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DESIGN AND EVALUATION OF AN AI-ENHANCED SPACE DEBRIS TRACKING SYSTEM UTILIZING RADAR DATA ANALYSIS

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Abstract — The growing number of space debris threatens operational satellites and upcoming space missions significantly. Existing Space Situational Awareness (SSA) infrastructure is challenged in precisely tracking, predicting, and characterizing the debris environment, especially small, large numbers of objects. The challenges stem from sensor coverage gaps, the intricacy of orbital perturbations, data processing bottlenecks, and the inability to estimate object characteristics important for precise risk assessment. In this paper, the state-of-the-art in tracking space debris is comprehensively covered, highlighting the constraints of classic techniques and new emerging possibilities for Artificial Intelligence (AI) that can be improved through radar data analysis. The common usage of Kalman Filters and the extensive body of studies employing AI/ML algorithms such as LSTMs and CNNs for determining orbits, predictions, and characterization are reviewed by us. Principal areas of research lacuna were seen to include sparse application of deep learning into direct radar data streams, an absence of rigorous focus on real-time identification, and the demand for comprehensive and meaningful comparisons among AI and non-AI alternatives in realistic situations. This study establishes the precursor for next-generation SSA systems employing AI by recognizing imperative challenges and lucrative areas of research that collectively would lead toward enhancing the security and sustainability of space activities.

Keywords—Space Debris, Space Situational Awareness (SSA), Artificial Intelligence (AI), Machine Learning (ML), Radar Data Analysis, Orbit Determination, Trajectory Prediction, Kalman Filter, LSTM, CNN, Deep Learning, Space Surveillance and Tracking (SST).

I. Introduction

A. Rationale

The growing use of near-Earth space has resulted in a corresponding growth in orbital debris, including dead satellites, rocket bodies, and fragmentation debris [1], [2]. This debris is a major collision threat to operational spacecraft. Successful Space Situational Awareness (SSA) – the capability to detect, track, identify, and predict the orbits of space objects – is imperative to forestall these dangers [7]. Nevertheless, SSA systems today have major challenges such as sensor performance shortfalls in detecting small pieces of debris, challenges in precise long-term orbit prediction due to sophisticated perturbations (e.g., atmospheric drag, the gravity anomalies of the Earth) [9], [11], and processing roadblocks [22]. Classic tracking and forecasting models, which are mainly Kalman Filter (KF) variant (EKF, UKF) oriented [10], [25], have been the SSA workhorse. Although robust under some assumptions, their performance may suffer with highly non-linear dynamics, unmodeled perturbations, or non-Gaussian noise. Statistical or conventional machine learning alone tends to struggle with the orbital data's high dimensionality and temporal nature [26]. There is a need for stronger and more adaptive techniques. Artificial Intelligence (AI) and Machine Learning (ML), especially deep learning, hold promise but their use specifically combining raw radar data streams for overall tracking and characterization is relatively less researched compared to conventional techniques or uses of lower-fidelity data such as TLEs [27], [32].

B. Objectives

The objective of this review is to critically assess the current status of space debris tracking techniques, with a focus on radar-based systems, and identify important research gaps that can be addressed with AI. Specific objectives are:

1. Review Traditional and AI Approaches: Briefly describe the universal application and limitations of traditional techniques (Kalman filters) and discuss the application of various AI/ML models (ANN, LSTM, CNN) in SSA research.

2. Assess Real-Time Data Integration: Assess the extent to which recent research integrates real-time sensor data (especially radar) versus historical or simulated data.

3.Examine Integrated Systems & Characterization: Research the development of integrated systems that perform detection, tracking, prediction, and characterization, particularly using AI with radar signatures (e.g., RCS).

4. Fill Research Gaps: Identify areas of missing research, such as the need for deep learning-based algorithms on unprocessed radar streams, efficient comparison with traditional baselines, and integrated visualization functionalities for field use.

II. Methods

This chapter describes the systematic approach used to carry out the literature review for identifying, selecting, analyzing, and synthesizing pertinent studies on AI-assisted monitoring of space debris via radar data. Following a prearranged process guarantees transparency, minimizes bias, and maximizes the credibility of the review results.

A. Eligibility Criteria:

A well-defined a priori set of eligibility criteria was developed to guarantee that the chosen studies addressed the review objectives directly and had a common scope. These criteria are used as the initial filter to include or exclude possible research articles.

a) Inclusion Criteria:

The inclusion criteria were used to identify the main research field:

Topic Relevance: Effort required to have peak applicability to the application of Machine Learning (ML), Artificial Intelligence (AI), or standard estimation techniques (primarily Kalman Filters and extensions thereof, used as a reference point) to perform the activities of object orbit determination (OD) space objects, trajectory prediction, or object characterization (i.e., size estimation, classification). This remains relevant to the core SSA activities.

Sensor Data Emphasis:

The major requirement was the utilization of radar data (real measurements or simulated data, and their derivatives such as Radar Cross Section - RCS) as a major source of input for the researched algorithms. This keeps the review aligned with the thesis emphasis on radar systems.

Publication Type:

Peer-reviewed scientific journals and well-established conference proceedings alone were eligible for maintaining a certain minimum scientific depth along with peer review.

Timeframe:

The cut-off date was restricted to publications after 2015. This time period was chosen to capture the swift development of AI/ML methods, especially deep learning, but still encompass very relevant early fundamental work on traditional methodologies (like Kalman Filtering methods applied in SSA) or basic ideas in AI.

Exclusion Criteria:

In order to stay relevant and targeted, the following type of studies was deliberately excluded:

Non-Radar Focus:

Research using exclusively optical sensor observations, laser ranging, or sensor fusion methods wherein the contribution or analysis of radar component was limited or non-separable was ruled out. This keeps the focus of the review on radar data analysis challenge and opportunity.

Irrelevant Applications:

Spacecraft attitude determination/control, mission planning, space weather impact unrelated to object tracking, or communications research even if employing AI or radar was out of scope.

Methodological Insufficiency:

Articles with insufficient description of methodology, dataset, validation process, or results, and therefore making their evaluation for validity or reproducibility impossible, were excluded. This criterion ensures the quality level of the review.

Language:

All studies in English language were included because of limitations in resources to translate.

Systematically, several trusted scientific archives and databases were searched to achieve comprehensive coverage of pertinent literature. The choice was made to provide principal publication sources of computer science, engineering, aerospace, and physics:

Core Databases:

IEEE Xplore, ScienceDirect (Elsevier), SpringerLink, MDPI were chosen as the principal sources because of their large collections of journals and conference proceedings of the respective concerned technical fields.

Preprint Servers:

arXiv has been added in order to procure the most up-to-date work and pre-peer-reviewed results due to the extremely fast pace at which AI/ML developments emerge.

General Academic Search Engines:

Google Scholar acted as a subsidiary source to provide help in detecting potentially overlooked publications and grey literature, applying further critical appraisal upon non-peer-reviewed material discovered.

C. Search Strategy:

A systematic search strategy was constructed to maximize the number of pertinent studies while minimizing irrelevant hits. This was done by constructing an articulated search query in keywords and Boolean operator form, modified where appropriate for each databasespecific syntax.

Keyword Grouping:

Keywords were grouped by theme:

Object Type: "space debris", "space object", "resident space object", "RSO"

Task: "tracking", "orbit determination", "prediction", "characterization", "classification", "state estimation"

Sensor/Data: "radar", "RCS", "radar cross section", "sensor data"

Method: "Kalman Filter", "EKF", "UKF", "artificial intelligence", "machine learning", "deep learning", "LSTM", "CNN", "neural network"

Boolean Operators: Both AND and OR combinations were employed. A typical structure was: (Object Type Terms) AND (Task Terms) AND (Sensor/Data Terms) AND (Method Terms). For example: ("space debris" OR "space object") AND ("orbit determination" OR "prediction") AND ("radar") AND ("LSTM" OR "Kalman Filter" OR "AI").

Iteration: Iteratively, the search approach was fine-tuned in the light of early results by reformulating keywords and combinations to raise the relevance and thoroughness of the generated articles.

D. Selection process:

A multi-step screening process was applied to systematically match the eligibility criteria to the returned records:

Duplicate Removal:

De-duplicated the retrieved records from multiple databases utilizing reference management tools (e.g., Zotero, EndNote).

Title and Abstract Screening:

Two reviewers independently screened the distinct records' titles and abstracts against the exclusion/inclusion criteria. Obvious studies that were not meeting criteria were excluded. Disagreement was resolved or discussed or else referred to a third reviewer.

Full-Text Review:

Full-text articles that survived the initial screening were screened by full text by at least two reviewers to determine eligibility on the basis of a close reading of the data sources, outcomes reported, and methodology. Exclusion reasons at this stage were documented.

E. Data Collection Process:

For each study deemed eligible after the full-text review, data were extracted using a standardized data extraction form (e.g., entered in a spreadsheet or database).
Standardization:
The design facilitated uniform extraction of key points across all studies included.
Pilot Testing: The form for extraction was pilot-tested with a few studies and refined to ensure clarity and completeness.

Extraction:

Separate data extraction was performed by two reviewers, where discrepancies were resolved through consensus discussion. Extracted information included bibliographic details, study purpose, methodology description, data characteristics, performance measures, and key findings/limitations.

F. Data Items:

The data sheet for collection was designed to capture specific variables necessary for synthesis of the review:
a) Outcomes & Data Sought:
Accuracy Measures: Specific figures given for prediction errors (RMSE, MAE, MAPE) and/or classification performance (Accuracy, Precision, Recall, F1-Score). Units were noted where applicable.
Model Performance Comparisons: Explicit comparisons drawn in research between different AI models, or between AI models and traditional baselines like Kalman Filters.
Data Utilization Information: Detailed information on the nature of data used (Real Radar Measurements, Simulated Radar Data, TLEs, RCS Signatures), dataset size, duration, and source where specified.
Characterization Methodologies: Description of techniques used for type classification of debris or estimation of physical parameters (e.g., size, mass, shape) and success rates or estimation errors reported.

b) Other variables & assumptions

Information regarding the regime focus of orbits (LEO, MEO, GEO) and specific orbit perturbations being addressed in models or simulations, along with any significant assumptions by the authors themselves regarding the methodology or data were documented.

G. Risk of bias assessment

A systematic assessment of RoB was conducted for every included study to assess the validity and reliability of the evidence derived. Even though a formal tool like ROBINS-I is developed for non-randomized interventions, its principles were used to assess biases relevant to simulation and algorithmic performance studies. The domains listed below were regarded as key to the assessment:
Selection Bias:

Potential for bias from non-representative data sets (e.g., non-realistic simulation parameters, empty orbital regimes) or non-random object choice for analysis.

Performance Bias:

Algorithm implementation and verification-related bias (e.g., suboptimal model tuning, lack of independent test sets, overfitting, unfair comparison to badly tuned baselines).

Detection Bias:

Outcome measurement or reporting bias (e.g., unsuitable metrics, lack of detail on metric calculation).

Reporting Bias:

Single, positive reporting of only positive results or measurements, excluding analysis of inferior performance.
Methodological Clarity:
Lack of information for replication or full understanding of methods employed.
Each investigation received an overall RoB judgment (e.g., Low, Moderate, High) based on judgment across these areas, and thus determined weight accorded to its findings in synthesis.
H. Effect Measures
The most important effect measures synthesized and derived were quantitative performance measures of algorithm performance on the SSA tasks:
For prediction and orbit determination: RMSE and MAE were given first priority since they are the absolute size of state vector errors in physical units (e.g., meters, m/s).
For classification/characterization: Accuracy, Precision, Recall, and F1-Score were used to measure the ability to correctly predict the debris types or properties.

I. Synthesis Methods:

Given the anticipated heterogeneity between AI models, datasets, radar parameters (real vs. simulated), performance metrics, and individual SSA tasks addressed in various studies, a purely quantitative meta-analysis was deemed unsuitable. A narrative, qualitative synthesis methodology was therefore adopted instead.
Grouping:

Results were grouped thematically by the primary methodology (e.g., Traditional KF-based, AI-based Prediction, AI-based Characterization) and key research questions (e.g., performance comparison, impact of real-time data, RCS signature analysis).
Tabulation: The key findings, particularly the performance results and model comparisons, were tabulated to facilitate comparison across studies (as depicted conceptually in Table I).
Narrative Summary: The findings were summarized narratively, highlighting consistent results, inconsistencies, trend identified (e.g., increasing deployment of deep learning), and limitations reported in the main studies.

J. Reporting Bias Assessment:

The potential impact of reporting bias (e.g., publication bias for positive outcomes) was considered at the synthesis phase. While statistical tests like funnel plots are difficult to apply reliably to heterogenous studies, the review looked for patterns like a scarcity of studies with negative or null results for specific AI applications, or asymmetry of reported effect sizes. Results were interpreted with caution, acknowledging that published literature may over-represent successful applications.

K. Certainty Assessment:

Overall confidence in the synthesized findings for different approaches was estimated informally using principles that are analogous to the GRADE (Grading of Recommendations, Assessment, Development and Evaluations) system. The following factors were considered:

Volume of Evidence: The number of studies that consider a given approach.
Risk of Bias: Global quality and RoB scores of the included studies.
Consistency: The degree of agreement of findings among more than

one study.

Directness: To what extent were the study populations, methods, and findings compatible with the review's most important questions (e.g., those studies that utilized real radar data were considered to be more direct than those using only TLEs).

Precision: While technical precision estimates were not calculated formally, the variability and range of reported performance metrics were considered.

III. RESULT

A. Study Selection

We found about 32 records from the initial search. Following duplicate removal and title/abstract screening, 23 articles were subjected to full-text review. Eventually, 18 studies were included according to the inclusion criteria and were the basis of this review.

B. Study Characteristics

Literature reviewed included:

Traditional Methods: There were many studies describing the use and adaptation of Kalman Filters (EKF, UKF, particle filters) for OD and prediction based on simulated and actual radar data [10], [25].

AI for Prediction:

An increasing amount of literature using ANNs, LSTMs, and other ML algorithms, sometimes trained with TLE data or numerically simulated trajectories, with potential for better prediction accuracy, particularly in high-drag conditions [27], [28], [30].

AI for Characterization:

Scientific studies employing ML classifiers (SVMs) and increasingly CNNs to identify objects or make inferences about properties from optical light curves or radar RCS signatures [20], [31], [32], [33].

Hybrid Models:

Limited but growing literature on hybrid models that bring together multiple approaches (albeit less attention on CNN-LSTM for radar data per se in comparison to other fields).

Data Sources: Major dependence on TLEs and simulated data. Fewer studies based on real radar data, particularly for training sophisticated AI models.

Synthesis:

Traditional Kalman filters remain the standard in operation, providing reliable performance when dynamic models are accurate and noise is friendly. AI techniques, particularly LSTMs, have potential for improved long-term forecasting by learning implicit complex dynamics but validation typically relies on simulated or TLE data. AI parameterization with RCS data is encouraging but restricted by signature complexity and the unavailability of much real data. Hybrid AI methods integrating spatial (CNN) and temporal (LSTM) learning for radar streams of data specifically are potentially powerful but relatively underdeveloped in the SSA literature compared to other uses.

F. Reporting biases

A positively skewed reporting of results on novel AI applications has been observed, occasionally with scant rigorous comparison with best conventional practice or exploration of failure cases.

G. Certainty of Evidence Assessment

High certainty is established for the constraints and abilities of conventional Kalman Filters under nominal conditions. High to moderate certainty is established regarding the potential for AI (mainly LSTMs) in improving prediction from sequence data but lower certainty concerning operational robustness from data constraint. AI radar data characterization today has low to moderate certainty with more studies into real, mixed data to emerge.

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IV. DISCUSSION

A. Results in Context of Previous Research

This review indicates that although Kalman Filters are proven SSA tools, AI/ML holds great potential to fill their gaps, especially in dealing with sophisticated perturbations and facilitating data-driven characterization. The literature demonstrates a clear trend toward investigating AI, aligning with developments elsewhere. However, there is a significant gap between AI research (usually simulation/TLE-based) and operational SSA systems using traditional filters and raw sensor inputs. Straight application of deep learning models such as CNNs and LSTMs to lightly or raw processed radar data streams toward concurrent tracking and characterization seems rather underdeveloped in relation to potential exhibited by applications such as computer vision and NLP.

B. Shortcomings of the Evidence

The most notable limitation found throughout the literature reviewed is the widespread use of simulated or low-precision TLEs. Actual radar data contain complexities (noise, clutter, biases, scheduling gaps, variability of signatures) not encountered in simulation. In addition, the essential challenge of data association is either dismissed or neglected by AI-centric research. Proper validation and direct comparison between AI models and well-tuned conventional filters based on the same, difficult datasets are often absent.

C. Limitations of the Review Process

This review depended on database searches and potentially excluded studies published in specialist journals or company reports. The qualitative synthesis method, although unavoidable because of study heterogeneity, restricts quantitative comparison. Bias and certainty assessment are dependent on reported data, which can be bad.

D. Practice, Policy, and Future Research Implications

There are a number of implications of the results:

Practice:

Low-level SSA can benefit from the addition of AI modules to tasks like better prediction at high drag or early object recognition, potentially in conjunction with existing KF-based techniques.

Policy:

Encouraging data sharing (actual radar data, realistic simulation) and shared evaluation metrics would accelerate development and enable improved benchmarking of AI techniques.

Future Work:

Key directions are:

Training and verifying deep learning models (CNNs, LSTMs, Transformers) from sequences of realistic radar data (including RCS).

Combining AI for concurrent OD, prediction, and characterization.

Conducting rigorous comparisons between optimized AI models and state-of-the-art Kalman Filters on challenging, open datasets.

Developing AI-enabled solutions to data association in dense debris environments.

Developing integrated, user-friendly dashboard systems with AI-informed insights for operators.

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