A Bayesian Location Estimation Technique for Mobile Ad Hoc Networks

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Abstract. In this paper[1], we propose a simple method to introduce a-priori information in position estimation for mobile ad hoc and sensor networks, in order to improve the estimation accuracy. The a-priori information is derived from the movement of the mobile node with respect to the position of fixed anchor nodes, and it is exploited to perform Bayesian estimation procedure. Numerical simulation results corroborate the effectiveness of the proposed technique, which outperforms the maximum likelihood one.

Keywords: Bayesian localization, mobile ad hoc networks, mobile sensor networks.

1 Introduction

The knowledge of node's position in large ad hoc wireless networks is considered as a primary need for the implementation of new context-aware applications, but also to improve the performance of routing and coordination functions in the network. It has been shown that geographic information can significantly improve the performance of wireless ad hoc and sensor networks, and a plenty of location-based routing algorithms have been developed for such networks ([A02],[CCL03]). In addition, for large sensor networks, location information is essential for intelligent coordination and data collection [A02]. GPS and similar systems can provide location information, but they rely on existent infrastructures and need special hardware, which is not always available at all nodes. Moreover, GPS system needs that at least three satellites must be visible by the receiver, which is often unavailable in presence of buildings in urban areas, and is impracticable in indoor application scenarios. Finally, absolute position is not always necessary to support the network, and relative local coordinates are sufficient in many situations; this is the case, for example, of position-based routing algorithms for ad hoc and sensor networks [CCL03].

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For such reasons, many researchers have proposed GPS-free positioning systems for WLAN networks [F05] and wireless ad hoc and sensor networks [Pa05]; they are all based on measuring some quantities related to node position, such as power, delay, or angle of arrival of the received signals from some stationary nodes with known coordinates. By using these measurements, these systems find out an estimation of node positions, via triangulation or other mechanisms. However, all these measurements are affected by noise and distortions due to both channel condition and environment characteristics. Statistical approach offers a unifying theoretical framework for location estimation in wireless networks [P03]. By using a statistical characterization of the noise and a radio propagation model, this method permits to take into account the different nature of noise and distortion on the measurements, for the particular application and environment. Moreover, the lack of quality in measurements encourages the use of a-priori information in the estimation procedure, in order to improve the accuracy of the positioning; such a-priori information can be easily deduced by previsions about the most likely future positions, in case of moving nodes. In this paper, we propose a simple method which exploits a-priori information in statistical-based location estimation for mobile ad hoc and sensor networks, in order to improve the estimation accuracy of positioning. The a-priori information is derived from knowledge about the movement of the mobile node with respect to the position of some fixed anchor nodes, and it is exploited in a Bayesian [K93] estimation procedure. In few words, we try to infer the trajectory of the node, exploiting its movement information to improve the position estimate accuracy.
The paper is organized as follows: in Section 2 we briefly present a background and related work on the problem, in Section 3 the statistical approach for location estimation is summarized, Section 4 describes the proposed bayesian positioning technique, in Section 5 some simulated results are presented. Finally, conclusions are drawn at the end of the paper.

2 Background and related work

Our approach aims to allow a node of wireless ad hoc and sensor networks to estimate its trajectory by itself, without any network support, by simply exchanging electromagnetic signals with some neighboring nodes, configuring a self-tracking mechanism; this is essential for the self-configuration capability requirements of such kind of networks. In particular, we consider a general model of ad hoc or sensor network, where both fixed and mobile nodes are present; we refer to the fixed nodes as Anchor Nodes (*ANs*), and suppose that their positions are known (by GPS equipment or manually positioning), whereas the other ones are Mobile Nodes (*MNs*), and have to localize themselves by exchanging signals with neighboring *ANs*. This is a particular case in a general class of estimation problems regarding self-configuration in wireless networks, where a small fraction of nodes in the network have known location, while the remaining ones must be positioned [P03]; in our case, the difference is that the unknown-position nodes are also mobile. This configuration corresponds to the case of particular applications of self-configuring networks, such as that for traffic monitoring, or for locating emergency and security workers.

Recently, there has been a lot of work on the problem of self-localization for ad hoc and sensor networks; in [Pa05] there is an exhaustive review of recently proposed techniques. However, most of them consider the case of static nodes, and, in case of mobility, do not consider the possibility of enhance the performance trying to estimate the trajectory of the node. More recently, some works have faced the problem, by resorting to the Bayesian approach. The idea of tracking mobile objects using Bayesian approach has been first exploited in other research fields, as for example, in robotics, and only recently in wireless node's positioning [Mo06]. In [Ar02] there is a review of methods for Bayesian tracking; in particular, in the general framework, the problem consists of the estimation of the a-posteriori distribution of the node's location after movement and observations; therefore, the estimation of the a-priori distribution is only a part of the problem. The optimal solution to this problem is not easy to determine, and it is impossible to evaluate the distribution analytically [Ar02], unless both the measurements and the trajectory admit Gaussian model (Kalman Filtering, [Ar02]). In practical cases, the trajectory is not really Gaussian-like, and other approximated approaches have been investigated, such as grid-based Markov model method, and Particle filtering [Ar02]. The first method requires significant memory and computational burden, whereas the second one reduces the complexity of the problem, but still remaining more costly respect to Kalman filtering. In particular, grid representation has been used efficiently for indoor WLAN network-based positioning [Mo05], whereas Particle filtering has been experimented for wireless sensor networks [Mo06]; however, in [Mo06] an off-line calibration to estimate the likelihood function is used, which is not fully compatible with ad hoc and sensor networks.

Respect to previous work, in this paper we propose an extension of the statistical approach already proposed, for example in [P03], in order to include information about the movement and improve the performance of the positioning, by resorting to a Bayesian formulation. Through the estimation of an opportune a-priori distribution, our method is more general then the Kalman Filter, but, avoiding any discrete representation of the space, would be less complex than other approaches based on grid-based Markov and Particle filtering methods, and, therefore, better suited for our case, that is networks without infrastructure.

3 The Statistical Approach for Location estimation

In this section, the statistical approach for location estimation is outlined. In our scenario, according to [P03], we consider the simple case of one node with unknown position, and a number of *ANs* with known positions, although, in practice, in ad hoc scenarios there are different nodes with unknown positions, that try to infer their positions in a cooperative manner. The node attempts to estimate its location by measuring the Received Signal Strengths (RSSs), or Time Of Arrivals (ToAs), or some other parameter, from *ANs* belonging to its transmission range. For most of these kinds of measurements, the statistical description is well known and has been characterized on experimental test-beds [P03]. Let us denote with $f_l\ (\boldsymbol{m} \mid z, \boldsymbol{\delta})$ the likelihood function [K93] of the random multivariate $\mathbf{m}$ modelling any kind of N

measurements available at the mobile node (in general referred to as N different *ANs*). Here z is the node position (i.e., z (x,y), with x and y node coordinates on a relative or absolute Cartesian system); $\boldsymbol{\delta}$ is a vector of parameters characterizing the environment and the accuracy of measurements (for example, in case of RSS measurements, $\boldsymbol{\delta}=(\delta_{dB}\ ,\ n_p)$, with δ_{dB} the standard deviation of the noise, and n_p the path-loss exponent [P03]). The likelihood function relates the measurements to the node actual position, and can be used to locate the node, by resorting to *Maximum Likelihood Estimation* (MLE) criterion [K93]. In particular, let us denote with $z(t=t_0)=z^0=(x^0, y^0)$ the first position (i.e., at instant t_0) of the mobile node, with $\mathcal{N}$ the set of *ANs* present in its transmission range, and, finally, with q_j the position of the *j-th AN*, $(j\in\mathcal{N})$. According to this notation, the Maximum Likelihood Estimation (MLE) of node position is the result of the following maximization:

$$\hat{z}^0 = \arg\max_{z} \left\{ f_l\left(\boldsymbol{m} \mid z, \boldsymbol{\delta}\right)\right\} \tag{1}$$

where, in this case, $\boldsymbol{m}=\{ m_j, j\in\mathcal{N}\}$ is the vector of measurements related to the signals received by the *ANs* in the set $\mathcal{N}$. The solution of the maximization (1) is generally found out by numerical algorithms; when some general conditions are satisfied, the solution of (1) is unique [P03], and only suffers from estimation inaccuracy due to noise presence and, eventually, multi-path propagation effects. The theoretic MLE performance limit is expressed by *Cramer Rao Lower Bound*, and has been evaluated and discussed in [P03] for such problem.

In order to improve the accuracy of the position estimation, an high number of measurements should be available, that is an high number of *ANs* in the communication range of the mobile node should be present. This is not likely to be, in a sensor as well as ad hoc network with few GPS equipped nodes. Therefore, we propose a simple method both to improve the position estimation accuracy, and to reduce the probability of obtain "false positives" due to bad measurement's condition, for example in case of absence of line of sight (LOS) component in the measured signal. This method exploits estimates of previous positions of the node as a-priori information by means of a bayesian statistical estimation procedure. More specifically, the position estimation technique is synthesized by resorting to the Maximum A-Posteriori (MAP) criterion [K93]. The general expression of a MAP estimator of position at instant t_0 is:

$$\hat{z}^0 = \arg\max_{z} \left\{ f_l\left(\boldsymbol{m} \mid z, \boldsymbol{\delta}\right)\cdot f_{Z^0}\left(z\right)\right\} \tag{2}$$

where $f_Z^0(z)$ is the probability density function (pdf) of the node position at instant t_0, also known as *a-priori* distribution. Here the problem is the accurate estimation of this distribution, with as lower as possible complexity to be added on the node; this estimation can be realized by observing the previous positions of the node and making previsions on next position. Although this is similar to what is done in grid-based Markov and particle filtering approaches [Ar02], we aim to exploit this idea with a simpler and lower computational cost method, in order to be better suited for infrastructure-less networks. In the next section we introduce a procedure, based on a simple mobility model, to estimate effectively the a-priori node position distribution.

Using this estimated distribution in the formula (2), we get the proposed Bayesian position estimator.

4 The Proposed Estimator of the A-priori Position Information

In order to estimate the a-priori distribution of the node position, we consider a statistical model for the node mobility enough simple to avoid a significant increase of the complexity and memory requirements on the node. Specifically, we use a mobility model for the node, which is based on *Markovian* property. According to such a model, the present node position, given the previous positions in the trajectory, is statistically related only to the two previous positions. This assumption allows one to strongly bound computational complexity of the estimation technique. The mobility model is a simplified version of the Probabilistic Random Walk model adopted in [CBD02], where the node moves along straight lines and randomly changes its direction of movement, following a *Markov* model with a given probability transition matrix. According to such a model, trajectories where the node makes changes of direction of 360° have null probability, and, in general, the probability that the node continues to follow the same direction is higher than the probability that the node changes direction. In our model we require that a node perform a simple operation: it has simply to state if it is presently moving toward a particular *AN*, or is moving far apart from it. Therefore, according to such a model, we describe the node movement as a simple *Markov* process with only two possible states (Fig.1). In the state 0, the node is moving toward a particular direction which gets the node closer to the *AN*, whereas in the state 1 the node is moving toward a particular direction which gets the node far apart from that particular *AN*. Assuming $p_0 > p_1$, the model privileges the continuity of the movement; in fact, if the node is moving in a particular direction which reduces (or increases) the distance from the *AN*, it is more likely that it continues to approach (or to depart) the AN. Following such a model, the state can be singled out simply by the knowledge of last two positions of the node. When the present node's state is known, it is possible to perform a prediction of its next position based on the model of Fig.1.

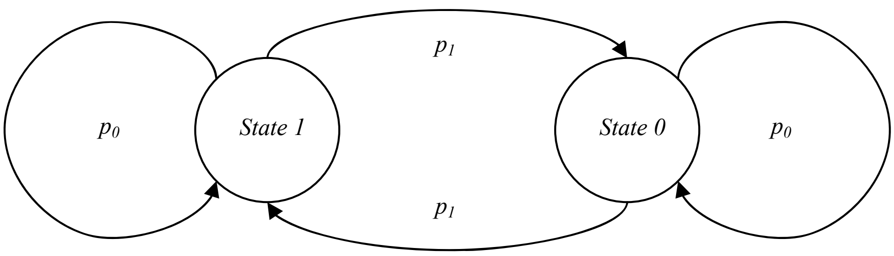

Fig. 1. Markov model of node movement

In order to clarify the above model, let us introduce a simple example: consider a square domain, in which a node is moving in a particular direction, and one *AN* (here denoted as node *j*) is located at the upper left corner (see Fig.2).

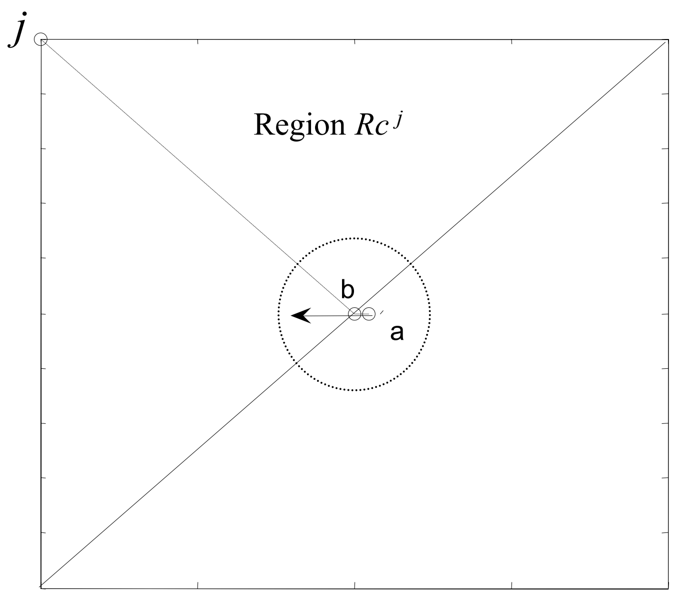

Fig. 2. Region of continuity of the movement

Assume that the node is moving from the right (position a) toward the left (position b); in this case, the node is moving along a direction which takes it closer to the *AN*. The only information that the node has to elaborate is if it is getting closer or farther from the *AN*, without measuring any direction or angle of movement. Then, what the node can simply state is the region where the node will be in the future (at the next measurement point), with higher probability. In the Fig.2, this region is referred to as R_c^j (region of continuity of the movement respect to *jth AN*).
Now, let us formally introduce our approach to estimate the a-priori statistical distribution. We underline that this probability distribution function is not stationary because its estimate is based on the two previous node positions, (z^{-1}, z^{-2}), which, of coarse, are time-dependent. In particular, according to the assumed mobility model and the above considerations, p_0 is the probability that the position of the node at instant t_0, z^0, falls in the region of continuity R_c^j (see again Fig.2), given the last two positions (z^{-1}, z^{-2}) and the position q_j of the *AN j*. As a consequence, we can affirm that:

$$
\begin{aligned}
&Pr\left[z^0 \in R_c^j\right] = p_0 \\
&Pr\left[z^0 \in \overline{R}_c^j\right] = p_1 = 1 - p_0
\end{aligned}
\qquad (3)
$$

where $\overline{R}_c^j$ is the complement region of $R_c{}^j$ in the considered domain.
On this basis, we can formulate the following probability density function for the node position z^0 at instant t_0:

$$
\begin{aligned}
&f_{Z^0}(z) = \begin{cases} \dfrac{p_0}{k} & \forall z \in R_c^j \\ \dfrac{p_1}{k} & \forall z \in \overline{R}_c^j \end{cases} \\
&k = p_0 \cdot A\left(R_c^j\right) + p_1 \cdot A\left(\overline{R}_c^j\right)
\end{aligned}
\qquad (4)
$$

where k is the normalizing constant, $A(R_c{}^j)$ is the area of the region of continuity and, of course, $A(\overline{R}_c^j)$ is the area of its complement. The pdf in (4) can be modified if we take into account that the node velocity is bounded; in particular, we suppose to known the maximum velocity $v_{\max}$ of the node. As a consequence, we can modify the function in (4) as follows:

$$
\begin{aligned}
&f_{Z^0}(z) = \begin{cases} \dfrac{p_0}{k} & \forall z \in R_c^j \cap C \\ \dfrac{p_1}{k} & \forall z \in \overline{R}_c^j \cap C \\ 0 & \forall z \in \overline{C} \cap R \end{cases} \\
&k = p_0 \cdot A\left(R_c^j \cap C\right) + p_1 \cdot A\left(\overline{R}_c^j \cap C\right)
\end{aligned}
\qquad (5)
$$

where C is the circle centred in the last node position z^{-1} with radius equal to $v_{\max} \cdot \Delta t$, where Δt is the sampling interval used by the node to localize itself. This modification realizes a twofold goal: it further reduces the probability of false solutions, and it lowers the complexity of the minimization in (2), reducing the size of the domain over which minimizes the MAP function. In Fig.2, the circular region C is represented.
Now, in the case of presence of more than one *AN* in the communication range of the node, we can deduce a more accurate *pdf* for the node position. For example, in case of 2 *ANs* (j and k), assuming statistical independence between the observations, equation (3), we can now partition the domain C in 4 regions, and assign the following probabilities:

$$
\begin{aligned}
&Pr\left[z^0 \in R_c^j \cap R_c^k \cap C\right] = p_0 \cdot p_0 \\
&Pr\left[z^0 \in \overline{R}_c^j \cap \overline{R}_c^k \cap C\right] = p_1 \cdot p_1 \\
&Pr\left[z^0 \in R_c^j \cap \overline{R}_c^k \cap C\right] = p_0 \cdot p_1 \\
&Pr\left[z^0 \in \overline{R}_c^j \cap R_c^k \cap C\right] = p_1 \cdot p_0
\end{aligned}
\tag{6}
$$

Therefore, similarly to the equation (5), we can obtain a more accurate a-priori statistical model:

$$
f_{Z^0}(z) = \begin{cases}
\dfrac{p_0 \cdot p_0}{k'} & \forall z \in R_c^j \cap R_c^k \cap C \\
\dfrac{p_1 \cdot p_1}{k'} & \forall z \in \overline{R}_c^j \cap \overline{R}_c^k \cap C \\
\dfrac{p_0 \cdot p_1}{k'} & \forall z \in R_c^j \cap \overline{R}_c^k \cap C \\
\dfrac{p_1 \cdot p_0}{k'} & \forall z \in \overline{R}_c^j \cap R_c^k \cap C \\
0 & \forall z \in R \cap \overline{C}
\end{cases}
\tag{7}
$$

where *k'* is the normalizing constant. With such pdf of the node position, we can finally formulate the position estimation problem as a Maximum A Posteriori (MAP) criterion, using equation (2).
In few words, following the Bayesian rule in the MAP formulation, the positions of node falling in the intersection of the continuity regions of all the *AN*s are encouraged, in the estimation procedure.
In the next section, we simulate a simple scenario and propose some examples to compare the performance of the proposed method with those of the MLE one.

5 Numerical Results

To show the effectiveness of proposed technique, we present the results of some simulation experiments of tracking estimation, performed on a Matlab platform[2]; we refer to a scenario similar to [P03], using exactly the same parameters for measurements and test-bed characterization. In particular, we suppose that the nodes are able to measure TOA of signals received from the other nodes. TOA measurements are the best candidate for future UWB-based wireless sensor networks, because, by exploiting the large bandwidth of UWB technology, they dramatically

[2] We wish to thank Ing. I.Capasso for its precious collaboration in programming the simulations.

improve the resolution in positioning [Ge05]. RSS measurements, which are generally the most inaccurate ones [P03] but are largely utilised since their implementations are the cheapest, can also be considered. We plan to consider RSS for next experimentations of our approach, but in this paper we only present results using TOA method.

As regards the statistical characterization, we assume that the measurements are described by the Additive White Gaussian Noise (AWGN) model, whose variance depends on the sensor characterization [P03]. More specifically, $\boldsymbol{m}=\{ m_j=\tau_j, j\in \mathcal{N}\}$ are the delay measurements from the *ANs* in the range of the node, and are modelled as a sequence of *i.i.d.* random variables with Gaussian distribution, that is $\tau_j \sim N(d_j/c, \delta^2)$, where c is the propagation speed, d_j is the distance between the node and the *AN* j, and δ^2 is the variance of measurement noise.

Now, consider a simple domain of 10 meters x 10 meters, in which a node is moving, and a total number of 4 *AN*s placed in the corners of the square domain. Consider that the node is moving with a constant velocity (1 m/s) on a straight line, and that it tries to estimate its own position measuring the TOA of signals received from each *AN* every Δt=1 second, for a total of M points trajectory. Moreover, as experimented in [P03], we set δ=6.1×10^{-9} sec, and, as in [CBD02], we have adopted p_0=0.7.

As regarding the estimation of the a-priori distribution in (7), the node evaluate the region of continuity $R_c^{\,j}$ with respect to each of its *ANs* by observing its two previous estimated positions, and, of course, this is possible starting from the third node position estimation in the trajectory; for the estimation of its first two positions, the node resorts to the MLE method.

Let us now present some simple examples of trajectory estimation. In the first example (Fig.3 *l-r*), a node is moving on a straight line, and does not change its direction during the movement; the second example (Fig.4 *l-r*) represents the same situation, but with a different angle of the trajectory, and then a different orientation respect to the *AN*s. In both cases, the MAP estimator (*right*) outperforms the ML estimator (*left*), reducing the mean square error on the position estimation[3]; in particular, for the case of Fig.3, e_z = 0.175 m^2 in the ML case and e_z = 0.0608 m^2 in the MAP case, for the case of Fig.4, e_z = 0.2090 m^2 in the ML case and e_z = 0.1194 m^2 in the MAP case. In the final example, we consider a different trajectory, where the node suddenly change its direction; again, the MAP method works better (e_z = 0.1924 m^2 in the ML case and e_z = 0.1741 m^2 in the MAP case), and the model is able to follow the change of direction, even though this change is considered less probable in the *Markov* model of the node movement we have used.

6 Conclusions

In this paper, we have shown that, introducing a-priori information in position estimation, it is possible to improve the accuracy of self-positioning for mobile ad hoc and sensor networks. In particular, some simple examples have shown that the

[3] $e_z = \frac{1}{M}\sum_{t=0}^{M-1}\left\| z^t - \hat{z}^t \right\|^2$

proposed method improves the accuracy of self-localization, performed by a mobile node which exploits measurements of signals exchanged with some fixed *ANs*. Moreover, the method is simpler than other approaches that try to estimate the trajectory of mobile nodes in infrastructured networks.

However, some aspects have to be more extensively investigated; for example, the effect of the number of available *ANs* and their positions on the a-priori distribution estimation accuracy, the opportunity of make use of a longer memory in trajectory estimation, the use of an adaptive setting of the probability parameter p_0.

Moreover, the method has to be more extensively tested in other situations, using for example simpler measurement methods such as RSS, in different environment conditions, and finally using experimental test beds.

Our approach in estimating the node movement resembles what the quantized RSS (QRSS) and proximity methods do to perform the estimation of the node position [PH03]. In such methods, the nodes use only one information bit (proximity) or few information bits (QRSS) to estimate its position; specifically, it has shown that *K*-level QRSS can perform approximately as well as RSS for even low values of *K*, whereas proximity method works worse than RSS, but in both cases complexity and cost are much lower. For future works, we plan to couple such methods with our a-priori position estimator, in order to realize an effective and low complexity method for trajectory estimation in ad hoc and sensor networks applications.

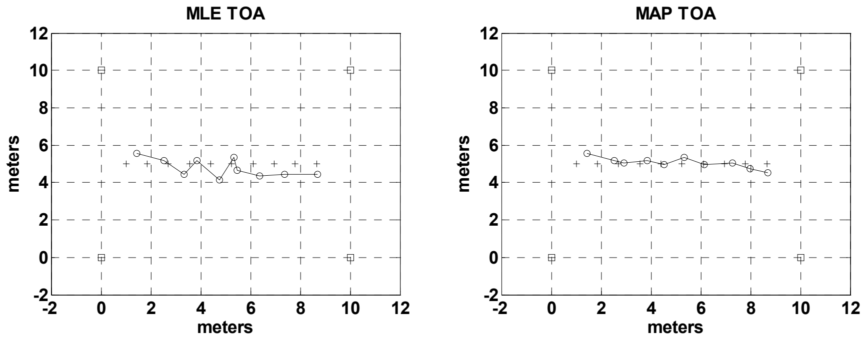

Fig. 3. Trajectory estimation, MLE (*left-l*), MAP (*right-r*); Crosses: true trajectory, Circle: estimation, Squares: *ANs* positions.

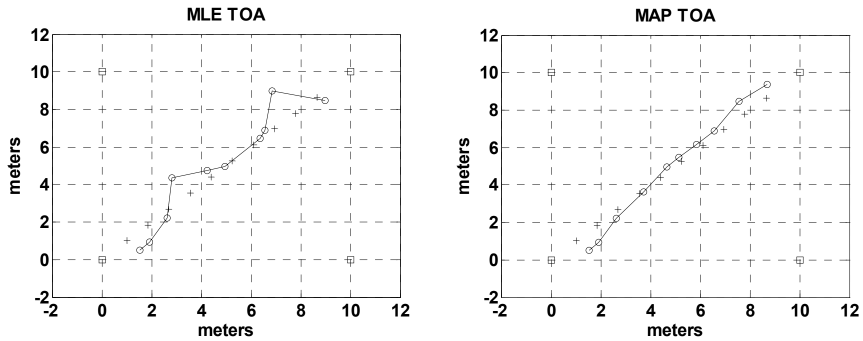

Fig. 4. Trajectory estimation, MLE (*left-l*), MAP (*right-r*) ; Crosses: true trajectory, Circle: estimation, Squares: *ANs* positions

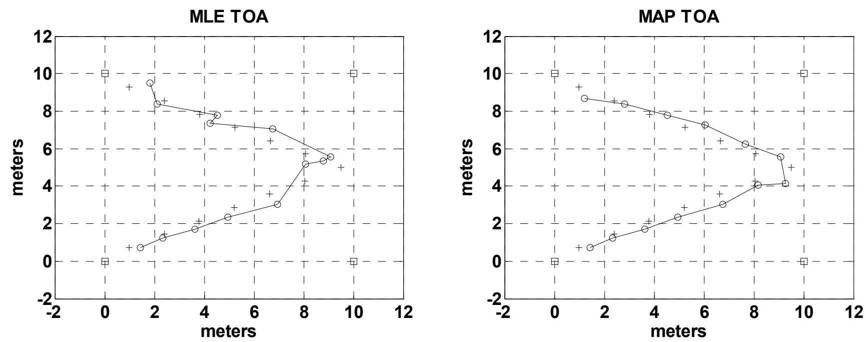

Fig. 5. Trajectory estimation, MLE (left-l), MAP (right-r) ; Crosses: true trajectory, Circle: estimation, Squares: ANs positions

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