Towards optimal energy-quality tradeoff in tracking via sensor networks

Alessio Benavoli and Luigi Chisci

Abstract— **The paper addresses tracking of a moving target by means of a wireless sensor network. A centralized tracking filter and procedure for selectively activating sensors around the expected target's position are combined. Unlike selective activation methods existing in the literature, which are concerned only with the tracking accuracy, the one considered in this work attempts to tradeoff tracking performance optimization versus lifetime maximization. A performance evaluation via Monte Carlo simulations shows the effectiveness of the proposed approach.**

Keywords : sensor networks; tracking; state estimation; Kalman filtering.

I. INTRODUCTION

Wireless sensor networks (WSN) provide nowadays an attractive solution to many civilian and military applications including for instance surveillance, localization, tracking, environmental monitoring, exploration, classification and accomplishment of several types of missions. From a research point of view, WSNs pose a number of challenging problems (e.g. deployment, routing, localization, scheduling, power control, etc.) which stay at the convergence point between communication, computing and control. For these reasons, WSNs have attracted a considerable amount of research work over the last few years [1]. A WSN is a set of a large number of low-cost and battery-powered nodes with sensing, processing and wireless communication capabilities. Since in most cases the batteries can neither be recharged nor be replaced, a key issue in order to maximize the network lifetime is to take care of energy consumption at any stage of the network's operation. Hence, energy management becomes a key factor for a successful operation whatever is the target application of the WSN. In particular, a parsimonious energy management requires efficient coordination among sensor nodes. To this end, existing methods developed in the literature rely on tree-based collaboration [2], group clustering [3] and collaboration [4], sensor scheduling [5], power control [6] and selective activation [7]-[9].

In this paper, the attention is devoted to tracking a moving target by means of a WSN. To this end, two types of sensors are used: binary sensors that simply detect the target's presence and passive sensors that provide measurements of the bearing angle. A centralized processing approach is undertaken, i.e. sensors transmit raw measurements to a central processing node wherein the overall tracking process is carried out. Since the energy consumption is essentially proportional to the number of active sensors, energy efficiency calls for the implementation, inside the central processing node, of a smart *selective activation* (SA) strategy [7]-[9] in order to choose how many and which nodes to activate around the target's location so as to attain an appropriate quality-energy tradeoff. The so called *frisbee* method, proposed in [7], heuristically activates sensors that are in a suitable circular neighborhood of the predicted target position and possibly keeps active sensors that were active at the previous sampling interval. Conversely, the *Global Node Selection* (GNS) technique, presented in [8], aims at systematically minimizing the filtered target's position *Mean Squared Error (MSE)* for a network of *Direction of Arrival* (DOA) passive sensors. However both SA methods make the sensor selection relying solely on the relative sensor positions w.r.t. the expected target location without any concern about the current sensor energy status. This is certainly efficient in terms of tracking quality but might be very inefficient in terms of energy and, thus, network lifetime. On the other hand, in order to maximize network lifetime without taking care of tracking quality, the obvious SA strategy is to select sensors with highest residual energy.

The objective of this paper is to investigate SA methods trading off the two often conflicting issues of tracking performance and network lifetime. To this end,

This work was not supported by any organization

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the idea followed in this paper has been:

(1) to fix the number m of sensors to be activated;

(2) to introduce an utility function that suitably takes into account both the position MSE, minimized by the GNS technique [8], and the residual energy, which should be maximized for the longest lifetime;

(3) to formulate the SA problem as the discrete optimization problem of maximizing such an utility over the set of possible choices of m out of the sensors' population.

The rest of the paper is organized as follows. Section II describes the sensor network and section III the centralized tracking algorithm, i.e. track initialization and filtering. Then section IV concentrates on the SA strategy and section V presents a performance evaluation of the proposed techniques via Monte Carlo simulations. Finally, section VI summarizes the paper and discusses some points for future research investigation.

II. SENSOR NETWORK

Let us consider a network consisting of two types of sensors, i.e. *detecting* sensors and *measuring* sensors, spread over a certain surveillance area. The former, referred to hereafter as D-sensors, are always active and detect the presence of a target within a certain range. The latter, referred to as M-sensors, provide, whenever active, a noisy measurement of the DOA (bearing angle). Let $\mathcal{D}$ and $\mathcal{M}$ denote the sets of D-sensors and, respectively, M-sensors. Further, let $\mathbf{p}_i = (x_i, y_i)'$ be the known position vector of sensor $i \in \mathcal{D} \cup \mathcal{M}$ and $\mathbf{p} = (x, y)'$ the unknown position vector of the target. Then each D-sensor provides a binary measurement

$$z_i \;=\; \begin{cases} 1, & \text{if } \|\mathbf{p} - \mathbf{p}_i\| < r \\ 0, & \text{otherwise} \end{cases} \quad , \qquad i \in \mathcal{D}$$

where $\|\cdot\|$ denotes euclidean norm and r is the detection range. Conversely, each M-sensor provides a real-valued noisy measurement

$$z_i \;=\; \angle\left(\mathbf{p} - \mathbf{p}_i\right) \;+\; v_i, \qquad i \in \mathcal{M}$$

where $\angle\cdot$ denotes the angle formed with the positive horizontal semi-axis and v_i is the measurement noise with zero mean and variance σ_i^2. It is assumed that measurements of different M-sensors are independent.

The objective is to use the sensor network for tracking a target moving in the surveillance area. To this end, a centralized processing approach is undertaken, i.e. sensor nodes transmit raw measurements to a *central fusion node* (CFN) wherein target tracking takes place and, for energy saving purposes, a selective activation strategy of M-sensors is also implemented. More precisely, it is assumed that the CFN knows:

- the position of all sensors, e.g. obtained by means of self-localization techniques [10], [11];
- the residual energy of all sensors;
- all binary measurements from D-sensors;
- all DOA measurements from *active* M-sensors.

Based on the above information, at each sampling interval, the CFN performs the following tasks:

- initializes and/or updates the target state based on available measurements (TRACKING);
- activates the appropriate M-sensors for the next sampling interval (SELECTIVE ACTIVATION).

The primary focus in this work will be on the quality-energy tradeoff in the attempt to increase the network lifetime while preserving the desired accuracy in the target tracking. Several simplifying assumptions will be adopted in the sequel:

- the measurements from the distributed sensors are processed in a synchronous way, i.e. simultaneously at the beginning of each sampling interval;
- the transmission delays are neglected;
- a single target at a time is being tracked;

III. TRACKING

A tracking system must update the target's kinematic state (i.e. positions and velocities) based on available measurements as well as on a dynamic model of the target motion. Let us introduce the target state $\mathbf{x} = [\mathbf{p}', v_x, v_y]' = [x, y, v_x, v_y]'$ where x, y and v_x, v_y are the cartesian position and, respectively, velocity coordinates. For a maneuvering target, good modelling of the motion is obtained with a multiple model:

$$\mathbf{x}(t+1) \;=\; \mathbf{A}_{m(t)}\mathbf{x}(t) + \mathbf{D}\mathbf{w}(t) \tag{1}$$

where: $m(t)$ is the discrete modal state which can range over μ possible modes, i.e. $m(t) \in \{1, 2, \ldots, \mu\}$;

$$\mathbf{A}_i = \begin{bmatrix} 1 & 0 & \frac{sin(\omega_i T)}{\omega_i} & \frac{cos(\omega_i T)-1}{\omega_i} \\ 0 & 1 & \frac{1-cos(\omega_i T)}{\omega_i} & \frac{sin(\omega_i T)}{\omega_i} \\ 0 & 0 & cos(\omega_i T) & -sin(\omega_i T) \\ 0 & 0 & sin(\omega_i T) & cos(\omega_i T) \end{bmatrix}, \mathbf{D} = \begin{bmatrix} \frac{T^2}{2} & 0 \\ 0 & \frac{T^2}{2} \\ T & 0 \\ 0 & T \end{bmatrix};$$

T is the sampling interval; $\mathbf{w} = [w_x, w_y]'$ is the process noise used to model uncertain accelerations, with zero mean and covariance $\mathbf{Q} = diag\{q_x, q_y\}$. Notice from the state transition matrices $\mathbf{A}_i$ that each mode $i \in \{1, 2, \ldots, \mu\}$ represents a coordinate turn in which the target is moving with constant speed (the magnitude of the velocity vector) and turning with a constant angular rate ω_i. In particular, $\omega_1 = 0$ yields a constant velocity model which can satisfactorily model a non maneuvering target. For maneuvering behavior, further modes can be introduced to model left ($\omega_i > 0$) and right ($\omega_i < 0$) turns with different angular rates. The time evolution of the modal state $m(t)$ is governed by a homogeneous Markov chain with suitably selected transition probabilities.

Hereafter the overall operation of the target tracker is described. Let us assume that at a given sampling interval, a subset $\mathcal{D}_a \subset \mathcal{D}$ of D-sensors first detect the target presence, i.e. $z_i = 1$ for $i \in \mathcal{D}_a$. Then the CFN must carry out the following steps.

- **Step 1 (Initialization)** - Initialize the state estimate $\hat{\mathbf{x}}(0|0)$ and covariance $\mathbf{P}(0|0)$.
- **Step 2 (Time-Update)** - Time-update the state estimate and covariance using the state dynamics (1).
- **Step 3 (Selective Activation)** - Selectively activate M-sensors, i.e. choose a suitable subset $\mathcal{M}_a \subset \mathcal{M}$ and deliver activation signals to sensors $i \in \mathcal{M}_a$.

For the subsequent sampling intervals, until there are available detections from D-sensors and/or real-valued measurements from active M-sensors the above procedure is repeated by replacing the initialization step with the following

- **Step 1' (Measurement Update)** - The CFN updates the state estimate and covariance using the available measurements possibly including the ones provided by D-sensors.

The initialization, time-update and measurement-update procedures will be discussed hereafter; selective activation will be treated in the next section.

A. Initialization

The intersection of the sensing circles of the D-sensors in $\mathcal{D}_a$ defines a convex region

$$\mathcal{R} = \{\mathbf{p} : \|\mathbf{p} - \mathbf{p}_i\| \le r, \ i \in \mathcal{D}_a\}$$

where the target position is constrained to be. A possible initialization is:

$$\hat{\mathbf{x}}(0|0) = \begin{bmatrix} \mathbf{p}_0 \\ 0 \\ 0 \end{bmatrix}, \ \mathbf{P}(0|0) = \begin{bmatrix} \mathbf{P}_0 & \\ & \frac{v_{max}^2}{9}\mathbf{I} \end{bmatrix} \quad (2)$$

where v_{max} is the maximum target speed and $(\mathbf{p}_0, \mathbf{P}_0)$ can, e.g., be chosen so that the 99.9% confidence ellipsoid associated to the normal distribution with mean $\mathbf{p}_0$ and covariance $\mathbf{P}_0$ is a good approximation of $\mathcal{R}$. In this paper the following heuristic definition of $\mathbf{p}_0$ and $\mathbf{P}_0$ has been adopted:

$$\mathbf{p}_0 = \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \frac{\sum_{i \in \mathcal{D}_a} \left(\sum_{j \in \mathcal{D}_a} \|\mathbf{p}_i - \mathbf{p}_j\| \right) \mathbf{p}_i}{\sum_{i,j \in \mathcal{D}_a} \|\mathbf{p}_i - \mathbf{p}_j\|}$$

$$\mathbf{P}_0 = \chi^2_{0.999} \ (r - r_0)^2 \ \mathbf{I}$$

where $\chi^2_{0.999} = 10.8$ and

$$r_0 \triangleq \frac{1}{|\mathcal{D}_a|} \sum_{i \in \mathcal{D}_a} \|\mathbf{p}_i - \mathbf{p}_0\|$$

Notice that $\mathbf{p}_0$ is a weighted average of the locations $\mathbf{p}_i$ of active D-sensors, each $\mathbf{p}_i$ being weighted by the sum of distances of sensor i from all other sensors in $\mathcal{D}_a$. Conversely, the expression for $\mathbf{P}_0$ arises from the observation that for an infinite number of D-sensors placed in a regular fashion around the target location, at distance r_0, the intersection region $\mathcal{R}$ turns out to be circle with radius $r - r_0$; hence, it is expected that this could be a reasonable approximation for a random location of many D-sensors around the target by taking r_0 as the average sensor distance from the predicted target's position. For more accurate initialization, the minimum volume ellipsoidal outer approximation or the maximum volume inner approximation of $\mathcal{R}$ [13] could be considered.

B. Time-update

At time t, the time-update is needed in order to compute the state prediction $\hat{\mathbf{x}}(t+1|t)$ and the associated covariance $\mathbf{P}(t+1|t)$ which, in turn, are fundamental in selecting the M-sensors to activate for time $t+1$. A bank of μ filters, one for each mode, must be employed and their interactions are handled via the well known IMM (*Interacting Multiple Model*) approach [12], which represents a good compromise between target modelling accuracy and computational complexity.

C. Measurement-update

Let $\mathcal{M}_a = \{i_1, i_2, \ldots, i_m\}$ be the set of M-sensors activated at the previous sampling interval. Then the measurement equation takes the form

$$\mathbf{z}(t) = \mathbf{h}(\mathbf{x}(t)) + \mathbf{v}(t) \quad (3)$$

where

$$\mathbf{z} = \begin{bmatrix} z_{i_1} \\ z_{i_2} \\ \vdots \\ z_{i_m} \\ x_0 \\ y_0 \end{bmatrix}, \quad \mathbf{h}(\mathbf{x}) = \begin{bmatrix} \angle(\mathbf{p} - \mathbf{p}_{i_1}) \\ \angle(\mathbf{p} - \mathbf{p}_{i_2}) \\ \vdots \\ \angle(\mathbf{p} - \mathbf{p}_{i_m}) \\ x \\ y \end{bmatrix}$$

and $\mathbf{v}(t)$ is the measurement noise with zero mean and covariance

$$\mathbf{R} \;=\; diag\{\sigma_{i_1}^2, \sigma_{i_2}^2, \ldots, \sigma_{i_m}^2, \mathbf{P}_0\}$$

Due to the nonlinearity of the measurement equation, an EKF (*Extended Kalman Filter*) can be used for each modal filter. For covariance measurement-update at time t, the output matrix is obtained via linearization around the predicted state estimate $\hat{\mathbf{x}}(t|t-1)$, i.e. [8]

$$\mathbf{C}(t) = \frac{\partial \mathbf{h}}{\partial \mathbf{x}}\Big|_{\mathbf{x}=\hat{\mathbf{x}}(t|t-1)} = \begin{bmatrix} -\frac{1}{r_{i_1}} sin(\theta_{i_1}) & \frac{1}{r_{i_1}} cos(\theta_{i_1}) & 0 & 0 \\ -\frac{1}{r_{i_2}} sin(\theta_{i_2}) & \frac{1}{r_{i_2}} cos(\theta_{i_2}) & 0 & 0 \\ \vdots & & & \vdots \\ -\frac{1}{r_{i_m}} sin(\theta_{i_m}) & \frac{1}{r_{i_m}} cos(\theta_{i_m}) & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{4}$$

where $(r_i, \theta_i)'$ is the position of sensor i relative to the predicted target location in polar coordinates.

IV. SELECTIVE ACTIVATION FOR OPTIMAL ENERGY-QUALITY TRADEOFF

Energy awareness is of paramount concern in the management of WSNs. Several methods for energy efficient target tracking have been devised such as group clustering [3], tree-based collaboration [2] and selective activation [7], [8], [9]. In particular, the latter approach, i.e. selective activation, will be pursued in this work as being the most suitable for centralized processing. The idea is to activate only part (possibly few) of the available M-sensors depending on their current energy status as well as on their position with respect to the predicted target location. Clearly, if all M-sensors are kept active the optimum localization accuracy is obtained at the price of the highest energy consumption. If, on the other hand, all M-sensors are inactive the lowest energy consumption is achieved at the price of the worst localization quality. In practice, a suitable compromise between these two limit situations should be desirable.

Hereafter, to measure the tracking performance the posterior (filtered) *position MSE* will be adopted. Let $\mathbf{P}_f$ denote the 4×4 posterior (filtered) state covariance and let $\mathbf{P}_{11}$ denote its principal 2×2 sub-matrix, then the position MSE is defined as $q(\mathcal{M}_a) = tr(\mathbf{P}_{11})$ and clearly depends on the choice of the active M-sensors $\mathcal{M}_a$. In [8] it has been shown that such a position MSE is lower bounded by:

$$q(\mathcal{M}_a) \geq \frac{4\bar{r}^2}{m} \tag{5}$$

where $m = |\mathcal{M}_a|$ is the number of active M-sensors and $\bar{r}$ is a sort of average radius defined as follows

$$\bar{r} \;=\; \left(\frac{1}{m} \sum_{i \in \mathcal{M}_a} \frac{1}{\sigma_i^2 r_i^2} \right)^{-1/2} . \tag{6}$$

Hence, if the tracking accuracy specification is $q(\mathcal{M}_a) \leq q_{max}$, one can heuristically choose m such that

$$\frac{4 \max_i \sigma_i^2 r_i^2}{m} < q_{max} \implies m > \frac{4 \max_i \sigma_i^2 r_i^2}{q_{max}}$$

Once the cardinality m of $\mathcal{M}_a$ has been selected for satisfactory expected tracking performance, there remains the problem to pick up m out of $M = |\mathcal{M}|$ M-sensors so as to comply with two conflicting needs:

- to minimize the MSE $q(\mathcal{M}_a)$ (*quality requirement*);
- to prolong as much as possible the network lifetime (*energy requirement*).

The reference [8] has addressed the sensor selection problem considering only the quality requirement, i.e. minimization of $q(\cdot)$. Let us consider the information (*inverse covariance*) measurement-update

$$\mathbf{J}_f \;=\; \mathbf{J}_p + \mathbf{J}$$

where: $\mathbf{J}_f = \mathbf{P}_f^{-1}$ is the posterior (filtered) inverse information matrix;

$$\mathbf{J}_p \;=\; \mathbf{P}_p^{-1} \;=\; \begin{bmatrix} \mathbf{J}_{11} & \mathbf{J}_{12} \\ \mathbf{J}_{12}' & \mathbf{J}_{22} \end{bmatrix}, \; \mathbf{J}_{11} \in \mathbb{R}^{2\times 2}$$

is the prior (predicted) information matrix and $\mathbf{J} = \mathbf{C}'\mathbf{R}^{-1}\mathbf{C}$ is the measurement information matrix, $\mathbf{C}$ being the output matrix (4) linearized around the predicted estimate. Then [8] has derived the following analytical expression for the quality cost:

$$q(\mathcal{M}_a) = \frac{tr(\mathbf{J}) + tr(\widetilde{\mathbf{J}}_p)}{det(\mathbf{J}) + det(\widetilde{\mathbf{J}}_p) + \sum_{i \in \mathcal{M}_a} \left(\widetilde{J}_{11} \frac{cos^2(\theta_i)}{\sigma_i^2 r_i^2} + \widetilde{J}_{22} \frac{sin^2(\theta_i)}{\sigma_i^2 r_i^2} + \widetilde{J}_{12} \frac{sin(2\theta_i)}{\sigma_i^2 r_i^2} \right)} \tag{7}$$

where:

$$\begin{aligned}
\widetilde{\mathbf{J}}_p &= \mathbf{P}_0^{-1} + \mathbf{J}_{11} - \mathbf{J}_{12}\mathbf{J}_{22}^{-1}\mathbf{J}_{12}' = \begin{bmatrix} \widetilde{J}_{11} & \widetilde{J}_{12} \\ \widetilde{J}_{12} & \widetilde{J}_{22} \end{bmatrix} \\
tr(\mathbf{J}) &= \sum_{i \in \mathcal{M}_a} \frac{1}{\sigma_i^2 r_i^2} \\
det(\mathbf{J}) &= \frac{1}{2} \sum_{i,j \in \mathcal{M}_a} \frac{sin^2(\theta_i - \theta_j)}{\sigma_i^2 r_i^2 \sigma_j^2 r_j^2}
\end{aligned} \tag{8}$$

Equations (7)-(8) express the quality cost in terms of the sensors ranges r_i and azimuths θ_i w.r.t. the predicted target location as well as of the prior information which is condensed in $\widetilde{\mathbf{J}}_p$. They reveal some interesting and quite intuitive hints about the quality-optimal sensor selection, i.e.

- sensors with low virtual distances $\sigma_i r_i$ from the predicted target location should be preferred;
- selected sensors should provide good angular diversity by surrounding the target in all directions;
- sensors that reduce the error in the directions where it is higher should also be selected.

However, the quality-optimal approach in [8] suffers from a major drawback; it is not, in general, efficient in terms of network lifetime. In fact, the selection of the subset of M-sensors minimizing MSE at each sampling interval is very likely to soon deplete the energy of some strategically located sensors. On the other hand, it is clear that for maximum lifetime the residual energies of different nodes should be kept as close as possible one to each other, which is clearly in contrast with the above discussed strategy. Let e_i denote the residual energy of sensor $i \in \mathcal{M}$ and $e(\mathcal{M}_a) = \sum_{i \in \mathcal{M}_a} e_i$ the overall residual energy of the active subset, then the lifetime-optimal sensor selection strategy is to take $\mathcal{M}_a$ maximizing $e(\mathcal{M}_a)$, i.e. choosing the m sensors with highest residual energies. To tradeoff MSE minimization and lifetime maximization objectives, the following utility function, to be maximized w.r.t. the sensor selection $\mathcal{M}_a$, is introduced

$$U(\mathcal{M}_a) = \left[c_1 + \frac{c_2}{q(\mathcal{M}_a)} \right] \; [\; c_3 + c_4 \; e(\mathcal{M}_a) \;] \tag{9}$$

with: $c_i \geq 0$ for $i = 1, 2, 3, 4$; $c_1 + c_2 > 0$ and $c_3 + c_4 > 0$. In the next section it will be shown how a suitable choice of the coefficients c_i allows to compromise the two objective according to the desired needs.

Hereafter the discrete optimization of (9) w.r.t. $\mathcal{M}_a$ is discussed. An exhaustive search over all combinations of sensors requires the evaluation of $\frac{M!}{m!(M-m)!}$ cases and is clearly not viable for $M \gg m$. The following procedure suggested in [8] has therefore been adopted.

Step 1. Select $\mathcal{M}_a = \{i_1, i_2\}$ giving maximum utility i.e.

$$\begin{aligned}
(i_1, i_2) &= \arg \max_{i_1, i_2 \in \mathcal{M}} U(\{i_1, i_2\}) \\
\mathcal{M}_a &= \{i_1, i_2\}
\end{aligned}$$

Step 2. While $|\mathcal{M}_a| < m$ do

$$\begin{aligned}
j &= \arg \max_{i \in \mathcal{M} \setminus \mathcal{M}_a} U(\mathcal{M}_a \cup \{i\}) \\
\mathcal{M}_a &= \mathcal{M}_a \cup \{j\}
\end{aligned}$$

Step 3. Set $k = m - 1$.
Repeat

if $\exists j \in \mathcal{M} \setminus \mathcal{M}_a : U(\mathcal{M}_a \setminus \{i_k\} \cup \{j\}) > U(\mathcal{M}_a)$
then $\mathcal{M}_a = \mathcal{M}_a \setminus \{i_k\} \cup \{j\}$; $k = m$
else $k = k - 1$

until $k = 0$.

V. SIMULATION RESULTS

In this section, a performance evaluation of the proposed centralized WSN-based tracking system is carried out. First of all, different tracking filters have been compared under the quality-optimal selective activation strategy [8]. Due to lack of space, the results of this comparison are not reported but are briefly summarized hereafter. It has been found that an IMM filter based on $\mu = 3$ coordinated-turn modes with angular rates $\omega_1 = 0$, $\omega_2 > 0$ and $\omega_3 = -\omega_2$ yields much better tracking accuracy than an EKF based on a single constant velocity mode during the maneuvers and comparable results when the target is not maneuvering; it has also been seen that the addition of further modes does not provide significant benefits.

Conversely, the goal of this section is to compare different sensor selective activation strategies in terms of their tradeoff between tracking accuracy and network lifetime. More precisely, different options for the coefficients c_i in the utility function (9) will be considered. For the sake of clarity, these options will be classified hereafter into five different types of SA (*selective activation*) strategies listed below.

- *q-optimal* SA, i.e. $c_4 = 0$, which clearly coincides with the strategy [8] that optimizes tracking position MSE (quality) but ignores lifetime (energy).
- *e-optimal* SA, i.e. $c_2 = 0$, which clearly selects the M-sensors with highest residual energy thus maximizing lifetime without paying any attention to quality.

- *e/q-optimal* SA, i.e. $c_1 = c_3 = 0$, which maximizes the ratio between the residual energy and the position MSE.
- *qe-optimal* SA, i.e. $c_2 = c_4 = 1$, $c_1 = 0$ and $c_3 > 0$, which maximizes the utility $e/q + c_3/q$ and thus allows, w.r.t. the *e/q-optimal* strategy, to put more emphasis on quality by increasing c_3.
- *eq-optimal* SA, i.e. $c_2 = c_4 = 1$, $c_3 = 0$ and $c_1 > 0$, which maximizes the utility $e/q + c_1 e$ and thus allows, w.r.t. the *e/q-optimal* strategy, to put more emphasis on energy by increasing c_1.

The comparison has been carried out via Monte Carlo simulations with 500 independent runs obtained for the same target trajectory (see fig. 1) by varying the sensors' locations and the measurement noise realization.

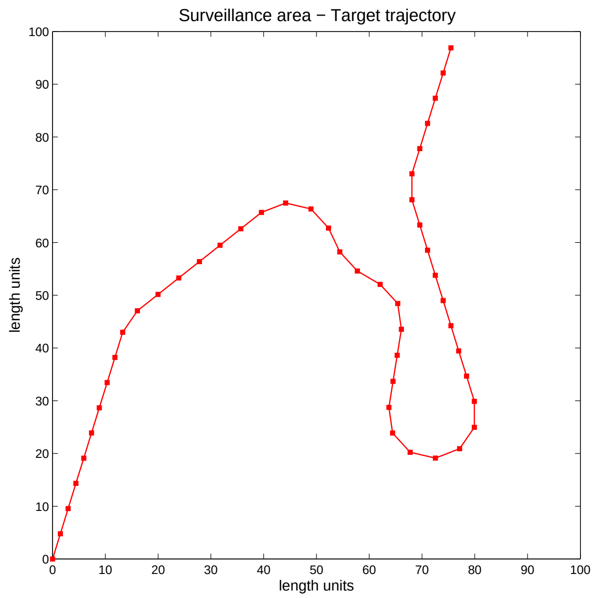

Fig. 1. Target trajectory

In all simulations the overall number of M-sensors is fixed to $M = 40$ and the number of activated M-sensors is $m = 5$. In view of the above discussed comparative evaluation of tracking filters, an IMM filter with $\mu = 3$ modes has been adopted. Further, the following types of metrics have been considered to evaluate the tracking system's performance: position and velocity MSE, standard deviation of the residual energy and number of alive M-sensors, i.e. sensors having sufficient residual energy for carrying out at least one measurement. Energy consumption from sampling time $t-1$ to t is modelled by

$$e_i(t) = \begin{cases} e_i(t-1) - e_a, & i \in \mathcal{M}_a \\ e_i(t-1) - e_{\bar{a}}, & i \notin \mathcal{M}_a \end{cases},$$

i.e. during a sampling interval each M-sensor consumes energy e_a or $e_{\bar{a}}$, with $e_a \gg e_{\bar{a}}$, according to whether is active or not. In order to get significant lifetime comparisons by simulations over a short time-interval (≈ 50 sampling intervals) a large value of e_a, corresponding to 14% of the initial energy, has been taken while $e_{\bar{a}}$ has been neglected.

Table I compares the time-averaged position and velocity MSE obtained with several types of SA strategies, namely: q, e, e/q, qe for different values of c_3 and eq for different values of c_1. Figs. 2-3 and 4-5 plot, versus time, the standard deviation of the residual energy and, respectively, the number of alive sensors for the same SA strategies.

SA strategy	position MSE	velocity MSE
q-optimal	1.276	1.496
qe-optimal ($c_3 = 1.5$)	1.292	1.497
qe-optimal ($c_3 = 0.3$)	1.299	1.517
e/q-optimal	1.326	1.532
eq-optimal ($c_1 = 0.6$)	1.456	1.608
eq-optimal ($c_1 = 2.5$)	1.907	1.872
eq-optimal ($c_1 = 6$)	2.392	2.087
e-optimal	2.587	2.111

TABLE I

POSITION AND VELOCITY MSE

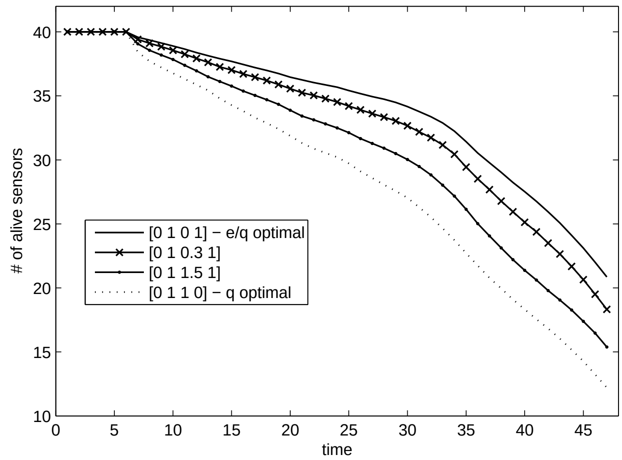

Fig. 2. Number of alive sensors for the q, qe and e/q-optimal SA strategies

The examination of the results in table I and figs. 2-5 allows to draw the following general remarks.

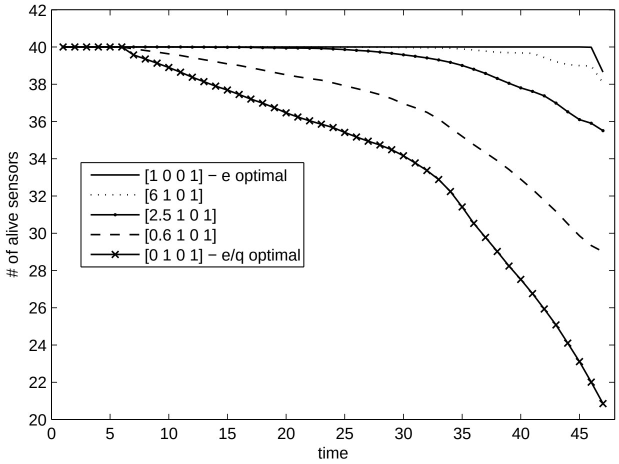

Fig. 3. Number of alive sensors for the e, eq and e/q-optimal SA strategies

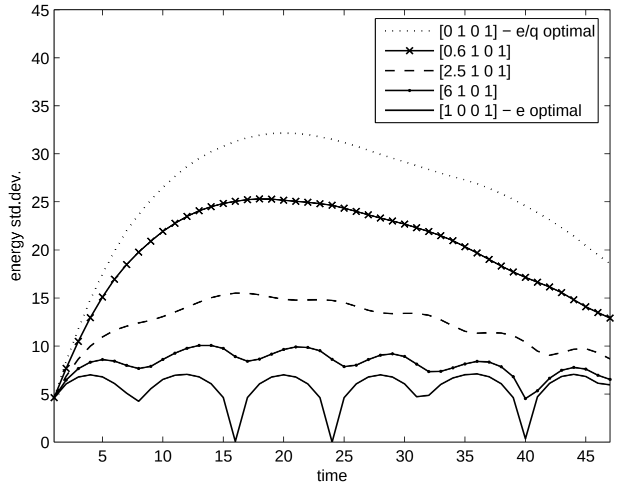

Fig. 4. Standard deviation of the residual energies for the q, qe and e/q-optimal SA strategies

- The choice of the coefficients c_i in (9) allows to properly tune the tradeoff between tracking quality and lifetime.
- Limit strategies, i.e. *q-optimal* and *e-optimal*, are very energy-inefficient and, respectively, quality-inefficient; hence, intermediate strategies (e.g. *qe* or *e/q* or *eq*) should be preferred.
- The residual energy standard deviation for the *e-optimal* strategy has a characteristic oscillatory time-behavior, see fig. 4, periodically assuming zero or quasi-zero values.

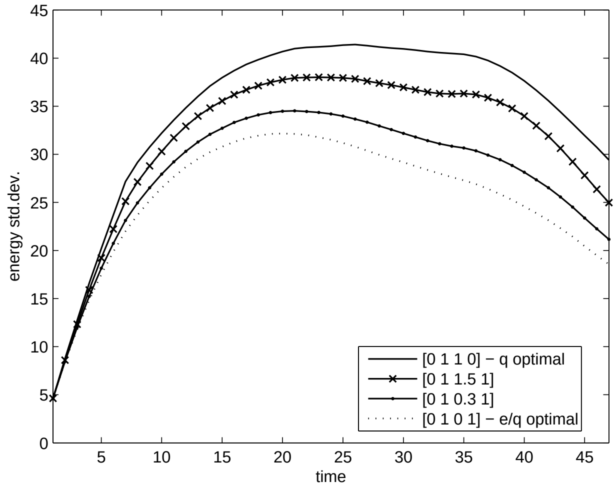

Fig. 5. Standard deviation of the residual energies for the e, eq and e/q-optimal SA strategies

VI. CONCLUSIONS

Preliminary work towards efficient target tracking via a wireless sensor network has been carried out, where efficiency is measured in terms of both tracking accuracy and network lifetime. In particular, a novel strategy for selective activation of sensors has been introduced. Unlike the selective activation strategies existing in the literature, the proposed one takes into account also the current energetic status of the sensors. Although the approach seems promising, the work should be continued in several directions:

- multitarget scenario by the inclusion of data association in the tracking procedure;
- asynchronous and/or multirate processing of measurements;
- inclusion of communication delays and energy consumptions;
- partially and/or fully decentralized processing;
- formulation of the selective activation as a lifetime maximization problem with a free number of active sensors, for a suitable *tracking-oriented* definition of the network's *lifetime*.

ACKNOWLEDGMENTS

The authors wish to thank Niccolò Bulgarini for his valuable collaboration in carrying out simulations and preparing figures, and Dr. Alfonso Farina of SELEX-Sistemi Integrati for interesting and fruitful discussions concerning the subject of this paper

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