WHOMoVeS: An Optimized Broadband Sensor Network for Military Vehicle Tracking

Mohamed Hamdi, Noureddine Boudriga
Communication Networks and Security Research Lab.
University of 7th of November at Carthage, Tunisia

***Abstract*— With the advance of sensing technologies and applications, advanced sensor networks are gaining increasing interest. For certain sensitive applications, heterogeneous sensors can be deployed in the monitored space to ensure scalability, high-speed communication, and long network lifetime. Hybrid sensor networks have capabilities to combine the use of both resource rich and resource impoverished sensor nodes. This paper proposes an heterogeneous broadband sensor network architecture for military vehicle tracking. Powerful sensor devices having important bandwidth and energy capabilities are used as a communication backbone and low energy sensors are used to track moving targets.**

I. Introduction

Wireless mobile sensor networks have received a lot of attention during the recent past, being used in a wide variety of applications. In fact, networked sensing is among the most promising technologies. Distributing sensors within a geographic area in order to gather physical data for later analysis allows efficient and collaborative control of various natural and human like events. One interesting application of Wireless Sensor Networks (WSNs) is target tracking in a hostile environment (i.e., where physical access is accompanied by some form of danger). Typically, military surveillance have constituted the primary application of sensor networks [1]. Existing WSNs deployed for battlefield monitoring consist of hundreds and thousands of low-cost nodes which could be either static or mobile. Multi-hop mechanisms are used to communicate the generated alerts, ending at special nodes (i.e., base stations, sinks). Previous approaches consider that the major role of a base station is to link a local sensor network to another one. However, in our sense, it can be more complex, especially for military applications.

The existing WSN approaches for the military context have not emphasized the prominent feature of this environment. The main difference between traditional and military WSNs resides in the special node role. Due to the sensitivity of the monitored environment, the quality of the gathered data should be considerably enhanced in order to minimize errors at the decision-making level. More accurately, a military WSN should give the opportunity to: (1) track mobile targets using multiple sensors, (2) proceed to frequent localization of mobile targets for a better trajectory identification, and (3) perform high resolution measurements to gain a precise knowledge about the monitored events.

These requirements conflict with the basic traditional sensor node features, which are limited computational and transmission capabilities. This paper proposes a broadband sensor framework for military vehicle localization and tracking called WHOMoVes (Wireless Hybrid Optimal Mobile Vehicle Sensing). From the network perspective, WHOMoVeS is characterized by two layers: the core layer and the sensor layer. The core layer includes special nodes which have not only important communication features but also enhanced sensing and localization capabilities (using GPS [2]). Our contribution can be summarized in the following points:

1) Setting a network architecture allowing to forward voluminous data across the sensor network and to activate adaptively some power-consuming functionalities,
2) Developing an approach for minimal sensor deployment based on the density allowing maximum target coverage,
3) Introducing a method to evaluate sensor measurement errors relying on the uncertainty related to sensor positions,
4) Investigating several parameters that should be monitored in order analyze the past behavior of a mobile target and predict its future positions,

The rest of the paper is structured as follows. Section II presents the network architecture and the main signalling and communication functionalities of WHOMoVeS. The problem of setting the minimal density bound for a coverage criteria is addressed in section III (for both static and mobile sensors). Section IV gives a tool for measuring the error related to the mobile target localization as a function of the uncertainty related to sensor positions. Section V discusses several tracking-related techniques. Finally, Section VI concludes the paper.

II. A Military Broadband Sensor Network

This section presents a hybrid sensor network called WHOMoVeS (Wireless Hybrid Optimal Mobile Vehicle Sensing) including two sensor node categories: (1) core sensors, and (2) simple sensors. The features of these categories, as well as the network topology allowing them to communicate, is presented in the following subsections. Furthermore, the basic messages of the underlying communication and signalling protocols are discussed.

A. Basic requirements

WSN features are determined by the nature of the applications. This subsection presents the salient WSN characteristics according to our context (i.e., target tracking in hostile environment).

- Deployment: The deployment of sensor nodes in a military environment can not be performed according to a deliberate choice. Due to the hostility of the physical environment, human control of sensor node localization is unfortunately impossible. Typically, sensor nodes are dropped from unmanned aircrafts in a specific area. The only parameter that can be effectively monitored is the sensor node density (number of nodes by unity of surface).
- Energy: The energy resources of a sensor node are limited by size and cost constraints. Energy is the most important parameter with regard to the WSN lifetime. The required lifetime depends on the context. It may vary from several hours to several days. Choices related to energy and mobility issues should be guided by the lifetime constraint. For instance, we will show that mobility, localization, and communication techniques could not be thought of without taking into consideration energy constraints. The importance of energy management is emphasized, in our context, by the volume of the transmitted data. In fact, high-resolution information about the monitored scene is often needed, requiring the use of advanced energy-aware techniques.
- Mobility: One prominent characteristic of our WSN is that it should be unnoticeable. In other terms, sensor node positions should be hard to determine for non-authorized parties. Attaching the sensor node to a moving object (out of the control of the sensor node) has several advantages:
  - Sensor nodes can be replaced in case of failure, preserving the coverage density of the monitored area,
  - Sensor nodes are more complex to locate by enemies, because their positions vary according to time,
  - A compromised sensor node becomes easier to identify because its neighbors change according to its movement.
- Coverage: The coverage of the controlled area depends of multiple parameters and is therefore complex to model. The coverage of a single sensor node is basically determined by the range of the attached sensors. Coverage requirements depend heavily on the sensitivity of the tracked targets. Sparse coverage corresponds to the case where the area of interest is *partly* covered by sensors. Dense coverage means that the monitored area is completely covered by sensors. In this paper, we introduce a novel requirement which is more strict than the aforementioned ones. To minimize the errors related to mobile target detection, we consider that an object is detected if and only if the number of sensor nodes that have detected it, at a specific instant, is greater than a predefined threshold. Clearly, this allows to minimize the uncertainty related to target position. However, the reader may argue that the benefit from setting this condition is questionable due to its negative impact on energy (i.e., network lifetime reduction) and QoS (i.e., congestions). This point will be discussed in the following sections.
- Infrastructure: Two common types of WSN communication models are currently used: infrastructure-based network, and ad hoc networks. In infrastructure-based networks, sensor nodes can only directly communicate with base station devices. Communication between sensor nodes is relayed via the base station. In ad hoc networks, nodes can directly communicate with each other without an infrastructure. Nodes may act as routers, forwarding messages over multiple hops on behalf of other nodes. In our context, a network infrastructure is clearly impossible to set. In addition, using a pure ad hoc communication model would increase the uncertainty related to sensor node positions. Therefore, we propose the use of a clustered ad hoc network where several fixed nodes act as base stations. This allows to locate mobile sensor nodes with respect to base stations.
- Robustness: The WSN that we consider should be difficult to destroy, meaning that it should be designed to act in a dangerous environment. To this purpose, mobile sensors should not be possible to locate by adversaries. In addition, the data exchanged through the WSN should not be possible to intercept.

B. WSN architecture

WHOMoVeS is composed of two layers: the *core layer* and the *sensing layer*. The core layer includes sensors which are equipped with powerful sensing and transmission capabilities. The sensing layer consists of miniature electromagnetic devices which is role is limited to the detection of hostile presence. The major application of WHOMoVeS is battlefield surveillance and tracking of military vehicles. Collaborative mobile target tracking approaches using electromagnetic sensors are under several ongoing studies. However, tracking alone may not provide adequate information regarding intruding vehicles. More details related to the vehicle itself, onboard personals and/or armament, might also be interested to gather. This means that image sensors should be used in conjunction with the electromagnetic sensors. Nevertheless, the use of image sensors can not be uncontrolled because they have a high sensing cost and they generate a huge volume of data. In fact, these factors limit the massive and continuous use of the image sensors. The volume of generated data not only poses a heavy burden in data delivery but also floods the useful image frames with huge amount of frames of non-interesting scenes. Moreover, the considerable power consumption of image sensors may reduce the network lifetime. Henceforth, imaging should be triggered by the tracking results of the sensing-layer devices, which use traditional tracking algorithms. From an architectural point of view, image sensors should be integrated within the broadband core layer-nodes. Using this approach, only the image scenes that exhibit a substantial interest, from the military strategy perspective, are sensed. Figure II.1 illustrates the architecture introduced in the foregoing discussion.

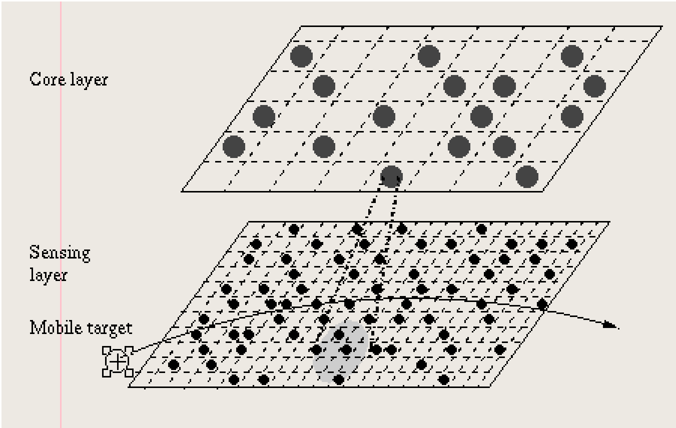

Fig. II.1. Layered broadband sensor network architecture.

C. The communication model

A sensor is assumed to perform three types of operations: (1) collecting information about presumably malicious tasks including target nature and relative position; (2) generating real-time events related to detected targets and transmission of the events to the closest core sensor; and (3) relaying the events generated by other sensors to the core sensors.

At the core layer, nodes are able to acquire and exchange voluminous high-resolution data related to the events detected by the low-level sensors. On the one hand, this layer constitutes a communication backbone allowing to spread data collected by elementary sensors on a wide area. From the other hand, it has enhanced sensing features permitting to refine the information gathered at the low-level. Therefore, the major functionalities that should be supported by core sensors are: (1) acquiring high-resolution data about the detected events (i.e., image or video data), (2) proceeding to dynamic activation of low-level sensors to minimize energy consumption, (3) forward voluminous data-packets via a broadband infrastructure, (4) analyze the events generated by low-level sensors in order to minimize erroneous decisions (e.g., by correlating and filtering the received alerts), and (5) communicate hostile presence to the adjacent core sensors so that they activate low-level sensors.

In the following, we present the major categories of the messages that are exchanged between the sensor nodes during the network lifetime.

- Application-layer messages: These messages are needed for the following purposes:
  - Introducing rules related to data aggregation, attribute-based naming, and clustering to the sensor nodes
  - Exchanging data related to location-finding algorithms
  - Time synchronization of the sensor nodes
  - Moving sensor nodes
  - Turning sensor nodes on and off
  - Querying the sensor network configuration and the status of nodes, and reconfiguring the sensor network
- Localization messages: We consider the relative localization technique to estimate sensor nodes positions. In this framework, a node is able to detect and track the location of the neighboring node by using a collaborative estimation technique and a particle filter applied to an array of sensors. To increase the accuracy of the location estimation, the sink may request all the nodes along the path to the sources to increase the number of samples (particles) for particle filtering. This process of local interaction does not require any beacon in place. In addition, a central processing unit is not required in order to determine the locations of the sources.
- Signalling messages: Instead of time synchronization between the sender and receiver during an application, such as in the Internet, the sensor nodes in the sensor field must maintain a similar time within a certain tolerance throughout the lifetime of the network. Combining with the criteria that sensor nodes must be energy efficient, low cost, and small in a clustered environment.

III. On optimal coverage

The major task to be achieved at the sensing layer is to accurately determine the position of a mobile target. In this section, we investigate the impact of sensor density in the monitored area on the quality of detection. We demonstrate that, under several realistic hypotheses, the number of sensors to be deployed in the hostile environment can be tuned to fit the detection requirements. We also demonstrate that node mobility affects the coverage-based deployment strategy.

A. Related work

One important issue for being able to deploy an efficient sensor network is to develop an optimal node placement strategy. In our context, since the sensors are randomly scattered, the major challenge is to determine the sensor density (i.e., number of sensors per unit of surface). Gosh and Das [3] consider that coverage is a measure of Quality of Service (QoS) because it allows assessing "how well each point in the sensing field is covered by the sensing ranges"[3]. However, we should be aware that coverage also affects some other network performance parameters such as routing complexity or congestion rate. This dilemma will be discussed in the following sections. Below we review the main deployment approaches that have recently appeared in the literature.

- k-coverage: A region A is said to be k-covered if every point belonging to A is within the sensing ranges of k sensors. According to this definition, stating that an area is covered requires enumerating all subregions resulting from the intersection of different sensor node-regions and verifying if each of these is k-covered. In [5], a less complex technique has been proposed based on the fact that a region is k-covered if, every sensor, the perimeter circle of the sensing region is within the perimeters of at least k other sensors.
- k-connectivity: The concept of k-connectivity is defined when there are at least k nodes-distinct paths between

every pair of nodes. In other terms, the network is k-connected if at least k nodes are within the transmission range of each sensor nodes. This coverage condition has been used in the literature to find, for a number N of sensors, a sensing range assignment that ensures k-connectivity. For instance, in [6], Gupta and Kumar have proved that if $\pi R_c^2 = \frac{\log(n)+c(n)}{n}$, then the network is asymptotically connected almost surely if $\lim_{n\to\infty} = \infty$.

- Path-observability: [5] defines the exposure of a moving object in a sensing field during time interval $[t_1, t_2]$ along a path $p(t)$ is defined as the integral:

$$E(p(t), t_1, t_2) = \int_{t_1}^{t_2} I(F, p(t)) \left| \frac{dp(t)}{dt} \right|,$$

where the sensing function $I(F, p(t))$ is a measure of sensitivity at a point on the path by the closest sensor or by all the sensors in the sensing field. This allows computing the maximum exposure path and the maximum breach path, which can be used to optimize the deployment strategy.

The following subsection highlights the major shortcut of the aforementioned approaches and presents an alternative concept (i.e.,k, t-coverage).

B. Density lower band

We assume that N sensors $s_1, .., s_N$ are randomly deployed in the monitored area with a density ρ_s. We suppose that a sensor is characterized by a sensing range R_s^s and a communication range R_s^c. We also suppose that all the elementary sensor nodes are binary, meaning that they detect one bit of information indicating whether the Euclidian distance between the sensor and the target is lower than R_s^s or not.

Supposing that targets are, at a fixed instant, randomly distributed over the monitored area, the probability that a point is observed by k sensors is given by the Poisson distribution [8]:

$$P = \frac{(\rho_s \pi (R_s^s)^2)^k}{k!} \exp(-\rho_s \pi (R_s^s)^2). \qquad \text{(III.1)}$$

It is noteworthy that, the efficiency of the network depends on the sensor density. In fact, increasing k would result in more accurate information about mobile targets provided that more sensor nodes are deployed. However, Equation III.1 may be not realistic because rather than a point in the monitored area, the target should be represented by a surface. In the sequel, we introduce a less strict criteria taking in to consideration this idea. The following definition introduces a new concept, called (k, t)-coverage, used to express a criterion for assessing deployment strategies.

Definition 3.1: Let $s_1, .., s_N$ denote N sensors deployed in an area A and t be a target having a radius R_t. If ν denotes the number of sensor nodes that include t within their sensing range, the (k, t)-coverage of the area A is expressed as follows:

$$C(N, k) = \text{prob}(\nu = k).$$

Based on this definition, our objective is to find the minimal density ρ_s leading to a maximum (k, t)-coverage. Figure III.1 represents a target centered in c_t covered by two sensors s_1 and s_3, while the sensor s_2 does not include t within its sensing range. The figure shows that (k, t)-coverage can be redefined by requiring that the sensing areas of k sensors intersect with the disc centered in c_t and having the radius $R_t + R_s^s$. The following proposition gives a lower bound for the sensor density based on this reasoning.

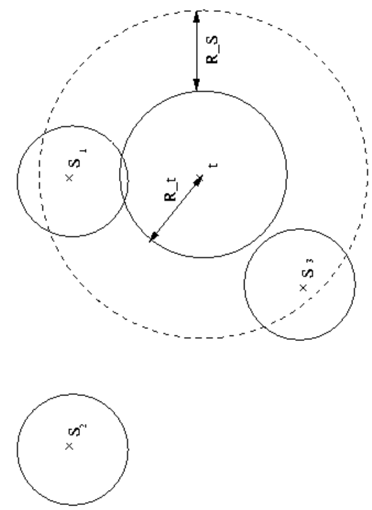

Fig. III.1. Density requirements for target coverage.

Proposition 3.2: Consider N sensor nodes that are uniformly deployed in an area A, then the minimal sensor density corresponding to a maximum k-coverage equals:

$$\rho_s^{min} = \frac{k}{\pi(R_s^s + R_t)^2}. \qquad \text{(III.2)}$$

Proof: The probability that a target t is covered by exactly k sensors is given by:

$$C(N, k) = \frac{(\frac{N}{A}\pi(R_s^s + R_t)^2)^k}{k!} \exp(-\frac{N}{A}\pi(R_s^s + R_t)^2).$$

This comes from two facts: (1) the probability that a target is covered by a sensor equals $\frac{\pi(R_s^s+R_t)^2}{A}$ (Figure III.1 allows to graphically demonstrate this result when the target is tracked by two sensor nodes), and (2) sensors are deployed independently from each others. Hence, it can be easily shown that $C(., k)$ reaches its maximum in N_0 such that:

$$\frac{N_0}{A}\pi(R_s^s + R_t)^2 = k.$$

(qed).

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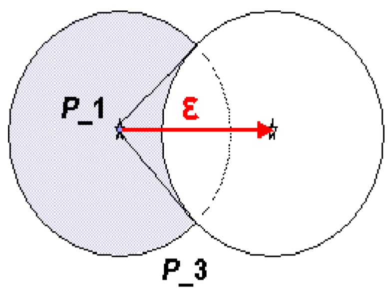
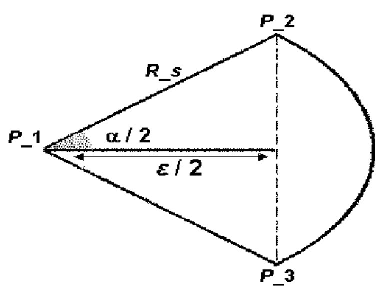
C. Impact of sensor mobility

The theorem proved in the previous subsection does not take into consideration the mobility of the sensor nodes. When positions are no longer static with respect to time, the minimum number of sensors that allow optimal target coverage should increase. This subsection focuses on the impact of sensor mobility on the minimal density.

In the literature, several mobility models have been investigated. In our context, we suppose that within a time interval $\Delta\theta$, sensors can move at a distance ϵ from its initial position in arbitrary direction. The hypothesis that sensor moves are isotropic (e.g., zero-knowledge about direction) is used to determine the greatest number of sensors that would be needed when mobility is introduced. The following proposition gives the probability that a target is not covered by a specific sensor after the time interval $\Delta\theta$.



(a)



(b)

Fig. III.2. Impact of mobility on target coverage.

Proposition 3.3: The probability that a target t is not covered by a sensor node after a time interval $\Delta\theta$ is expressed by:

$$p = 1 - \frac{2\arccos(\frac{\epsilon}{2R_s^s})(R_s^s)^2 - \epsilon\sqrt{(R_s^s)^2 - (\frac{\epsilon}{2})^2}}{\pi(R_s^s)^2}. \quad \text{(III.3)}$$

Proof: We first compute the area A_0 that is no longer covered by the sensor after $\Delta\theta$. According to Figure III.2(a), A_0 is defined by:

$$A_0 = \pi(R_s^s)^2 - 2(A_1 - A_2),$$

where A_1 is the area of the portion induced by $\widehat{P_1P_2P_3}$, and A_2 is the size of the triangle $P_1P_2P_3$. Hence, A_0 can be written as follows:

$$\begin{aligned}
A_0 &= \pi(R_s^s)^2 - 2(\tfrac{\alpha}{2}(R_s^s)^2 - A_2) \\
&\quad \{\text{The area } A_1 \text{ equals } \tfrac{\alpha}{2}(R_s^s)^2\} \\
&= \pi(R_s^s)^2 - 2(\tfrac{\alpha}{2}(R_s^s)^2 - \tfrac{\epsilon}{2}\sqrt{(R_s^s)^2 - (\tfrac{\epsilon}{2})^2}) \\
&\quad \{\text{The area } A_2 \text{ equals } \tfrac{\epsilon}{2}\sqrt{(R_s^s)^2 - (\tfrac{\epsilon}{2})^2}\} \\
&= \pi(R_s^s)^2 - 2(\tfrac{\arccos(\frac{\epsilon}{2R_s^s})}{2}(R_s^s)^2 - \tfrac{\epsilon}{2}\sqrt{(R_s^s)^2 - (\tfrac{\epsilon}{2})^2}) \\
&\quad \{\text{The angle } \alpha \text{ equals } \arccos(\tfrac{\epsilon}{2R_s^s})\}
\end{aligned}$$

Therefore, the probability that the target is not covered by the sensor is $p = \frac{A_0}{\pi(R_s^s)^2}$.

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This result is useful to tune the number of sensors across time. In fact, the density ρ_s can be updated to ρ'_s such that $\rho'_s = \rho_s(1 + p_k)$. This can be interpreted as a condition for the mobility model, which should minimize p_k for a minimal number of extra sensors.

IV. Assessing localization uncertainty

Existing localization approaches [7], [8], [9] do not integrate the uncertainty related to sensor position when assessing a self-organizing sensor network. In the following, we demonstrate that the detection efficiency of the sensor network increases according to the average number of sensors per target. According to this result, we propose a sensor deployment algorithm that allows defining sensor positions according to the application requirements. The parameter k can effectively change according to the nature of the observed target in the sense that it should be decreased when the target size increases. Let $\overrightarrow{t}$ and $\overrightarrow{m}$ be two vectors representing respectively the target position and the measured features (i.e., angle corresponding to the target location). If the target is covered by k sensors, the angle α_i corresponding to the sensor i has the following expression:

$$\alpha_i = tan^{-1}\frac{y_i - y}{x_i - x}, \quad \text{(IV.1)}$$

where $\overrightarrow{t} = (x, y)$ and $\overrightarrow{s_i} = (x_i, y_i)$ denote respectively the position of the mobile target and sensor i. The position $\overrightarrow{t}$ is therefore computed according to these angles. The uncertainty characterizing this positioning system can be assessed by studying the variations related to the function g defined as follows:

$$(\alpha_1, .., \alpha_k) = g(\overrightarrow{t}, \overrightarrow{m}).$$

For instance, when $k = 4$, we can consider the determinant of the Jacobian Matrix $J(g)$ defined by:

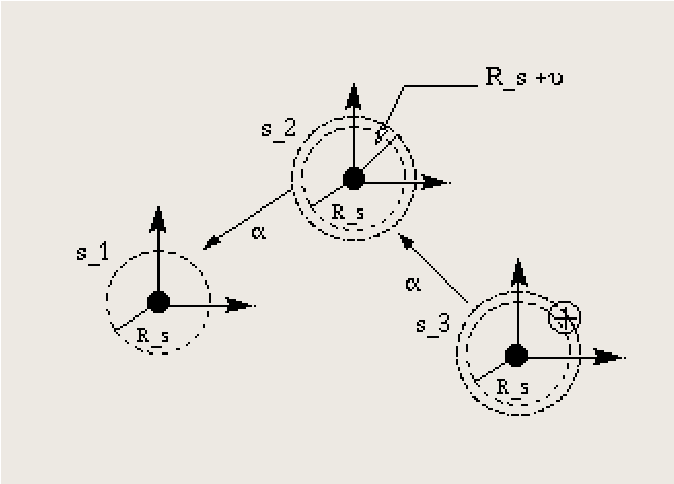

Fig. IV.1. Error propagation during alert transmission.

$$|J(g)| = \frac{\begin{vmatrix} -sin(\alpha_1) & cos(\alpha_1) & sin(\alpha_1) & cos(\alpha_1) \\ -sin(\alpha_2) & cos(\alpha_2) & 0 & 0) \\ -sin(\alpha_3) & cos(\alpha_3) & 0 & 0 \\ -sin(\alpha_4) & cos(\alpha_4) & 0 & 0 \end{vmatrix}}{\begin{vmatrix} \beta_1 & 0 & 0 & 0 \\ 0 & \beta_2 & 0 & 0 \\ 0 & 0 & \beta_3 & 0 \\ 0 & 0 & 0 & \beta_4 \end{vmatrix}},$$

where $\beta_i = cos(\alpha_i)(x_i - x) + sin(\alpha_i)(y_i - y)$. Clearly, computing this jacobian allows estimating the target position according to the uncertainty related to sensors positions.

The second source of uncertainty is that low-level sensors also act as relaying nodes towards core sensors. In other terms, every time the alert message crosses a router, an error is added to the target position. Figure IV.1 shows how the uncertainty made on the location of t propagates from the source to the end sensor. The position $\overrightarrow{t} = (x_t, y_t)$ of the mobile target is perceived by the sensor s_3 as:

$$\left\{ \begin{array}{lcl} x_t & = & x_{s_3} + r_t \cos(\tau_t), \\ y_t & = & y_{s_3} + r_t \sin(\tau_t). \end{array} \right.$$

If ν denotes the uncertainty related to s_3 position, then the uncertainty of the information gathered by s_3 and sent to s_2 is expressed by:

$$U(s_3, t) = \int \int_{\mathfrak{D}} \phi(x, y) dx dy,$$

where $\phi(x_{s_1}, y_{s_1}) = (x + r_t \cos(\tau_t), y_{s_1} + r_t \sin(\tau_t))$ and $\mathfrak{D} = \{(x, y) : R_s^s \leq (x - x_{s_3})^2 + (y - y_{s_3})^2 \leq (R_s^s + \nu)^2\}$.

V. Mobile target tracking

If $\overrightarrow{t^\theta}$ is a vector representing target position at time θ and $\overrightarrow{m^\theta}$ is a vector representing the measured features at time θ, our method would rely on solving an equational system:

$$f(\overrightarrow{m^\theta}, \overrightarrow{s^\theta}) = g(\overrightarrow{t^\theta}), \tag{V.1}$$

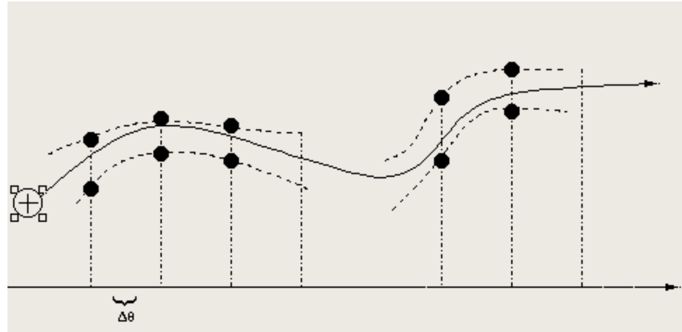

Fig. V.1. Mobile target tracking.

where $\overrightarrow{s^\theta}$ represents the sensors' position as time k. Henceforth, this model allows a more precise error control with regard to the previous approaches where the position $\overrightarrow{t}$ is obtained through the resolution of a system $\overrightarrow{m^\theta} = h(\overrightarrow{t^\theta})$. Moreover, we propose to refine the information about the position of a mobile target at an instant θ (obtained by solving Equation 2) by considering its position at the previous observation instants. This permits to: (1) build a motion model for the tracked targets, and to (2) enhance the position estimate efficiency because former positions may convey some information that is not included in the monitored metrics. To this end, we propose to extend the Joint Probabilistic Data Association Filters (JPDAFs) [10], that have been previously used in robotics applications [11] to the context of WSN. The state vector X_θ models the coordinates and the velocity of the mobile target:

$$X_{\theta+\Delta\theta} = \begin{pmatrix} I_{2,2} & \Delta\theta I_{2,2} \\ 0_{\mathfrak{M}_2} & I_{2,2} \end{pmatrix} X_\theta + \begin{pmatrix} \frac{\Delta\theta^2}{2} I_{2,2} \\ \Delta\theta I_{2,2} \end{pmatrix} \epsilon_1^\theta,$$

where $I_{2,2}$ and $0_{\mathfrak{M}_2}$ are respectively the identity matrix and the zero matrix in dimension 2, and ϵ_θ represents the error process due to the uncertainty on $\overrightarrow{s^\theta}$).

We also suppose that measurements $\widetilde{t^\theta}$ are available according to the stochastic process:

$$Y_\theta = \arctan\left(\frac{x_t^\theta - \widetilde{x^\theta}_t}{y_t^\theta - \widetilde{y^\theta}_t}\right) + \epsilon_2^\theta,$$

where ϵ_2^θ is a zero-mean gaussian error independent of ϵ_2^θ.

Under these assumptions, particle filtering allows to compute an estimate $\overrightarrow{t'^\theta}$ of $\overrightarrow{t^\theta}$ such that the covariance matrix can be controlled according to:

$$M = \sum_i^N = \gamma_\theta^i (s_\theta^i - t'^\theta)(s_\theta^i - t'^\theta)^T.$$

In Figure V.1, we represent the trajectory of a mobile target and the related tracking uncertainty. The reader can notice that the target is not detected between the third and fourth intervals of time. This emphasizes the importance of time sampling. In fact, low-level sensors should provide the corresponding core sensor with a sufficient number of samples in order to analyze the past moves of the target, and to predict its future behavior. Dashed lines in Figure V.1 represent the uncertainty bounds characterizing target position. According to the previous discussion, particle filtering allows predicting sensor positions in a near future without exceeding the amount of uncertainty characterizing the past measurements.

VI. CONCLUSION

In this paper, we have introduced a new framework for mobile military vehicle localization and tracking. Multiple facts of the problem have been addressed. From the architectural point of view, we have considered two sensor categories: (1) low-level sensors, and (2) core sensors. Collaborative target localization have been discussed and a network dimensioning approach based on minimal density has been proposed. A tracking methodology has also been presented.

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