Hybrid Sensor Networks: Space Debris Tracking through Intelligent Distributed Space Systems and Ground-Based Observations

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ABSTRACT

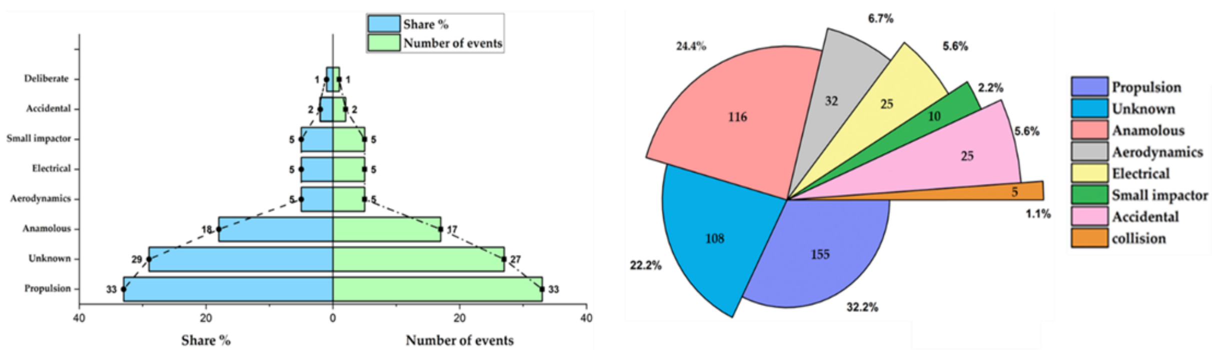
Resident Space Objects (RSOs) are anthropogenic entities orbiting Earth, often persisting for extended periods. These objects, which include debris from space launches, orbital missions, and fragmentation events, pose significant threats to operational space assets. The escalating concern over orbital congestion is further driven by recent technological advancements such as launch ride-sharing, the proliferation of small launch vehicles, and the deployment of large-scale satellite constellations. According to statistical data published by the European Space Agency (ESA) in 2023, the space environment is approaching critical congestion levels. The situation is expected to deteriorate as commercial operators like SpaceX and One-Web plan to deploy mega-constellations comprising thousands of satellites. This trend suggests a potential cascade of collision events, commonly called the Kessler syndrome, which could eventually halt space operations. To mitigate collision risks, spacecraft operators must enhance their situational awareness regarding potential threats posed by RSOs. This requires comprehensive tracking of the total number of objects in space and continuous estimation of the probability of accidental collisions. Accurate tracking and characterization of RSOs are essential for implementing effective Collision Avoidance (CA) maneuvers. This capability is vital not only for maintaining the safety and integrity of current space assets but also for enabling future applications such as interplanetary exploration, space tourism, and Point-to-Point Suborbital Transport (PPST). Currently, RSOs are monitored and cataloged using ground-based observational systems. Previous studies have explored the feasibility of utilizing space-borne radars and laser systems for RSO tracking, but challenges related to size and power consumption have prompted a shift toward alternative solutions. Although ground-based sensors offer wider sky coverage and the ability to track debris over multiple passes, they are highly susceptible to atmospheric conditions such as cloud cover, weather changes, and atmospheric turbulence, which degrade tracking accuracy. In contrast, Space-Based Space Surveillance (SBSS) offers a viable solution for RSO tracking, providing superior sensor resolution, tracking accuracy, and independence from weather conditions. While both ground-based and space-based sensors have inherent limitations, integrating them into a hybrid sensor network significantly enhances overall tracking performance. This integrated approach creates a complementary system that improves tracking accuracy, ensures continuous Low Earth Orbit (LEO) coverage, and strengthens the effectiveness of CA capabilities. Such an integrated strategy is critical for maintaining the safety and sustainability of space operations in the increasingly congested LEO environment. This paper proposes a multi-sensor data fusion strategy that employs hybrid sensor networks composed of intelligent Distributed Space Systems (iDSS) and ground-based sensors to achieve seamless, real-time tracking and continuous surveillance of space debris. A verification case study is conducted on a constellation of iDSS designed to perform SBSS for Space Domain Awareness (SDA).

Keywords: Avionics, Space Systems, Sensing, Tracking, Data Fusion, Electro-Optics, Space-Based Space Surveillance, Distributed Satellite Systems, Space Domain Awareness, Extended Kalman Filter.

1. INTRODUCTION

Space debris, often referred to as "space junk," consists of a diverse array of objects, including inactive satellites, discarded rocket stages, and fragments resulting from collisions and disintegration events. As reported by the European Space Agency (ESA), there are currently over 34,000 objects larger than 10 cm, 900,000 objects ranging from 1 cm to 10 cm, and approximately 128 million particles between 1 mm and 1 cm orbiting the Earth [1]. These objects travel at velocities capable of causing catastrophic damage to active satellites upon impact, potentially generating even more debris. This self-perpetuating process, known as the Kessler Syndrome, could eventually halt space operations [2]. Indeed, suspending all space missions would not prevent the continued accumulation of space debris, as the risk of collisions among existing Resident Space Objects (RSOs) persists. Fig.1 presents a categorical breakdown of various fragmentation events, highlighting their respective contributions to the overall history of spaceflight. In Low Earth Orbit (LEO), the number of RSOs is significantly high due to the increased spatial density and the presence of large rocket bodies and spacecraft in near-polar orbits. Projections indicate that debris larger than 10 cm will triple over the next 200 years, leading to a tenfold rise in the probability of collisions in this region. This situation is anticipated to worsen as the frequency of spacecraft launches continues to grow.

Tackling the growing issue of space debris, which jeopardizes the long-term sustainability of space operations, demands a multifaceted strategy. Key initiatives include strengthening regulatory frameworks, advancing Active Debris Removal (ADR) technologies, and enhancing Space Situational Awareness (SSA). These efforts not only aim to mitigate existing risks but also ensure the sustainable use of the space domain in the future.



(a) **(b)**

Fig.1. (a) Various fragmentation event causes and their corresponding shares (2007-2022), (b) Categorial representation of fragmentation events in the history of space flight [3].

Developing and enforcing comprehensive regulations is essential for mitigating space debris. Such rules could mandate spacecraft designs with shorter operational lifespans, reducing the likelihood of them becoming long-term debris after mission completion. However, this approach faces significant challenges in global coordination and enforcement yet remains critical for ensuring long-term debris mitigation. On the other hand, ADR approaches require significant technological innovation and carry high costs and risks, particularly due to the possibility of generating additional debris during removal operations. Implementing Space Situational Awareness (SSA) technologies is comparatively more straightforward than ADR, as it leverages existing infrastructure and expertise. SSA plays a pivotal role in safeguarding space assets by tracking and cataloging RSOs in Earth's orbit. Enhanced SSA capabilities allow for accurate predictions of RSO trajectories, facilitating timely Collision Avoidance (CA) maneuvers thereby preventing future collision events. Numerous countries and private entities already possess SSA capabilities, and improving these systems is considered a cost-effective and impactful approach to addressing the orbital congestion [4].

The inherent limitations of ground-based measurements underscore the significant advantages of utilizing space-borne measurements for tracking RSOs [5], [6]. This approach, known as Space-Based Space Surveillance (SBSS), has proven highly effective in terms of tracking accuracy and robustness against adverse weather conditions [7]. However, SBSS is constrained by a limited Field of View (FOV) and short observation durations. Previous research has investigated the feasibility of using space-borne radar and laser systems for RSO tracking but the challenges related to their size and power requirements have led to a shift towards alternative methods. Comprehensive studies indicate that optical measurements are more suitable for RSO tracking compared to Radars and laser ranging systems [8]. Recent advancements in Electro-Optical Sensor (EOS) technologies, including Charge-Coupled

Devices (CCDs) and Complementary Metal-Oxide-Semiconductors (CMOS), have significantly improved optical detection capabilities within the context of SSA.

Although both ground-based and space-based sensors possess inherent limitations, their integration within a hybrid sensor network significantly enhances overall tracking capabilities. This fusion creates a complementary system that improves tracking accuracy, ensures continuous coverage of LEO, and enhances the effectiveness of CA strategies. Such an integrated approach is vital for ensuring the safety and sustainability of space operations amidst an increasingly congested LEO environment. This paper introduces a multi-sensor data fusion methodology leveraging hybrid networks, composed of iDSS and ground-based sensors, to enable seamless real-time tracking and persistent surveillance of space debris. A validation case study is presented involving an intelligent Distributed Satellite Systems (iDSS) constellation performing SBSS in support of Space Domain Awareness (SDA). The multi-sensor data fusion scheme employed in this paper is illustrated in Fig.2. The results demonstrate the effectiveness of the proposed tracking methodology, highlighting the potential for advancing research by integrating SBSS capabilities with traditional ground-based sensors.

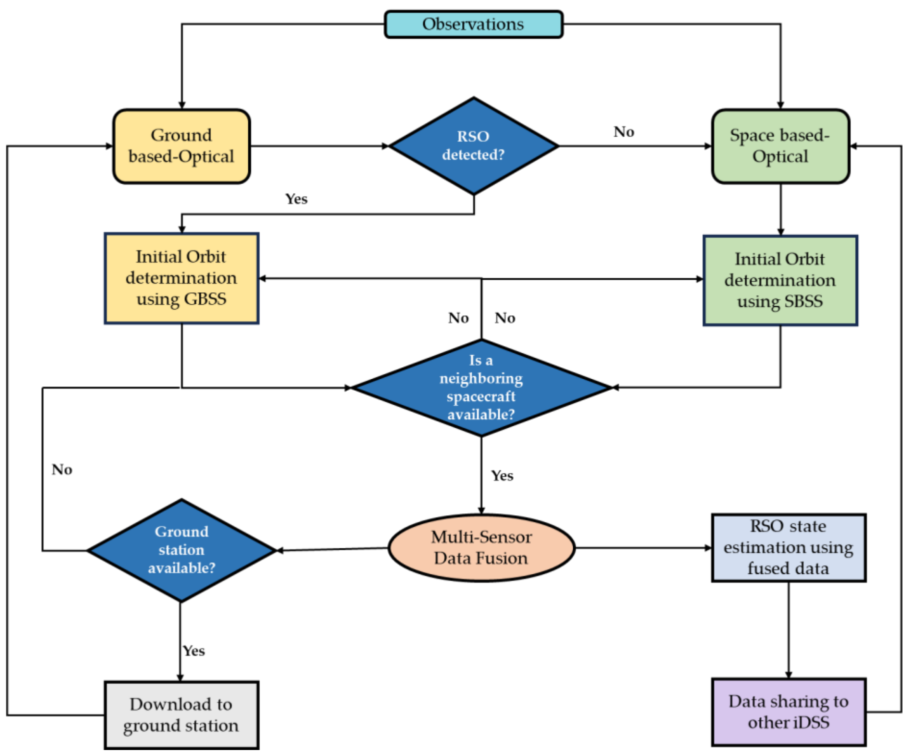


Fig.2. RSO tracking algorithm flowchart**.**

2. MULTI-SENSOR DATA FUSION

The process of tracking RSOs using EOS involves capturing an image where the RSO appears as a streak traversing a stationary star pattern against a diffuse background. This occurs when the RSO enters the FOV of the sensor for a defined time interval. The pixel coordinates of the RSO are then transformed into the overall azimuth and elevation angles, θ and φ, relative to the host platform [9]. This establishes the bearing between the RSO and the satellite. The resulting measurement vector for an ESO sensor is expressed as:

$$\theta_i = \tan^{-1}\left(\frac{y_T - y_i}{x_T - x_i}\right) + w_1, \tag{1}$$

$$\varphi_i = \tan^{-1}\left(\frac{z_T - z_i}{\sqrt{(x_T - x_i)^2 + (y_T - y_i)^2}}\right) + w_2, \tag{2}$$

where (x_i, y_i, z_i) is the position of the ith sensor in ECI coordinates, i = 1, ⋯, N where N is the number of sensors, and $w = [w_1, w_2]^T$ is the measurement noise with a covariance of $\mathbf{R}_i$, (x_T, y_T, z_T) is the RSO position coordinates in the ECI frame. Tracking RSOs involves continuous monitoring and trajectory prediction of various objects orbiting the Earth. Traditional approaches, which rely on data from single sensors such as radar or optical telescopes often provide limited and sometimes inaccurate estimates. Given the multidimensional nature of RSO dynamics, which require real-time precision, an integrated approach that effectively fuses data from multiple sources is imperative [10]. Fusing the data from independent sensors enables the generation of more accurate and reliable estimates than any individual sensor can achieve alone. These sources may range from heterogeneous sensor types to temporally separated observations from the same sensor. The primary benefits of data fusion over single-sensor methodologies include enhanced redundancy, diversity, and complementarity, all of which significantly improve tracking robustness. A comprehensive taxonomy of data fusion techniques is illustrated in Fig. 3 [11].

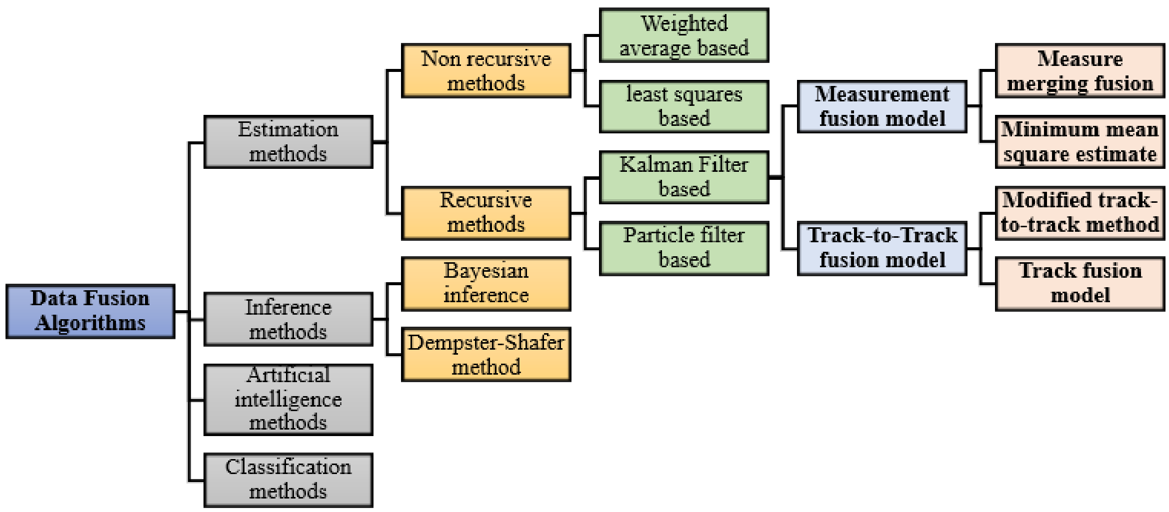


Fig.3. Taxonomy of data fusion techniques.

The proposed multi-sensor data fusion architecture facilitates the fusion of multi-sensor observations of iDSS and ground-based sensors to estimate the kinematic state RSOs. In real-time surveillance missions, where timely data processing is paramount, it is essential to utilize accurate algorithms for RSO tracking. These algorithms must be capable of operating onboard the iDSS, enabling swift data transmission during ground station passes. To meet this requirement while adhering to the limited computational and storage resources of onboard systems, sequential estimation techniques, such as the Kalman Filter, are particularly effective. In this context, the Extended Kalman Filter (EKF) is well-suited for onboard implementation. Given the inherent computational limitations of spaceborne systems, a simplified model of system dynamics has been employed. In LEO, RSO motion is predominantly affected by two major perturbations: Earth's oblateness and atmospheric drag. Consequently, the governing equations of motion are formulated as follows:

$$\frac{d\mathbf{v}_{\mathrm{T}}}{dt} = -\frac{\mu_{\oplus}}{r_{\mathrm{T}}^3}\hat{\mathbf{r}}_{\mathrm{T}} - \frac{3}{2}\frac{J_2 \mu_E R_E^2}{r_{\mathrm{T}}^4}\{[1 - 5(\hat{\mathbf{r}}_{\mathrm{T}}\hat{\mathbf{c}}_3)^2]\hat{\mathbf{r}}_{\mathrm{T}} + 2(\hat{\mathbf{r}}_{\mathrm{T}}\hat{\mathbf{c}}_3)\hat{\mathbf{c}}_3\} - Dv_{\mathrm{T}}^2\hat{\mathbf{v}}_{\mathrm{T}} \tag{3}$$

where $\hat{\mathbf{r}}_{\mathrm{T}}$ and $\mathbf{v}_{\mathrm{T}}$ are the position and velocity of the target i, respectively,

$\hat{\mathbf{c}}_3$ is Earth rotation axis,

$D = \frac{1}{2}\rho C_d \frac{A_t}{m_t}$,

ρ is the neutral atmospheric density,

C_d is the drag coefficient,

A_t is the area of the target exposed to the incoming atmospheric flux and,

m_t is the mass of the target.

For the EKF the state vector can be mathematically expressed as: $\boldsymbol{X}_{\boldsymbol{k}}^{\boldsymbol{e}} = \begin{bmatrix} \boldsymbol{r}_{\boldsymbol{t}}^{\boldsymbol{e}} \\ \boldsymbol{v}_{\boldsymbol{t}}^{\boldsymbol{e}} \end{bmatrix}$

The covariance matrix at the prediction step is given by:

$$\boldsymbol{P}_{\boldsymbol{k}}^{\boldsymbol{p}} = \boldsymbol{\phi}_{\boldsymbol{k}} \boldsymbol{P}_{\boldsymbol{k-1}}^{\boldsymbol{e}} \boldsymbol{\phi}_{\boldsymbol{k}}{}^{\boldsymbol{T}} + \mathbf{Q} \tag{4}$$

At each time step k, the state transition matrix is given as:

$$\boldsymbol{\phi}_{\boldsymbol{k}} = \boldsymbol{E} + \boldsymbol{J}_{\boldsymbol{k}} \boldsymbol{\Delta t} \tag{5}$$

where:

E is the Identity matrix,

Q = Process noise,

$\mathbf{J}_k = \begin{bmatrix} 0 & \mathbf{E} \\ \mathbf{J}_{g,r} + \mathbf{J}_{J_2,r} & 0 \end{bmatrix}$.

The methodology to obtain $\mathbf{J}_{g,r}$ and $\mathbf{J}_{J_2,r}$ is described in [7].

The state transition matrix can be exploited to obtain the predicted state as:

$$\boldsymbol{X}_{\boldsymbol{k}}^{\boldsymbol{p}} = \boldsymbol{\phi}_{\boldsymbol{k}} \boldsymbol{X}_{\boldsymbol{k-1}}^{\boldsymbol{e}} \tag{6}$$

The correction step takes into account the sensor measurements to update the predicted state and the covariance as:

$$\boldsymbol{X}_{\boldsymbol{k}}^{\boldsymbol{e}} = \boldsymbol{X}_{\boldsymbol{k}}^{\boldsymbol{p}} + \boldsymbol{K}_{\boldsymbol{k}}(\boldsymbol{Z}_{\boldsymbol{k}}^{\boldsymbol{m}} - \boldsymbol{Z}_{\boldsymbol{k}}^{\boldsymbol{p}}) \tag{7}$$

$$\boldsymbol{P}_{\boldsymbol{k}}^{\boldsymbol{e}} = (\mathbf{E} - \boldsymbol{K}_{\boldsymbol{k}} \boldsymbol{H}_{\boldsymbol{k}})\, \boldsymbol{P}_{\boldsymbol{k}}^{\boldsymbol{p}} \tag{8}$$

where K_k is the Kalman gain matrix,

$$\mathbf{K}_k = \mathbf{P}_k^p \mathbf{H}_k^T \left(\mathbf{H}_k \mathbf{P}_k^p \mathbf{H}_k^{\mathrm{T}} + \mathbf{R} \right)^{-1} \tag{9}$$

The matrix $\boldsymbol{H}_{\boldsymbol{k}}$ is obtained by linearizing the measurement model about the RSO state [12]. The main concept of the proposed Measurement Fusion (MF) methodology involves merging measurements before filtering. In this strategy, an Extended Kalman Filter (EKF) is employed, albeit with modifications to the measurement model. Specifically, alterations are made to the measurement matrix H, the measurement vector z, and the measurement noise w, along with its covariance matrix R (illustrated in Fig.4). These adjustments facilitate the fusing of measurements into a unified augmented observation vector as:

$$\boldsymbol{z}_{\boldsymbol{t}} = [[\boldsymbol{z}_{\boldsymbol{t}}^{\boldsymbol{1}}]^T [\boldsymbol{z}_{\boldsymbol{t}}^{\boldsymbol{2}}]^T] \tag{10}$$

$$\boldsymbol{H}_{\boldsymbol{t}} = [[\boldsymbol{H}_{\boldsymbol{t}}^{\boldsymbol{1}}]^T [\boldsymbol{H}_{\boldsymbol{t}}^{\boldsymbol{2}}]^T] \tag{11}$$

$$\boldsymbol{w_t} = [[w_t^1]^T[w_t^2]^T] \tag{12}$$

$$\boldsymbol{R_t} = \begin{bmatrix} R_t^1 & 0 \\ 0 & R_t^2 \end{bmatrix} \tag{13}$$

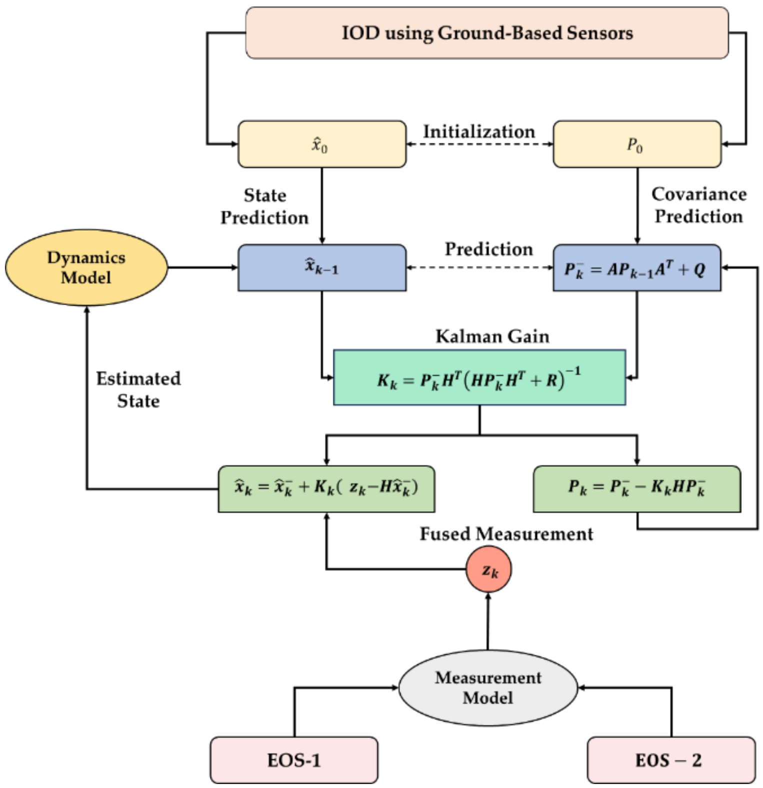


Fig.4. Multi-sensor data fusion algorithm**.**

3. CASE STUDY

A single EOS does not offer the accuracy required for real-time RSO tracking. However, using multiple EOS facilitates the measurement of range, thereby enabling accurate 3D positioning of the RSO via straightforward techniques like triangulation. Numerous studies have emphasized the increasing congestion in LEO, particularly at altitudes between 500 and 1500 km, with high orbital inclinations [13]. Hence, the proposed iDSS constellation is designed to estimate the states of the RSOs within this congested LEO region. The iDSS constellation in this study is assumed to be deployed in sun-synchronous orbits to mitigate visibility constraints that typically hinder RSO tracking. Moreover, the iDSS constellation is assumed to carry out Earth observation and SBSS tasks simultaneously, constituting a piggy-backed mission [14]. Additionally, the iDSS constellation (illustrated in Fig.5) functions as a vital service provider for other operational satellites and suborbital vehicles by employing a robust data exchange mechanism facilitated through Inter-Satellite Links (ISL) [10], [15]. The orbital parameters of the iDSS constellation are listed in Table 1 [16].

Table 1. Orbital parameters of the iDSS.

H (km)	Inclination (deg)	RAAN (deg)	Number of satellites
700	98.7	270, 90, 170	24 satellites in 3 orbital planes

The initial orbit determination of the RSO is derived through ground-based sensors, with their positions defined in a Cartesian coordinate system, as outlined in Table 2, utilizing the methodology outlined in our previous work [17]. The initial state estimates of the RSO are transmitted to the iDSS within a hybrid sensor network framework. These estimates serve as inputs for the multi-sensor data fusion algorithm discussed in previous sections. The complete mission scenario is depicted in Fig.5. The multi-sensor algorithm constitutes a critical element of the Autonomous Tracking System (ATS) for SSA as illustrated in Fig.6.

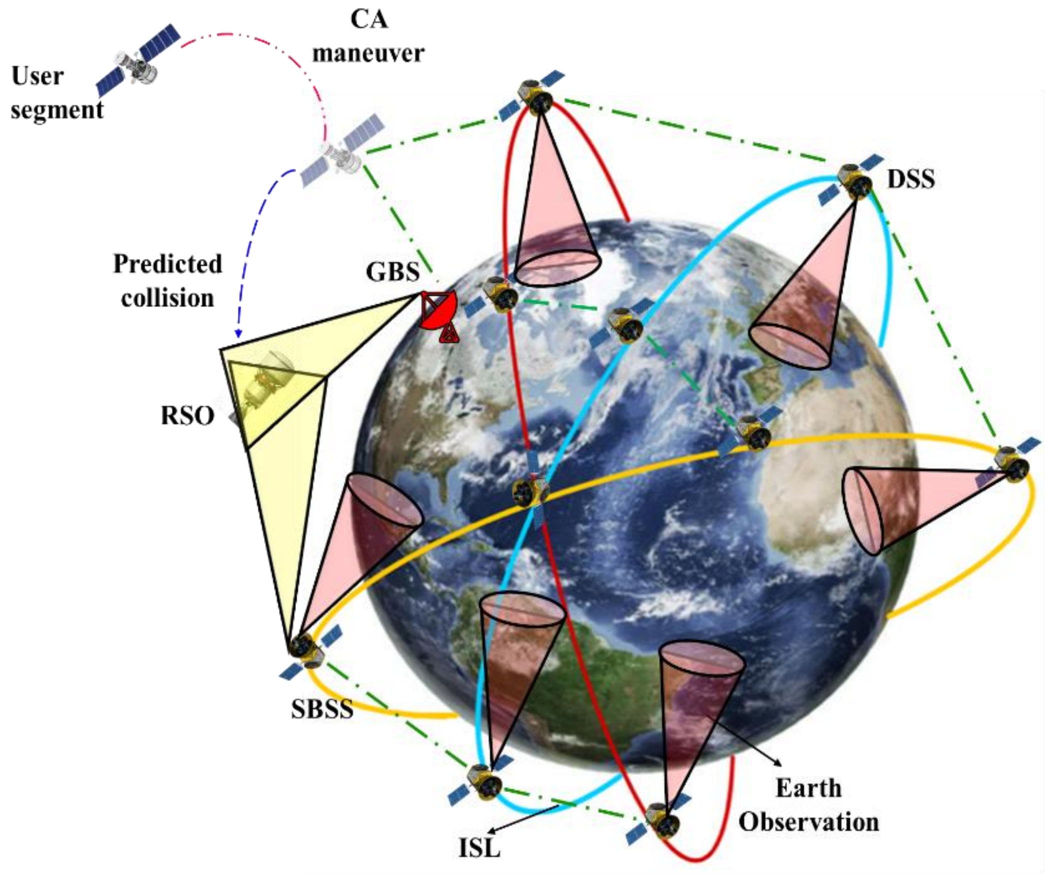


Fig.5. RSO tracking using hybrid sensor networks mission scenario**.**

Table 2 Ground-Based sensor positions.

Cartesian co-ordinates	$\boldsymbol{X_i}$ (km)	$\boldsymbol{Y_i}$(km)	$\boldsymbol{Z_i}$ (km)
Sensor 1	1880.82	13.78	6221.92
Sensor 2	-1502.52	-5.24	6356.15

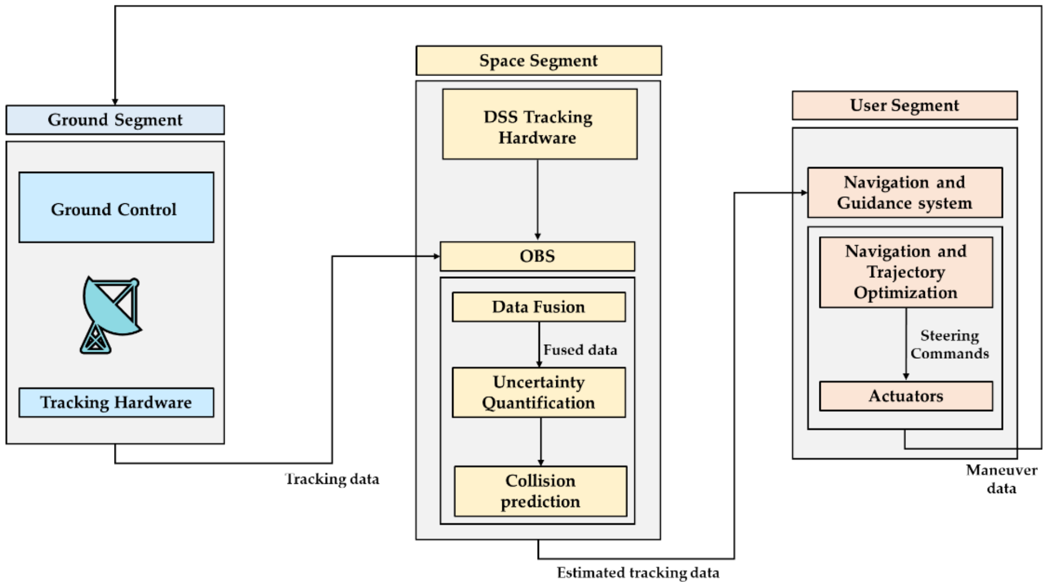


Fig.6. Autonomous tracking system architecture**.**

4. RESULTS AND DISCUSSIONS

This section presents a discussion of the simulation results. The convergence between the ground truth and the estimated states of the RSO are illustrated in Fig. 7. To evaluate the algorithm's performance, Root Mean Square Error (RMSE) plots for the estimated RSO state have been generated, as shown in Fig. 8. The error in the estimated states can be expressed as follows:

Table 3 Initial Conditions for the multi-sensor data fusion algorithm.

Measurement noise matrix R		**Process noise matrix Q**		**Initial Covariance P_0**	
σ_{m1} (arc sec)	σ_{m2} (arc sec)	$\sigma_{r,Q}$	$\sigma_{v,Q}$	σ_{r0} (km)	σ_{v0} (km/sec)
3	3	1e-2	1e-4	5	0.003

$$RMSE_{\text{pos}} = \left\{\frac{\sum_{t=1}^{T_t} \left[(x_G - x_t^e)^2 + (y_G - y_t^e)^2 + (z_G - z_t^e)^2\right]}{T_s}\right\}^{1/2} \tag{13}$$

$$RMSE_{\text{vel}} = \left\{\frac{\sum_{t=1}^{T_t} \left[(v_{Gx} - v_X^e)^2 + \left(v_{Gy} - v_Y^e\right)^2 + (v_{Gz} - v_Z^e)^2\right]}{T_s}\right\}^{1/2} \tag{14}$$

where (x_G, y_G, z_G) indicate the ground truth position of the RSO trajectory at each epoch, (x_t^e, y_t^e, z_t^e) is the estimated position of the RSO at each time step, (v_{Gx}, v_{Gy}, v_{Gz}) is the ground truth velocity of the RSO trajectory at each epoch, (v_X^e, v_Y^e, v_Z^e) is the estimated velocity of the RSO at each time step and T_s is the total time of the simulation. Notably, the integration of space-based and ground-based sensors significantly enhances accuracy and enables continuous RSO state estimation. This demonstrates the potential synergy between GBS and SBSS, underscoring the advantages of a combined approach for SDA applications.

The measurement model in Equation 1,2 is based on the ranges between the iDSS and the RSO. As the RSO moves along its orbital trajectory, an increase in the relative ranges diminishes the significance of these measurements, leading to a divergence in the estimation process as the RSO exits the sensor FOV. When visibility criteria are met, the measurements contribute to the RSO state estimation. However, when no measurements are available, the Kalman gain reduces to zero, effectively converting the EKF into a non-linear state propagator. As the RSO exits the FOV of the current iDSS satellite, it is assumed to enter the FOV of the adjacent iDSS satellite, and the tracking data is seamlessly transmitted to an adjacent iDSS unit through the ISL network, facilitating uninterrupted RSO tracking. In cases where no adjacent iDSS satellite is immediately available, the system can utilize data from ground-based sensors to maintain uninterrupted tracking. Additionally, the iDSS constellation acts as a service provider to other operational satellites and suborbital vehicles by enabling data exchange through the ISL network. This capability allows for the sharing of critical information, aiding in the implementation of CA maneuvers in the event of a predicted conjunction.

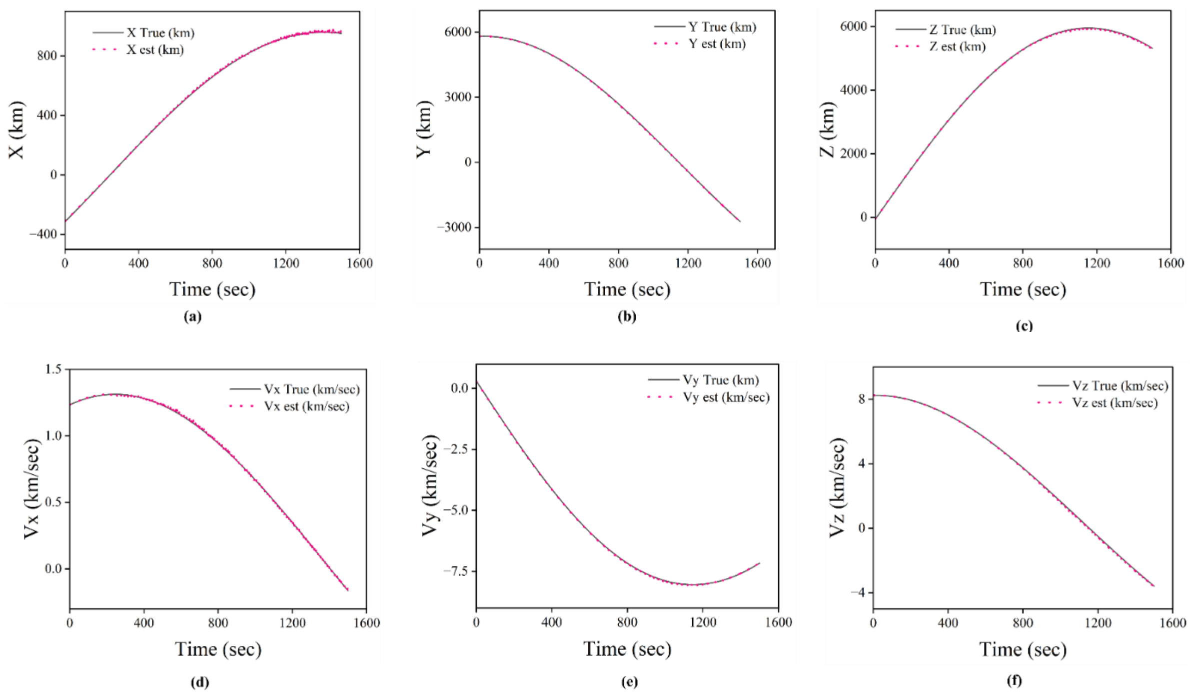


Fig.7. RSO state estimation plots for the proposed multi-sensor data fusion scheme by integrating GBS and SBSS**.**

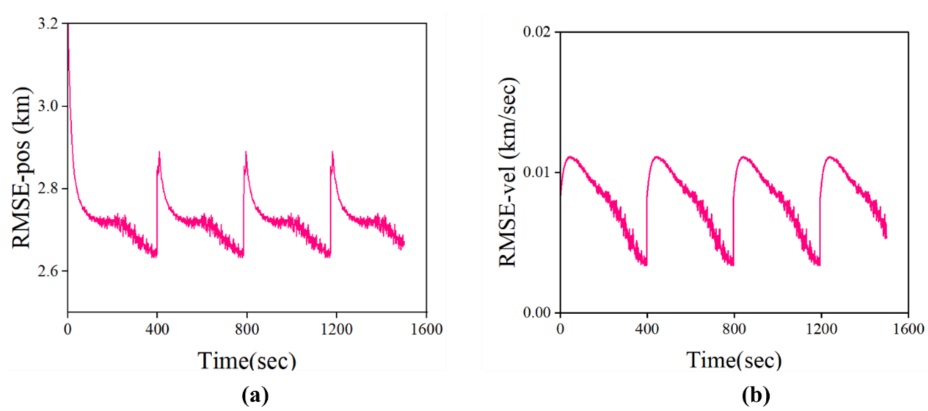


Fig.8. RMSE in position and velocity estimates using multi-sensor data fusion**.**

5. CONCLUSION AND FUTURE WORK

Space-Based Space Surveillance (SBSS) focuses on tracking and predicting the trajectories of Resident Space Objects (RSOs) using space-based sensors. Traditional ground-based tracking methods, such as radar and optical telescopes, provide limited and inaccurate estimates, which impacts the tracking accuracy. Given the complexity of RSO dynamics and the demand for real-time tracking, a comprehensive approach that integrates data from multiple sources is essential for effective Space Domain Awareness (SDA). The key advantage of fusing data from multiple sensors over single-sensor tracking lies in the redundancy, diversity, and complementarity of measurements. This paper proposes a multi-sensor data fusion strategy that employs hybrid sensor networks comprising iDSS and ground-based sensors to achieve seamless, real-time tracking and continuous surveillance of space debris. A verification case study is conducted on a constellation of iDSS designed to perform Earth observation and SBSS tasks simultaneously, constituting a piggy-backed mission. Results substantiate the validity of the proposed technique. Future research could focus on utilizing advanced high-resolution cameras and stereo-vision sensors for even greater accuracy and reliability in RSO state estimation. Moreover, the development of Artificial Intelligence (AI)-driven autonomous navigation and guidance algorithms holds promise for improving the responsiveness and adaptability of space surveillance systems for SDA.

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