

Sensor Management Fusion Using Operating Conditions

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Abstract –System control includes sensor management, user refinement, and mission accomplishment (SUM). An example of simultaneous tracking and identification includes (1) mission goals of resource appropriation and goal priorities, (2) user selection of targets and areas of coverage, and (3) fusion of data and sensory information. Many sensor management (SM) approaches are data-driven which includes filtering, aggregation, and normalization; however that does not include intelligent design. A top-down approach would facilitate the use of the right sensor, collecting the needed information, at the correct time. In order to better design SM algorithms, we utilize sensor, target, environmental, and automatic target recognition performance models for automatic target exploitation (ATE) prediction. Similar to pruning nodes in a Bayes net aggregation, a sensor manager can utilize the operating conditions (OCs) {i.e. sensor, target, environment} to condition the cost function, sensor-to-target assignment constraints, and scheduling times. An example is presented of determining task value of electro-optical sensor selection and scheduling based on the range to target, target size, and environmental conditions (e.g. occlusions). The key aspect of the SMOC provides accurate assignment and scheduling based on up-to-date database information, a capabilities matrix, and pragmatic sensor use to improve task satisfaction.

Keywords: Tracking, Sensor Management, Performance Models, Performance Evaluation, Metrics, Scenarios

1 Introduction

Recent events have changed domain applications for multisensor information fusion and target tracking from locating a small number of large targets to maintaining tracks on a large number of targets of varying sizes. Increasingly complex, dynamically changing scenarios have evolved that require intelligent sensor management (SM) strategies [1, 2]. These intelligent strategies have to be evaluated over various locations, observing changing targets, and detecting unknown threats. Such a scenario of interest for “*Layered Sensing*” is an urban setting for Homeland Defense. Layered sensing incorporates many research issues in intelligent tracking, sensor development, and information fusion. Figure 1 shows a layered sensing scenario that incorporates high-altitude platforms for target detection, surveillance unmanned aerial vehicles (UAVs) for target tracking, and individual audio reports

from ground stations for target identification. To assist in the coordination of these layered assets, it is imperative to (1) understand the performance driving each system [2], (2) determine the metrics [3] for effective collaboration, and (3) proactively utilize the sensors to achieve real-world mission satisfaction. [4]

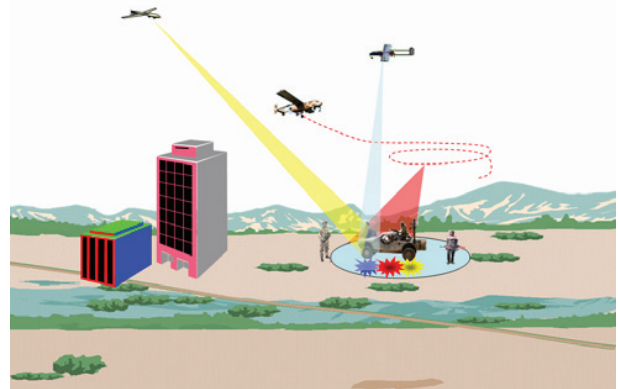


Figure 1. Layered Sensing

Real world applications of target tracking SM [5] are embedded in larger operational goals such as surveillance, targeting, and force assessment that includes both *entity estimation* and *situation control*. The Information Fusion Community has adopted the Data Fusion Information Group (DFIG) model [6], shown in Figure 2, with emphasis placed on sensors and their estimations from the real world. SM is but a piece of a larger information fusion system including user requirements, registration algorithms, net-centric distribution communications [7, 8], and situational awareness (SA). [9] Level 1 fusion, which includes target tracking and identification [10], is merely a technique to provide SA. SA in and of itself is a picture of the environment that requires situation assessment (i.e. number, movement, ID, and behavior [11] of targets). This information aggregation supports a user’s real world decision-making goals of security, strike packages, and positioning forces. However, the performance assessment of the situation can also be viewed as a *control problem*. The control problem requires tools and techniques for decision support such as metrics and analysis to place sensors, waveform diversity to choose operating modes, and situation characterization to relay information to other distributed users. The real world is complex; however, effective methods of performance analysis will aid users to appreciate and trust

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graph LR
    RW((Real World)) --> S0[Sensors And Sources L0]
    S0 --> E1[Explicit Fusion L1 Machine]
    S0 --> T2[Tacit Fusion L2/3 Human Sense-making/Analysis]
    E1 --> T2
    T2 --> HD5[Human Decision Making L5]
    HD5 --> L6[L6 Mission Management]
    L6 --> RM4[Resource Management L4]
    RM4 --> P[Platform]
    RM4 --> GS[Ground Station]
    P --> S0
    GS --> S0

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This paper describes a SM strategy based on operating conditions. Section 2 outlines sensor management strategies. Section 3 illustrates a scenario and Section 4 presents results and performance modeling. Section 5 draws conclusions.

When there are multiple layered radar/EO sensors, an efficient SM strategy plays an important role in achieving high overall performance as shown in **Figure 3**. *Sensor management* can be treated as a general strategy that controls sensing actions, including generating, prioritizing, and scheduling sensor selections and actions. Sensor management has mainly two themes: *sensor assignment* and *sensor scheduling*.

Sensor scheduling - determines when and which sensor will take what action (e.g., pointing to target or area).

[illegible]

2.1 Performance Models

2.2 Sensor Assignment

The general assignment problem consists of decision variables x_{ij} , usually in a matrix and some weighted cost function. Standard formulation is:

$$\text{Decision variable: } x_{ij} = \begin{cases} 1 & \text{if } i \text{ is assigned to } j \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Let A be the set of allowed assignments and c_{ij} be the *cost* of assigning i to j .

$$\begin{aligned} &\text{minimize} && \sum_{(i,j) \in A} c_{ij} \cdot x_{ij} \\ &\text{s.t.} && \sum_{j: (i,j) \in A} x_{ij} \leq 1, \quad \text{for all } i \\ &&& \sum_{i: (i,j) \in A} x_{ij} \leq 1, \quad \text{for all } j \\ &&& x_{ij} = 0,1 \quad \text{for all } (i,j) \in A \end{aligned} \quad (2)$$

From this definition, the constraints require that each sensor i be assigned to one target j . If the matrix A is ones and zeros, all assignments are of equal value. However, by varying the weighted parameters, c , in the matrix, we can represent different qualities (e.g. range to target, target size). The weighted matrix, represented as a *Network Graph* (weighted or directed weighted) is shown in **Figure 4**. The entries in the matrix represent the distance, where ∞ represents an impossible path. The *weighted graph* (WG) is solved by standard techniques, such as the Hungarian algorithm, while the directed weighted graph is solved by the *Dijkstra's algorithm* or the Traveling Salesman Algorithm. Note: the WG assumes all sensors can see all objects and the DWG assumes you can not always see the objects (e.g. occlusions). Thus, a combination of algorithms would be needed for robust myopic SM as well as non-myopic approaches with occlusions (e.g. urban setting).

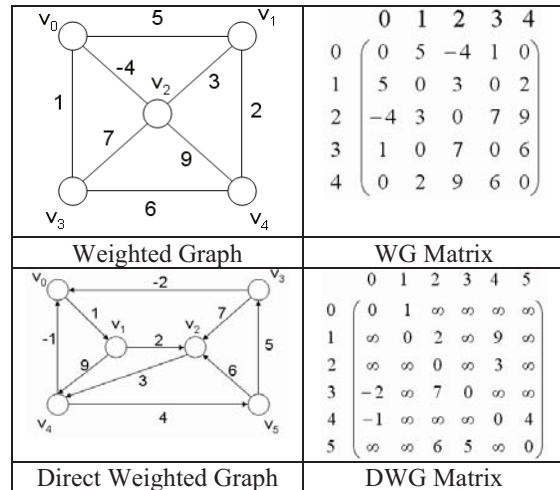


Figure 4: Graph Theory for Assignments.

Given the constraint of varying mission needs, various objects that pose a threat, and other scenario specific variations; to complete the object tracking task, we need to explore sensor tasking, which essentially is a *sensor*

scheduling problem, which includes choosing the available sensor with the highest probability of achieving the task (e.g. target ID).

2.3 Sensor Scheduling

The *scheduling problem* was formalized in logistics and utilizes *queuing theory*. Jobs enter the queue and are serviced by various *priority schedules* based on the length of time it takes to process the information. A classic example is a work-breakdown structure (WBS) for a project (as formalized by a Gantt Chart for logistics support, manufacturing, or business cycles) shown in **Figure 5**.

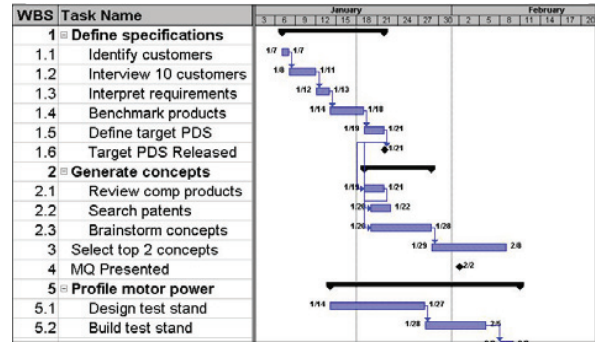


Figure 5: Gantt Chart.

To compose the Gantt chart (or queuing scheduling), three things are needed: the *jobs* (e.g. sensors available), the length of *time* it takes to service the job (e.g. sensor exploitation and movement), and the *rules* (e.g. priority and order). Another constraint can be included in the capabilities matrix, A , which is a realization of the performance model results of a target-to-sensor assessment (e.g. synthetic aperture radar can produce target detections through clouds while an EO sensor can not). An example of sensor scheduling includes robotics and sensor networks (communications theory) utilizing wireless technologies in the commercial world. As an example relevant to target tracking, **Figure 6** shows two graphical examples from the robotics literature on sensor scheduling:

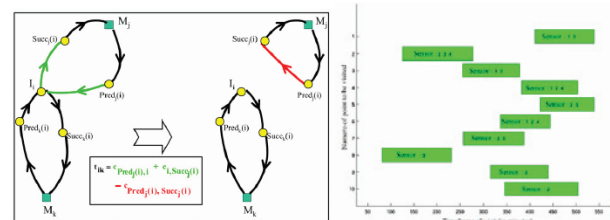


Figure 6: Sensor Scheduling.

(F. Janez, "Optimization method for sensor planning," *Aerospace Sci. & tech.*, 2007)[20]

Given this simple introduction to the mathematical formulation of both sensor assignment and sensor scheduling, **sensor tasking** then a combination of *tracking* (stochastic estimation given orbital models), *control* (assignment with various robust parameters), *association* (matching measurements to targets), *identification fusion* (e.g. combination of EO and RF data), *assignment* (matching sensors to objects), and *scheduling* (timing of observations). The ability to *search*, *detect*, *track*, and *characterize* targets for the sensor tasking problem based on the scheduling and weighted assignment. Some popular techniques include:

1. **Assignment**: Hungarian, S-D Assignment (via Integer linear programming constrained optimization via Lagrangian relaxation where S is spatial dimension) [21]
2. **Dynamic Programming** (e.g. target tracking) – Stochastic DP, multi-frame assignment (branch and bound); (Jonker-Volgenant-Castanon - JVC) Auction Algorithm followed by Munkres Algorithm [22] {Auction algorithm resembles simulated annealing - trying random variations of the current solution}
3. **Shortest Path** : Dijkstras, Bellman-Ford, TSP, A* [18], AO* [23]
4. **Longest Path**: Knapsack (volume filing) [24]
5. **Priority Scheduling rules**: First-come-first serve (FCFS), Last-In-First-Out (LIFO), Earliest Due Date [18]
6. **Minimum Slack Time**: measures the "urgency" of a job by its slack time [18]
7. **Tardiness**: minimizes the number of tardy jobs - Hodgson's Algorithm [18]
8. **Concatenated sequencing**: Johnson's Algorithm (sensor 1 comes before sensor 2) [18]
9. **Sensor Quality/Resolution** : Longest First (i.e. SAR), Shortest First (i.e. EO)

The key to implementing these algorithms (given that they are all related to optimization, control, and stochastic estimation) is providing some realism to the *cost function*, the *constraints*, and the *time horizon* of the batch processing. Numerous disciplines utilize these techniques, with the set-up tailored to the application (logistics, communication, target tracking, etc) and the scenario (specific sensors and targets of interest). Thus, the SM algorithms should take advantage of performance models over operating conditions (sensor, target, environment) to derive a top-down SM system.

2.4 Example of SM with Varying OCs (SMOC)

A simple example highlights the point. Sensor observations determine the validity of the application of these methods. With a high signal-to-noise ratio (SNR), they are work well. When there is **clutter**, it produces errors in the assignment and association routines such as urban trackin. Thus, the Sensor Tasking solution

implemented can be exercised in a simulation environment from which a *performance analysis* results of the methods sensitivities over **operating conditions** (sensors, targets, and environments) to determine the **robustness** of the solutions to varying SNR conditions and ID challenges (or cue) the Intel operator. Leveraging the operator in the tasking methods can vary the mission-goal priorities and needs (which essentially alters the optimization problem in real-time).

CASE 1: Environment : When targets are occluded, there is no point scheduling the sensor to look. However, tracking prediction performance modules would be able to predict when the target would emerge for observation.

CASE 2: Target : Given the target type (size, features), it would be known which sensor (EO versus SAR) would be best utilized to identify the target of interest

CASE 3: Sensor: Various sensors provide varying resolutions to the target observation.

Together, through either *cost function* (quality of sensor reports), *constraints* (sensor not available), or updates to the *assignment matrix* (sensor 1 can not look in two places), based on the *situation analysis* (where the targets are and the prediction of where they will be); a *sensor tasking analysis* can be completed to schedule the next looks based on either a myopic or non-myopic time horizon, to optimize multiple-target tracking and ID, or to cue an operator to impending threats in a densely cluttered environment.

2.5 Mathematical Task Valuation

Assuming that the SM seeks to optimize a task {T} from observing the real world state {RW}, we can determine the value of a hypothesis observation state {H} by these steps.

- Estimate {RW} with {H}, and assign a weight to each hypothesized task: $\mu\{H\}$
- Approximate result is that
$$|\{RW\} - \{H\}| \approx \mu\{H\} \quad (3)$$
- Each possible {RW} under {H} must be considered and weighted by the mission goal
- Estimate $mg(\{RW\})$ with $mg'(\{H\}, \mu\{H\})$
- Develop the cost function:
$$F(g(\{RW\}), h(\{RW\}, \{H\}))$$
- Determine the variational contribution of each event based on the real world OC :
$$\{RW'\} = \{ \{ \partial H \}, p(\{ \partial H \}) \}$$
- Task value =
$$\partial f(mg(\{RW\}), h(\{PW\}, \{H\})) / \partial T \quad (4)$$

$$\text{Task effectiveness} = \partial \{H\} / \partial T \quad (5)$$

The **minimization-of-uncertainty** approach is predicated on the accuracy modeling and the appropriate use of that

uncertainty. The fundamental assumption is that uncertainty reflects the “distance” between the true observation ($\{RW\}$) and the perceived observation ($\{H\}$). Note that the “uncertainty” need only be monotonic or proportional to some true measure of probability. As long as our concept of uncertainty tracks the $\{RW\} - \{H\}$ distance, the minimization will be coincident. (NOTE: the monotonic function $u\{H\} = f(|\{RW\} - \{H\}|)$ has different proportionality constants in different directions so that a mission-based task weighting will be skewed based on the uncertainty relationships - such as a covariance matrix for target location and length-to-width target recognition).

Optimal control

Choose tasks $\{T_t\}$ at time t with observations $\{O\}$ such that

$$\int f(g(\{RW\}, \{O\}), h(\{RW\}, \{H\})) dt \quad (6)$$

is minimized.

To represent the effectiveness of tasks, the goal is to minimize $\int f dt$ by choice of $\{T_t\}$. To accomplish the minimization, compute Δf given T_t for a scheduling time interval Δt :

$$\Delta f = f(g[\{RW\}, \{O\}_{t+\Delta t}], h(\{RW\}, \{H\}_{t+\Delta t})) - f(g[\{RW\}, \{O\}_t, h(\{RW\}, \{H\}_t)]) \quad (8)$$

2.6 SM over the Environment

Sensor management has to schedule the next look in a system; where the observation has to be registered. Registration could be a 2D FFT phase correlation approach or a feature-matching approach to previous data or a ground reference system. The FFT phase correlation would include Fourier windowing and other techniques such as spatial Fourier analysis to optimize the registration. Typical features include points, ridges, edges, corners, junction, peak amplitudes, and shapes. Thus, if the sensor manager knows something about the environmental terrain, it would be able to schedule which sensor and when a new look is needed that would have a good chance of being registered. One example is occlusions. When the environment presents many occlusions, it might be easy to register the data, but the target might be obscured. The SMOC approach could include

- Non-myopic reasoning (with adjustable horizons)
- Linkage between hypotheses (multiple looks or different sensor looks)
- Concept of object type (from performance model of identification to target size)
- Concept of resource (from database information to affect the sensor selection)

2.7 System Performance Metrics

The goal of any multisensor system analysis is to have a track gain over improved lifetime, timeliness, accuracy, and throughput. The information fusion gain can be assessed as Measures of Effectiveness (MOE) or Measures of Performance (MOP). MOPs include the standard MTT parameters of number of targets tracked, throughput, time, and P_D . MOEs include force protection, situation analysis, and event occurrence. Using the MOEs and the MOPs, a SM can determine both the assignment and the scheduling information. Key metrics include:

Pattern recognition algorithms applied to ATR problems are typically trained on a group of desired objects in a library to gain a statistical representation of each object's features. The algorithm aligns input signatures to the library templates and determines the best correlation value for the aligned features for high **Confidence** ID. A threshold is often applied to the best score to reject questionable objects before identification or class label decisions are made. Although this process seems straightforward, misidentification or rejection of an input object as a viable target occurs because of conditions that unexpectedly alter the features used in the identification process. The output of the automatic target exploitation (ATE) is to determine the correct sensor-to-target given the environmental conditions to optimize the target ID.

Multi-target tracking performance metrics includes number of targets tracked; however, the system performance metric is throughput. **Throughput** can be determined as the average rate, peak rate, and variability of the system to deliver information to the user. The **average rate** (events processed / time) is the average load that can be sustained by the sensor over an extended period of time. The **peak rate** tells the network what type of surge traffic must be coped with, either by dedicating data-rate capacity or by allocating sufficient buffer space to smooth out measurement surges. **Variability** measures the source burstiness and is an indication of the extent to which statistical multiplexing is needed for distributed tracking.

Timeliness is a QoS metric for system performance; however, system **Delay** (or *latency*) is a system-level metric which can be measured with time to assessment or delay variation. *Transfer delay* measures the delay imposed by the network on data transferring from a source to a destination. *Delay variation* is an important parameter for real-time applications, in which the data displayed at the destination must appear at a smooth continuous rate matching the rate generated at the source.

2.8 Robustness

Using track accuracy and track lifetime can afford **Robustness** including specifications of SM designs (e.g. robust design), trusted reliability (e.g. robust decision making and estimation and insensitivity to parameter variation (e.g. robust control). The SM explores the sensitivity of performance over a variety of conditions to

ensure that system design relates to robust performance [25]. Essentially, a robust assessment, extending from confidence and reliability, would lead to performance bounds that give an envelope of performance to support a managed expectation to users of MTT performance.

Tracking algorithms for the real world require a pragmatic understanding of the complexities surrounding the application such as the number and types of targets, the sensors including their physical parameters and communication links, and the varying environmental conditions.[26] Utilizing static and dynamic environmental conditions can lead to host of challenges for MTT algorithms. Typically, with weak applicability to the real world, MTT algorithms focus on performance assessment over different target densities, ordered set of detection policies (e.g. Probability of Detection > 0.8), and various forms of clutter (e.g. Gaussian and Poisson).

3 Scenario

A UAV is monitoring a semi-truck moving down a highway during the afternoon. The vehicle then turns off the highway onto a side street partially obscured by vegetation, buildings, and terrain. The UAV's current trajectory will result in the vehicle being partially or full obscured by vegetation, buildings, or terrain as it travels down the road. By monitoring the operating conditions, the UAV can adjust the flight path and/or sensor gimbal to mitigate the adverse sensing conditions. The actions taken by the sensor manager, such as directing the platform to modify the flight path to follow the road or adjusting the flight path and sensor pointing direction to better view the truck and roadway, will help the sensor maintain track on the target vehicle and improve identification performance. Another SM action could potential be to switch sensor modes from EO to another sensor if available.

4 Results

SM is driven by operating conditions. EO Imagery is chipped out from the publicly releasable CLIF April 2006 Sample Set available from the SDMS website at <https://www.sdms.afrl.af.mil> and for questions contact sdms_help@mbvlab.wpafb.af.mil.

4.1 Target Identification

Using the EO Imagery, a mission goal is probability of task success which includes *sensor-to-target assignment* and *scheduling*. The assignment problem is decomposed into a series of selections which completed for analysis and shown in Figures 7 - 12. Various operating conditions were varied to determine the effects of occlusion. Database information of roads and trees, along with the target location prediction and the sensor location (to determine the range and line-of-site to the target) can be used to determine when a target would be observable for sensor scheduling..

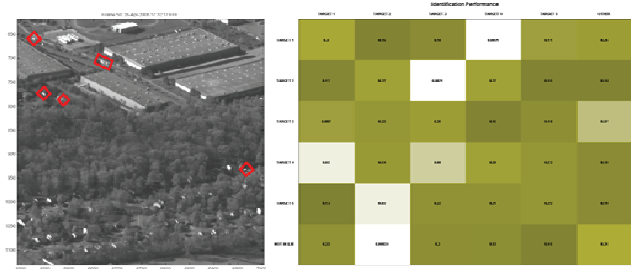


Figure 7. Better than 99% obscured targets, unknowns being selected as targets.

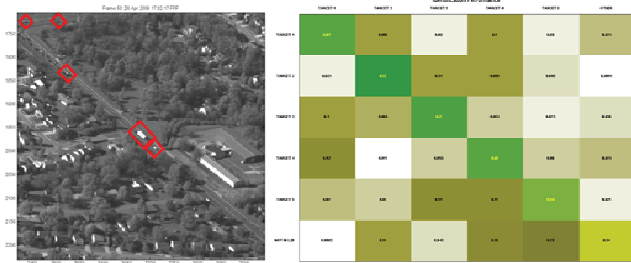


Figure 8. Targets in the clear at long range.



Figure 9. Example of better than 99% obscured targets, one target misidentified.

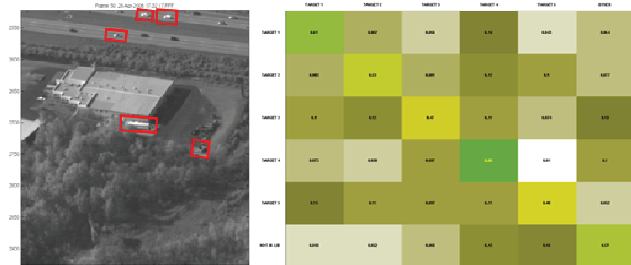


Figure 10. Example of 25% obscured target, misidentified Target and partially clipped target.

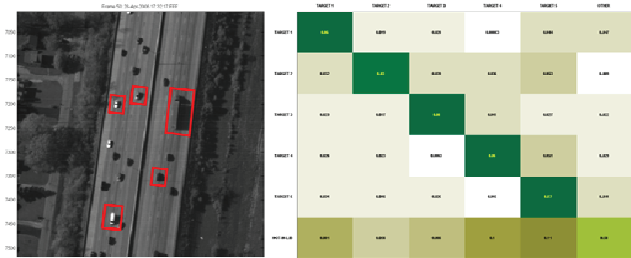


Figure 11. Example of targets in the open on the highway, no obscuration

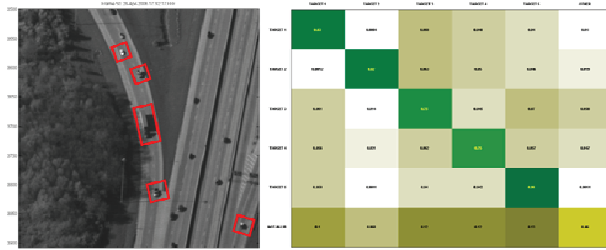


Figure 12. Example of turning targets in the open on the highway, no obscuration.

4.2 Probability of Task Success

To determine the task success we utilize the *task value* and the *task effectiveness* to determine the capability of the SM to utilize the target, environment, and sensor performance models. The range curves (presented in the [Figures 13-15](#)) were generated for a nominal target size of a mid to large sized vehicle such as a pick-up truck, van or SUV; utilizing the CLIF data. For the task valuation over the sensor model, the parameters of the EO camera are presented in Table 1. The environmental model included the urban terrain information and the road networks.

Table 1: for EO sensor parameters

Depression angle	90 degree
Horizontal FOV	2.2 degrees
Vertical FOV	1.65 degrees,
f#	1.9
Optical CCD sensor	320 by 240 pixels.

Figure 13 shows the SM task valuation of detection (blue), recognition (green), and identification (red). Since $P(ID) = P(ID|Rec, Det) P(Rec|Det) P(Det)$ we see that the SM ID task valuation is lower than the task valuation for assigning and scheduling a sensor for detecting and locating a target for a given range.

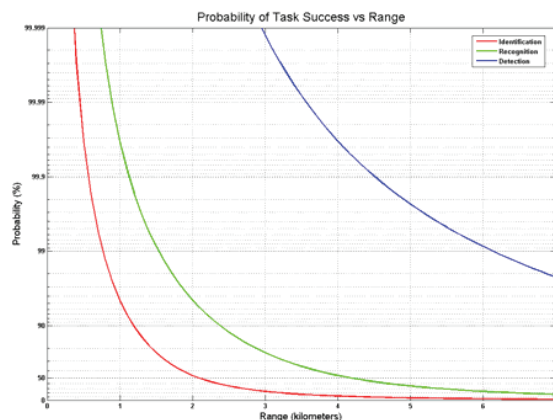


Figure 13. Expected EO ATR algorithm range performance

Figure 14 and 15 show the case where a target occlusion requires pragmatic scheduling and assignment of sensors.

Since the target is moving on a road, the scheduling problem was simplified to known locations of where the target would be observable. The difference of task completion degrades for the case when the target is partially obscured versus completely obscured.

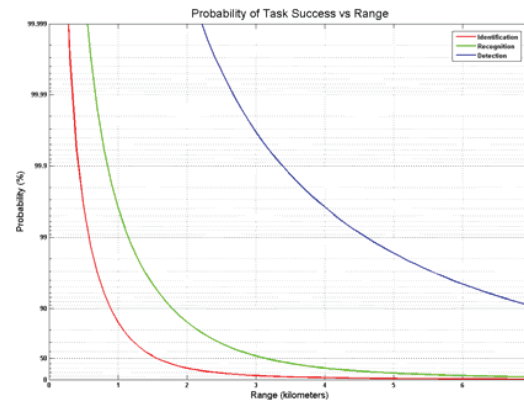


Figure 14. Expected EO ATR algorithm range performance with no obscuration present with 25 % target obscuration

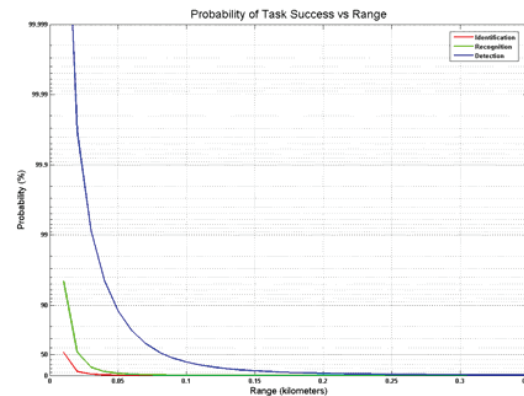


Figure 15. Expected EO ATR algorithm range performance with better than 99.5% target obscuration (7 km, but zoomed to see the changes for 0 to 0.35 km)

5 Discussion & Conclusions

The Sensor management by Operating Conditions (SMOC) strategy utilized performance models of the target, sensor, and environment to assign and schedule sensors to targets for a given environmental condition. The SMOC approach enhances SM robustness by ensuring task success associated with mission goals. Future SM designs are based on the information in the cost function, constraints, and sensor tasking; which requires accurate OC models with associated uncertainty analysis. As an exemplary case, we showed and electro-optical target tracking example with environment occlusions,. Future work will assess the sensitivity of the task valuation relative to the quality of the performance models, varying fusion strategies of simultaneous tracking

and identification, and adaptive goal alterations through mission and user changes relative to a capabilities matrix.

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