Space and Time Localization in Wireless Sensor Networks

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Abstract **- Wireless sensor networks *(WSN)* are an increasingly attractive means to bridge the gap between the physical and virtual world. *WSNs* are envisioned to be used to fulfill complex monitoring tasks. Space and time play a crucial role in wireless sensor networks, since sensor nodes are used to collaboratively monitor physical phenomena and their space-time properties. A number of techniques and distributed algorithms for location estimation and time synchronization have been developed specifically for sensor networks. There are many similarities in space and time domains. This affects the location estimation and time synchronization, ranging from applications and requirements to basic approaches and concrete algorithmic techniques. An improved approach for space and time localization in *WSNs* is given in this paper. The main aspect of the algorithm is the use of a mobile beacon for both localization and synchronization. A mobile beacon is a node that moves around the sensor's field and it is aware of its time and position, equipped with a Global Positioning System (*GPS)* receiver. The synchronization component uses the packets required by the positioning component to improve its performance. The positioning component benefits from the communication, required by the synchronization component to decrease errors. A set of experiments and simulations are presented to evaluate the performance of the algorithm in order to reduce communication and processing resources and save energy and network resources.**

Keywords - space localization; time synchronization; mobile beacon; delay measurement; wireless sensor networks; global positioning system

I. INTRODUCTION

Enabled by technological advancements in wireless communications and embedded computing, wireless sensor networks were first considered for military applications, where large-scale wireless networks of autonomous sensor nodes would enable the unobtrusive observation of events in the real-world. The use of sensor networks has also been considered for various civil application domains.

The categories time and location are fundamental for many applications of sensor networks, due to the close integration of sensor networks with the real world. Interpretation of sensing results or coordination among sensor nodes are some of the implementations, time synchronization and sensor node localization are fundamental and closely related services in sensor networks.

In the synchronization problem [20, 21, 22, 23, 24, 25], the nodes' local clocks must be synchronized based on a reference node or in Coordinated Universal Time (*UTC*).

On the other hand, in the positioning problem [11, 12, 13], the concept of a reference system between sensor nodes is performed by identifying the physical location (e.g., latitude, longitude, and altitude) of these nodes. In general, traditional solutions such as the Network Time Protocol (*NTP* [26]) and Global Positioning System *(GPS*) are not suitable for sensor networks due to resource limitations. Furthermore, current solutions for the synchronization [20, 21, 22, 23, 24, 25] and positioning [11, 12, 13] problems are independent from each other and consequently, these problems are solved separately. As a result, the independent execution of these algorithms leads to lower efficiency regarding cost and accuracy. As it is demonstrated in this paper, by jointly solving these two problems, both synchronization and positioning errors can be reduced and energy can be saved.

In some previous work [4, 14, 15], algorithms for time-space localization are proposed. In this paper, an improved algorithm for solving this problem using a mobile beacon is proposed. A mobile beacon is a node that is aware of its time and position (e.g., equipped with a *GPS* receiver) and that has the ability to move around the sensor field. This beacon can be a human operator, an unmanned vehicle, an aircraft, or a robot. A mobile beacon has been successfully applied to solve the positioning problem. To the best of our knowledge, the current work is the first to address the use of a mobile beacon in synchronization and time-space localization problems. The proposed time-space localization algorithm can synchronize nodes by using the packet delay measurement [23, 24]. Synchronization can be improved by the extra packets required for location discovery. The algorithm is implemented for different network topology.

Existing solutions for time synchronization and node localization do not cover all important parts. Here, an integrated solution to jointly solve the localization and data routing problems in sensor networks is proposed, using a mobile beacon equipped with *GPS*, for grid, but also for randomly chosen network topology, reducing communication and processing resources, also saving energy and network resources.

In the next section, the related work is described. Section *3* presents an overview and definition of the positioning and synchronization problems in *WSNs*. Section *4* is presenting different types of topologies for wireless sensor networks used in our work. Section *5* describes the

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proposed algorithm, which is evaluated in Section *6*. Section *7* presents the conclusions and future work.

II. RELATED WORK

There are different ways of classifying general *space and time localization algorithms,* they can be classified according to the measurement assumptions as four types: 1) connectivity-only 2) range-based 3) angle-based 4) hybrid. A comparison between the well - known algorithms such as *DV-Hop (Distance and Euclidean),* Euclidean and Multi-lateralization can be obtained from [3]. The comparison is done in the context of specific constraints of sensor networks, such as error tolerance and energy efficiency, results indicate that there is no single algorithm that performs "best" and that there is possibility for further improvement.

A number of localization methods rely on connectivity information only. These types of methods are also referred to as "range-free" methods. The *Centroid method* [5] estimates the location of an unknown node as the average of its neighbors' locations. The *APIT* method *(Ad Hoc Positioning* [6] estimates the node location by isolating the area using various triangles formed by beacons. The *DV-Hop method* [7] counts the hop numbers to beacons and uses them as crude estimates for distances. Range-free methods require no additional hardware, but they generally only work well when networks are dense. Sparse networks by nature contain less connectivity information, and thus they are more difficult to localize accurately.

Range-based methods include the *Ad Hoc Positioning System (APS*) methods such as *DV-Distance and Euclidean* proposed in [7, 8]. In [9], ranging data are exchanged between the neighbors to refine the initial location guess. While those methods compute the absolute node locations, the *GPS-Free method* [10] calculates the relative node locations from the distance measurements. Compared to range-free methods, range-based methods give more accurate location estimates when ranging data is reliable. However, depending on the deployment environment, ranging techniques based on *RSSI-Received Signal Strength Indicator* tend to be error-prone and strong filtering is required. The ranging error could ultimately destroy the localization accuracy if it is allowed to propagate through the network unbounded.

Different methods generally exploit the trade-off between the estimation accuracy and the estimation coverage. For instance, given the same network scenario, the Euclidean method is capable of generating more accurate location estimates of a smaller subset of nodes, whereas the *DV-Hop* method has better coverage but worse accuracy. Regardless of the tradeoff, a common characteristic shared by distance-based *algorithm* is that they require a relatively high network density in order to achieve better results. Based on the extensive simulation of *DV-Distance, Euclidean* and *multilateration methods* performed in [16], it can be concluded that those distance-based *GAHLA*s “require an average degree of *11-12* nodes within the ranging neighborhood in order to achieve *90%* localization coverage with *5%* accuracy [16]."

Even though the future of AoA sensing devices is still unclear, some works have been published on localization using angle information. Simulation studies in [16] also show that when AoA (angle of arrival) of the signals is used in addition to the distance measurement, the localization accuracy and coverage can be drastically improved.

A combination of the above techniques can be employed to form a hybrid method. For instance, a hybrid method is proposed in [17] that uses both *APS* and Multi-dimensional Scaling *(MDS)*.

The probabilistic method and particle filters have been used in visual target tracking and computer vision location systems [18, 19] in the context of robotics. The particle filter method is also used to obtain the mobile node location based on received signal strengths from several known-location base stations in wireless cellular networks. The probability grid system in is a centralized probabilistic localization algorithm that updates the distribution based on a grid system.

Some recent researches [27, 28, 29] have proposed the use of mobile beacons to assist the nodes of a *WSN* in estimating their positions. A mobile beacon is a node that is aware of its position (e.g., equipped with a *GPS* receiver) and that has the ability to move around the sensor field. This beacon can be a human operator, an unmanned vehicle, an aircraft, or a robot. The localization algorithm proposed by Sichitiu and Ramadurai [27] uses mobile beacons to allow nodes to compute their positions by using range-based distance estimations. A similar but range-free positioning system is proposed by Ssu et al. [29]. In Pathirana et al. [28], the mobile beacon itself computes the positions, instead of the nodes. Mobile beacons have also been used to localize nodes in underwater *WSNs* [30]. In these networks, a boat equipped with a *GPS* receiver can be used as a mobile beacon or can send *GPS* position information to submerged equipment. These solutions address only the spatial localization problem, ignoring the need for time localization.

In the Flooding Time Synchronization Protocol (*FTSP*) [23], all delays in the packet transfer time are computed to synchronize precisely both sender and receiver using only one broadcast. An accuracy of about $1.5\ \mu s$ is reported. The multihop synchronization algorithm includes a leader selection (root node) and a flooding-like algorithm to propagate the timing information. Multiple floodings can be used to compute the clock drift. A similar algorithm is Delay Measurement Time Synchronization (*DMTS*) [24], which reports a single hop accuracy between $2\ \mu s$ and $32\ \mu s$. These synchronization solutions solve only the time synchronization problem, ignoring the need for a common spatial reference system.

Global Positioning System (*GPS)* [1] is a good example of a time-space localization system that can both localize and synchronize sensor nodes; however, to equip all the sensors in a *WSN* with a *GPS* receiver is not a good solution because it increases their cost, size and energy consumption. Romer [31, 32] also addressed and solved these two problems separately. Then, Romer and Mattern [33] presented both problems as related to each other, but no integrated solution was proposed. The Synapse algorithm is proposed [14], a time-space localization algorithm that computes the average multi-hop time of a packet to synchronize the nodes. Also, the Lightness algorithm [15] had been proposed, a novel and lightweight time-space localization algorithm that is able to localize and synchronize all nodes in a *WSN* with the communication cost of a single flooding.

In this paper, an improved algorithm for localization in time-space, using a mobile beacon, referring different network topologies is proposed to solve this problem.

III. WIRELESS SENSOR NETWORKS

Sensor networks consist of sensor nodes, computing devices that include a power source, a transceiver for wireless communication, a processor, memory, sensors, and potentially also actuators. Although the exact properties and capabilities of these components may vary, a common property of sensor nodes is their resource scarcity.

Multiple sensor nodes form a wireless network, whose topology and other properties do also depend on the application context. A large class of sensor networks can be characterized as multi-hop ad hoc networks, where sensor nodes do not only act as data sources, but also as routers that forward messages on behalf of other nodes, such that no additional communication infrastructure is required for operating the network.

The output of the sensor network may be used for various purposes. The output is delivered to a human user for further evaluation. It may be used to control the operation of the sensor network without human intervention by enabling/disabling sensors, or by controlling operation parameters of sensors (sampling rate, sensitivity, orientation, position). Using the output of the sensor network to control sensors or actuators can effectively create a closed-loop system that strives to achieve a particular nominal condition in the sensor network or in the real world.

The characteristics of wireless sensor networks can present a number of major challenges to the development of algorithms, protocols and systems. The main technical challenges are resource and energy constraints, network dynamics, network size and density, unattended and un-tethered operation.

It is important to ensure that resource usage and energy consumption are equally spread among the nodes of the network. If some nodes exhaust their battery quickly and fail early, resulting permanent network partitions may render the network in-operational. Usage of resources may lead to bottlenecks such as network congestions. Sensor nodes send sensor readings along a spanning tree to a base station for evaluation. Nodes close to the base station will run out of power since they forward messages from nodes further away.

Depleted batteries and corruptive environmental conditions (e.g., pressure, humidity, temperature, destructive chemicals) often lead to node failures. Temporary environmental obstructions may influence the communication range of nodes. Nodes may be mobile, new nodes may be added to replace failed ones. All these issues may lead to frequent topology changes in sensor networks. Temporary network partitions are likely to exist in sparse networks.

Despite intermittent connectivity, messages can be forwarded across partitions by mobile nodes as illustrated in Figure *1*.

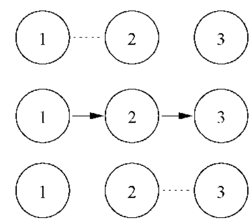


Figure *1*: Message transport across partition boundaries through node mobility.

The delay of the message flow can be arbitrarily high and is hardly predictable unless the mobility pattern of node *2* in the figure *1* is known in advance. Ensuring robust operation of a sensor network in such setups can be a very challenging task.

A. The Positioning Problem

To define the positioning problem in Wireless Sensor Networks, we take a *WSN* composed of p nodes, with a communication range of c units, and distributed in a two-dimensional squared sensor field $S = [0, q] \times [0, q]$.The network is presented by a graph $P = (L,M)$ with $L = \{l_1, l_2, . . . ,l_n\}$ like a set of sensor nodes; $h_i, j_i \in M$ *iff* l_i reaches l_j , i.e., the distance between; l_i and l_j is smaller than c; $u(e) \leq c$ is the weight of edge $e = h_i, j_i$, i.e., the distance between l_i and l_j . We also consider only two dimensions for a node's location, but the methods presented here can be extended to accommodate three dimensions. P is Euclidean graph in which every node has a coordinate $(x_i, y_i) \in R^2$ in a two-dimensional space, which represents the location of node i in S. Here there are: the unknown node, which is a node that doesn't know its position, then settled node which was initially an unknown node, but has managed to estimate its position by using a positioning system. Also, there is a beacon node or anchor, which is always aware of its physical position and helps to locate other nodes. Its position is obtained by manual placement or by external means such as a *GPS* receiver. This node forms the basis for most positioning systems in *WSN*s. The *positioning problem* is stated as finding the position of as many unknown nodes as possible, referring to a given multihop network, represented by a graph, and a set of beacon nodes and their positions.

An example of a positioning system is localization with a mobile beacon proposed by Sichitiu and Ramadurai [27]. Once the nodes are deployed, the mobile beacon travels through the sensor field broadcasting messages that contain its current coordinates. When an unknown node receives more than three messages from the mobile beacon, it computes its position being based on the received coordinates and on the *RSSI* (Received Signal Strength Indicator) distance estimations. The communication cost for the *WSN* is null, since the nodes do not need to send any packets.

An advantage of this mobile beacon approach is that the nodes' positions are computed based on the same node -mobile beacon, keeping the mean localization error low and preventing the propagation of this error. It avoids the use of nodes equipped with *GPS*, except for the mobile beacon.

An important aspect that influences the position estimates is the trajectory of the mobile beacon. The less rectilinear the trajectory, the better the estimates will be. Rectilinear trajectories must be avoided. Two possible trajectories are evaluated in this work: sinusoidal and spiral trajectory.

B. *Time synchronization*

The significance of physical time for sensor networks has been reflected by the development of a number of time synchronization algorithms in the recent past. Most computer systems in use today are based on clocked circuits and hence contain so-called digital clocks. Such hardware clocks are a valuable tool for time synchronization, since they can be used to maintain synchronization over time [2].

A typical hardware clock consists of a quartz-stabilized oscillator and a counter that is incremented by one every oscillation period. If the periodic time T of the oscillator is known, the counter h can be used to obtain approximate measurements of real-time intervals in multiples of T.

The clock counter displays value $h(t)$ at real time t and is incremented by one at a frequency of f. The rate of the counter is defined as $f(t) = dh(t)/dt$. An ideal digital clock would have a rate of 1 at all times. The periodic time of the oscillator and hence the clock rate depend on various parameters such as age of the quartz, supply voltage, environmental temperature and humidity. This clock drift is formally defined as the deviation of the rate from 1 or:

$$\rho(t) = f(1) - 1 \tag{1}$$

Since sensor nodes are typically operated under a well-defined range of the above parameters, it is reasonable to assume a maximum possible drift ρ_{max}, such that:

$$|\rho(t)| \leq \rho_{max} \tag{2}$$

Obtaining temporal constraints is typically implemented by communication among sensor nodes. In practice, the relationship between synchronized time and hardware clock is often not linear. By repeating the line fitting procedure frequently, a linear approximation of that nonlinear relationship can be achieved. The hardware clock can be considered a time sensor, calibrated using the observed past behavior of synchronized time. The precision of the chosen approach should be evaluated and the imprecision of time synchronization algorithm should be decreased, depending on the age of time marks and hop-distance between nodes of the sensor network, providing accuracy ordered in milliseconds.

In this work, the actual time of the network is considered, in which the nodes must be synchronized (e.g., *UTC*), is represented simply by t. The hardware clock of node i is defined as $t_i(t)$, since it is a monotonically non-decreasing function of t. Because no hardware clock is perfect, $t_i(t)$ has two components: $t_i(t) = d_i t + o_i$, where o_i is the offset, i.e., the difference between t and t_i at that instant, and d_i is the drift, i.e., how the local clock gradually deviates from t due to conditions such as temperature or battery voltage. The unsynchronized node is a node whose clock is not synchronized with the reference; synchronized node is a node which was initially unsynchronized, but managed to synchronize its local clock by using a synchronization system; the beacon node is the node that already has a synchronized clock (e.g., by using *GPS*) and it is called a beacon node. The *synchronization problem* is stated in finding the offset and drift (o_i, d_i) of as many unsynchronized nodes $i \in N$ as possible, by a given multihop network, represented by a graph, a set of beacon nodes and their synchronized clocks. In the packet *delay measurement*, all delays in the packet transfer time are estimated to synchronize precisely both sender and receiver by using only one packet. The packet delay measurement synchronization technique has been used in a number of synchronization protocols for *WSNs* [23, 24].

C. *Localization in Time and Space*

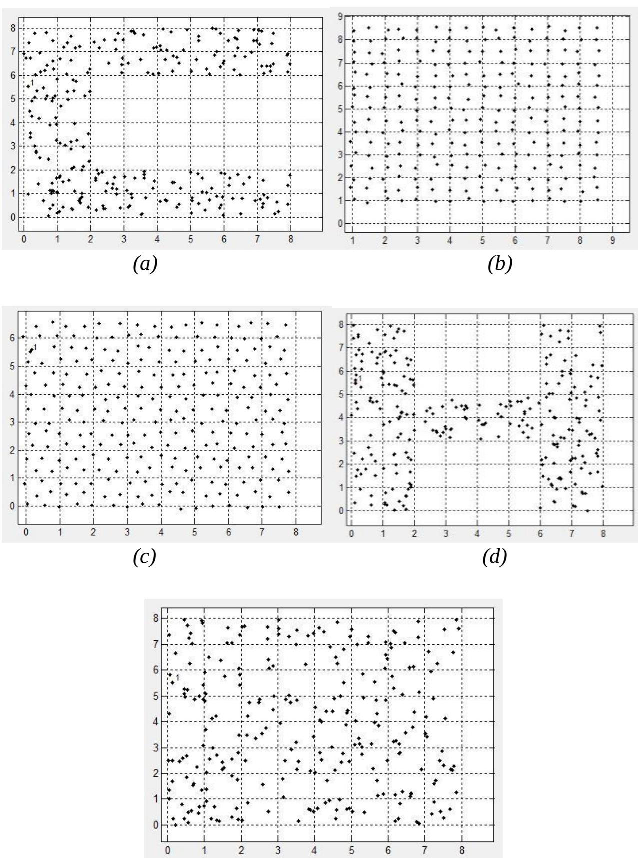
In a wireless sensor network, most of the applications that require position information also require time information. Number of similarities can be identified [14, 15].

The need of both time and space information and the similarities between them, have shown the importance of combining these two problems into a single one: *localization in time and space*. Doing so, energy and network resources could be saved, also the opportunity to improve time and position estimations in contrast to the scenarios in which these problems are solved separately is given. Synchronization algorithms can take advantage of the greater number of beacon nodes required by the positioning algorithms, while positioning algorithms can take advantage of the techniques and additional communication resources used to synchronize nodes.

The *time-space localization problem* can be stated as finding the position (x_u, y_u) and time $t_u(t)$ for all unsynchronized and *unknown nodes*, by a given multihop network, represented by a graph and a set of *beacon nodes*, their *positions* (x_b, y_b) and *synchronized clocks* $t_b = t$, where *u* and *b* belong to the sets of unknown nodes and beacon nodes, respectfully.

IV. WIRELESS SENSOR NETWORK TOPOLOGIES

Several wireless sensor networks topologies are considered in our work and they are presented on Figure *2*. The first network topology presented here is *C* – random network topology (Figure 2 *(a))*. Together with the presented *H* – random topology (Figure 2 *(d))* are irregular network topologies, as well as the random topology, shown in Figure *2 (e)*.



(a) *(b)* *(c)* *(d)* *(e)*

Figure *2*: Network topologies - *(a) C* – random topology *(b)* Disturbed grid topology *(c)* Disturbed hexagonal topology *(d) H* – random topology *(e)* Random topology

The C and H – random topologies are random topologies, but irregular ones, because only a part of the square of the surface is considered.

Disturbed grid topology and disturbed hexagonal topology shown on Figure *2 - (b), (c)* are more regular network topologies than previous mentioned ones.

V. A MOBILE BEACON APPROACH FOR LOCALIZATION IN TIME AND SPACE ALGORITHM

An improved approach for space and time localization, for different network topologies, is presented in this section. The positioning component is essentially the mobile beacon localization algorithm [27]. The synchronization component obeys the same principle as the positioning algorithm, but it is extended to deal with time estimations [4]. These two components are combined in the algorithm. The *delay measurement technique* is used to synchronize nodes.

Different network topologies are employed, generated by our algorithm.

Once nodes are deployed, the mobile beacon travels through the sensor field broadcasting messages that contain its current coordinates and timestamp. When an unknown node receives a packet from the mobile beacon, it can estimate the packet travel time and, based on the times tamp stored in the packet, its own offset. Also, when an unknown node receives more than three messages from the mobile beacon, it can estimate its position based on the received coordinates and on the *RSSI* distance estimates. Since the nodes will require at least three packets for positioning, synchronization can be improved by computing the average offset of all packets. An advantage of this algorithm is that the communication cost of localizing and synchronizing regular nodes is null, since these nodes do not need to send any packets.

Set of position information is given as a variable, also, set of received timestamps. Timer to send packets is put, position and time information through variables is given. After that, the nodes' *GPS* info is returned, packets' travel distance estimation is given, the nodes' position is computed. Later, packets' travel delay estimation is given and also the nodes' offset is computed. Case if this node is a beacon node is explored and number of references is tested, if there are three received messages from mobile beacon, it confirms enough references and proceeds with the algorithm.

The running application of this algorithm is presented on figure *3*. The red color point is the mobile beacon which is moving through the sensor network, marked with blue color on the figure *3*. The options for choosing five types of sensor networks is put here whether the user wants to choose grid oriented network, randomly chosen network, hexagonal network topology, or *H* and *C* random network topologies, presented in the previous section. Also, information about the parameters used and display options are given. Choice by the user, according to the parameters and network topology, is enabled.

Running the sensors, the energy, which the mobile beacon is spending on moving itself and sending messages, is overviewed. This energy is much bigger than the one which is spent on local calculations for each sensor in the *WSN*. This is very low energy consumption.

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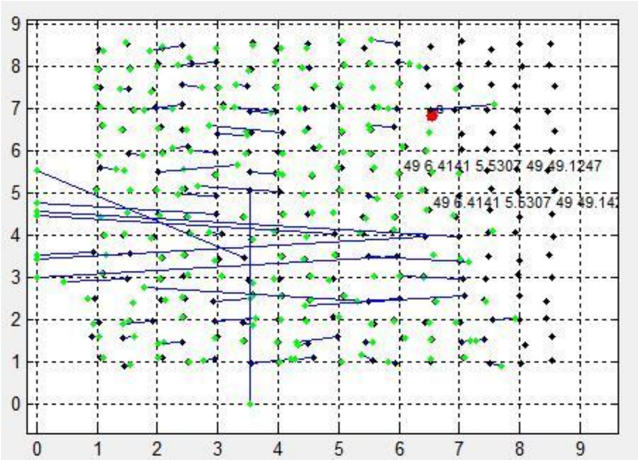


Figure *3*: The running application of the algorithm

VI. EVALUATION

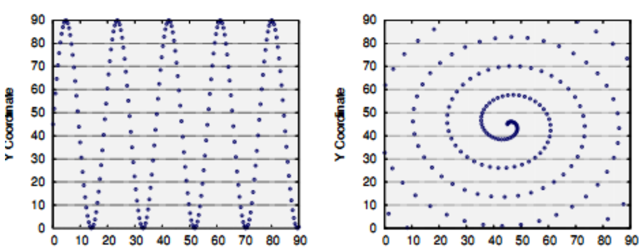
The evaluation of our algorithm is done, by performing simulations, parameters used and their values are given in the next table.

An experiment was done within the sensor field *92 x 92 m*^{2}. *256* nodes are employed, for different network topologies, we have chosen five types of network topology, explained previously, for this evaluation. The density of a sensor network is picked to be *0,03* nodes/*m*^{2} and the communication range is *15 m*.

TABLE I. SIMULATION PARAMETERS AND THEIR VALUES

Parameter	**Value**
Sensor field	*92 × 92 m*^{2}
Number of nodes	*256* nodes (different network topologies)
Density	*0.03* nodes/*m*^{2}
Communication range	*15 m*
Number of beacons	*1* - mobile beacon
RSSI inaccuracy	*10 %* of communication range

The evaluation is done by taking two types of trajectories for the mobile beacon: sinusoidal and spiral trajectories, presented on figure *4*.



a) b)

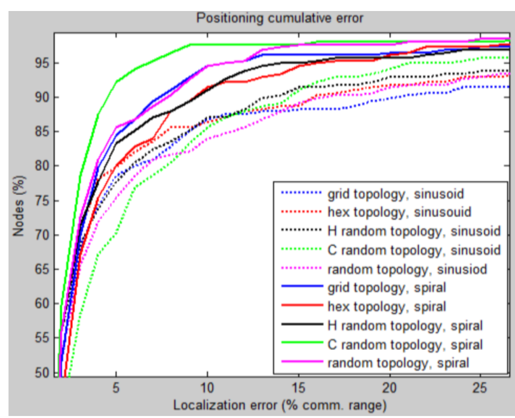
Figure *4*. Evaluated trajectories for the mobile beacon: a) sinusoidal; b) spiral trajectory.

On the next figure, localization error, synchronization error and also impact of *RSSI* inaccuracy are presented, in different color, for two evaluated trajectories of the beacon, sinusoidal an spiral ones, and for five types of network topologies: *C* – random topology, disturbed grid topology, disturbed hexagonal topology, *H* – random topology and random topology.

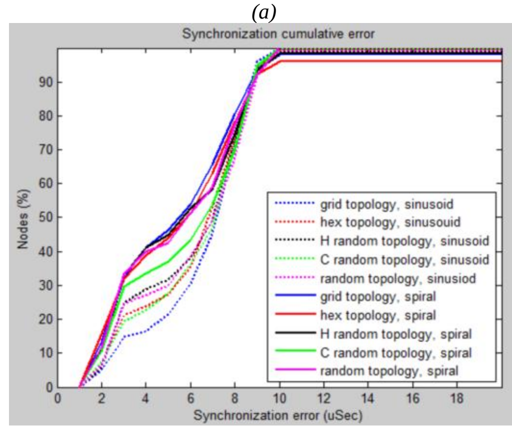
Localization Error - the distribution of position errors among the sensor nodes is depicted in Figure *5 (a).* The cumulative error identifies the percentage of nodes (*y*-axis), with a positioning error, smaller than a parameterized value (*x*-axis). A sharp curve means that the majority of nodes has a small error. This graph also shows that spiral trajectories result in better positioning than sinusoidal ones, since these trajectories are less rectilinear.

Synchronization Error - the distribution of synchronization errors among the sensor nodes is depicted in Figure *5 (b).* In this case, the cumulative error identifies the percentage of nodes (*y*-axis) with a synchronization error smaller than a parameterized value (*x*-axis). Again, a sharp curve means that the majority of nodes have a small error.

Impact of RSSI Inaccuracy – since the fact that the distance estimations using *RSSI* measurements are not accurate, depending on the environment, such an inaccuracy may lead to greater errors in the estimated positions. The evaluation of this impact is done by adding some noise to the real distances. This noise is generated by a normal distribution, with the actual distance as the mean and a percentage of this distance as the standard deviation. The comparison between the increase of the standard deviation of the normal distribution and the actual distance for the algorithms is presented on Figure *5(c)*.



(a)



(b)

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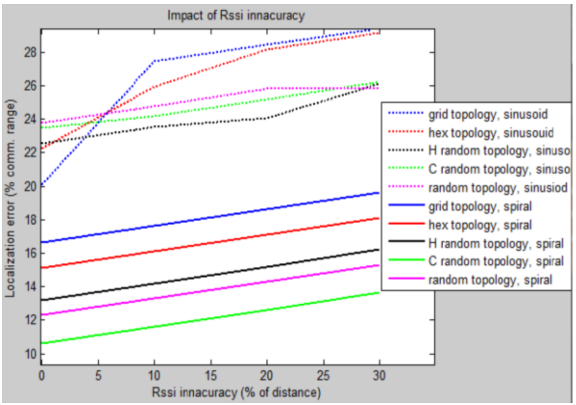

(c)

Figure 5. *(a)* Positioning cumulative error *(b)* Synchronization cumulative error *(c)* Impact of *RSSI* inaccuracy

It can be noticed that the positioning part takes advantage of the synchronization part to improve its performance, which shows the significance of solving both positioning and synchronization problems at the same time.

VII. CONCLUSION

Due to the close integration of sensor networks with the real world, the categories time and location are fundamental for many applications of sensor networks, to interpret sensing results or for coordination among sensor nodes. Time synchronization and sensor node localization are fundamental and closely related services in sensor networks.

Existing solutions for these two basic services have been based on a rather narrow notion of a sensor network as a large-scale, ad hoc, multi-hop, un-partitioned network of largely homogeneous, tiny, resource-constrained, mostly immobile sensor nodes that would be randomly deployed in the area of interest. However, recently developed prototypical applications indicate that this narrow definition does not cover a significant portion of the application domain of wireless sensor networks.

Existing solutions for time synchronization and node localization do not cover all parts of space and time in wireless sensor networks problem. Different, proposed approaches should be implemented to support these concepts adequately.

In this paper, we have proposed and evaluated an improved algorithm for the time-space localization, a mobile beacon approach, for different network topologies. By using a mobile beacon, all sensor nodes are able to localize themselves both in time and space. The beacon node sends packets and all regular nodes are able to synchronize and compute their positions with a zero communication cost algorithm. The proposed algorithm shows the importance of combining both positioning and synchronization into a single unified problem: localization in time and space. By doing so, the proposed algorithm manages to improve synchronization in the algorithm, comparing to the previous implemented approaches. In this case, communication and processing resources can be reduced, thus saving energy and network resources.

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