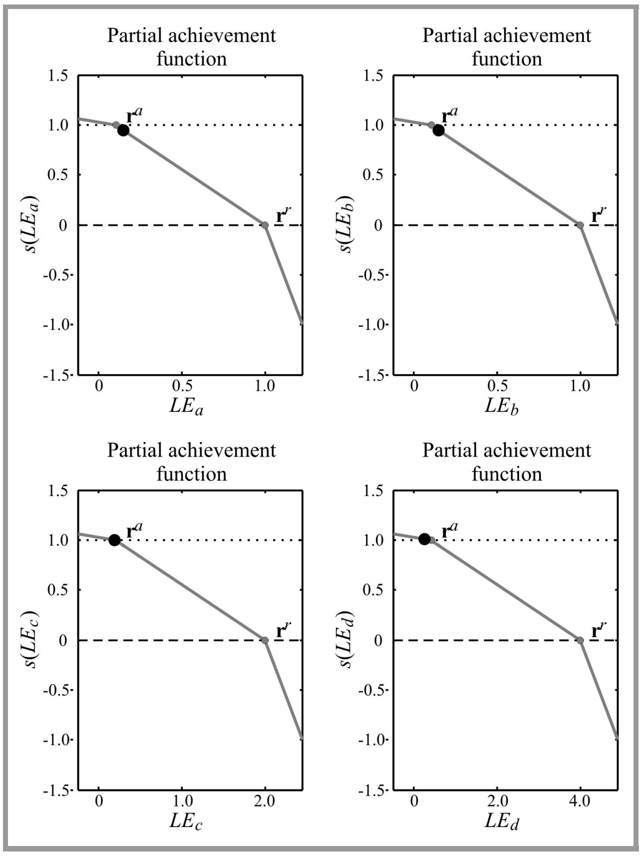

Fig. 6. Partial achievement functions.

The corresponding objective and partial achievements values are collected in Table 3.

Table 3
Values in criterion space for selected solution

Task	Localization error LE	Partial achievement value $s(LE)$
a	0.1447	0.9503
b	0.1414	0.9540
c	0.1961	1.0077
d	0.3248	1.0125

Partial achievements functions are also depicted in Fig. 6. The solution is marked with the dot for each partial achievement function.

A trade-off between efficiency and accuracy. Time consumed on localization in case of centralized algorithm increases proportionally to the network dimension, as it can be seen in Table 4.

Table 4
Localization error and computation times for different network sizes

Number of nodes	Localization error LE [%]	Computation time [s]
200	0.11	1.4
500	0.15	7.6
1000	0.29	29.4

The trade-off between efficiency and accuracy is expected. To decrease the calculation effort the optimal value of another SA control parameter (P) have to be estimated. In the SA implementation used in the second phase of the TSA scheme at each value of the coordinating parameter T (temperature), $P(N-M)$ non-anchor nodes are randomly selected for modification (where N denotes the number of sensors in the network, M the number of anchors, and P a reasonably large number to make the system into thermal equilibrium). The parameter P plays the important role – it influences the estimated location accuracy and calculation time.

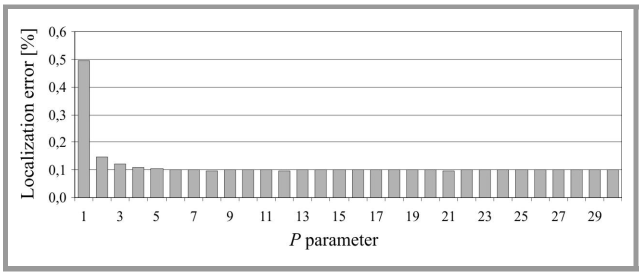

Fig. 7. Localization error for various values of P.

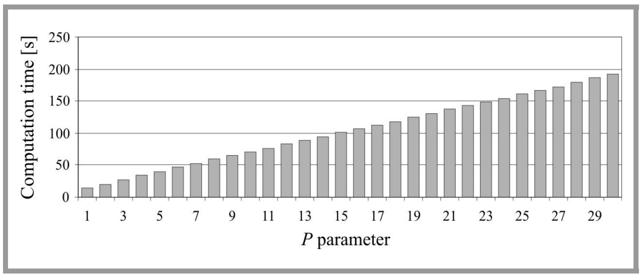

Fig. 8. Computation times for various values of P.

Figures 7 and 8 present the results of numerical tests performed for the network with 2000 nodes and various values of P.

To calculate the optimal value of the parameter P for a given network we can solve the two-criterion optimization problem:

$$\min_{P}(\Delta t, LE), \tag{7}$$

where Δt denotes a calculation time, LE a localization error defined in Eq. (3).

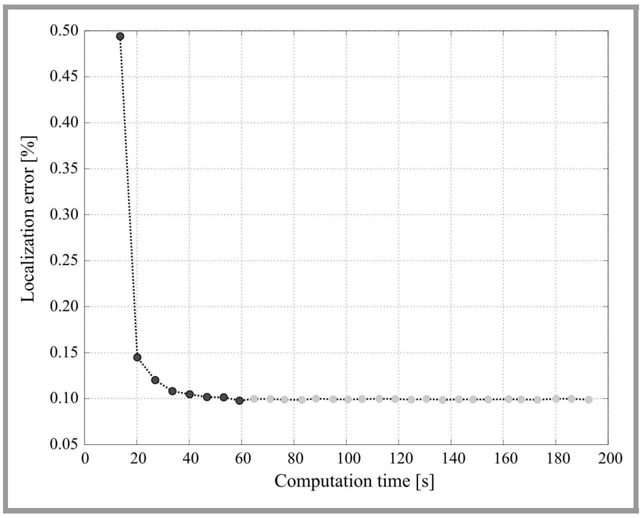

Fig. 9. The solution of the problem (7) for the network with 2000 nodes.

Figure 9 illustrates the Pareto frontier for the network of 2000 nodes. In order to select the preferred solution we also used the reference point method. As an aspiration and reservation level we assumed that computation time can not exceed ten seconds, and localization error must be less then 1% (see Table 5).

Table 5
Aspiration and reservation levels

Reference vector	Calculation time [s]	Localization error [%]
$\mathbf{r}^a$	10	0.10
$\mathbf{r}^r$	60	1.00

In Table 6 values of partial achievement functions for both criteria and the scalarizing achievement function for all undominated solutions are presented. We can see that the best value of achievement is for the solution calculated for $P = 2$.

Table 6
Undominated solutions and corresponding achievement function

P	Computation time [s]	Localization error LE	PAF*		SAF**
			$s(t)$	$s(LE)$	
1	13.6	0.4940	0.9280	0.5622	0.5624
2	**20.2**	**0.1448**	**0.7960**	**0.9503**	**0.7962**
3	27.0	0.1201	0.6600	0.9777	0.6602
4	33.6	0.1081	0.5280	0.9910	0.5282
5	40.2	0.1047	0.3960	0.9948	0.3961
6	46.8	0.1017	0.2640	0.9981	0.2641
7	53.2	0.1014	0.1360	0.9985	0.1361
8	59.2	0.0977	0.0160	1.0006	0.0161

* PAF – partial achievement function,
** SAF – scalarizing achievement function.

The optimal values of parameter P corresponding to the solutions of the task Eq. (7) for different networks are illustrated in Table 7. Because TSA should be the general purpose localization scheme that can be used to different dimension problems we solved the more general problem for five networks with various dimensions (automatically the number of criteria was ten). The preferred solution was obtained for $P = 4$. The results of calculations performed for network with 200 to 10000 nodes and $P = 4$ are presented in Table 8.

Table 7
Optimal values of parameter P for different size of network

Number of nodes	200	500	1000	2000	4000
Calculated P	4	4	4	2	2

Table 8
Localization errors and computation times for different sizes of network

Number of nodes	LE [%]	t [s]
200	0.1275	0.4
500	0.4124	2.2
1000	0.1387	8.0
2000	0.1081	33.6
4000	0.1086	125.8
5000	0.1581	189.8
10000	0.1193	790.4

7. Summary and Conclusions

In this paper we outline the main properties and criteria that should be considered while estimating the location of nodes with unknown positions in the sensor network. We stressed the importance of such criteria like localization accuracy, hardware cost, energy consumption and calculation capabilities. The main objective was to develop the efficient and robust localization algorithm. We presented and evaluated the hybrid scheme that combines simple geometry of triangles and stochastic optimization technique. The big effort was on tuning the parameters of the optimization algorithm. Finally, we demonstrated that our method provides quite accurate location estimates in the sensible computing time even in the case of unevenly distributed nodes with known positions.

Acknowledgement

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