# Sensor Management in Command & Control

**Abder Benaskeur**
Decision Support Systems Section, DRDC-Valcartier
2495 Pie-XI Blvd. North,
Val-Bélair (Québec), Canada G3J 1X5
Phone: 1-418-844-4000 ex.4396
E-mail: Abderrezak.Benaskeur@drdc-rddc.gc.ca

**Abstract**

The sensing resources represent an important source of information on which the Command & Control ($C^2$) process bases most of its reasoning. Therefore, a major prerequisite to the success of the whole $C^2$ process is the effective use of these scarce and costly resources. This is the problem of sensor management that has to do with how best to manage and coordinate the use of sensing resources to improve data acquisition and ultimately perception and comprehension. Conscious of the important role sensor management has to play in modern $C^2$ systems, the Decision Support Systems (DSS) Section at Defence Research & Development Canada - Valcartier (DRDC-V) is currently studying advanced sensor management concepts and applications, to increase the survivability of the current Halifax and Iroquois Class ships, as well as their possible future upgrades. The objective of the reported part of this study is twofold i) to present the sensor management problem and the requirements for its solution ii) to demonstrate, through a tracking application, the benefits that can be gained by the closed-loop management of the sensors.

## 1. **Introduction**

The essence of the $C^2$ process is acquiring information, assessing how this information affects current activities, determining a course of action and directing the implementation of this action. This process is well schematized by the Observe-Orient-Decide-Act (OODA) loop (see Figure 1). Therefore, an important prerequisite to the success of the whole $C^2$ process is the effective use of available sensing resources, which defines the problem of sensor management. This explains why this class of problems has become increasingly common in $C^2$ applications.

Sensor management in $C^2$ has to do with how best to manage, coordinate and organize the use of scarce and costly sensing resources in a manner that improves the process of data acquisition, and ultimately those of perception and comprehension, *i.e.*, the situation awareness of the decision maker. Management that ultimately reduces to making decisions regarding alternate sensing strategies is driven by many factors such as information requirements and the priority of events.

Sensor management can be considered as part of the process refinement problem. According to the Joint Directors of Laboratories' (JDL) model (Figure 2), process refinement represents Level 4 of data fusion and is concerned with the optimization of the whole fusion process. As such, sensor management extends beyond the “data fusion” paradigm that concerns Level 0 to Level 3 of the JDL model. The fusion problem involves the effective exploitation of data from sensors, under the assumption that the sensors' configuration is defined beforehand. Nevertheless, data fusion systems cannot be of any help if the data at their inputs doesn't contain a minimum amount of exploitable information, and it is the aim of sensor management to improve the quality of this data.

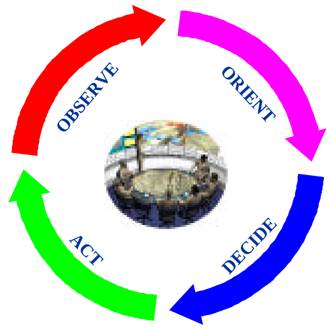



**Figure 1: OODA loop of $C^2$ process**

In Section 2, the different management tasks are presented. Requirements for their solution are detailed in Section 3, while an illustrative application is presented in Section 4 to show the benefit that can be gained by the use of adaptive management policies. Some concluding remarks are given in Section 5. The objective of the reported work is twofold i) to present the sensor management problem and the requirements for its solution ii) to demonstrate the benefits that can be brought by an adaptive management of the sensor suite.

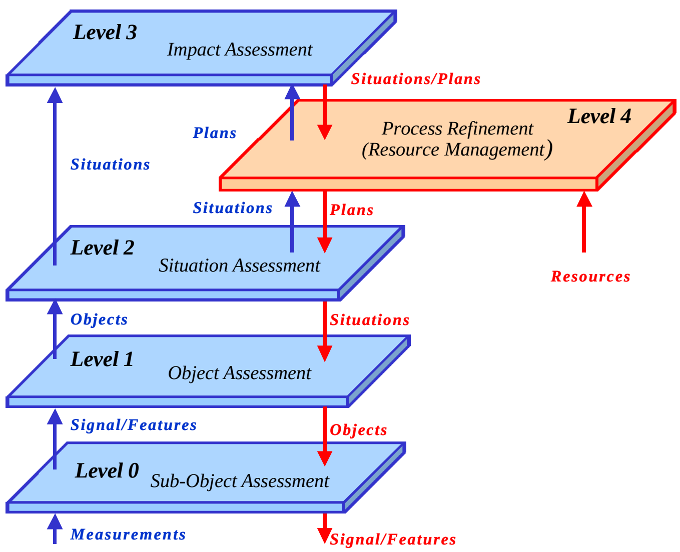



**Figure 2: JDL model of data fusion process**

## 2. **Management tasks**

Sensor management is concerned with the study and the implementation of ways to improve and optimize the on-going sensing process, and consequently the data fusion process. This management essentially concerns the control, the configuration and/or the allocation of the available sensors to allow for an optimal achievement of the sensing objectives, *viz.*, improving the perception while reducing the operator workload and the resources' use/consumption. Based on the newly available contextual information, the management system develops options for collecting further information, allocates and directs the sensors towards the achievement of the mission goals and/or tunes the parameters for the real-time improvement of the sensing/fusion process. Whenever there are insufficient resources to perform all the desired tasks, the sensor management must allocate the available sensors to those tasks that maximize the effectiveness of the sensing process.

Sensor management problems define a kind of a hierarchy. Such a representation allows for efficiently tackling all of the questions related to sensor management, by subdividing them into many smaller sub-problems that can be considered separately. The resulting decomposition of the management tasks is described below, and is summarized by Figure 3.

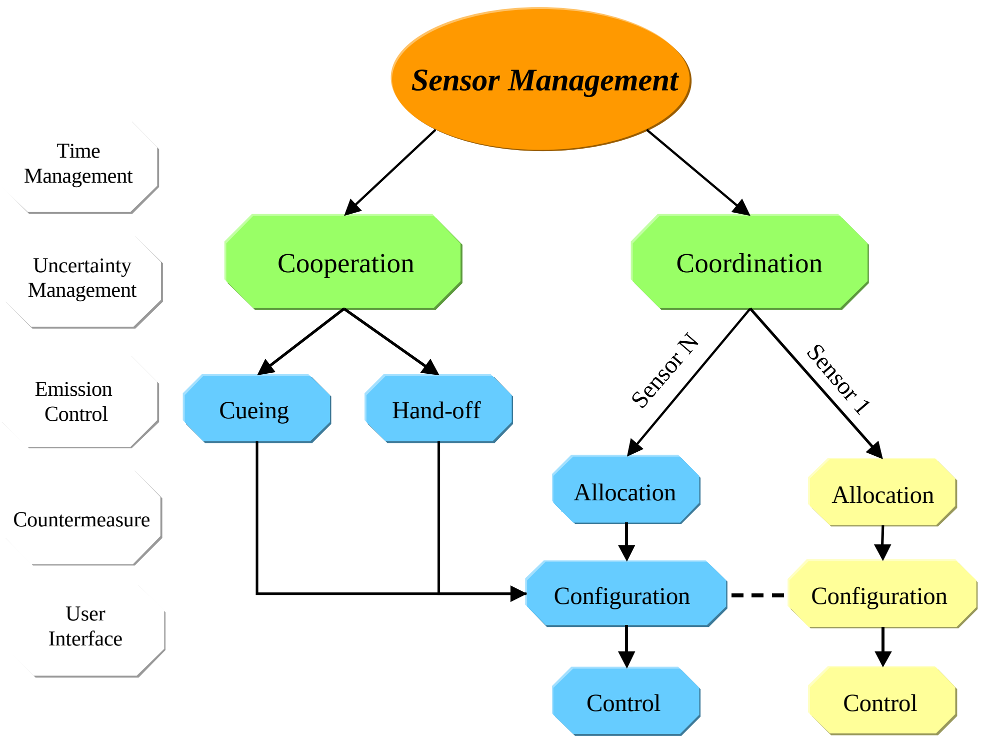



**Figure 3: Sensor management tasks**

## 2.1 *Single-sensor problem*

Single-sensor problem concerns the management of a single multi-mode/multi-function sensor. The following represents the different levels of management that can be performed on it.

### 2.1.1 *Control*

Control concerns the lowest level of management. The role of the controller is to ensure that the hardware-level (servo-control) goals are being achieved with the desired level of performance.

### 2.1.2 *Configuration*

Configuration implicitly assumes the existence of several sensing strategies and/or modes. The operating mode and/or configuration for the considered sensor might therefore be selected at run-time to achieve the best performance.

### 2.1.3 *Allocation*

Allocation essentially concerns a decision-making about what information needs to be gathered from the environment, and what actions need to be taken to best gather it. For the target tracking, this may for instance include pointing the sensor to update tracks and/or search for new ones that enter the volume of interest. Note that very important issues for the sensor allocation problem are the target priority assignment and the sensor capability/status establishment. The allocation optimization criterion must be a function of both of the performance of the sensor against the targets and the priorities of the targets.

## 2.2 *Multi-sensor problem*

Multi-sensor problems concern the management of a set of sensors that can be co-located on the same platform or distributed over a set of platforms. The single sensor situation being a special case of the multi-sensor situation, all of the above cited management tasks are also encountered in the multi-sensor case. Nevertheless, other management problems, that are specific to the multi-sensor case, arise. These problems mainly concern the inter-sensor cooperation and/or coordination tasks (see Figure 3).

### 2.2.1 *Coordination*

The available (limited) sensors must be partitioned among the tasks (targets) in accordance with the individual needs/priorities of these tasks. This is known as the pairing problem (the distribution of the sensors or the sensor combinations across the targets).

### 2.2.2 *Cooperation*

The management of the sensors may require that different sensors cooperate to acquire measurements on a common target. This, for instance, consists in dynamically tasking some sensors to fill the coverage gaps of other sensors, and therefore provide relevant observations in the areas of tactical interest. The two primary cooperative functions are the cueing and the hand-off. The cueing is the process of using the detections or tracks from a sensor ***A*** to point another sensor ***B*** toward the same target or event. The hand-off occurs when the sensor ***A*** has cued the sensor ***B*** for transferring the surveillance or the fire-control responsibility from ***A*** to ***B***. Hence, the response time/performance of sensor ***B*** may be improved by providing it with the detections, the measurements or the tracks from sensor ***A*** with different characteristics. This may also be used to ensure a continuity of the tracking, when a tracked target passes out of the (spatial and/or temporal) coverage of a sensor ***A*** to enter the one of a sensor ***B***.

## 2.3 *Implicit management tasks*

Besides the above-cited tasks, several other issues will need to be addressed by the sensor management system. These represent the tasks induced by the constraints imposed by the environment, the doctrines and/or the technology. Below are presented some of the most important to be considered.

### 2.3.1 *Time management*

Is of prime importance for any management system to ensure synchronization and real-time operations. Sensor management system is often called upon to respond to high data rates and time-critical requirements under severe limitations.

### 2.3.2 *Uncertainty management*

Behavior must degrade gracefully in the presence of increasing uncertainties. Since it often operates on the basis of incomplete, inaccurate, missing and/or misleading information, the sensor management should make the best use of the accurate pieces of information it possesses. An internal model of uncertainty (probability, possibility/fuzzy sets and/or belief) must therefore be used.

### 2.3.3 *Emission control*

Active sensing equipment such as radars may betray their existence, by emitting energy, and therefore increase the vulnerability of the whole combat system. The use of such sensors thus needs to be minimized to control their emission when/where there is a strong requirement on a “silent” work such as the Low Probability of Intercept feature (so called LPI radar). The optimization criterion may be the detectability and/or the identification of our own sensor suite. Controlling the emitted power, its duration and the spatial coverage of the active sensors can be used to reduce the emission.

### 2.3.4 *Countermeasure management*

This aims at reducing the effects of the enemy countermeasures on the performance of the sensor suite. This concerns the Electronic Protection (EP) that aims at taking actions to protect sensors from any effects of friendly or enemy employment of an electronic warfare that degrades, neutralizes, or destroys the friendly combat capability.

### 2.3.5 *Operator interface*

Since, in the $C^2$ context, the ultimate authority and responsibility belong to the human operators, the management system must allow taking into account their commands and preferences by providing an interaction interface with the operators.

## 3. **Management requirements**

Handling the sensor management problem presumes that the required performance of the closed-loop system can be specified quantitatively to allow the definition of the management objective. A performance index can then be calculated (or measured) and used to evaluate the system's performance (*i.e.*, the deviation from the desired behavior). On the basis of this deviation, actions are undertaken to make the system meet the specification. The cycle "performance evaluation-action selection and execution" continues on during the lifetime of the system. Hence, of a major importance to solve any management and control problem are the following tasks i) goal specification, ii) performance evaluation, iii) action selection.

### 3.1 ***Goal specification***

Generally, specifications can be divided into two categories: performance specifications and robustness specifications. Both need to be explicitly specified to achieve the management goals. Although the boundaries between the two cannot always be clearly specified, the performance specifications describe the desired response of the nominal system (*i.e.*, in absence of uncertainty). The robustness specifications limit the degradation of the performances in presence of uncertainty that may come under various forms. Another important requirement is to keep the management effort (time and resources consumption) minimal. The latter often acts rather as a constraint in the problem statement.

These specifications depend however on how the problem is modeled. In the literature, there are mainly three main approaches. The first formulation presents sensor management as a control problem; the second uses an optimization formulation, while the third is based on decision theory and related utility concepts.

#### 3.1.1 ***Control formulation***

In this case, one specifies the desired level of performance (or the reference trajectory) defining the management goal that the closed-loop system tries to achieve. The difference between this reference trajectory and the measured level of performance provides a good index of the system actual behavior with respect to the desired behavior. This index is used as an action selection (or control design) basis to reduce, and/or maintain as small as possible, any observable discrepancy.

#### 3.1.2 ***Optimization formulation***

If sensor management is modeled as an optimization problem, rather than specifying a desired performance level, the user defines a cost function that, once optimized, leads to the most desirable outcome. This optimization would lead to the best trade-off between the sensing action payoff and the associated costs.

#### 3.1.3 ***Decision formulation***

When a decision formulation is used, there is no specified level of performance. As in the case of the optimization formulation, the objective is to choose the action that maximizes some quantity, known as the expected utility function. Therefore, what is specified here is the utility of executing a given action in a given situation. The best solution is the one that offers the highest utility, *i.e.*, the best achievable performance.

### 3.2 *Performance evaluation*

As discussed in the previous section, central to the management problem is the performance evaluation issue. Using the available resources, candidate solutions are constructed. These alternatives usually provide a large number of possible combinations; a subset of candidates is intelligently selected to represent the primary categories of alternatives [Waltz and Llinas, 1990]. The criteria for evaluating these alternatives must be defined quantitatively in the form of measures of merit that can be determined for each candidate. These measures must allow the discrimination between alternatives [Waltz and Llinas, 1990].

Given the knowledge of the current state of the environment and the objective, choosing the optimal management policy therefore boils down to finding a metric that serves as an action selection basis, or utility function. Such a utility function is required to grade the benefits from the different possible actions so that the "best" solution can be chosen. For instance, in the data fusion context, the information update paradigm may lead to an intuitive method of addressing the metric selection problem. One of the most used metric is the Fischer Matrix [Nash, 1977] that concerns the track uncertainty in the Level-1 Data Fusion (L1DF).

### 3.3 *Action selection*

Given the goal specifications, the environment changes and the performance measures, the core of the sensor management and control problem amounts to selecting the appropriate course of actions. To meet the specifications, the management system should, in its action selection process, be able to reason and make commitments on the environment changes (*i.e.*, reactive planning) and commitments on revised goals (*i.e.*, deliberative planning). Dependent on the underlying problem and the model adopted, different techniques exist for action selection.

#### 3.3.1 *Control formulation*

Control theory is relevant to the design and the analysis of dynamic systems, especially those that have to operate in a closed-loop mode (*i.e.*, make use of feedback). The action selection problem defined above is the essence of the control design that consists in selecting the action $\boldsymbol{u}$ for a process $\boldsymbol{P}$ so that its output $\boldsymbol{y}$ follows the desired specifications $\boldsymbol{r}$, while not requiring too much control effort (time/resource consumption). A more realistic requirement is that the discrepancy between the process output and specification remains within some fixed bound. When control is used, there are two sources for its activation. These are the goal modifications and relevant environmental changes, each one corresponding to a different control strategy. Feedforward control[1] is concerned with the goal changes, while feedback control[2] handles changes in the environment. These feedback and feedforward control models offer a set of vocabularies to describe runtime behavior in any adaptive system. The design challenge for such systems is to

---

[1] That corresponds to the purely deliberative planning model.
[2] That corresponds to the purely reactive planning model.

develop ways to combine the feedforward and feedback components of the control, and integrate them in a tightly coupled fashion. Ideally, the adaptive system should consist of both components integrated. This combination of feedforward and feedback models allows for tackling the general problem class of variable specifications within a variable environment.

### 3.3.2 *Optimization formulation*

Optimization-based algorithms, either linear or non-linear, are among the techniques that have been applied the most to the sensor management problem. There are often a number of different alternatives (actions) to choose from when confronted with such an optimization problem. One-step-ahead (or myopic) approaches consider only the immediate effects of the selected actions. Sometimes actions with poor immediate effects can have better long-term ramifications. The action that makes the right tradeoffs between the immediate rewards and the future gains might represent the best possible solution. Solving such multi-stage optimization problems requires more elaborate techniques. Among them, the dynamic programming approach has witnessed much interest from the sensor management community. Dynamic programming refers to a collection of algorithms that can be used to compute optimal policies given a perfect model of the environment as a Markov decision process. The most widely used version of dynamic programming depends on a recursive algorithm that determines the minimum costs based on the final state and works backwards.

### 3.3.3 *Decision formulation*

The sensor management problem is often presented as a decision one. The correctness and optimality of the result, *viz.* action, hinges on the "rationality" of the decision-making process that prescribes the sensing actions. Although there are a wide variety of contexts in decision-making, all decision-making problems have the three following elements i) a set of decisions available to the decision maker, ii) a set of possible outcomes and the probabilities of these outcomes, iii) a value model (utility) that prescribes results for the various combinations of decisions and outcomes. Once these elements are known, the decision maker can find an "optimal" decision. Solving such a decision problem can be done efficiently using graphical methods such as decision trees or influence diagrams. Using the utility theory terminology, sensor management would be reformulated as the definition of a utility function $\boldsymbol{U}(\boldsymbol{a}_i, \boldsymbol{x}_j)$, to evaluate the gain in taking an action $\boldsymbol{a}_i$, given the environment state $\boldsymbol{x}_j$, and the cost $\boldsymbol{c}_i$ associated with the action. The optimal sensing action $\boldsymbol{a}^*$ is the one that maximizes the expected utility.

## 4. Application: adaptive sensor allocation problem

In the $C^2$ context, the main objective of an ideally effective tracking system is to establish a number of clean, stable tracks that correspond exactly to the number of objects in the physical environment. This requires acquiring and maintaining unambiguous, stable tracks corresponding to the perceived population of the real objects within the volume of interest, and estimating the state of each tracked object. The effectiveness of countering an attack depends heavily on the accuracy and timeliness of the track information. This explains the large amount of work that aims at improving tracking performance through sensor management and control.

4.1 ***Problem statement***

The case of one or more sensors tracking a set of distinct targets will be considered. Each one of these sensors is assumed to have different performance and utilization cost. An interesting management concept to be illustrated is the dynamic allocation of the sensor(s) against the target(s). The selected allocation policy will be the one that minimizes some objective function. The latter may, for instance, combine in some way the performance and the cost associated with the different sensor/target pairings. Three scenarios that depend on the number of the targets and the sensors considered will be presented i) one sensor against one target, ii) one sensor against two targets iii) three sensors against two targets. For this last scenario, both cases of not prioritized and externally prioritized targets will be considered. We use linear programming-based optimization approach to determine sensor/track assignment, where the trace of the error covariance matrix maintained by a Kalman filter [Kalman, 1960] serves as cost coefficients in the objective function.

4.2 ***Dynamical model***

The tracked targets are assumed to be moving in 2D space, where the input may change unforeseeably, and therefore is modeled as a random variable. The state to be estimated is composed of the target's coordinates that define the state vector $\boldsymbol{x}$. The dynamical equation of such targets can be expressed as

$$\boldsymbol{x}_{k+1} = \boldsymbol{F}\boldsymbol{x}_k + \boldsymbol{\Gamma}\boldsymbol{v}_k$$

where $\boldsymbol{v}$ is a random variable that reflects the unforeseeable variation of the dynamics and/or the modeling errors. Note that for simplicity, a linear model is assumed. The use of non-linear dynamical equations should not affect the management policy. The process noise covariance matrix is $\boldsymbol{Q}$. The observation equations are expressed as

$$\boldsymbol{z}_{i_k} = \boldsymbol{H}_i\boldsymbol{x}_k + \boldsymbol{w}_k$$

where $\boldsymbol{k}$ is the observation time, $\boldsymbol{i}$ is the number of the sensor and $\boldsymbol{H_i}$ is the observation matrix, that is given for each of the three considered sensors by

$$\boldsymbol{H}_1 = \begin{bmatrix} 1.5 & 0 \end{bmatrix}$$
$$\boldsymbol{H}_2 = \begin{bmatrix} 0 & 1.5 \end{bmatrix}$$
$$\boldsymbol{H}_3 = \begin{bmatrix} 1.2 & 0 \end{bmatrix}$$

The measurement noise $\boldsymbol{w}$ is assumed to be the same for the three sensors, with a covariance matrix $\boldsymbol{R}$. Also, associated with each sensor there is a utilization cost, given by $\boldsymbol{c_1} = \boldsymbol{c_2} = 21$ and $\boldsymbol{c_3} = 19.5$.

Since the primary goal of tracking is to reduce the uncertainty in the target's kinematic information, a metric is required to quantify the information gained by the sensing actions. A Kalman (or Kalman-like) filter is often used for the estimation of the target's state vector.

Therefore, a natural metric[3] for the tracking performance might be based on the error covariance matrix maintained by the Kalman filter. One recursive form of the Kalman filter is given by

$$\widehat{\boldsymbol{P}}_{k+1|k+1}^{-1} = \left[\boldsymbol{F}\widehat{\boldsymbol{P}}_{k|k}\boldsymbol{F}^T + \boldsymbol{Q}\right]^{-1} + \boldsymbol{H}_i^T\boldsymbol{R}^{-1}\boldsymbol{H}_i$$
$$\widehat{\boldsymbol{P}}_{k+1|k+1}^{-1}\widehat{\boldsymbol{x}}_{k+1|k+1} = \left[\boldsymbol{F}\widehat{\boldsymbol{P}}_{k|k}\boldsymbol{F}^T + \boldsymbol{Q}\right]^{-1}\boldsymbol{F}\widehat{\boldsymbol{x}}_{k|k} + \boldsymbol{H}_i^T\boldsymbol{R}^{-1}\boldsymbol{y}_{i_{k+1}}$$

Minimizing the trace of the covariance matrix is equivalent to reducing the sum of the variances of the different variables in the state vector. To take into consideration the utilization cost, the following objective function will be considered

$$\min_{\boldsymbol{a}}\left[trace(\widehat{\boldsymbol{P}}_{k+1|k+1}) + \lambda\boldsymbol{a}\boldsymbol{c}\right]$$

where $\lambda$ is a weighting factor, $\boldsymbol{a}$ is the action set, and $\boldsymbol{c}$ is the sensing cost. The above-given equations give the general form of the objective function and the dynamical equations that act as constraints in the optimization formulation. The exact expressions depend heavily on the scenario. In the following, the expressions for the considered scenarios will be given and the results discussed.

### 4.3 *One sensor against one target*

The first case to be considered is the one of one sensor tracking one target. The problem consists here in choosing, at each time period and after the time alignment, between the two following actions: no measurement ($\boldsymbol{a} = 0$) that results in no state update, or measurement ($\boldsymbol{a} = 1$), which allows for performing a state update. This decision will be made taking into consideration the cost $\boldsymbol{c}$ of the sensing action. This problem can be regarded as the one of an adaptive selection of the track's update rate. Note that, in the case of one against one, two static policies are possible

1. measurement all the time, which provides the best performance but results in a high cost.
2. no measurement all the time, which results in the lowest cost but an unboundedly growing estimation error.

The management objective here is to design an adaptive policy that makes the best trade-off between the two above-given extreme solutions. The goal is to reduce the sensing cost (by reducing the update frequency) while keeping the estimation error small. Such an optimization problem can be formulated as

$$\min_{\boldsymbol{a}}\left[trace(\widehat{\boldsymbol{P}}_{k+1|k+1}) + \lambda\boldsymbol{a}\boldsymbol{c}\right]$$

To simplify the notation, the subscribe ($k$+1|$k$+1) will be dropped from the expression of the covariance matrix, that is

$$\widehat{\boldsymbol{P}} \equiv \widehat{\boldsymbol{P}}_{k+1|k+1}$$

[3] Several alternative metrics were proposed in the literature.

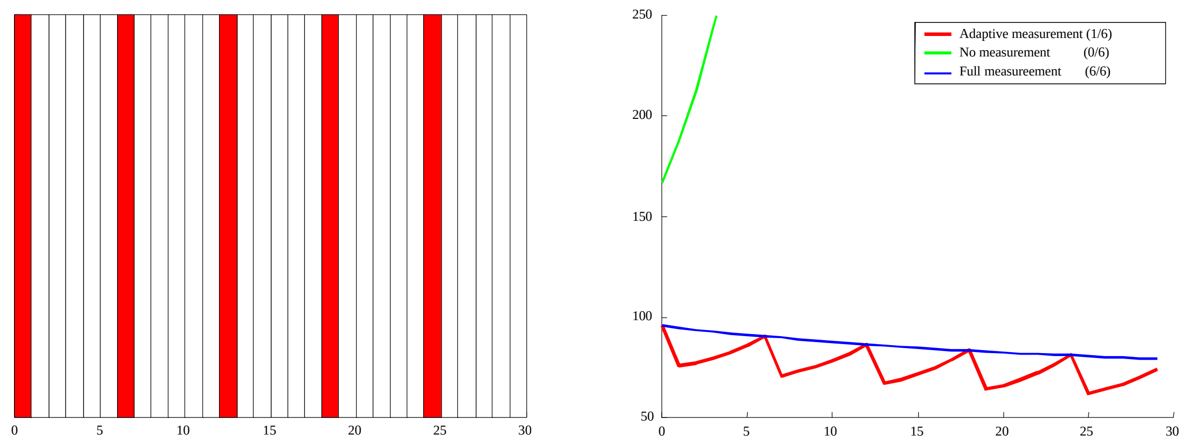
The above optimization problem is subject to the constraint

$$\hat{\boldsymbol{P}}^{-1} = \left[\boldsymbol{F}\hat{\boldsymbol{P}}_{k|k}\boldsymbol{F}^T + \boldsymbol{Q}\right]^{-1} + \boldsymbol{a}\boldsymbol{H}^T\boldsymbol{R}^{-1}\boldsymbol{H}$$

where $\boldsymbol{H}$ is the observation matrix of the considered sensor. The other constraints are

$$\boldsymbol{a} \in \{0, 1\}$$
$$0 \leq \lambda \leq 1$$

The optimization results are given in Figure 4. Figure 4 (a) shows the optimal update rate (*i.e.*, 1/6) that takes into consideration both the track quality and the measurement cost. Red bars indicate the periods where the measurement is performed. As it is shown in Figure 4 (b), the adaptive update strategy yields the best trade-off. The results compare the adaptive update strategy with the two static strategies (*i.e.*, 6/6 and 0/6 update rates). Note that the zero update strategy leads the estimation process to divergence. Since no information on the target is gathered from the environment, the error covariance matrix will continue to grow unboundedly.




**(a) Update rate** **(b) Trade-off cost/performance**

**Figure 4: 1 sensor against 1 target.**

### 4.4 ***One sensor against two targets***

In the case of one sensor tracking two targets, the problem consists in choosing, at each time period and after time-alignment for both targets, between the three following alternatives

1. No measurement for both targets ($\boldsymbol{a}_1 = \boldsymbol{a}_2 = 0$)
2. Measurement for target 1 only ($\boldsymbol{a}_1 = 1$).
3. Measurement for target 2 only ($\boldsymbol{a}_2 = 1$).

while taking into account the cost $\boldsymbol{c}$ of the sensing action. It assumed that the two targets have equal priorities. This problem is similar to the previous one, where an optimal update rate is to be calculated. The difference lies mainly in the fact that the system must simultaneously track two targets with only one sensor. In order to minimize the overall uncertainty in the information about the two targets, some compromise needs to be found. In this case, a decision basis metric may, for instance, be given by the sum of the traces of the two error covariance matrices. The optimization problem can be formulated as

$$\min_{\boldsymbol{a}_1,\boldsymbol{a}_2} \left[ trace(\hat{\boldsymbol{P}}_1) + trace(\hat{\boldsymbol{P}}_2) + \lambda(\boldsymbol{a}_1 + \boldsymbol{a}_2)\boldsymbol{c} \right]$$

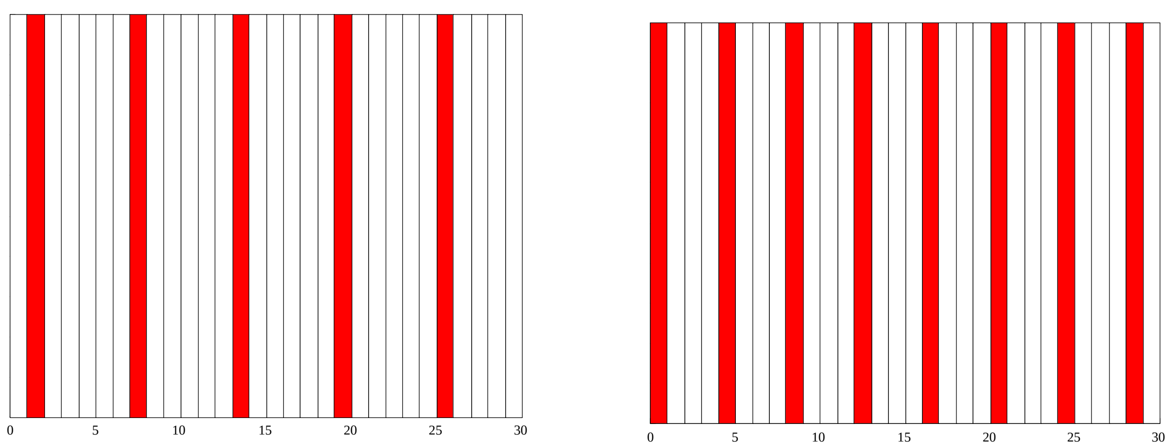
subject to

$$\hat{\boldsymbol{P}}_1^{-1} = \left[ \boldsymbol{F}\hat{\boldsymbol{P}}_{1_{k|k}}\boldsymbol{F}^T + \boldsymbol{Q} \right]^{-1} + \boldsymbol{a}_1\boldsymbol{H}^T\boldsymbol{R}^{-1}\boldsymbol{H}$$
$$\hat{\boldsymbol{P}}_2^{-1} = \left[ \boldsymbol{F}\hat{\boldsymbol{P}}_{2_{k|k}}\boldsymbol{F}^T + \boldsymbol{Q} \right]^{-1} + \boldsymbol{a}_2\boldsymbol{H}^T\boldsymbol{R}^{-1}\boldsymbol{H}$$

and

$$\boldsymbol{a}_1 + \boldsymbol{a}_2 \leq 1$$
$$\boldsymbol{a}_1 \in \{0, 1\}$$
$$\boldsymbol{a}_2 \in \{0, 1\}$$
$$0 \leq \lambda \leq 1$$

The results are given in Figures 5 and 6. For this scenario, all the static allocation policies lead to divergence. The sensor must be shared between the two targets to guarantee that the two error covariance matrices remain bounded. The optimal sharing policy is the one that minimizes the above-given objective function.




**(a) Target 1** **(b) Target 2**

**Figure 5: Update rate for the case of for the case of 1 sensor against 2 targets.**

## 4.5 ***Three sensors against two targets***

The last case to be considered is the one of three sensors against two targets. Constructing pseudo sensors, which are combinations of the basic sensors, treats situations where more than one sensor may be assigned to the same target. The number of sensors (either actual or pseudo) is thus equal to $2^{S}$-1, where $\boldsymbol{S}$ is the number of the individual (actual) sensors.

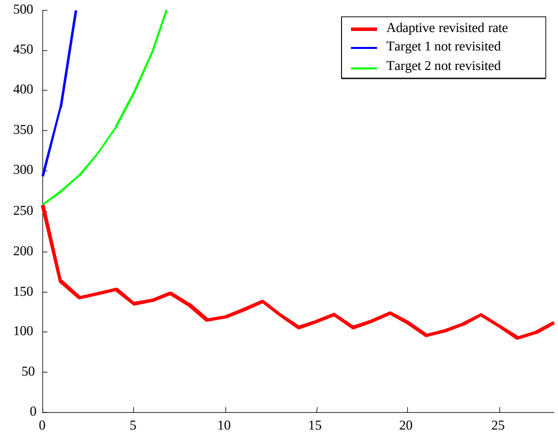



**Figure 6: Trade-off cost/performance for the case of 1 sensor against 2 targets.**

The optimization problem consists in assigning the $2^{S}$-1 combinations to the targets in the way that yields the best trade-off uncertainty/cost. The optimization problem is formulated as follows

$$\min_{(\boldsymbol{a}_{1_i},\boldsymbol{a}_{2_i})}\left[\beta_1 trace(\hat{\boldsymbol{P}}_1)+\beta_2 trace(\hat{\boldsymbol{P}}_2)+\lambda\sum_{i=1}^{M}(\boldsymbol{a}_{1_i}+\boldsymbol{a}_{2_i})\boldsymbol{c}_i\right]$$

where $b_1$ and $b_2$ represent relative priority factors for targets 1 and 2, respectively. Two situations will be investigated in the following

1. no priority (*i.e.*, $b_1 = b_2 = 1$) : the two targets are assumed to be of the same importance.
2. prioritized targets (*e.g.*, $b_1$ =.5; $b_2$ = 1) : target 2 is assumed more important than target 1.

The optimization problem is subject to the constraint

$$\hat{\boldsymbol{P}}_1^{-1}=\left[\boldsymbol{F}\hat{\boldsymbol{P}}_{1_{k|k}}\boldsymbol{F}^T+\boldsymbol{Q}\right]^{-1}+\sum_{i=1}^{M}\boldsymbol{a}_{1_i}I_i$$
$$\hat{\boldsymbol{P}}_2^{-1}=\left[\boldsymbol{F}\hat{\boldsymbol{P}}_{2_{k|k}}\boldsymbol{F}^T+\boldsymbol{Q}\right]^{-1}+\sum_{i=1}^{M}\boldsymbol{a}_{2_i}I_i$$

where the information brought by the sensing action $\boldsymbol{i}$ (*i.e.*, when $\boldsymbol{a_i} = 1$) is given by

$$I_i=\begin{cases}\boldsymbol{H}_i^T\boldsymbol{R}^{-1}\boldsymbol{H}_i, & for \quad i=1,3\\ \sum_{j\in C(a_i)}\boldsymbol{H}_j^T\boldsymbol{R}^{-1}\boldsymbol{H}_j, & for \quad i>4\end{cases}$$

where $C(\boldsymbol{i})$ is the set of all sensors that form the combination $\boldsymbol{i}$ (*e.g.*, $C(6)$ ={2,3}). The cost of the sensing action $\boldsymbol{i}$ is simply the cumulative sum of the costs of the selected sensors (within a given combination)

$$c_i = \begin{cases} c_i, & for \quad i = 1,3 \\ \sum_{j \in C(a_i)} c_j, & for \quad i > 4 \end{cases}$$

The set of constraints is given by

$$\sum_{i=1}^{M} a_{1_i} \le 1$$
$$\sum_{i=1}^{M} a_{2_i} \le 1$$
$$a_{i_j} \in \{0,1\}$$
$$0 \le \lambda \le 1$$

To ensure that the same sensor will not be allocated to both targets at the same time, the following constraint is added.

$$C(a_1^*) \cap C(a_2^*) = \emptyset$$

where ($\boldsymbol{a_1}$*, $\boldsymbol{a_2}$*) is the solution to the above-given optimization problem. The optimal update policies for the two above-described situations are given in Figures 7 to 9. It is noticed that when the targets are of the same importance, the attention of the sensors is relatively equally shared between the targets. The noticed difference results from the targets dynamics, mainly the velocity. The higher is the target's velocity the higher will be the revisit rate. In the case of prioritized targets, target 2 (see Figure 8 (b)) is, as expected, revisited more often than target 1 (see Figure 8 (a)).

## 5. Conclusion

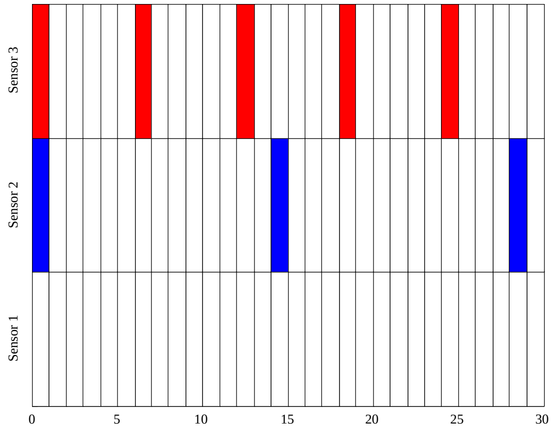
Sensor management has to do with how to best coordinate and organize the use of sensing resources in a manner that synergistically improves the process of data fusion. Based on contextual information, the sensor manager develops options for collecting further information, allocates and directs the sensors towards the achievement of mission goals and/or tunes the parameters for the real-time improvement of the effectiveness of the sensing process. As can be noticed from the discussion and results of the previous sections, the costly sensing resources can be adaptively managed. Compared with static policies, adaptive management may help reducing the utilization of scarce resources, while keeping the system performance within acceptable bounds.

## 6. References

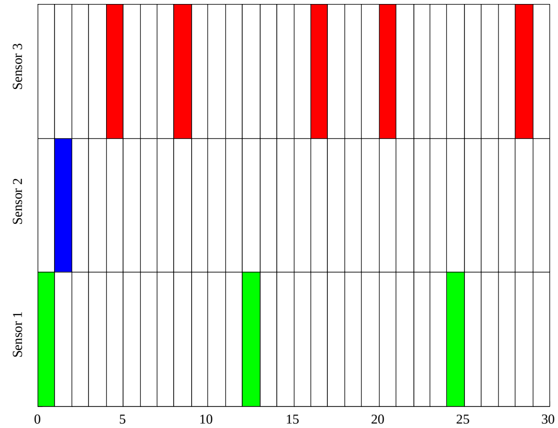
[Kalman, 1960] R.E. Kalman. *A new approach to linear filtering and prediction problems*. Transactions of the ASME, Journal of Basic Engineering, 82:34--45, 1960.

[Nash, 1977] J.M. Nash. *Optimal allocation of tracking resources*. In Proceedings of the 1977 IEEE Conference on Decision and Control, New Orleans, LA, 1:1177--1180, 1977.

[Waltz and Llinas, 1990] E. Waltz and J. Llinas. *Multi-sensor Data Fusion*. Artech House, Boston, 1990.

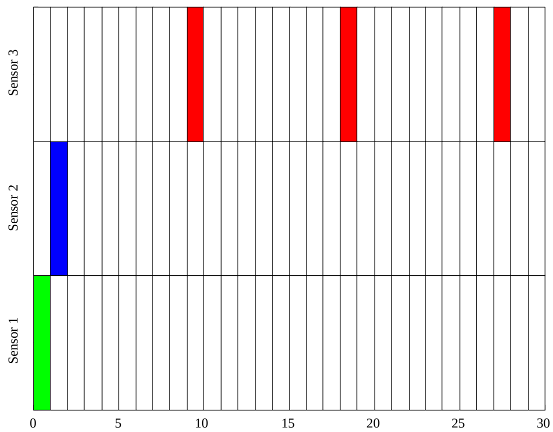



**(a) Target 1**

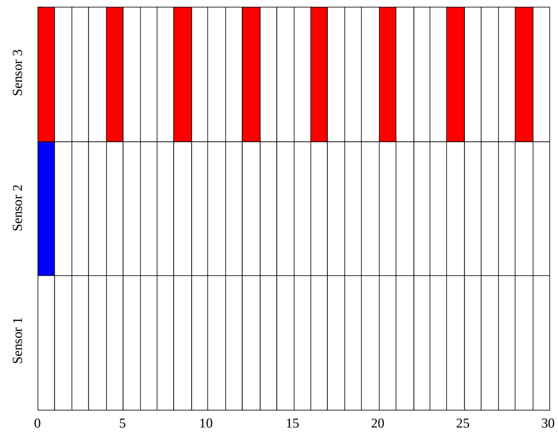



**(b) Target 2**

**Figure 7: Update rate for the case of 3 sensors against 2 targets (no priorities).**

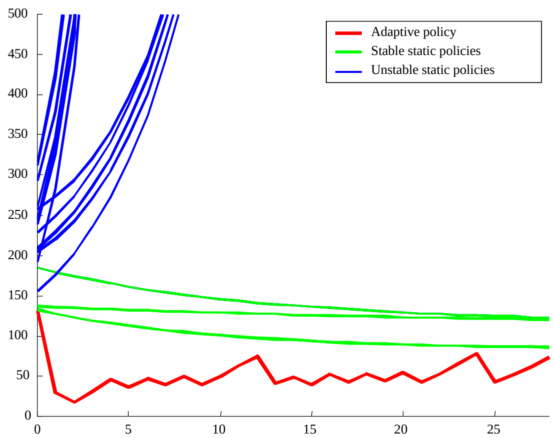



**(a) Target 1**

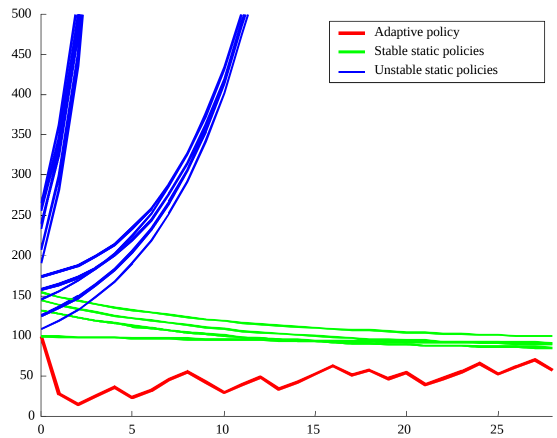



**(b) Target 2**

**Figure 8: Update rate for the case of 3 sensors against 2 externally prioritized targets.**




**(a) No priorities**




**(b) Prioritized targets**

**Figure 9: Trade-off for the case of 3 sensors against 2 targets.**