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Dynamic Sensor Tasking for Space Situational Awareness

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Abstract— **This paper examines the problem of tracking multiple spacecraft using a combination of ground- and space-based sensors. The problem is formulated in a simplified two-dimensional setting to reduce computational complexity while retaining elements of the problem that pose theoretical or practical difficulties (such as inverse square-law dynamics). As a baseline approach for comparision purposes, a centralized Extended Kalman Filter (EKF) estimator is used to provide position/velocity estimates of all tracked objects. These estimates and their associated covariances are used to execute a closed-loop sensor tasking approach to determine which sensors will track which objects. A tasking approach from the literature is utilized as a baseline methodology and compared to an ad-hoc modification which may offer improved performance in certain situations. The paper concludes with a numerical example demonstrating the approaches as well as a summary of avenues for future research.**

I. Introduction

Space Situational Awareness (SSA), that is, the monitoring of activities surrounding in- or through-space operations and the assessment of their implications, has received a great deal of attention in recent years, motivated initially by the publication of the Rumsfeld Commission Report [1] and more recently by the successful anti-satellite missions performed by both China and the United States [2], [3].

There are multiple decompositions of what SSA represents; from a capabilities point of view, SSA includes such things as:

- the ability to detect and track new and existing space objects to generate orbital characteristics and predict future motion as a function of time;
- monitoring and alert of associated launch and ground-site activities;
- identification and characterization of space objects to determine country of origin, mission, capabilities, and current status/intentions; and
- understanding of the space environment, particularly as it will affect space systems and the services that they provide to users;
- the generation, transmission, storage, retrieval, and discovery of data and information produced by sensor systems, including appropriate tools for fusion/correlation and the display of results in a form suitable for operators to make decisions in a timeframe compatible with the evolving situation.

An excellent summary of the current system used by the United States to perform the detection and tracking functions of SSA, the Space Surveillence Network (SSN), is contained in [4], which includes current methods for tasking the network as well as proposed improvements.

This paper is organized as follows. We first establish a precisely posed mathematical formulation of a simplified form of the SSA sensor network tasking problem to establish a benchmark problem and common framework for testing the wide variety of proposed methods estimation and control of collaborating and networked systems. We will focus on the specific problem of tracking orbiting space objects, and will formulate a centralized estimation/sensor management strategy based on the Extended Kalman Filter combined with a Fisher Information gain based tasking strategy which can be used as a point of departure for future distributed approaches. We furthermore propose an ad-hoc modification of the tasking strategy that provides an alternate value model to base sensor tasking decisions on, and provide a numerical example that illustrates the possible benefits of this proposed approach. We conclude with a discussion of extensions and future work related to the problem and approaches discussed in this paper.

II. System Model & Dynamics

We will propose an extremely simplified model for the detection and tracking of space objects as an initial focus for this work. The model is represented graphically in Figure 1. This paper will use the nomenclature developed in [5] to the maximum extent possible, extending this framework in certain areas where necessary. Let $\mathcal{S} = \{s_1, s_2, \ldots, s_m\}$ represent the set of *sensors*, that is, an entity that will accept tasks and will produce data and information; let $\mathcal{O} = \{o_1, o_2, \ldots, o_n\}$ represent the set of *objects*, that is, an entity

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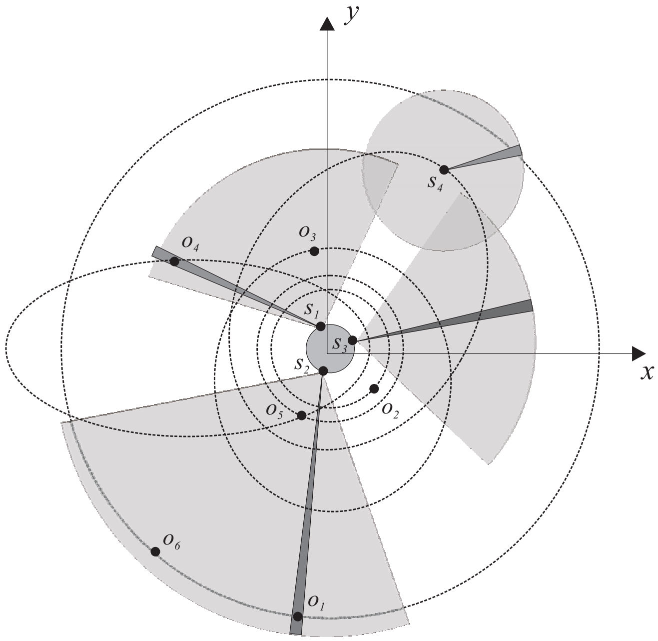

Fig. 1. Simplified planar model of orbital and sensor platform dynamics

that is not controllable or able to be tasked, and furthermore which it is desired to establish information about.

Sensors and objects will occupy one of two physical domains captured by the problem: the planet surface, where the resulting motion is dictated by the rotation of the planet about its axis; or in an orbit, where the resulting motion is dictated by orbital equations of motion. We will assume that all of the objects being tracked reside in the space domain and allow sensors to reside either in orbit or on the planetary surface. We will denote the set of all sensors on the planet surface as $\mathcal{P}$; that is, $\mathcal{P} = \{s_j : s_j \text{ is on the planet surface}\}$, and the set of all sensors in orbit as $\mathcal{K}$; that is, $\mathcal{K} = \{s_j : s_j \text{ is in orbit}\}$.

We restrict ourselves to a two-dimensional case simply to limit the computational complexity of the numerical simulations and to allow easier visualiztion of the results. The extension of the methodologies presented here to the three-dimensional case is a trivial exercise. Thus, sensors and objects will possess a state vector including position and velocity in two dimensions, represented in a inertial Cartesian coordinate with origin fixed at the center of the Earth, that we denote as $X_j^{\mathrm{s}} = [x_j^{\mathrm{s}}, y_j^{\mathrm{s}}, \dot{x}_j^{\mathrm{s}}, \dot{y}_j^{\mathrm{s}}]^{\mathrm{T}}, j = 1, 2, \ldots, m$ for sensors and $X_i^{\mathrm{o}} = [x_i^{\mathrm{o}}, y_i^{\mathrm{o}}, \dot{x}_i^{\mathrm{o}}, \dot{y}_i^{\mathrm{o}}]^{\mathrm{T}}, i = 1, 2, \ldots, n$ for objects, respectively.

The dynamics of motion for entities will be determined by the domain (surface or orbital) that they occupy. Thus, for terrestrial sensors,

$$\dot{X}_j^{\mathrm{s}} = \begin{bmatrix} \dot{x}_j^{\mathrm{s}} \\ \dot{y}_j^{\mathrm{s}} \\ -\omega_{\mathrm{E}}^2 x_j^{\mathrm{s}} \\ -\omega_{\mathrm{E}}^2 y_j^{\mathrm{s}} \end{bmatrix}, \forall s_j \in \mathcal{P}, \tag{1}$$

where ω_{E} is the earth's angular velocity. For space-based sensors,

$$\dot{X}_j^{\mathrm{s}} = \begin{bmatrix} \dot{x}_j^{\mathrm{s}} \\ \dot{y}_j^{\mathrm{s}} \\ \frac{-\mu_{\mathrm{E}} x_j^{\mathrm{s}}}{(d_j^{\mathrm{s}})^3} \\ \frac{-\mu_{\mathrm{E}} y_j^{\mathrm{s}}}{(d_j^{\mathrm{s}})^3} \end{bmatrix}, \forall s_j \in \mathcal{K}, \tag{2}$$

where μ_{E} is the Earth's gravitational constant and $d_j^{\mathrm{s}} \triangleq \sqrt{(x_j^{\mathrm{s}})^2 + (y_j^{\mathrm{s}})^2}$.

All objects to be tracked are assumed to be in orbit, and thus

$$\dot{X}_i^{\mathrm{o}} = f(X_i^{\mathrm{o}}) = \begin{bmatrix} \dot{x}_i^{\mathrm{o}} \\ \dot{y}_i^{\mathrm{o}} \\ \frac{-\mu_{\mathrm{E}} x_i^{\mathrm{o}}}{(d_j^{\mathrm{o}})^3} \\ \frac{-\mu_{\mathrm{E}} y_i^{\mathrm{o}}}{(d_j^{\mathrm{o}})^3} \end{bmatrix} + W_i, \forall o_i \in \mathcal{O}, \tag{3}$$

where $d_i^{\mathrm{o}} \triangleq \sqrt{(x_i^{\mathrm{o}})^2 + (y_i^{\mathrm{o}})^2}$ and W_i represents process noise that affects the dynamics of the objects, typically used to represent unknown or unmodeled forces.

Remark 2.1: More complex models of entities can include the ability to maneuver objects in orbit (that is, an ability to induce an impulsive change to their velocity state); the inclusion of angular orientation and angular velocity states that describe an object's attitude (which may in turn affect the ability to bring a sensor to bear in time to achieve a task); states that represent object properties such as albedo, radar cross-section, temperature, etc. (some of which could depend on the object's position, velocity, and attitude, and which would have effects on the ability of certain sensors to detect and or track an object); and the effects of perturbations including earth oblateness effects (J2), N-body gravitational effects, drag, solar pressure, and other non-conservative and/or non-deterministic forces that will affect the motion of entities in orbit. The trade between the computational tractability of the resulting model (and any estimation or tasking approaches based upon it) and the fidelity that the model represents the true motion of the various objects is a trade that must be evaluated for each situation - some effects may be better handled through detailed physics modeling (which is potentially too computationally intensive to include for the multi-object system) which is then appropriately abstracted to efficiently include the primary effects for a system-level tasking model.

III. SENSORS

For this work, we will model sensors as simple range-angle sensors; we first define

$$\rho(X_i^{\mathrm{o}}, X_j^{\mathrm{s}}) = \sqrt{(x_i^{\mathrm{o}} - x_j^{\mathrm{s}})^2 + (y_i^{\mathrm{o}} - y_j^{\mathrm{s}})^2}, \tag{4}$$

$$\psi(X_i^{\mathrm{o}}, X_j^{\mathrm{s}}) = \tan^{-1}\left(\frac{y_i^{\mathrm{o}} - y_j^{\mathrm{s}}}{x_i^{\mathrm{o}} - x_j^{\mathrm{s}}}\right) - \tan^{-1}\left(\frac{y_j^{\mathrm{s}}}{x_j^{\mathrm{s}}}\right). \tag{5}$$

We will use the shorthand notation $\rho_{i,j} \triangleq \rho(X_i^{\mathrm{o}}, X_j^{\mathrm{s}})$ and $\psi_{i,j} \triangleq \psi(X_i^{\mathrm{o}}, X_j^{\mathrm{s}})$ for the remaining development where it does not cause ambiguity.

We will restrict the sensors to generate data only within a limited *field-of-regard*, e.g. an area around the sensor's position that it can effectively detect and track targets within. We denote this area as Γ_j and define it's boundary as the area swept out by a ray of lengthΔ_j relative to the sensor's current position (the sensor's maximum range) and an angle Ψ_j measured in both directions from the local vertical direction at the sensor location (the sensor's maximum off-zenith viewing angle). Thus

$$\Gamma_j = \left\{ X : \rho(X, X_j^{\mathrm{s}}) \leq \Delta_j \text{ and } \psi(X, X_j^{\mathrm{s}}) \leq \Psi_j \right\}. \quad (6)$$

These quantities are illustrated in Figure 2. For ground-based sensors, which are limited by the local horizon, $-\pi/2 \leq \psi_i \leq \pi/2$; space based sensors, assuming they are allowed to arbitrarily re-orient their sensor payloads, would allow $-\pi \leq \psi_i \leq \pi$.

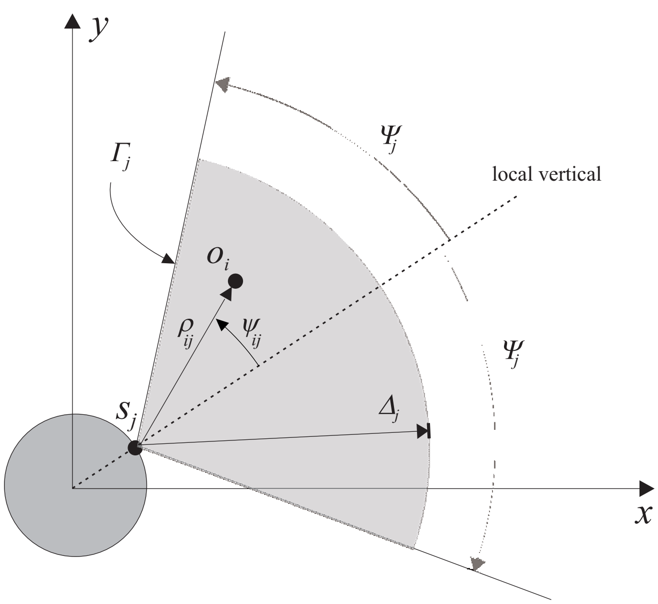

Fig. 2. Definition of quantities involved in sensor model

Remark 3.1: Note that the sensor model developed here differs from the range-angle sensor model developed in [5]. In (5) the angular measurement is defined as relative to the local vertical direction at the sensor's current location whereas in [5], the angular measurments are defined with respect to the intertial reference frame axes. Equation (5) is a more accurate model of the measurements that range-angle type sensors provide (e.g., azumith-elevation-range type measurements), as well as retaining the nonlinear transformations between local-vertical and earth-inertial coordinate frames which increase the measurement nonlinearity that must be dealt with in the problem.

Remark 3.2: More complex sensor models would include more detailed representations of sensor characteristics such as sensor noise characteristics, probability of detection and how this varies with parameters such as object distance, object velocity, and other object properties; limitations on sensor capabilities such as slew rates, minimum elevation angles; and variations of the required time to acquire an object before sensor data is produced with these parameters.

IV. Estimation

Our development of a centralized estimator for this system will follow the development of [5], although there are several minor changes due to differences in the sensor model as noted in Section III, above, and the reduction to two dimensions for the sake of simplicity.

We will only require estimation of the state vectors of the objects; we will assume that the sensors know their own position and the positions of those they can communicate with exactly. For centralized estimation, we restrict our development to the sampled-data EKF (SDEKF) of [5].

A. Forecast Step

We denote the forecast state estimate of object i by $\bar{X}_i(t) = [\bar{x}_i \, \bar{y}_i \, \dot{\bar{x}}_i \, \dot{\bar{y}}_i]^{\mathrm{T}}$. Data is assumed to be produced by the sensors at discrete instants with regular intervals of period h, thus leading to data assimilation activities defined at instances $t = kh, \; k = 1, 2, \ldots$. The data assimilation state estimate as $\hat{X}_i(kh) = \left[\hat{x}_i \, \hat{y}_i \, \dot{\hat{x}}_i \, \dot{\hat{y}}_i\right]^{\mathrm{T}}$, the pseudo forecast-error covariance as $\bar{P}_i(t)$, and the pseudo data-assimilation error covariance as $\hat{P}_i(kh)$. Thus, the forecast step of the centralized SDEKF will consist of the state estimate propagation

$$\dot{\hat{X}}_i(t) = f(\hat{X}_i(t)), \; t \in [(k-1)h, kh], \quad (7)$$

and the pseudo error-covariance forecast

$$\dot{\bar{P}}_i(t) = \hat{A}_i(t)\hat{P}_i(t) + \hat{P}_i(t)\hat{A}_i^{\mathrm{T}}(t) + Q_i, \; t \in [(k-1)h, kh], \quad (8)$$

where

$$\hat{A}_i(t) = \frac{\partial f(X(t))}{\partial X}|_{X(t)=\hat{X}_i(t)} \quad (9)$$

is the Jacobian of f evaluated along the trajectory of the state estimate, and $Q_i = E(W_i^{\mathrm{T}} W_i)$. Beyond the restriction to two dimensions, the form of $\hat{A}(t)$ here is identical to that given in [5].

B. Tasking

The resource management problem can now precisely be stated as: decide, based on known information (e.g., the differential equations of motion, the known locations of the sensors and their associated fields of regard, and the estimated positions of any satellites that are currently in the field of regard of a sensor), which of the objects in the sensor's current field of view to observe at the current time. There have been several approaches to this problem that have been examined in the literature [6]. For the current work, we will examine the approach of [7] and then propose an ad-hoc modification of it to address a potential deficiency.

For the following development, denote the set of sensor indices that have data for a particular object at o_i at time kh as $\mathcal{S}_i(k) = \{j : X_i^{\rm o}(kh) \in \Gamma_j(kh)\} \subset \mathcal{S}$ and denote the number of such sensors as $|\mathcal{S}_i(k)| = M_i(k)$. We will drop the explicit dependence on the time variable where it does not cause ambiguity to do so.

1) Fisher-Information Based Tasking: The tasking approach of [7] is based on the information form of the covariance update equation (25),

$$[\hat{P}_{i+1}]^{-1} = [\bar{P}_i]^{-1} + \sum_{j=1}^{M_i} \Omega_{i,j}, \tag{10}$$

where $\Omega_{i,j}$ is the Fisher Information Matrix for sensor $(S_i)_j$, e.g., the jth element of the set S_i, observing object i. We compute $\Omega_{i,j}$ as

$$\Omega_{i,j} = \hat{C}_{i,(S_i)_j}^{\rm T} R_{(S_i)_j} \hat{C}_{i,(S_i)_j}, \tag{11}$$

where R_j is the covariance of the measurement noise $V_j(kh)$, and the linearized measurement map for sensor j applied to object i, $\hat{C}_{i,j}(k)$, is defined as

$$\hat{C}_{i,j}(k) = \left. \frac{\partial g(X(kh), Y(kh))}{\partial X} \right|_{\substack{X(kh) = \hat{X}_i(kh), \\ Y(kh) = X_j^{\rm s}(kh)}} . \tag{12}$$

Due to our modified definition of the angle measurement used in the current work, this in turn yields (dropping the dependence on k without ambiguity)

$$\hat{C}_{i,j} = \begin{bmatrix} C_{i,j}^{\rho} & 0^{1\times 2} \\ C_{i,j}^{\psi} & 0^{1\times 2} \end{bmatrix}, \tag{13}$$

where

$$C_{i,j}^{\rho} = \begin{bmatrix} \frac{x_i^{\rm o} - x_j^{\rm s}}{\rho_{i,j}} & \frac{y_i^{\rm o} - y_j^{\rm s}}{\rho_{i,j}} \end{bmatrix} \tag{14}$$

$$C_{i,j}^{\psi} = \begin{bmatrix} \frac{-(y_i^{\rm o} - y_j^{\rm s})}{\rho_{i,j}^2} & \frac{x_i^{\rm o} - x_j^{\rm s}}{\rho_{i,j}^2} \end{bmatrix}. \tag{15}$$

With the Fisher Information Matrix $\Omega_{i,j}$ computed, we can compute the corresponding Fisher Information Gain for sensor j observing object o_i as

$$\mu_{i,j}^{\rm F} = {\rm tr}(\Omega_{i,j}). \tag{16}$$

2) Modified Approach: A modified form of $\mu_{i,j}$ is proposed based on the observation that the Fisher Information approach described above only takes into account the potential reduction of the covariance matrix as it's measure of value, without looking at the estimate covariance matrix size directly. We therefore propose the following *ad-hoc* modification of the Fisher-Information approach that directly accounts for the size of the covariance estimate:

$$\mu_{i,j}^{\rm M} = \alpha\ {\rm tr}(\Omega_{i,j}) + (1-\alpha)\ \beta\ {\rm tr}(\bar{P}_i^{\rm o}) \tag{17}$$

where α is a Pareto variable that allows the information gain to be continuously varied between a purely Fisher information gain approach to a purely covariance forecast based approach, and β is a scaling variable used to normalize the relative sizes of the ${\rm tr}(\Omega_{i,j}(k))$ and ${\rm tr}(\bar{P}_i^{\rm o}(k))$ terms in (17).

Note that the definition (17) invalidates the interpretation of this quantity as the potential reduction in the size of the estimate covariance as was the case for $\mu_{i,j}^F$.

3) Tasking Solution: We now formulate the following linear programming problem: find the binary variables $\xi_{i,j}$, $i = 1, 2, \ldots N$, $j = 1, 2, \ldots, M_i$, that maximize

$$\sum_{i=1}^{N} \sum_{j=1}^{M_i} \mu_{i,j}\ \xi_{i,j}, \tag{18}$$

subject to

$$\sum_{i=1}^{N} \xi_{i,j} \quad \le \quad T, j = 1, \ldots, M_i, \tag{19}$$

where $\xi_{i,j} \in \{0,1\}$, and where $\mu_{i,j}$ represents either $\mu_{i,j}^F$ or $\mu_{i,j}^M$, depending on which tasking method is being used. Note that (19) simply enforces a limit that each sensor can look at no more than T objects at any instant. For notational convenience, we will assemble the the variables $\xi_{i,j}$ into the elements of a matrix, e.g. $\Xi(i,j) \triangleq \xi_{i,j}$

To solve the sensor management problem, at each time step we determine what measurements will be available for each object (e.g., computing the set S_i); we then use the forcast state estimate for the object $\bar{X}_i(kh)$ to compute either the $\mu_{i,j}^F$ or $\mu_{i,j}^M$ for each sensor-object pair. Once this has been completed across all sensor-object pairs, we form $\Omega_{i,j}$, and then solve the linear program (18).

The resulting Ξ determines which object each sensor will collect data on for that time step. Using this solution, we define the set of indices of all sensors directed to observe object i at a time step as $J_i^* = \{j : \xi_{i,j}^* \neq 0\}$ and the total number of such sensors as $|J_i^*| = l_i$ (dropping the dependence on k), then the data collected on object i at time kh is given by $Y_i(kh) = [Y_{i,1}, Y_{i,2}, \ldots Y_l]^{\rm T}$, where

$$Y_{i,j} = g(X_i^{\rm o}(kh), X_{(S_i)_{(J_i^*)_j}}^{\rm s}(kh)). \tag{20}$$

C. Data Assimilation

Assuming that an object has at least one sensor observing it at time kh (e.g., $S_i \neq \emptyset$ and $J_i^* \neq \emptyset$), then we can assign the index $j' = (S_i)_(J_i^*)_j, j' = 1, 2, \ldots, l_i$ and compute the data assimilation gain $K_{i,j'}$ as

$$K_{i,j'} = \bar{P}_{i,j'}^{xy} [\bar{P}_{i,j'}^{yy}]^{-1}, \tag{21}$$

where

$$\bar{P}_{i,j'}^{xy} = \bar{P}_i \hat{C}_{i,j'}^{\rm T} \tag{22}$$

$$\bar{P}_{i,j'}^{yy} = \hat{C}_{i,j'} \bar{P}_i \hat{C}_{i,j'}^{\rm T} + R_{j'}. \tag{23}$$

The data-assimilation state estimate is then given by

$$\hat{X}_i(kh) = \bar{X}_i(kh) + K_{i,j'}(k)[Y_i(kh) - \bar{Y}_i(kh)] \quad (24)$$
$$\hat{P}_i(kh) = \bar{P}_i(kh) - K_{i,j'}(k)\bar{P}^{yy}_{i,j'}(k)K^{\mathrm{T}}_{i,j'}(k), \quad (25)$$

where $\bar{Y}_i(kh) = \left[\bar{Y}_{i,1}, \bar{Y}_{i,2}, \ldots \bar{Y}_{l_i}\right]^{\mathrm{T}}$, where

$$\bar{Y}_{i,j'} = g(\bar{X}_i(kh), X^{\mathrm{s}}_{j'}(kh)). \quad (26)$$

Note that if $S_i = \emptyset$ (e.g., no sensors can observe the object i) or $J_i^* = \emptyset$ (e.g., the tasking solution directed the sensors that could observe object i to observe a different object instead), then we simply define $\hat{X}_i(kh) = \bar{X}_i(kh)$ (e.g., there is no data on object i to assimilate, so the forecast estimate is the only estimate produced at this time step).

V. Numerical Examples

A. Description

To numerically demonstrate the differences in the tasking methods previously discussed, a network of four ground-based sensors and one orbiting sensor were simulated. The four ground-based sensors were placed ninety degrees apart on a 2-D Earth with the space based sensor following a high eccentricity orbit partially covering Low Earth Orbits (LEO) through Geostationary Orbits (GEO) orbits. Sixteen objects were simulated in a variety of orbits ranging from LEO through GEO, including non-circular (eccentric) orbits. Sensor and object positions and velocities were generated using a seventh order Runge-Kutta method for a period of two sidereal days divided into 1000 evenly spaced intervals based on predefined initial conditions using (2) and (3).

Sensor data was derived from this orbit data using (4) and (5) and adding zero mean Gaussian noise, using a standard deviation on range measurements of $\sigma_\rho^2 = 10^{-1}$ km^2 and on angular measurments of $\sigma_\psi^2 = 10^{-6}$ rad^2. The sample period for the numerical integration was also used as the sampling period for when the sensors could sample new data from observed objects.

The sensor regions were defined with $R = [10000, 44157, 25371, 9371, 30000]$ km and $\Psi = [180°, 10°, 20°, 50°, 15°]$. The orbiting sensor, listed first, could sense objects in any direction within a fixed radius.

The estimator is initialized with the object initial positions and velocities corrupted by additive Gaussian noise with a standard deviation of 10 km (for x or y position) or 1 m/s (for $\dot{x}$ or $\dot{y}$ velocity values).

B. Metrics

To demonstrate the relative performance of the two tasking approaches discussed in this paper, we will use two metrics that consolidate estimate covariance information across all of the objects being tracked. These metrics both make use of the determinant of the estimated object covariance matrix, $\hat{P}_i$, due to its relationship to the hypervolume V of this covariance as follows:

$$\det\,(\hat{P}_i) = \prod_{p=1}^{4} \lambda_p = \prod_{p=1}^{4} \sigma_p^2. \quad (27)$$

Thus, the hypervolume of the estimate error ellipsoid $V_i \propto \sqrt{\det\,\hat{P}_i}$. Due to this relationship, we define

$$J_{\text{avg}}(kh) = \frac{1}{N}\sum_{i=1}^{N} \det\,\left(\hat{P}_i(kh)\right), \quad (28)$$
$$J_{\max}(kh) = \max_{i=1,\ldots,N} \det\,\left(\hat{P}_i(kh)\right). \quad (29)$$

C. Results

Three difference cases were simulated and then compared. We compare three cases:

- Case A: $\mu^F_{i,j}$ is based on the pure Fisher Information gain approach (IV-B.1), and the number of objects able to be simultaneously sensed by a sensor is unity ($T = 1$).
- Case B: $\mu^M_{i,j}$ is based on the modified approach (IV-B.2), and $T = 1$.
- Case C: Sensors are allowed to measure data simultaneously on all objects within their viewing limitations (e.g., $T = \infty$). This eliminates the need to make any decisions, and represents a lower bound for performance of any decision making algorithm.

A comparison of these cases based on the metrics defined earlier are shown below in Figures 3 (showing J_{avg}) and 4 (showing $J_{\max}$). Note that since Case C represents a lower bound on the achieveable performance for Cases A and B, we subtract it's metric value from the values of the other cases to better showcase the differences between the two approaches.

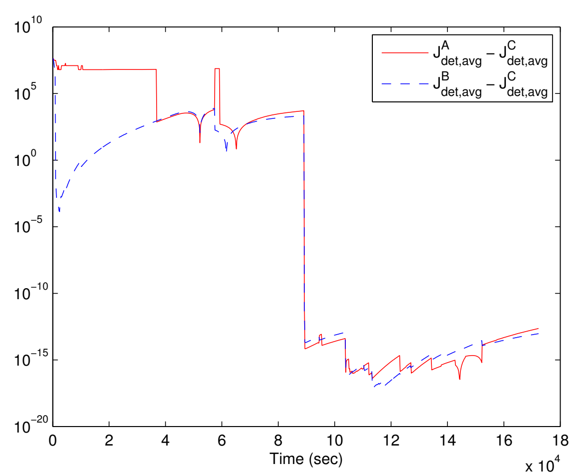

Fig. 3. Cases A and B compared using $J^{A,B}_{\text{avg}} - J^{C}_{\text{avg}}$ plotted on a logarithmic scale.

It can be seen from these figures that the modified approach presented in this paper is beneficial during a significant portion of the simulation period. As will be discussed in the

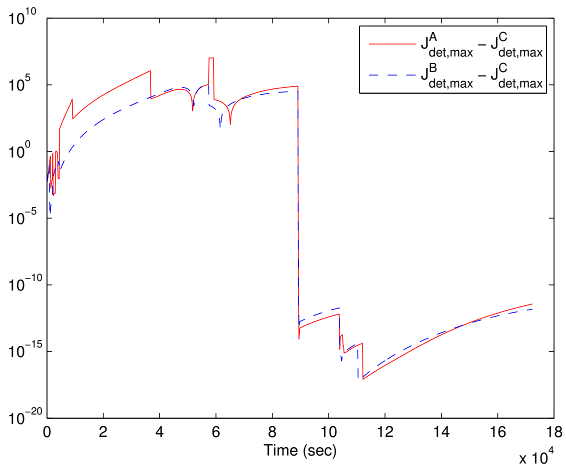

Fig. 4. Cases A and B compared using $J^{A,B}_{\max} - J^{C}_{\max}$ plotted on a logarithmic scale.

next section, more work is required to develop a rigorous understanding of when such behavior can or cannot be expected and/or to examine such results over a representative distribution of sensor and object parameters to see if such results extrapolate beyond the particular example provided here.

VI. Conclusions

This paper establishes a simple benchmark problem that can be used to frame basic research efforts in estimation and resource management for SSA applications. A sensor management approach is implemented based on both a Fisher Information strategy and an ad-hoc modification to this strategy that directly incorporates a term proportional to the estimate covariance size in a weighted combination fashion. The proposed modification shows some promise in performance comparisons with the original approach.

Future research efforts along the lines of this inquiry include:

- A more rigorous examination and formulation of the ad-hoc modification approach presented here, and in particular an investigation as to how the approaches might compare or be synergistic with covariance control approaches for sensor management [6];
- Development of more realistic communications topology modeling for the sensor network, specifically for the space-based sensors, and an investigation into the applicability of distributed estimation [8], [9], [10] and/or collaborative control approaches to address the estimation and tasking problems, respectively;
- Investigations into what benefits the use of higher-order estimation approaches such as Unscented Kalman Filters or more general sigma-point/particle filters or other approaches [11], [12] would provide in terms of allowing better decisions to be made in the tasking of the sensor network.

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