Prediction-based Localization for Mobile Wireless Sensor Networks

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Abstract—**In this paper, we propose two extensions of SDPL (Speed and Direction Prediction-based Localization) method. The first is called MA-SDPL (Multiple Anchors SDPL) which uses multiple mobile anchors instead of only one. Each anchor has its own trajectory and its own departure point. The goal is to ensure a total coverage of the sensor field and to multiply the chance of receiving anchor beacons. Anchor Beacons help localizing mobile sensors. As a consequence, the location estimation will be enhanced. The second method deals with one mobile anchor but with the ability of multi-hoping, that is, when a sensor estimates that it is well enough localized, it sends beacons to its h-neighborhood about its current location, hence, it plays the role of an additional anchor. This solution reduces the cost comparing to when using multiple anchors and allows rapid location propagation. Simulation results show that the two extensions improve better the ratio of localized sensors and reduce the location error compared to the basic SDPL. We have also tested them in a noisy environment to be closer to a real deployment.**

Keywords—Localization; Prediction; Mobile Anchor; Mobile Wireless Sensor Networks.

I. INTRODUCTION

With the advent of Internet of things [1][2], mobile wireless sensor networks (MWSN) play a major role in this new technological life style. Indeed, many applications can benefit from such networks. For example, in smart cities, sensors can be attached to vehicles, animals and human beings. In Emergency Response, first responders can be equipped with sensors to detect useful data and victims in the hit area, and to keep in touch with the command center [3]. Nowadays, the applications of MWSN are limited only by our imagination.

Localizing mobile sensors is a very challenging problem that did not receive enough research. Still, there are no standards except GPS localization. One of the recent proposed methods for MWSN is SDPL [4] (Speed and Direction Prediction-based Localization) that estimates the sensor position with the prediction of its real speed and direction that the sensor moves with. SDPL assumes that a mobile anchor moves in the sensor field and sends periodically position beacons to help localizing mobile nodes.

In this paper, we propose two extension methods of SDPL. The first is MA-SDPL that considers multiple mobile anchors. The goal is to heighten the number of beacons that a node receives and thus, to get more accurate estimations. The second is called MH-SDPL that works with the multi-hoping fashion. In MH-SDPL, when a node is well localized, it participates in the beaconing process; hence, it plays the role of an additional anchor. We conduct a series of tests and compare the results with the basic SDPL.

The paper is organized as follows. Section III describes the basic SDPL method. Section IV and V present in details the two proposed methods MA-SDPL and MH-SDPL. In section VI, simulation results are presented and discussed. We finish this paper with a conclusion and future work.

II. RELATED WORK

Locating mobile sensors is a very challenging problem [5] since sensors change frequently their positions and often with no information about their next destinations. Many GPS-less localization methods have been proposed in the literature to localize mobile sensors. Among the most promising methods, we find the probabilistic ones.

Authors is [6] propose the use of the probabilistic Monte Carlo method to predict of the next position using received anchor beacons and the maximum speed of the mobile nodes. The method does not consider any information about the direction of the nodes and assumes that all the nodes move with the same maximum speed.

The method proposed in [7] uses a mobile robot to predict the position of nodes in an indoor environment. The method is based on a Probabilistic Graphical Model (PGM) that estimates the sensor node position using range-only measurements of the received signal strength indicator (RSSI). Even if the method was validated by real-world experiments attesting that the probabilistic model is suitable, but the method do not consider the mobility of nodes. More surveyed localization methods can be found in [8].

Authors in [4] propose a method called Speed and Direction Prediction-based Localization to predict the real speed and the direction of the mobile nodes to increase the accuracy of the localization estimations. Since our work is an enhancement of SDPL, in the next section we detail this method.

III. SDPL (SPEED AND DIRECTION PREDICTION-BASED LOCALIZATION)

SDPL [4] is a distributed probabilistic method based on the prediction of the real velocities and directions a node moves with. This allows unknown mobile nodes to better localize themselves. In addition, a single mobile anchor travels in the field and periodically sends messages that contain its current location (see Fig. 1). Only the anchor can obtain its exact coordinates at any time (e.g. equipped with GPS) or in the case of a predefined trajectory, it can get its current position knowing its velocity and its trajectory. SDPL is mainly based on the prediction of the velocity and the direction of unknown nodes. To do so, SDPL authors supposed that nodes follow a rectilinear movement during small intervals (see Fig. 2) where nodes have a constant velocity and direction during certain time periods (Δt). This reflects the reality where nodes (e.g. Human beings, cars, etc) keep their speed and direction, at least, for moments. This allows nodes to predict positions at time $T = T_0 + \Delta T$ with the following equations:

$$P_u(T) = \vec{V_u} \times \Delta T + P_u(T_0) \rightarrow \begin{cases} x_u = V_u \times cos\theta \times \Delta T + x_u(T_0) \\ y_u = V_u \times sin\theta \times \Delta T + y_u(T_0) \end{cases} \quad (1)$$

Where $\theta$is the angle between the abscissa axe and the speed vector $\vec{V}$. The speed is calculated as follows:

$$V_u = \frac{\sqrt{\left(x_u\,(T_0) - x_u\,(T_s)\right)^2 + \left(y_u\,(T_0) - y_u\,(T_s)\right)^2}}{T_s - T_0} \quad (2)$$

Where T_0 and T_S are times corresponding to two positions already estimated. If the calculated speed is equal to zero, the node deduces that it is static during Δ.

The angle θ defines the node direction. θ is calculated as follows:

$$\tan\theta = \frac{y_u(T_0) - y_u(T_s)}{x_u(T_0) - x_u(T_s)} \quad (3)$$

In case where a node has already estimated many positions and cannot receive anchor messages, it calculates the speed of each couple of its previous positions and takes the mean as its next speed prediction. In addition, to predict the direction angle, the node makes a linear regression with these positions to deduce, then, the line that provides a best fit for the data points using the *least squares* approach (See Fig. 3).

After the prediction of the speed and the direction, a node estimates its coordinates (x,y) as follows:

$$\begin{cases} x = x_{prev} + \cos\theta \times speed \times T_{dif} \\ y = y_{prev} + \sin\theta \times speed \times T_{dif} \end{cases} \quad (4)$$

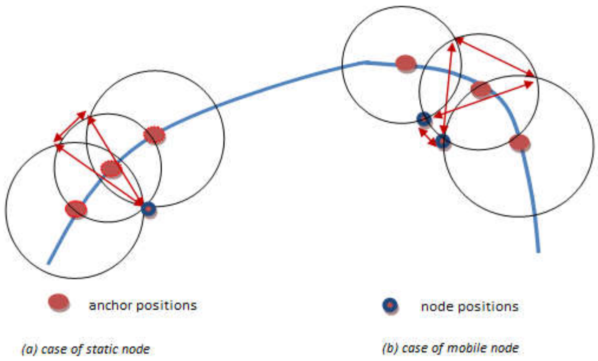

Figure 1: Estimation with three anchor messages.

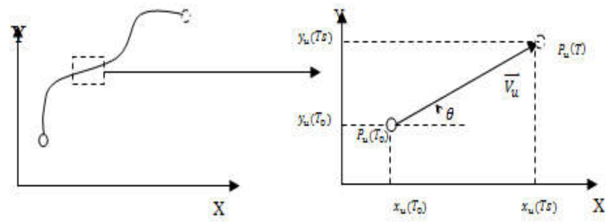

Figure 2: Speed and Direction Prediction in SDPL.

Where (x_{prev}, y_{prev}) is the last estimated position; $(speed, \theta)$ are respectively the predicted speed and direction angle; $\boldsymbol{T_{dif}}$ is the time between current time and time of the last estimation.

The idea of predicting the velocities and directions of the moving sensors is very promising and allows reducing the localization error [4]. But, one of the major drawbacks of SDPL is that at the beginning, the localization process relies on one single mobile anchor. That means that if the anchor stops to move for some reason or fails to cover the sensor area, the localization process fails and many sensors cannot localize themselves. To increase the chance of localizing sensors, we propose an extension of SDPL that works with multiple mobile anchors called MA-SDPL.

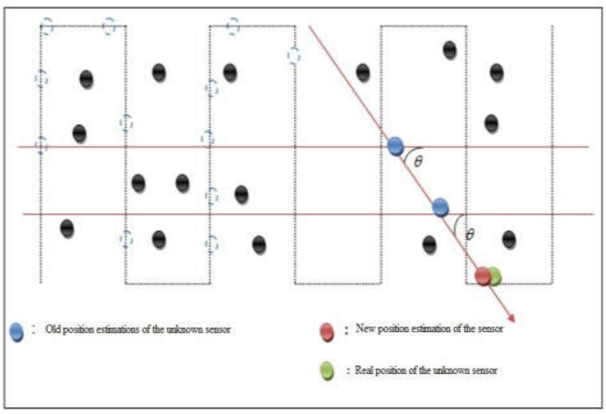

Figure 3: Location estimation with SDPL.

IV. MA-SDPL (Multiple Anchors- SDPL)

In an application such as Emergency Response, many fire trucks and ambulances circulate in the hit area to help evacuating victims. Anchors can be placed in such vehicles. From such scenario, the idea of using multiple anchors is come from. That is, embedding anchors on emergency vehicles. MA-SDPL relies on multiple mobile anchors to ensure the coverage of the sensor area and to increase the number of beacons a mobile sensor receives. Each mobile anchor has its own trajectory and velocity. When an anchor moves, it sends periodically beacon messages that contains its ID and its current location defined by the (x, y) coordinates (See Fig. 4).

The localization technique is the same as the basic SDPL. The difference lies in the number of beacons a node receives in an interval of time. The more the number of anchors is the more the number of beacons an unknown node receives. Thus, the occurrence of the case of velocity and direction prediction (that is when the unknown node receives more than three anchor messages) will be very high. Hence, the node estimates better its position.

In an application such as Emergency Response or Military Battle, the environment is very noisy and anchor messages may not be received properly by the other sensors. Fig. 5 presents an example where some anchor neighbors are deprived of receiving location messages because of the noise. As a consequence, they cannot localize themselves accurately.

In Section VI.D, we will present the effect of noise on the localization error of MA-SDPL.

The idea of using multiple anchors to ensure the total coverage of the sensor area is good but not always realistic. The trajectory and the velocity is a key condition. Some sensors still cannot get anchor messages if the different anchors don't travel around them. In addition, not all applications need to use several anchors. Also, it may be costly since each anchor should be without energy constraints and may use GPS system. To overcome this condition, we propose a new extension of SDPL called Multi Hop SDPL.

V. MH-SDPL (Multi Hop- SDPL)

MH-SDPL is based on the multi-hop localization that is when a sensor has a good enough estimation of its position; it plays the role of an anchor. In other words, it sends its estimated position to its neighbors to help them localizing themselves. The goal of MH-SDPL is to minimize the cost of using multiple anchors. For example, in a disaster management application, the main anchor is a rescue helicopter that sends position messages to the responders in the hit area (see Fig. 6).

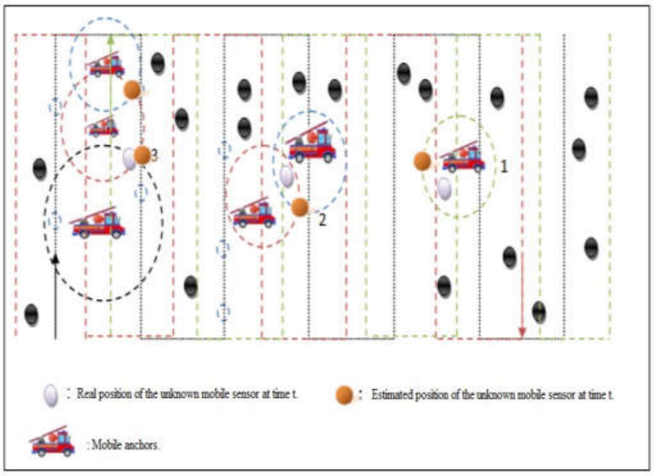

Figure 4: Emergency vehicles as mobile anchors.

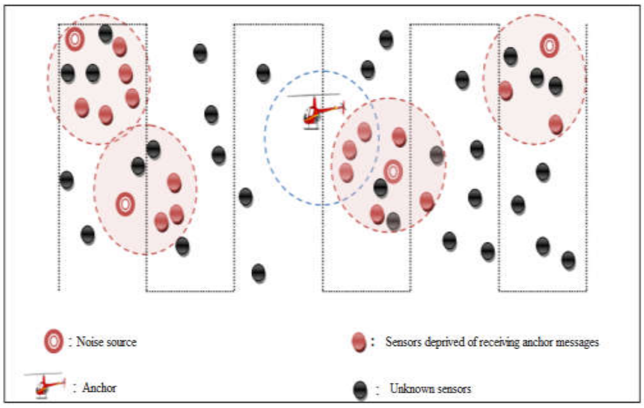

Figure 5: Noisy Environment Effect.

Sensors placed in fire trucks or in ambulances receive these messages and localize themselves and in turn they send their location estimations to the sensors attached to the rescuers in their vicinity. We call such localization, 2-hop localization and so on. The following figure shows an example of 2-hop localization in the case of an emergency application.

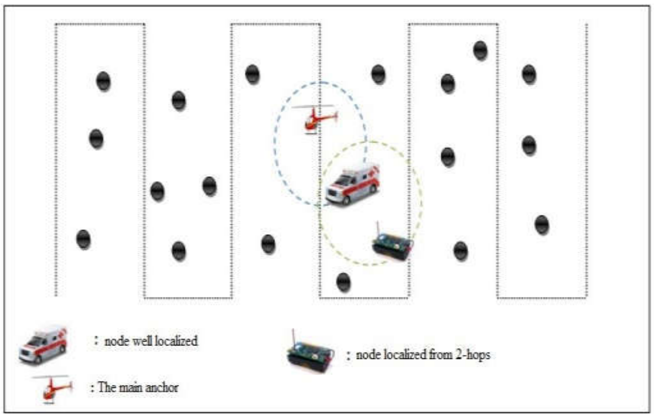

Figure 6: Multi- hop localization.

VI. PERFORMANCE EVALUATION

To evaluate the two extensions of SDPL, we opted for simulation. Our simulations are performed using the Network Simulator (NS) [9] version ns-allinone-2.34. NS2 is widely used in academic network researches. To analyze the simulation results, the main metric is the localization error. The localization error is calculated as the Euclidian distance between the actual and the estimated position of a node. We consider the average localization error over all sensors.

We have chosen SCAN as a trajectory for the mobile anchors. For node mobility, we use the random waypoint mobility model [10] where each node can vary its speed and direction at each own time step. Table 1 summarizes the simulation parameters used in our tests.

A. MA-SDPL : Impact of Number of Anchors

In the following test, we study the impact of the number of the anchors on the localization error using MA-SDPL. In this test, anchors follow the SCAN trajectory and have different start points. The travelling time was set to 100s.

As we can notice from Fig. 7, with the increase of the number of mobile anchors, the localization error decreases. In fact, the more the number of mobile anchors is the more unknown nodes receive position messages from these anchors and the case of speed and direction prediction will be more frequent; hence nodes improve their location estimations. This explains the decrease of the mean error.

TABLE I. SIMULATION PARAMETERS

Parameter	Default value
Number of nodes	100
Area size	200x200 m²
Mac layer	800.11
Communication range	30m
Antenna	Omni Antenna
Propagation	TwoRayGround
Mobility Model	RandomWayPoint
Anchor speed	20m/s
Anchor trajectory	SCAN
Sensors Maximum Speed	5 m/s

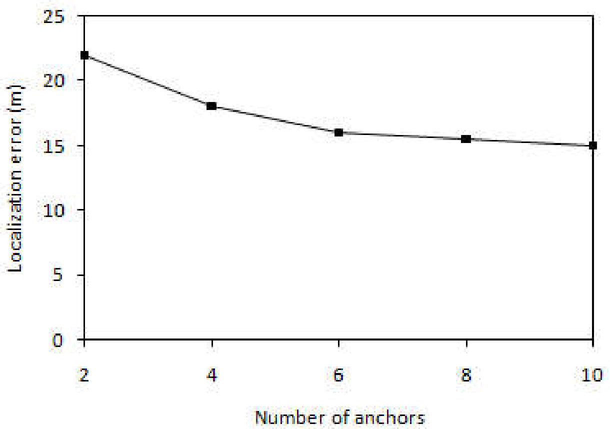

Figure 7: Number of Anchors VS Localization Error.

B. MA-SDPL: Impact of Travel Rounds

Travelling many times the sensor area has its impact on the localization error. When a mobile anchor travels many time the zone, unknown nodes receive more position messages. Fig.8 shows the results obtained by deploying four mobile anchors that travel more than one round the sensor area. Note that increasing the number of rounds is similar to increasing the travelling time.

Initially, nodes have no knowledge about their positions. From the first round, nodes begin to estimate their positions hence the first round is a transition from the random positioning to a more accurate positioning. Obviously, when anchors travel the sensor area many times, unknown nodes receive more position messages from these anchors. And the more a node receives anchor messages, the more it uses the prediction of the speed and the direction which allows improving its location estimation.

C. *MA-SDPL: Impact of Diffusion Interval*

Another important factor is the anchor diffusion interval. The smaller the interval is, the more the number of anchor message a node receives. This effects directly its location estimations. Fig. 9 shows that when this interval is small, the location error decreases because the unknown node gets more information related to its mobility from the anchors and when it cannot receive any anchor messages, it uses easily the prediction case. This improves its location estimation.

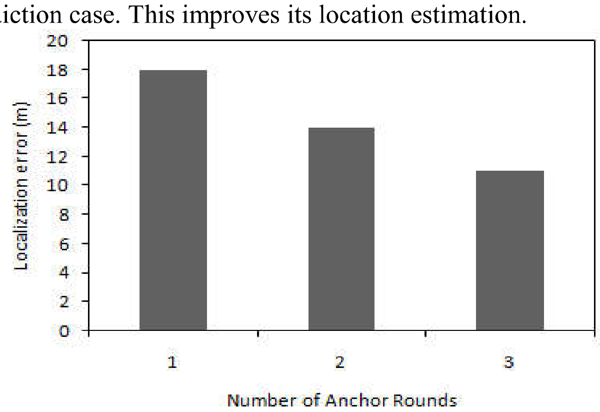

Figure 8: Anchor travel rounds VS Localization Error.

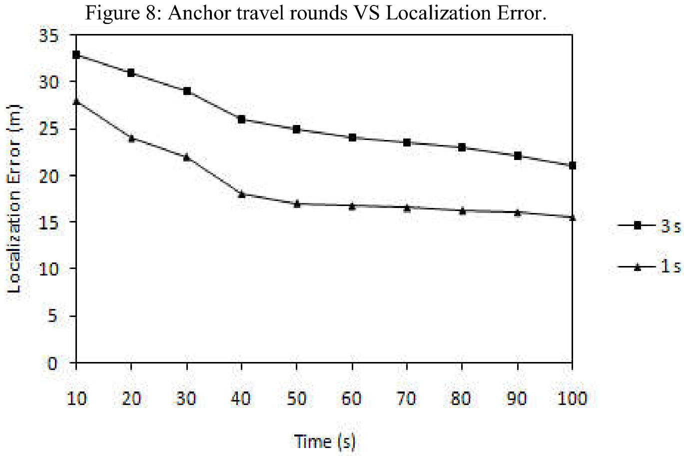

Figure 9: Diffusion Interval VS Localization Error.

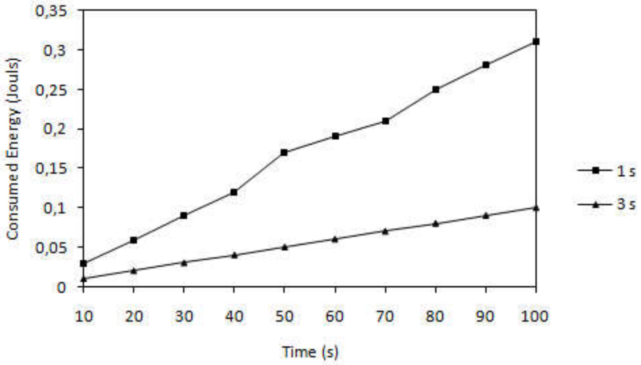

Figure 10: Diffusion Interval VS Consumed Energy.

However, receiving much anchor messages consumes sensor energy. Fig. 10 shows the impact of the diffusion interval on the total energy. When the diffusion interval is small, the anchors send many messages in the localization interval. This means that unknown sensors receive also many messages which deplete their energy.

D. MA-SDPL : The impact of a Noisy Environment

We have tested MA-SDPL under a noisy environment and called it MA-SDPL-N. 30% of noise means that 30% of the nodes inside a noisy zone cannot receive any anchor messages or receive them with erroneous information. Note that the test was conducted with 4 mobile anchors following SCAN trajectory.

The noise has its bad effect on the localization process (see Fig. 11). In fact, in a noisy environment, location messages may not be received by unknown nodes or the messages may contain wrong information. In one side, the nodes inside a noisy area cannot receive anchor messages and are obliged to draw random samples from the zone which increases the uncertainty leading to a high localization error. In the other side, those who are in less noisy zone receive some anchor messages but not sufficiently, hence they use more frequently the prediction case successively without refining their estimations with anchor messages. This increases the average location error.

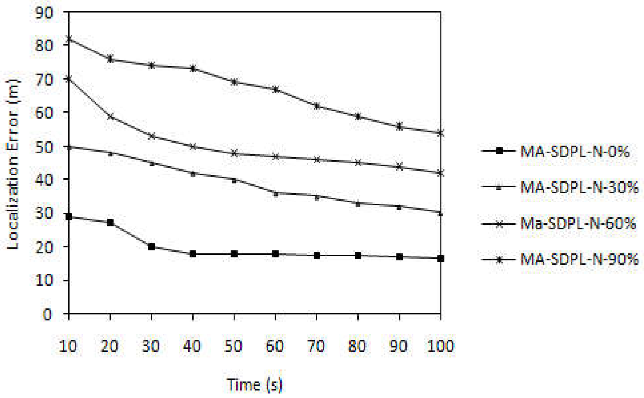

Figure 11: MA-SDPL-N.

E. MA-SDPL VS MH-SDPL

In the first test, we compare the average consumed energy between the two methods MA-SDPL and MH-SDPL. For MH-SDPL, only one mobile anchor is used unlike MA-SDPL where four mobile anchors were deployed. For both methods, mobile anchors follow SCAN trajectory. Note that in this test, MH-SDPL is 2-hop localization.

We notice from Fig. 12 that for both methods the consumed energy is proportional to the execution time. Indeed, over time, nodes with MA-SDPL receive more anchor messages which consumes their energy. In the case of MH-SDPL, more nodes consider themselves as well localized and send their locations to their neighbors. As a consequence, their energy consumption of sending increases as well as the neighbors' energy consumption of receiving.

F. SDPL, MA-SDPL and MH-SDPL

In this section, we compare the three methods, the basic SDPL, MA-SDPL and MH-SDPL in terms of the number of localized nodes and the average error. Four (4) mobile anchors were used for MA-SDPL while for the others only one was used. MH-SDPL is of 2-hops.

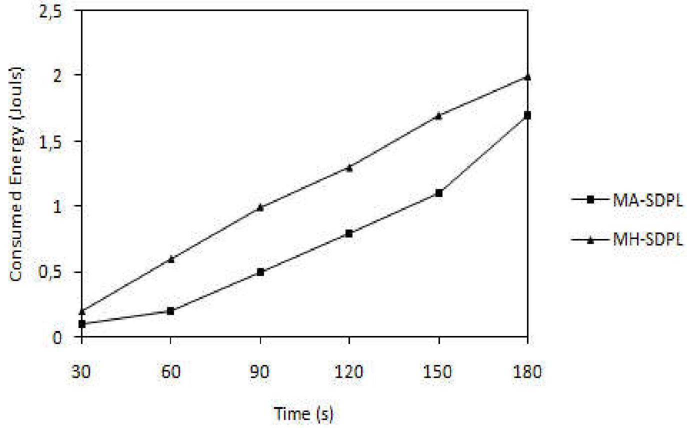

Figure 12: MA-SDPL VS MH-SDPL.

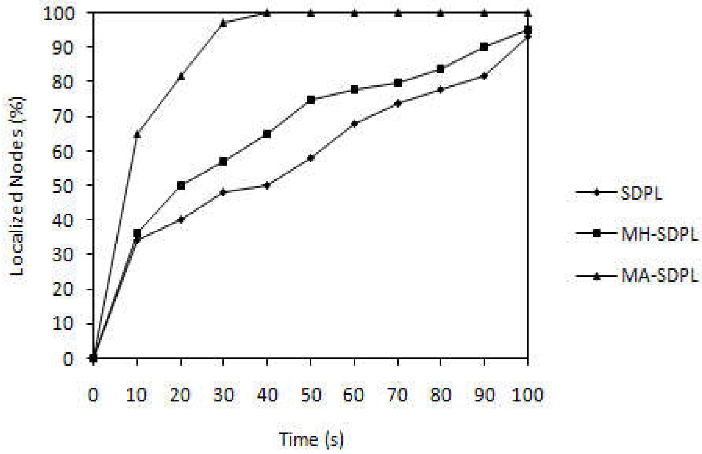

Figure 13: Localized nodes: SDPL VS MA-SDPL VS MH-SDPL.

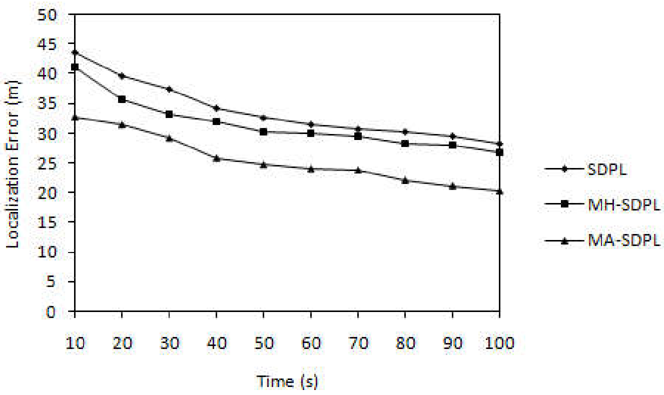

Figure 14: Localization Error: SDPLVS MA-SDPL VS MH-SDPL.

Thanks to the multiple mobile anchors used in MA-SDPL and the fact that each anchor begins with its own start point (in our case the four corners of the square area), unknown sensors have more chance to receive anchor messages hence to localize themselves even before that anchors travel the whole area. This explains the total coverage after just 40 seconds from the beginning of localization process (see Fig.13). In MH-SDPL, even with only one mobile anchor, the fact that well localized sensors participate in turn in the localization process by sending their location estimations to their neighbors, this help those nodes that cannot receive anchor messages to be localized or even enhance their location estimations. So the number of the localized nodes will increase.

Fig. 14 shows that by the end, MA-SDPL with four anchors gives results about 26% better than MH-SDPL with 2-hop localization and 31% better than the basic SDPL.

VII. CONCLUSION

Our goal, in this paper, was to improve the method SDPL (Speed and Direction Prediction-based Localization) in terms of coverage, consumed energy and localization error. To do so, we have proposed to use multiple mobile anchors instead of one to cover the whole area rapidly and to help localizing the unknown sensors by giving them the chance of receiving location messages from more than one mobile anchor. From the simulation results, this new extension of SDPL called MA-SDPL has proven to be efficient. Indeed, the localization error was reduced considerably. In addition, the more the number of mobile anchors is, the less the localization error is. We have also tested MA-SDPL under a noisy environment. Obviously, when the noise is high, the average error is high too. In the case where multiple anchors are not available, we have proposed that some sensors play their roles. This is when a sensor is well enough localized; it plays the role of an anchor and sends in turn its location to its neighborhood while keeping its own mobility. The latter extension was called Multi-hop-SDPL. Overall, the results are promising and many applications can benefit from these localization methods. For instance: Disaster Management, Tracking mobile elements, Smart Cities and others.

Real world experiments are currently ongoing with MICAz [11] motes while the mobile anchor is an embedded mobile wireless sensor placed on a civil drone commonly known as UAV (Unmanned Aerial Vehicle) of type Quadcopter [12]. In the case of multiple anchors, another drone of type Hexacopter is used and some other vehicles. Also, we are planning to test our solutions considering 3D localization.

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