MULTI OBJECT TRACKING USING NON-LINEAR FILTERING TECHNIQUES

By

Ali Raza Malik

NATIONAL UNIVERSITY OF MODERN LANGUAGES ISLAMABAD

June, 2025

MULTI OBJECT TRACKING USING NON-LINEAR FILTERING TECHNIQUES

By

Ali Raza Malik

MS-EE, National University of Modern Languages, Islamabad, 2025

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF

THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

In **Electrical Engineering**

To

FACULTY OF ENGINEERING & COMPUTING

NATIONAL UNIVERSITY OF MODERN LANGUAGES ISLAMABAD

NATIONAL UNIVERSITY OF MODERN LANGUAGES FACULTY OF ENGINEERING AND COMPUTING

THESIS AND DEFENSE APPROVAL FORM

The undersigned certify that they have read the following thesis, examined the defense, are satisfied with overall exam performance, and recommend the thesis to the Faculty of Engineering and Computer Sciences for acceptance.

Thesis Title: Multi Object Tracking Using Non-Linear Filtering Techniques.

Submitted By: Ali Raza Malik **Registration #:** 14 MS/EE/F21

Master of Science in Electrical Engineering

Title of the Degree

Electrical Engineering

Name of Discipline

Dr. Hammad Dilpazir	
Name of Research Supervisor	Signature of Research Supervisor
Dr. Noman Malik	
Name of Dean (FEC)	Signature of Dean (FEC)
Brig Shahzad Munir	
Name of Director General	Signature of Director General

June, 2025

AUTHOR'S DECLARATION

I Ali Raza Malik

Son of Sajid Hussain Malik

Discipline Electrical Engineering

Candidate of Master of Science in Engineering at the National University of Modern Languages do hereby declare that the thesis Multi Object Tracking Using Non-Linear Filtering Techniques submitted by me in partial fulfillment of MSEE degree, is my original work and has not been submitted or published earlier. I also solemnly declare that it shall not be submitted in the future to obtain any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be canceled and the degree revoked.

Signature of Candidate

Ali Raza Malik

Name of Candidate

23 June, 2025

Date

ABSTRACT

In this research, the problem of redundant detections of tracks in distributed sensor networks for multi-object tracking is addressed. Measurement noise and network-induced errors often result in multiple detections of the same object, complicating the accurate estimation of object count and position. This makes it challenging to accurately determine the true number of objects and their locations. Track-to-track association algorithms help address this issue. Many such algorithms have been developed and can be broadly categorized into two types: statistical algorithms and clustering-based algorithms. A key clustering-based approach is the fuzzy track-to-track association algorithm, which is the focus of this research. A variation of this algorithm is tested on data generated from a model simulating a multi-sensor, multi-target environment. In real-world sensors, errors typically arise in azimuth, elevation, and range, so this thesis proposes an error model based on these parameters. The association algorithm's resolutions are also grounded in this realistic error model. Additionally, time synchronization is critical before performing track association. This thesis employs a linear predictor to synchronize tracks before association, and the performance of the algorithm is analyzed under these conditions.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

CEP	Circular Error Probable
CAP	Circular Area Probable
T2TA	Track-To-Track Association
M2TA	Measurement-To-Track Association
M2MA	Measurement-To-Measurement Association
MTT	Multi-Target Tracking
MOT	Multi-Object Tracking
STT	Single-Target Tracking
TDL	Tactical Data Link
DSN	Distributed Sensor Network
C4SIR	Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance
ECI	Earth-Centered Inertial
ECEF	Earth-Centered Earth Fixed
ENU	East-North-Up
FCM	Fuzzy C-Means
JPDA	Joint Probabilistic Data Association
PDA	Probabilistic Data Association
GNN	Global Nearest Neighbor
KF	Kalman Filter
EKF	Extended Kalman Filter
UKF	Unscented Kalman Filter
PF	Particle Filter
ICI	Inverse Covariance Intersection
CI	Covariance Intersection
UAV	Unmanned Aerial Vehicle
AUV	Autonomous Underwater Vehicle
GNSS	Global Navigation Satellite System
LiDAR	Light Detection and Ranging

Radar	Radio Detection and Ranging
RF	Radio Frequency
WGS84	World Geodetic System 1984
MOTA	Multiple Object Tracking Accuracy
MOTP	Multiple Object Tracking Precision
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
UWB	Ultra-Wideband
SVM	Support Vector Machine
DNN	Deep Neural Network

ACKNOWLEDGMENT

I am deeply thankful to Allah Almighty for granting me the strength, patience, and perseverance to complete this research work. His blessings have been a constant source of guidance throughout this journey.

I owe my heartfelt gratitude to my parents, whose unconditional love, prayers, and unwavering support have been the foundation of my academic journey. Their encouragement has been my greatest source of strength during difficult times. I would like to extend my sincere thanks to my research supervisor, Dr. Hammad Dilpazir, for his consistent guidance, insightful feedback, and encouragement. His supervision during the critical stages of this thesis has been instrumental in bringing this work to completion. I am also grateful to Dr. Javvad-ur-Rehman, who initially supervised my research. His early mentorship and academic input played a significant role in shaping the initial direction of this study, and his contribution remains sincerely appreciated.

I am truly thankful to my colleagues, who supported me throughout this journey not only through their helpful discussions but also by accommodating me with time management, covering responsibilities when needed, and providing the flexibility that allowed me to focus on this research. Their cooperation and understanding made a meaningful difference in balancing academic and professional commitments.

DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have been the one that is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time. I would also like to dedicated this thesis to myself for persevering through every late night, every doubt, and every deadline. It stands as a personal reminder of resilience, growth, and the quiet strength found in persistence.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Airborne radars are essential for intercepting airborne targets, as well as for surveillance and reconnaissance operations. These radars operate at very high frequencies and have various modes such as Track While Scan (TWS), Situational Awareness Mode (SAM), and Single Target Tracking (STT) [1]. However, airborne radars have limitations in range, which can impact the performance of aerial missions. Improving radar range would enhance mission effectiveness, and this can be achieved by addressing the design limitations of these radars. One solution to extend range is connecting multiple radars through a wireless network, overcoming design constraints. A Tactical Data Link (TDL) serves as the network connecting multiple aircraft, allowing them to share data. This networked approach reduces uncertainty in target information, thereby improving the range and accuracy of airborne sensor networks [2]. However, sharing information over the network introduces challenges, such as multiple sensors reporting the same target multiple times. To resolve the issue of redundant reports, a Track-to-Track Association (T2TA) algorithm is applied. For example, consider two aircraft moving in the same direction, tracking a single target moving away from them in an overlapping coverage area shown in figure 1.1. Due to radar inaccuracies, each aircraft may report the target's position slightly differently [3]. When they share this data over the TDL, sensor inaccuracies, varying sampling rates, and communication delays can cause the target to appear twice on each aircraft's display.

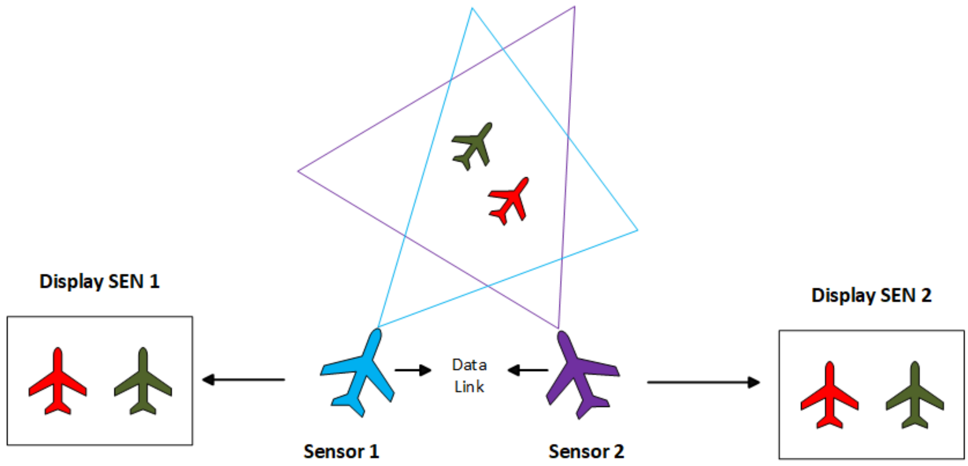

Figure 1.1: Two sensors tracking one target and sharing data over TDL

A robust T2TA algorithm is required to prevent the issue of the same track being reported multiple times over the TDL. The challenge becomes even more complex as the number of targets and sensors increases as shown in figure 1.2

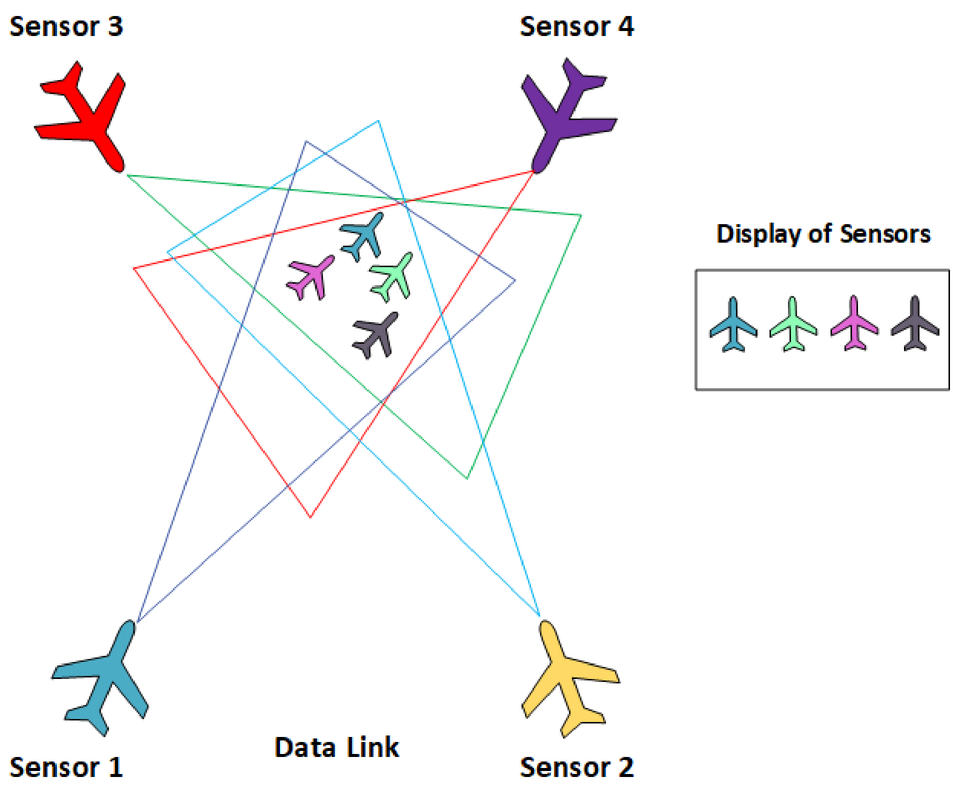

Figure 1.2: Multiple sensors tracking multiple targets and sharing data over TDL

In figure 1.2 four sensors are transmitting data over a TDL while operating within an overlapping coverage area. This shared coverage leads to uncertainty about whether the sensors are tracking the same targets or different ones. The possible sensor-target combinations for the situation shown in figure 1.2 include:

- **A.** A single target is being tracked by all four sensors.
- **B.** Four different targets are being tracked, with each sensor locking onto a separate one.
- **C.** Two targets are present, with some sensors tracking one and others tracking the second. One variation could involve one sensor tracking one target while the other three sensors focus on the second target.
- **D.** Three targets are being tracked, with one pair of sensors tracking the same target while the other two track two different targets.

Multi-Target Tracking (MTT) systems are designed to detect, track, and counter aerial threats. These systems rely on a variety of heterogeneous sensors that share information over a network [4]. Each sensor generates its own sensor-level tracks from its processed data, while system-level tracks are created by fusing the sensor-level tracks with data received from other sensors on the network. Since sensors operate within overlapping coverage areas, it is crucial to determine which tracks correspond to the same targets and which correspond to different ones. This process of correlating tracks before fusion is known as track-to-track association.

A Distributed Sensor Network (DSN) is an architecture where multiple sensors are connected via a network. Each sensor, or node, generates some form of data, and the network may operate using wired or wireless communication protocols [5]. The nodes can consist of a few large sensors or many small micro-sensors, and they can be either mobile or stationary. The topology of this network may be static or dynamic.

In traditional target tracking methods, CEP/CAP algorithms have been widely used due to their simplicity and ease of implementation. The CEP method provides a statistical measure that defines a circular region within which a target is expected to appear with a certain probability, typically 50%. It is based on fixed thresholding, assuming Gaussian noise distributions around target estimates. CAP extends this concept by calculating the probability of correct association within a circular error region, offering a slightly more refined statistical approach than pure CEP.

While CEP/CAP-based methods are computationally efficient and suitable for low-noise environments, they struggle in real-world multi-sensor scenarios where track uncertainty is dynamic, sensor noise levels vary, and overlapping tracks create complex association challenges. Their reliance on fixed error thresholds limits adaptability, especially in distributed sensor networks with high target densities or asynchronous sensor updates.

1.1.1 Research gap and Motivation

Existing multi-target tracking systems rely heavily on data association algorithms to synchronize and fuse information from multiple sensors. Centralized fusion systems, for instance, aggregate data from all sensors at a central node, where advanced algorithms process and correlate the information [6]. However, centralized systems are prone to latency, high communication costs, and vulnerability to single-point failures. On the other hand, distributed fusion systems enable each sensor to share its processed tracks with others, reducing dependency on a central node. Despite their scalability, these systems face significant challenges, such as inconsistencies in track parameters, asynchronous data updates, and sensor-specific biases.

Traditional track-to-track association methods, such as the CEP method, lack adaptability and fail to accommodate varying levels of uncertainty. CEP is widely used in radar and tracking systems to evaluate the precision of measurements and track association. While CEP provides a simple and intuitive way to measure accuracy, its reliance on fixed thresholds makes it less effective in scenarios with dynamic noise levels or varying environmental conditions. This limitation highlights the need for more adaptive methods, such as fuzzy clustering-based approaches, to improve track association accuracy in complex environments [7].

The need for robust, adaptive, and efficient track-to-track association algorithms has become evident with the increasing deployment of distributed sensor networks in real-time applications. Recent advances in fuzzy clustering techniques have shown promise in addressing these challenges. For instance, fuzzy clustering methods provide flexibility in handling uncertainties, enabling enhanced track fusion and association in environments with overlapping sensor coverage and dynamic targets [8]. However, these approaches often lack comprehensive evaluations in realistic, multi-sensor scenarios, and their performance under dynamic conditions remains an open research question [9].

1.2 Problem Statement

Traditional track-to-track association algorithms, such as CEP, while computationally efficient, often struggle to maintain accuracy in scenarios with high noise, overlapping tracks, or limited temporal synchronization. These methods rely on rigid probabilistic boundaries that are insufficient to handle complex, real-world scenarios, leading to disassociation and reduced tracking reliability.

To address these limitations, this research proposes a Fuzzy Logic-based T2TA. By leveraging fuzzy membership functions, this approach can adaptively handle uncertainty and variability in sensor data. The proposed method incorporates a robust mechanism for track synchronization and association, making it well-suited for high-clutter, multi-sensor environments. The algorithm aims to improve accuracy and robustness in track association while maintaining competitive computational efficiency, addressing the limitations of existing systems and enhancing the operational capabilities of distributed sensor networks.

1.3 Research Question

The main research questions are as follows:

- What impact do varying track parameters (e.g., noise levels, target movement) have on the performance of Fuzzy Logic versus CEP in track association?
- What are the computational trade-offs of using Fuzzy Logic in real-time, multi-object tracking scenarios?

1.4 Objectives

- To design and implement a Fuzzy Logic based T2TA algorithm.
- To compare the performance of Fuzzy Logic with CEP in track association scenarios.
- To analyze the impact of track parameters on algorithm effectiveness.

- To identify potential real-world applications and constraints of Fuzzy Logic in multi object tracking.

1.5 Scope of Study

This research focuses on the development and evaluation of a T2TA algorithm within the context of multi-object tracking in distributed sensor networks, specifically airborne radar systems. The study aims to address the challenges posed by redundant target reports in scenarios where multiple sensors operate within overlapping coverage areas.

Algorithm Development: The primary focus will be on the design and implementation of a fuzzy clustering-based T2TA algorithm. This algorithm will be evaluated for its effectiveness in correlating tracks from multiple sensors, minimizing redundancy, and enhancing the accuracy of target tracking.

Simulation and Testing: The proposed algorithm will be tested using simulated data to mimic real-world conditions. Various scenarios will be created to evaluate the algorithm's performance under different target and sensor configurations, including varying numbers of targets, sensors, and environmental conditions.

Performance Metrics: The study will utilize performance metrics such as accuracy, precision, recall, and processing time to assess the effectiveness of the T2TA algorithm. These metrics will provide insights into the algorithm's efficiency and robustness in practical applications.

Comparison with Existing Methods: The fuzzy clustering-based T2TA algorithm will be compared against traditional track association methods. This comparison will highlight the advantages and potential limitations of the proposed approach in handling track association in dynamic environments.

Application Context: While the research is rooted in airborne radar systems, the findings may also have implications for other domains that require multi-object tracking, such as robotics and autonomous vehicles, thereby broadening the applicability of the developed algorithm.By defining these boundaries, this research aims to contribute valuable insights and advancements in the field of multi-object tracking, ultimately enhancing the operational capabilities of sensor networks in surveillance and reconnaissance operations.

1.6 Contribution and Significance

This research contributes to the field of MTT in distributed sensor networks, specifically airborne radar systems, through the development of a novel fuzzy clustering-based T2TA algorithm. The contributions and significance of this study are outlined as follows:

Innovative Fuzzy Clustering T2TA Algorithm:

Provides a dynamic solution for track association, outperforming traditional fixed-threshold methods like CEP by adapting to variations in track parameters.

Improved Accuracy and Reduced Redundancy:

Reduces redundant reports in overlapping sensor networks, improving target tracking accuracy and situational awareness.

Comparative Analysis:

Offers insights through a detailed comparison of the fuzzy clustering algorithm with traditional methods, aiding future algorithm development.

Simulation Framework:

Establishes a realistic testing environment that can be used for evaluating diverse tracking algorithms.

Broad Application Potential:

Extends fuzzy clustering-based T2TA applications to other fields requiring multi-object tracking, including autonomous navigation and robotics.

Real-Time Fuzzy Logic Applications:

Demonstrates fuzzy logic's strengths in handling uncertainty in real-time defense scenarios.

The proposed T2TA algorithm enhances operational effectiveness in complex environments by improving target tracking accuracy and reliability, benefiting both defense and civilian applications in real-time, multi-object tracking contexts.

1.7 Organization of Thesis

Chapter 2 of this thesis provides a brief overview of the existing research in this field. It begins with an explanation of radar technology, followed by a discussion on how radars are used to track targets. This chapter also covers the different reference frames used in airborne target tracking and reviews the traditional track-to-track association and fuzzy track-to-track association algorithms discussed in the literature. Chapter 3 outlines the methodology used for data generation and the testing of our algorithm. Chapter 4 presents the results of our proposed algorithm across various sensor-target scenarios, along with the relevant discussion. Finally, Chapter 5 summarizes the conclusions of this research and explores potential future directions.

CHAPTER 2

LITERATURE REVIEW

2.1 Basics of Radar

Radar, which is short for Radio Detection and Ranging, is a crucial application of microwave technology. It is extensively utilized to obtain information about distant objects by sending electromagnetic signals towards them and analyzing the returning echoes. A significant feature of electromagnetic signals is their ability to pinpoint the location of objects. When these waves encounter a sudden change in the medium's conductivity, a portion of the energy is absorbed, while the rest is reflected or re-radiated. This reflected signal, known as an echo, is captured by a powerful antenna and analyzed to determine the object's position.

As noted by Skolnik and others, the first known effort to detect objects using electromagnetic radiation took place in 1904, when Christian Hülsmeyer, an engineer from Düsseldorf, used waves to bounce off a ship, leading to the patent of the telemobiloscope. In the 1920s, several researchers, including R. C. Newhouse, G. Breit, M. A. Tuve, G. Marconi, L. S. Alder, and likely many others in the United States and other nations, were obtaining patents and Scenarioing with radar technology. While these were among the earliest uses of radar, the term "radar" itself was not yet in use. The term was coined in 1940 by two U.S. Navy officers, Lieutenant Commanders Samuel M. Tucker and F. R. Furth, as an abbreviation for "RAdio Detection And Ranging." As with many other technological innovations, significant early advancements in radar occurred during World War II. Since that time, radar technology has advanced rapidly and continues to progress, with widespread applications in both commercial fields, such as airport, police, and weather radars, and military domains, including search and track radars.

Principle of Radar

A radar system comprises four primary components:

- **a.** Transmitter
- **b.** Antenna
- **c.** Receiver
- **d.** Display and Control Equipment

The transmitter generates an RF signal with sufficient power and directs it to the antenna. The antenna then emits this RF signal (or pulse) into space in a specific direction. As the signal travels, it encounters objects in its path, and part of the signal is reflected back. The antenna captures these reflected signals, referred to as received signals. Because these signals are usually very weak, they are amplified and then processed for detection. When an object or target is present, it creates an echo in the received signal, causing the detector's output to increase sharply. The time interval between the transmission of the signal and the reception of the echo is used to calculate the target's distance.

There are two primary types of radar systems: monostatic and bistatic. A monostatic radar system utilizes a single antenna for both transmission and reception. In a bistatic radar system, however, two separate antennas are used for these functions. figure 2.1 depicts both monostatic and bistatic radar systems.

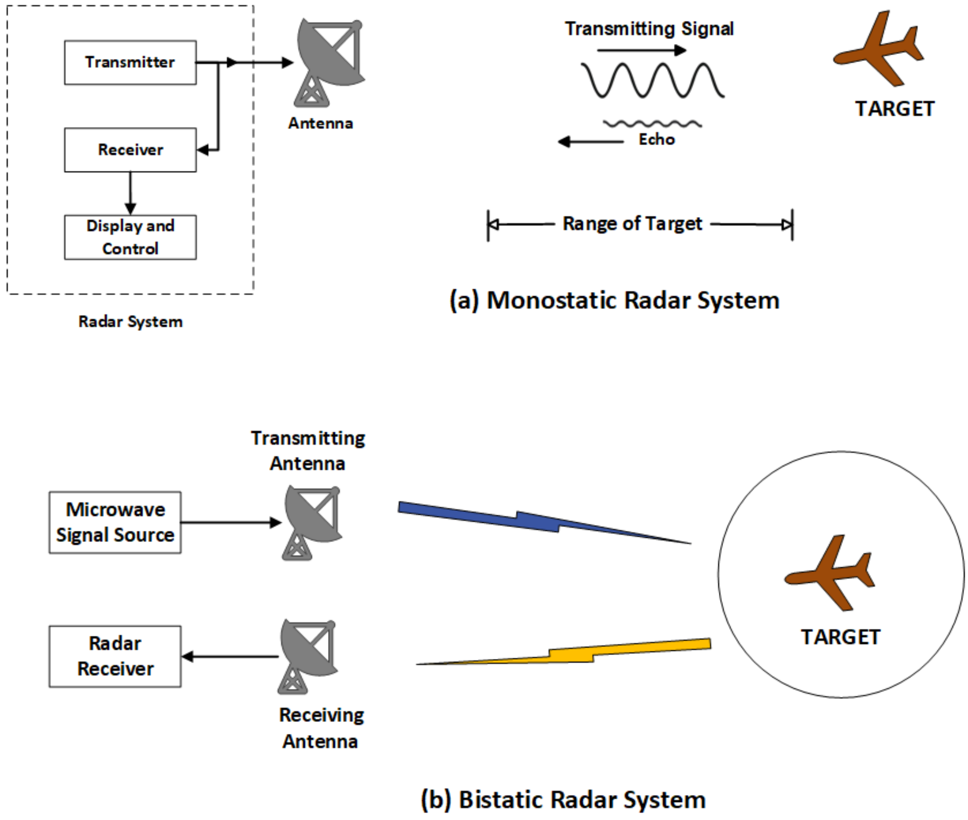

Figure 2.1: Illustrative Diagrams of (a) Monostatic Radar System and (b) Bistatic Radar System.

2.2 Radar Tracking

Tracking involves a radar to measure key data about a target to determine its path and forecast its future positions. Radars usually track targets by assessing range, azimuth angle, elevation angle, Doppler shift, or a combination of these parameters. Although many radars can function as tracking radars if the data is processed correctly, a dedicated tracking radar is specifically designed for angle tracking. Tracking radars can be classified into various categories based on the tracking methods they use. There are at least four different radar techniques for tracking targets, which are outlined below.

2.2.1 Single-Target Tracker (STT)

A single-target tracker continuously monitors one target at a high data rate, with military tracking radars typically observing ten targets per second. It employs a closed-loop servo system to track both range and angle, ensuring the radar remains aligned with a moving target. Monopulse trackers are highly accurate and resistant to countermeasures, which is why they are favored for military air defense systems using STT. In a monopulse radar, angle measurements are made using two slightly angled beams. The radar transmits using the combined signal of these beams and receives signals from both the sum and difference of the two beams. The angle measurement comes from the difference pattern, while the sum pattern is used for detection and range measurement. The sum pattern also provides a reference for detecting angle errors. To measure angles in two dimensions, four slightly angled antenna beams are required. A monopulse tracker generally includes three receiving channels: one for range and two for angle.

2.2.2 Multi Object Tracking (MOT)

MOT refers to the task of detecting, identifying, and continuously tracking multiple objects in a sequence of images or video frames. The process begins with object detection, where algorithms identify the presence and location of objects in each frame. The challenge then shifts to associating these detected objects across frames, ensuring that each one retains a consistent identity over time. This becomes complex in real-world scenarios, where objects may move unpredictably, occlude each other, or change appearance due to variations in lighting or perspective. To handle these challenges, MOT employs various techniques such as Kalman filtering for predicting object positions, data association algorithms like Joint Probabilistic Data Association (JPDA) for matching detections to tracked objects, and Multiple Hypothesis Tracking (MHT) for handling uncertainties in associations. T2TA is used to combine information from multiple sources or sensors to improve tracking accuracy. MOT is critical in fields like autonomous driving, where it's essential to track pedestrians and vehicles, video surveillance, and sports analytics, where players or objects like balls are tracked in real-time for performance evaluation.

In computer vision, the proposed fuzzy T2TA framework enhances real-time tracking accuracy, making it valuable for applications that require reliable identification and tracking of multiple objects in complex environments. For self-driving cars, the framework can improve sensor fusion, enabling autonomous systems to better track pedestrians, vehicles, and obstacles, leading to safer navigation in dynamic environments. In sea, air, and surface surveillance, the methodology strengthens the ability to monitor multiple targets across different terrains and conditions, making it ideal for defense and border security operations. Lastly, in missile defense, the advanced T2TA techniques help in accurately tracking high-speed, unpredictable targets like missiles, enabling more effective interception and response strategies.

A. Measurement To Track Association (Nearest Neighbor Algorithm)

The work [10] introduces a novel approach to similarity learning for MOT by focusing on dense sampling of object regions rather than relying solely on sparse ground truth matching. This method, termed Quasi-Dense Similarity Learning, samples hundreds of object regions between image pairs for contrastive learning, leading to a more robust feature space for object association. The authors of QDTrack integrate this similarity learning framework with several existing object detectors, eliminating the need for displacement regression or motion priors typically used in MOT systems. By relying on a nearest-neighbor search during inference for object association, the method significantly simplifies the tracking process. Furthermore, the method demonstrates versatility as it can effectively learn instance similarity from static images without the necessity of video training data or tracking supervision. Extensive Scenarios across various MOT benchmarks validate the effectiveness of QDTrack, with the method achieving state-of-the-art performance on the large-scale BDD100K MOT benchmark. The simplicity of the approach, combined with its minimal computational overhead, makes QDTrack a competitive alternative to more complex tracking systems. In response to the growing demands of autonomous driving, [11] introduces an enhanced visual detection network tailored for speed and accuracy. Building upon the CenterNet framework, CenterNet-Auto addresses key challenges in autonomous driving, particularly the need for real-time object detection. By leveraging a backbone based on the RepVGG model and structural re-parameterization technology, the network efficiently fuses multi-scale features and integrates feature pyramids alongside deformable convolution to improve detection across various object sizes. A notable innovation in CenterNet-Auto is the introduction of the Average Border Model, aimed at addressing occlusion problems commonly encountered in driving scenes. This model enhances object localization by utilizing boundary feature information. When tested on the BDD dataset, CenterNet-Auto demonstrates a significant improvement over its predecessor, achieving 55.6% accuracy while maintaining a speed of 30 FPS, thereby satisfying the rigorous performance requirements for real-time autonomous driving scenarios. The development of 3D object tracking is critical in enhancing the performance of autonomous driving systems. In this context, [12] introduces a Point-Track-Transformer (PTT) module, addressing the challenges posed by sparse or occluded point clouds at long distances. Current LiDAR-based 3D single object tracking methods often struggle with ambiguous feature extraction due to these limitations, resulting in poor tracking performance. To mitigate this, the PTT module applies the powerful Transformer architecture, generating attention-based features to guide the tracker toward crucial target information. This method significantly improves tracking ability in complex scenarios. By embedding PTT into a novel 3D single object tracking network, PTT-Net, the authors demonstrate the benefits of modeling interactions among point patches in the voting stage and capturing contextual information between objects and backgrounds in the proposal generation stage. Evaluated on the KITTI and NuScenes datasets, PTT-Net shows a substantial performance boost over the baseline, particularly in the Car category with an improvement of approximately 10%. Additionally, the model excels in sparse scenarios, operating in real-time at 40 FPS on an NVIDIA 1080Ti GPU. These advancements, coupled with the open-source code availability, underscore the potential of transformer-based methods in pushing the boundaries of 3D object tracking for robotics and autonomous vehicles.

The integration of 3D LiDAR technology in autonomous vehicle systems has been pivotal in improving object detection and tracking accuracy. The paper [13] addresses the specific challenge of vehicle detection by proposing a novel clustering algorithm that extracts vehicle candidates from preprocessed LiDAR point cloud data. The use of a Support Vector Machine (SVM) classifier then refines the vehicle detection process, ensuring robust identification of targets from the clustered data. In the tracking phase, the Kalman filter is employed alongside the Global Nearest Neighbor (GNN) algorithm to track vehicles. Notably, the tracking results further enhance detection accuracy, highlighting the importance of integrating detection and tracking steps in a feedback loop. The proposed method was validated through a testing platform, demonstrating its efficacy in real-world autonomous vehicle applications. This study illustrates the effectiveness of combining machine learning techniques like SVM with classical tracking algorithms, such as Kalman filters, in real-time vehicle detection and tracking, providing valuable insights into enhancing LiDAR-based autonomous systems. Small object detection is crucial in many real-time applications like autonomous driving and navigation, where traditional object detection techniques often fail to deliver satisfactory performance. The paper [14] proposes an innovative approach specifically targeting this challenge. The authors introduce a specialized network called SODNet, which integrates advanced feature extraction and information fusion techniques to detect small objects effectively. The core of the approach is the Adaptive Spatial Parallel Convolution module (ASPConv), which enhances spatial information acquisition by employing multi-scale receptive fields. This adaptation allows for better feature extraction for small objects, addressing a common limitation in existing deep learning methods. Additionally, a split-fusion sub-module (SF) is integrated to reduce the computational complexity of ASPConv, ensuring that the network maintains real-time processing capabilities. To further enhance detection accuracy, a Fast Multi-scale Fusion module (FMF) is employed, combining semantic and spatial information through fast upsampling operators. This approach improves small object detection performance by fusing feature maps of varying resolutions, while maintaining computational efficiency. Comparative Scenarios demonstrate the effectiveness of this method, showing significant improvements in both accuracy and speed on multiple benchmark datasets. This research provides valuable insights into enhancing small object detection in time-critical applications, offering a balanced solution between detection accuracy and real-time performance. With the increasing deployment of radar across diverse applications, accurate target classification has become a critical necessity. The paper [15] provides an in-depth review of radar micro-Doppler signature analysis and its role in target recognition. Micro-Doppler signatures are particularly useful for recognizing targets that exhibit micro-motions, such as walking humans or rotating parts of vehicles, making them valuable for applications in both defense and commercial sectors. The review systematically examines the evolution of micro-Doppler-based target classification techniques, discussing various feature extraction methods and classification approaches employed in radar systems. As radar technology continues to advance, the increased sensitivity to physically smaller targets with lower velocities or radar cross-section thresholds has led to a rise in misinterpreted signals, emphasizing the importance of reliable classification techniques. Furthermore, the paper discusses the limitations and challenges of current micro-Doppler-based methods, including their susceptibility to environmental factors and sensor noise. It also identifies future research directions, such as improving the robustness of classification algorithms and expanding the application of micro-Doppler analysis to new areas. This review provides a foundational understanding of micro-Doppler-based radar classification, making it a significant contribution to the development of radar-based target recognition systems.

In the ever-expanding domain of Machine Learning (ML), a range of algorithms is employed to tackle diverse predictive and analytical challenges. The paper [16] provides a comprehensive examination of five widely used ML algorithms-K-Nearest Neighbor (KNN), Genetic Algorithm (GA), SVM, Decision Tree (DT), and Long Short-Term Memory (LSTM). This analysis is particularly relevant to applications requiring robust classification and prediction models, as the paper compares both the performance and the origins of these algorithms. It reveals that, in many real-world tasks, LSTM and SVM exhibit superior accuracy, reliability, and adaptability, particularly in complex scenarios like time series forecasting and high-dimensional data classification. By quantitatively and qualitatively reviewing recently published studies, the authors demonstrate the strengths and weaknesses of each algorithm. For example, LSTM networks are highlighted for their exceptional performance in handling sequential data, such as in time-series analysis or natural language processing, while SVM is noted for its robustness in classification tasks with clear decision boundaries. On the other hand, KNN and DT are simpler and easier to implement, but their performance is often sensitive to noisy data and high-dimensionality. The Genetic Algorithm is recognized for optimization tasks, yet it may not always perform as well in predictive tasks compared to SVM or LSTM. This comparative study sheds light on the trade-offs between accuracy, computational complexity, and the specific nature of each algorithm's application. Additionally, the authors forecast the future of machine learning, emphasizing the growing role of automation and AI not only in technology but also in societal and humanitarian domains. The findings from this analysis guide the selection of appropriate algorithms depending on the problem context, ensuring optimized performance for predictive tasks. The problem of data association is central to MOT, particularly in cluttered environments where distinguishing between targets and irrelevant measurements is challenging. The study [17] investigates how different DA methods, specifically PDA, JPDA, and the Loopy Sum-Product Algorithm (LSPA), perform in complex environments. Each method varies in terms of its approach to assigning measurements to targets, which directly impacts both tracking accuracy and computational efficiency. This study focuses on enhancing the well-known LSPA by integrating a distance-weighting probabilistic data association (DWPDA) approach, which had previously shown promise when used with PDA by improving accuracy without significantly increasing computational complexity. However, contrary to expectations, when this distance-weighting method was combined with LSPA, it did not improve either tracking accuracy or computation time. Despite this outcome, the paper highlights the ongoing challenge of balancing accuracy and computational cost in multi-target tracking within clutter, a crucial consideration for real-time applications like radar-based object tracking. The significance of this research lies in its evaluation of DA methods in a cluttered tracking environment—a context that is highly relevant to radar and sensor fusion systems. LSPA, for instance, offers an advantage in terms of accuracy over PDA and outperforms JPDA in terms of speed, making it a viable candidate for MOT in real-time systems. However, the findings also underscore the limitations of modifying established algorithms such as LSPA, reinforcing the need for further innovation in DA methods to address the computational demands of complex tracking scenarios. In the context of autonomous driving, multi-object detection and tracking are critical challenges due to the complexity and unpredictability of real-world driving environments. The review paper [18] addresses this challenge by focusing on the integration of multiple sensor modalities—such as cameras, LiDAR, radar, and ultrasonic sensors—with Deep Neural Networks (DNNs). The fusion of sensor data using DNNs is highlighted as a promising approach to improving the perception system of autonomous vehicles, especially in scenarios where a single sensor may fail to provide sufficient information. The review evaluates state-of-the-art techniques involving the three primary sensors: camera, LiDAR, and radar, in combination with DNNs for MOT. It emphasizes the importance of sensor fusion to achieve a more comprehensive understanding of the driving environment, ultimately enhancing detection and tracking performance. The integration of DNNs allows for more sophisticated object detection and tracking algorithms that can handle the diverse and dynamic conditions encountered in autonomous driving. Furthermore, the paper proposes a new perception model for autonomous vehicles, built on the fusion of multiple sensing modalities with DNNs. This model is designed to overcome the limitations of individual sensor systems and to optimize performance in terms of accuracy, reliability, and real-time processing capabilities. The study concludes that while significant advancements have been made, there remains substantial room for optimization in sensor fusion techniques, particularly in improving the overall system's robustness and efficiency. This paper's focus on sensor fusion and DNN-based methods is particularly relevant for addressing the challenges of real-time multi-object detection and tracking in autonomous systems, making it an important contribution to the field of autonomous vehicle technology.

Multi-drone multi-target tracking presents unique challenges that single-drone systems struggle to overcome, particularly in situations where target occlusion or identity association across multiple views becomes problematic. The paper [18] addresses these challenges by leveraging multiple drones for enhanced tracking. It introduces the MDMT dataset, specifically designed to evaluate occlusion-aware multi-drone tracking performance. With 88 video sequences and over 2.2 million bounding boxes, including more than 543,000 occlusion-labeled instances, this dataset provides a comprehensive benchmark for testing tracking algorithms in occlusion-heavy environments. The authors propose a novel solution to the occlusion problem through the Multi-matching Identity Authentication network (MIA-Net). MIA-Net utilizes a local-global matching algorithm to resolve identity association challenges across drones, enabling robust multi-view target tracking. By efficiently mapping occluded targets using multiple drone perspectives, MIA-Net significantly improves tracking performance in scenarios where occlusions obscure critical tracking information. To measure performance, the study introduces a new evaluation metric called the Multi-device Target Association score (MDA), which assesses the cross-view target association capabilities of tracking algorithms. Extensive Scenarios demonstrate that MIA-Net, in combination with the MDMT dataset, offers significant advancements in identity association and occlusion resolution in multi-drone tracking systems. This research provides valuable insights into how multi-drone systems can overcome the limitations of single-drone tracking, especially in cluttered or occlusion-prone environments, making it an important contribution to the field of collaborative autonomous systems and multi-object tracking. In the context of advanced driver assistance systems (ADAS) and autonomous driving (AD), efficient MOT is essential for accurate perception and decision-making. The paper [19] explores the capabilities of the GNN filter, highlighting its foundational role in Bayesian tracking frameworks within the automotive industry. The study emphasizes the evolution of random finite set (RFS) theory, which offers a rigorous mathematical framework for tackling the MOT problem. The authors present a systematic comparative analysis between traditional random vector-based Bayesian filters, which often rely on rule-based heuristic track maintenance, and RFS-based Bayesian filters. Through Scenarios on the nuScenes validation dataset, the research reveals that RFS-based tracking can outperform conventional methods, addressing the persistent challenge of effective MOT in real-world applications. A key contribution of this work is the introduction of the Poisson multi-Bernoulli filter using the global nearest neighbor (GNN-PMB) specifically for LiDAR-based MOT tasks. The GNN-PMB tracker demonstrates remarkable simplicity and effectiveness, achieving competitive results on the nuScenes dataset. Notably, it ranks third among all LiDAR-only trackers on the nuScenes 3D tracking challenge leaderboard, showcasing its capability to deliver high-performance tracking without unnecessary complexity. This research underscores the potential of RFS-based methods in enhancing the robustness and accuracy of multi-object tracking in autonomous systems, offering a promising direction for future developments in the field. Accurate target localization in indoor environments poses significant challenges due to the inherent fluctuations in received signal strength (RSS) measurements. The paper [20] addresses these challenges by proposing two innovative range-free algorithms that leverage RSS measurements for mobile target localization. The authors highlight the limitations of traditional trilateration methods, which often produce inaccurate location estimates in wireless sensor networks (WSNs). The proposed localization schemes, utilizing support vector regression (SVR) and an enhanced SVR combined with a KF, allow for direct estimation of target locations from field measurements, circumventing the need for distance calculations. This is particularly advantageous in dynamic environments where conventional methods struggle. Notably, the SVR-based approach requires only three RSS measurements to determine a mobile target's location, providing a significant improvement over existing localization techniques such as generalized regression neural networks (GRNN). Through rigorous simulations, the authors demonstrate the efficacy of the SVR-based algorithms in noisy radio frequency (RF) conditions and dynamic target movements. The results indicate that these methods achieve superior localization performance compared to both trilateration and GRNN-based systems. This research not only advances the state of indoor localization techniques but also emphasizes the potential of SVR in enhancing accuracy and robustness in challenging environments.

B. Hungarian Algorithm

Identity miss association in MOT remains a significant challenge, especially when objects are mistakenly associated with incorrect identities. The paper [21] tackles this issue by proposing an approach that emphasizes the use of multiple cues and a focus on mitigating identity confusion, referred to as "switchers." This novel methodology stems from two key motivations: (1) the necessity of using diverse cues from multiple sources to ensure robust tracking in complex environments where reliance on a single cue may be unreliable, and (2) the need for greater attention on switchers, which are critical in understanding potential identity issues. The proposed method combines cues not just from object appearance but also from tracklet surroundings and historical appearance features, offering a unified approach to mitigating identity confusion. Additionally, the tracking classifier learns strategies specific to switchers, allowing it to adapt to varying situations and effectively address identity misassociation. The extensive Scenarios conducted by the authors demonstrate the efficacy of this approach in handling the identity-switching problem, with competitive results achieved across multiple MOT benchmarks. By incorporating multi-cue tracking and a switcher-aware classification system, this research advances the state-of-the-art in multi-object tracking, offering a promising direction for reducing identity mismatches in challenging tracking scenarios. Another significant development in multi-object tracking is presented in the paper [22] This work tackles a common limitation in traditional MOT methods where low-score detection boxes, such as those representing occluded or partially visible objects, are discarded. Such discarding leads to missed detections and fragmented trajectories, hindering the overall tracking performance. The authors propose a solution by associating nearly all detection boxes, including those with lower scores, rather than focusing solely on high-confidence detections. Their approach involves evaluating the similarities between these lower-score boxes and existing tracklets to distinguish true objects from background noise. By applying this method to several state-of-the-art trackers, the authors report consistent improvements in IDF1 scores, ranging from 1 to 10 points, indicating a significant reduction in identity fragmentation. In addition, the paper introduces ByteTrack, a high-performance tracker that leverages this association technique. The tracker achieves exceptional results on popular MOT benchmarks, including an 80.3 MOTA, 77.3 IDF1, and 63.1 HOTA on the MOT17 test set, all while maintaining real-time processing speeds of 30 FPS on a single GPU. ByteTrack also demonstrates state-of-the-art performance on other challenging datasets such as MOT20, HiEve, and BDD100K, making it a highly effective solution for both accuracy and efficiency in multi-object tracking. This method aligns well with the ongoing improvements in object association and trajectory maintenance in MOT, especially in scenarios with occlusions or fragmented detections, directly addressing key challenges in maintaining track consistency. In their paper [23] the authors offer an insightful analysis of 3D MOT, particularly within the widely adopted "tracking-by-detection" paradigm. The study highlights how, despite advancements in 3D MOT methods, an overarching analysis of their limitations has been lacking. The authors categorize the tracking pipeline into four key components: pre-processing of detection, association, motion modeling, and life cycle management. By analyzing failure cases across these components, they identify critical weaknesses in existing systems. To address these challenges, they propose Simple Track, a robust yet straightforward baseline framework that incorporates targeted improvements in each of the identified components. Simple Track is rigorously tested on the Waymo Open Dataset, achieving state-of-the-art results with only minor modifications to current techniques. This highlights its potential for enhanced performance without significant computational or structural overhauls. Additionally, the paper critiques the current MOT benchmarks, questioning whether they adequately reflect the real-world capabilities of these tracking systems. By probing deeper into the nuances of benchmark datasets, the authors reveal interesting findings about their distributions and failure cases. This evaluation leads to a discussion on how 3D MOT can continue to evolve by addressing real-world challenges, particularly those highlighted through their detailed analysis of Simple Track's performance.

In their paper [24] the authors focus on addressing the challenges associated with vehicle detection and tracking in intelligent transportation systems. They propose a hybrid approach that combines an enhanced version of YOLOv5s, a popular object detection model, with an optimized DeepSORT tracking algorithm to improve detection accuracy and real-time tracking of vehicles. Key innovations in the detection model include the introduction of the Attention-based Intra-scale Feature Interaction (AIFI) module, which enhances the model's ability to detect vehicles faster and more accurately. In the tracking phase, the KF algorithm of DeepSORT is optimized by using vehicle width rather than the length-to-width ratio to improve the accuracy of vehicle state predictions. Additionally, the re-identification network of DeepSORT incorporates an improved ResNet36 backbone for more effective feature extraction. Scenarioal results highlight the superiority of the proposed approach over the original algorithms. In particular, the authors report notable improvements in target detection metrics such as recall rate (7.7%), average accuracy (15.5%), and detection speed (14.2%). In terms of multi-object tracking performance, significant gains are made in multi-object tracking precision (MOTP) and accuracy (MOTA) by 14.84% and 9.62%, respectively, while the fragmentation rate of tracked trajectories is reduced by 32.52%. These findings demonstrate that the improved algorithm meets the demands for accurate, real-time vehicle detection and tracking in intelligent transportation systems. The use of infrastructure-based sensors, such as roadside LiDAR, is emerging as an important method to facilitate autonomous driving systems, especially as the industry approaches Level 5 autonomy. In the paper [25] the authors focus on reducing latency in vehicle detection and tracking without sacrificing accuracy. Their work proposes a hybrid system that employs LiDAR data for tracking vehicles and achieves low-latency processing (100 ms) through architectural optimizations. The vehicle detection architecture is built upon an improved ResNet18 model, which enhances the bird's eye view (BEV) mapping and refines the loss function to increase detection accuracy. The key innovation in the tracking algorithm involves an enhanced version of the Hungarian algorithm. This improvement better matches objects across consecutive frames by incorporating time-space logicality and trajectory similarity, effectively addressing short-term occlusion issues. The system's performance was tested using both the KITTI dataset and MATLAB/Simulink simulations, yielding highly competitive results. For vehicle detection, F1-scores reached 96.97% (KITTI) and 98.58% (MATLAB/Simulink), while multi-object tracking metrics such as MOTA and ID-F1 scored 88.12%/90.56% and 95.16%/96.43%, respectively. Additionally, the optimized computation speed is particularly notable, making the system well-suited for real-time applications in intelligent transportation systems. The integration of multiple sensing modalities, such as cameras and radar, has become increasingly important for enhancing MOT capabilities in autonomous vehicles (AVs). In the paper [26] the authors propose a Tracking-By-Detection (TBD) framework, CaRA-MOT, that leverages both camera and radar data for robust 3D-MOT. This integration addresses the challenges posed by variable environmental conditions, a key concern in the safe deployment of AV systems. A key feature of CaRA-MOT is its memory mechanism, which improves object re-identification (Re-ID) by incorporating object class match identification, spatial proximity, and velocity similarity. This memory-based approach enables more accurate tracking of objects across frames, particularly in scenarios where objects may become temporarily untracked or occluded. The system also employs a class-based score filter during preprocessing to optimize tracking across different object classes, enhancing overall robustness. The framework's performance is demonstrated on the nuScenes dataset, achieving notable results such as an AMOTA score of 58.3%, an AMOTP of 0.875m, and 336 IDS (Identity Switches). These metrics underscore the system's ability to reduce identity switches and maintain high tracking accuracy, setting a new benchmark in 3D multi-object tracking.

In the field of 3D MOT, handling occlusion and distinguishing between similar objects are critical challenges that degrade tracking performance, particularly in complex scenes. The paper [27] introduces a novel approach to address these challenges by employing a 3D-specific distance-based Intersection over Union (IoU) method, called 3D-DIoU, to improve tracking robustness and speed. The proposed method manipulates the speed and position of objects from previous frames to estimate the likely location of occluded objects, enhancing the ability to track objects through challenging environments where visibility is temporarily lost. This method integrates a distance IoU non-maximum suppression (DIoU-NMS) process to accurately detect objects in 3D space and subsequently uses 3D-DIoU for data association, ensuring better alignment of predicted and detected objects across frames. By adopting this hybrid approach of DIoU-NMS and 3D-DIoU for object association, the tracking speed and accuracy are significantly improved. Scenarioal results on widely-used benchmarks, such as the Waymo Open Dataset and nuScenes dataset, demonstrate that the proposed method outperforms existing 3D MOT approaches in terms of tracking accuracy and robustness, particularly under occlusion conditions. This work emphasizes the potential of 3D-specific methods in enhancing object tracking performance in point cloud data. Graph-based methods have become increasingly popular in 3D MOT due to their flexibility in representing dynamic interactions between objects across multiple frames. The paper [28] addresses the challenges of manually designing heuristics and handcrafted features for data association, which can often lead to suboptimal performance. Instead, the authors propose a unified, learning-based approach that leverages a graph structure for joint processing of detection and track states. Their method introduces a Neural Message Passing network for data association, which is fully trainable and processes detections in an online manner. This graph-based structure naturally facilitates track initialization and addresses challenges like false positive detections, improving overall track stability. The learnable nature of this approach eliminates the need for manual feature design, making it more adaptable to complex environments. The paper demonstrates the efficacy of this approach by achieving a state-of-the-art performance of 65.6% AMOTA with 58% fewer ID-switches in the nuScenes tracking challenge 2021. This was the best-performing LiDAR-only submission and secured second place overall. This work highlights the potential of graph-based and neural network models in improving tracking stability and reducing identity switches in 3D MOT. In sports analytics, particularly for football game analysis, MOT is crucial for player tracking and performance evaluation. The paper [29] addresses the challenges posed by tracking players in video footage captured from one side of the field. Key obstacles include frequent player occlusions, varying player sizes due to perspective changes, inconsistent lighting, and the difficulty of distinguishing between players of the same team based on appearance alone. The authors adopt the widely-used tracking-by-detection paradigm, where an object detector is applied to each frame, and a tracker associates these detections to generate player trajectories. Two types of detectors are compared: a classical object detector that relies on background modeling, and a deep learning-based detector, which provides a more robust solution in complex, dynamic environments such as football fields. This approach highlights the importance of combining detection algorithms with effective tracking models, particularly in situations where visual obstructions and similar appearances of objects (in this case, players) can significantly challenge tracking accuracy. The use of both traditional and deep learning-based methods for detection underscores the ongoing evolution of MOT techniques in handling real-world sports data.

Tracking algorithms often grapple with the challenges of unreliable detections and identity switches in MOT. In [30], the authors tackle these challenges by proposing a tracking-by-detection approach called BoostTrack. This method introduces several lightweight, plug-and-play enhancements that can significantly boost MOT performance, especially in real-time settings. A key innovation in BoostTrack is its detection-tracklet confidence score, which is used to scale the similarity measure between detections and tracklets, implicitly favoring high-confidence associations. The authors also move beyond the conventional Intersection over Union (IoU) metric, incorporating Mahalanobis distance and shape similarity to improve the accuracy of matching tracklets with detections. Additionally, to address the problem of low-detection score bounding boxes, BoostTrack introduces a confidence-boosting mechanism that targets both existing tracked objects and previously undetected ones. These additions are orthogonal to other existing approaches, making BoostTrack compatible with various MOT methods. BoostTrack's real-time execution speed, combined with these innovations, allows it to outperform standard benchmark solutions in the HOTA metric, particularly on the challenging MOT17 and MOT20 datasets. The method ranks first among online methods, underscoring its effectiveness in reducing identity switches and improving overall tracking accuracy, even in complex, cluttered environments. Efficient vehicle tracking and counting at traffic intersections present unique challenges, particularly concerning real-time performance and common MOT issues such as target occlusion and detection errors. In [31], the authors propose a novel shallow feature fusion algorithm based on the SORT framework, termed SFFSORT, designed to enhance vehicle detection and tracking capabilities. This method seeks to bridge the gap between computational efficiency and accuracy, addressing the resource-intensive nature of joint detection and tracking frameworks. SFFSORT improves upon traditional methods by utilizing shallow feature fusion, resulting in a more efficient algorithm that outperforms both SORT and DeepSORT. The Scenarioal results indicate a MOTA of 60.9% and an IDF1 score of 65.5% on the MOT16 dataset, along with 60.1% MOTA and 64.7% IDF1 on MOT17. Furthermore, the authors leverage this tracking algorithm to develop a comprehensive vehicle counting framework that operates effectively with road traffic videos from the Malaysian transportation department. The SFFSORT approach successfully addresses tracking challenges related to detection inaccuracies, demonstrating its robustness in real-world applications. Notably, the framework is capable of achieving lane-level vehicle counting even in scenarios with limited labeled data, highlighting its potential for deployment in traffic monitoring systems.

C. Probabilistic Data Association (PDA)

In the realm of computer vision, particularly within video surveillance and traffic monitoring, advancements in visual object tracking have garnered significant attention. The survey [32] provides a comprehensive examination of contemporary data association methods within MOT frameworks. The authors focus on the critical task of data association through uniquely defined similarity functions and filters, which are essential for effectively linking detected objects across frames. This survey emphasizes the Tracking-By-Detection approach, which extends beyond mere object detection and identification to address the challenges of filtering and association. By categorizing various data association techniques ranging from legacy probabilistic and hierarchical methods to newer hybrid models the paper elucidates the performance metrics such as stability, accuracy, robustness, speed, and computational complexity. The qualitative analysis of these models aims to highlight their strengths and identify areas needing improvement, providing a valuable resource for researchers looking to advance the field. The review acknowledges the inherent difficulties in quantitatively assessing data association results independently within proposed MOT frameworks. Nonetheless, it systematically outlines fundamental ideas and comparisons among various techniques used to enhance performance in vehicle and pedestrian tracking scenarios. This work not only identifies successful models but also pinpoints weaknesses, offering insights for future research directions in data association strategies.

Recent advancements in MOT have emphasized the significance of effectively managing occlusions and enhancing data association techniques. The paper [33] introduces a novel method that addresses these challenges by improving object detection and data association in single views, while also fusing data from multiple views using the Ordered Weighted Aggregation (OWA) algorithm. This work leverages a deep learning model, specifically Mask R-CNN, to achieve more accurate object detection within a tracking-by-detection framework. The authors enhance data association and trajectory estimation by combining various similarity metrics alongside the innovative probability density-based OWA (PD-OWA) approach. To match inter-frame detected objects, they utilize the Kernel Density Estimation (KDE) to assign weight coefficients to each camera view, effectively determining the significance of data from each perspective. The Scenarioal results demonstrate that this multi-view data fusion strategy not only improves object detection accuracy but also enhances tracking performance, achieving MOTA scores of 81.6% and 79.6%

on the "PETS09-S2L1" and "EPFL Terrace" video sequences, respectively. This study underscores the potential of integrating multiple camera perspectives and sophisticated aggregation techniques in overcoming the challenges posed by occlusions in complex tracking scenarios. In the context of multi-target tracking, especially in cluttered environments, the challenges of accurately associating measurements with targets are significant. The paper [34] addresses these challenges by focusing on the optimization of the JPDA model within a multi-static radar system framework. This study highlights the computational burdens faced by existing multi-target tracking algorithms, which often require exhaustive joint measurement-to-track assignments, leading to inefficiencies. To overcome these issues, the authors explore heuristic algorithms, specifically PSO and Grey Wolf Optimization (GWO), to optimize the JPDA model. By employing these nature-inspired algorithms, the study aims to enhance the performance of target tracking in scenarios where measurement paths and origins introduce uncertainty. The primary objective of the proposed model is to minimize the Mean Absolute Error (MAE) between the estimated trajectory of the tracks and the true target states. By tuning the position and velocity of the trackers towards the targets using these heuristic approaches, the paper demonstrates promising results in improving tracking accuracy in cluttered environments, showcasing the potential for heuristic methods to effectively address the complexities inherent in multi-target tracking systems. In scenarios involving dense group targets, effective data association presents significant challenges due to mutual occlusion and interference among the targets. The paper [35] addresses these complexities by proposing a novel algorithm that adapts the track-before-detect (TBD) paradigm for low-observable environments. The authors highlight that traditional multi-target TBD algorithms often assume spatial separation among targets, rendering them inadequate for group target scenarios where mutual interference is prevalent. To overcome this limitation, they introduce a Group Target Maximum-Likelihood Probabilistic Data Association (GT-ML-PDA) algorithm. This innovative approach divides the tracking process into two stages: first, estimating the trajectory of the group center, followed by individual target trajectory estimation. To further enhance the algorithm's performance, the study proposes two strategic modifications: adjusting the equivalent measurements and extracting independent measurement sets for each target. Simulation results demonstrate the efficacy of the GT-ML-PDA algorithm, showing its ability to accurately track multiple individual targets within a group, even amidst significant clutter. This work emphasizes the importance of adapting tracking methodologies to complex environments, thereby contributing valuable insights into the ongoing challenges of multi-target tracking in real-world applications.

The challenges of localization in cooperative UAV swarms are crucial, particularly when addressing data association ambiguities arising from homogeneous visual appearances. The paper [36] tackles these issues by introducing a robust localization system that leverages PDA for vision-based measurements. In this work, the authors design a cooperative localization framework wherein each UAV shares its information with others, facilitating robust localization for UAVs lacking Global Navigation Satellite System (GNSS) support. They take into account the impact of position uncertainty from assisting UAVs on the overall localization performance, which is a significant consideration in swarm operations. To address data association challenges specifically related to visual measurements, the authors employ a modified directional joint PDA (MDJPDA) algorithm. This innovative approach incorporates a directional weighting factor, effectively reducing localization errors that can occur due to variations in the observation angle. Simulation and Scenarioal results presented in the paper demonstrate that the proposed algorithm significantly outperforms existing methods, such as the EKF, the modified PDA (MPDA), and the modified joint PDA (MJPDA) algorithms, in terms of both localization accuracy and robustness. This study contributes valuable insights into enhancing localization strategies in UAV swarms, highlighting the effectiveness of cooperative approaches in addressing data association ambiguities. In the realm of multi-spacecraft operations, effective tracking and data association are essential for mission success. The paper [37] introduces a novel method that enhances data association through a systematic approach to orbit uncertainty propagation. The proposed framework comprises three critical components: uncertainty propagation, data association, and orbit estimation. By leveraging dynamic information, this method significantly improves data association performance. The authors derive second-order solutions for state and measurement prediction, which serve as the foundation for optimal association. To address computational efficiency, the optimal association problem is solved using a contract network algorithm, streamlining the process while maintaining accuracy. Additionally, the method incorporates a second-order EKF for precise orbit estimation of each spacecraft. Simulations conducted within the study demonstrate the method's effectiveness in tracking four spacecraft simultaneously, achieving close to

100% data association precision. This research highlights the proposed method's efficiency and effectiveness, providing a robust solution to the challenges faced in multi-spacecraft tracking scenarios. In the domain of intelligent driving, multitarget tracking is critical for ensuring safety and efficiency. The paper [38] addresses the challenges posed by complex multitarget maneuvers, measurement outliers, and unknown environmental parameters that adversely affect tracking accuracy. The authors introduce the Multiconstrained Generalized Probabilistic Data Association Filtering (MCGPDAF) algorithm, which utilizes target position and heading information to construct constraint parameters. This approach calculates the association probability between effective measurement combinations and target tracks, effectively mitigating measurement association anomalies and prior information errors. The robustness of this algorithm facilitates accurate tracking of multitarget states under challenging conditions. Furthermore, the study presents a multitarget tracking method based on composite perception fusion, employing correlation sequential track association and covariance cross fusion algorithms. This combination enhances the association and estimation of target states across multiple sensors, thereby improving tracking accuracy. Simulation and real vehicle Scenario results indicate significant performance improvements: the MCGPDAF algorithm achieves reductions in root mean square error (RMSE) and mean absolute percentage error (MAPE) by an average of 23.97% and 24.35%, respectively. Additionally, the average improvements in MOTA and MOTP are 14.68% and 15.71%. When compared to single-sensor multitarget tracking, the composite perception fusion based on the MCGPDAF algorithm shows further enhancements in RMSE and MAPE by 26.43% and 27.15%, respectively, highlighting the practicality and effectiveness of this tracking method.

Addressing the challenges of target tracking in cluttered environments, the paper [39] proposes a novel approach that integrates probabilistic data association with a target existence assisted Bayesian detector (TE-BD). This method innovatively incorporates feedback from the predicted target position and the existence probability from the tracker to enhance detection and tracking efficiency. The core concept of the proposed method is to improve target detection while allowing the radar system to quickly terminate tracking when a target is no longer detected. The authors derive a prior information-assisted target detection model, outlining the general steps of the TE-BD scheme within the integrated probabilistic data association (IPDA) framework. Simulation results demonstrate the effectiveness of the IPDA-TE-BD approach compared to existing methodologies, showcasing significant improvements in cluttered scenarios. This contribution highlights the potential of feedback mechanisms in enhancing target tracking performance in complex environments, emphasizing the relevance of probabilistic data association techniques in modern tracking systems. In the realm of MTT, the paper [40] provides a comprehensive overview of data association techniques, which are crucial for effective tracking in complex and uncertain environments. The authors emphasize the significance of data association within MTT and its challenges, noting that it remains a persistent issue across various applications, including security, transportation, and military operations. This review presents a structured approach to understanding the evolution of data association methods over recent decades. It begins with an introduction to the fundamentals of MTT and outlines common data association algorithms. The authors then delve into detailed descriptions of several mainstream algorithms, highlighting their mechanisms and applications. Finally, the paper summarizes the discussed methods, providing a clear overview of their contributions to the field. This comprehensive examination of data association techniques serves as a valuable resource for researchers and practitioners seeking to enhance MTT systems, particularly in addressing the complexities and uncertainties inherent in real-world scenarios. The paper [41] addresses the challenges associated with tracking extended objects (EOs) that yield an unknown number of measurements at each time step. As advancements in sensor technology enable more detailed measurements, the task of correctly identifying the origins of these measurements becomes increasingly complex. To tackle this issue, the authors propose a novel message passing inference method that significantly reduces the computational burden of determining marginal association probabilities. Instead of exhaustively enumerating all possible measurement partitions or association hypotheses, the algorithm leverages an overcomplete representation of data association uncertainty, achieving linear complexity relative to the number of measurements and targets. Utilizing factor graph theory and the sum-product algorithm (SPA), this approach demonstrates effective performance when compared to traditional data association methods. The authors highlight the algorithm's potential to enhance tracking accuracy and efficiency in scenarios where extended objects are present, offering a robust solution to a common problem in the field. This innovative methodology provides valuable insights into improving data association for multi-object tracking, particularly in environments where the number of measurements can vary significantly.

D. Measure to Sensor Fusion (M2SF)

The paper [42] explores the integration of physical and virtual objects within the IoT ecosystem, which generates vast amounts of heterogeneous and sparse data from numerous wireless sensor devices. As IoT aims to enhance services through effective data utilization, data fusion emerges as a critical technique to minimize data size, optimize traffic volume, and extract significant information that can lead to improved IoT services. The authors highlight the necessity for interoperable technologies that facilitate the integration and division of validated data among diverse IoT devices. They propose a design framework that addresses the challenges associated with multi-sensor data fusion, particularly in autonomous systems enabled by IoT. The paper reviews traditional and advanced data fusion algorithms and presents two models: a single filter model and a multi-filter model. In their Scenarioal results, the authors demonstrate that the multi-filter model significantly reduces the error rate from 30% with the single filter method to 25% with the multi-filter approach, showcasing a notable enhancement in tracking accuracy. This study not only emphasizes the importance of effective data fusion in the IoT landscape but also provides valuable insights into improving object tracking through innovative data integration techniques. In [43] the authors address the growing demand for reliable perception systems in the autonomous and automotive industries by introducing a robust tracking framework that combines data from millimeter wave radar and monocular cameras. This innovative method aims to enhance localization accuracy through decision-level sensor fusion, capitalizing on the strengths of radar's depth perception and the camera's cross-range resolution. The framework employs a tri-Kalman filter setup to maintain tracking continuity, even in the event of single sensor failures. By utilizing intrinsic calibration parameters from the camera and sensor placement height, the system generates a bird's-eye view of the environment, facilitating the estimation of the 2-D positions of targets detected by the camera. The authors utilize the Hungarian algorithm for effective association of radar and camera measurements within each frame. The Scenarioal results demonstrate promising performance metrics, including high MOTA and MOTP, alongside significantly low missed detection rates. This approach holds potential for enhancing perception capabilities in both large-scale and small-scale autonomous systems, contributing to safer operational environments in robotics and autonomous driving applications. In the paper [44] the authors investigate the effectiveness of three widely used tracking algorithms such as EKF, UKF, and PF in the context of multi-sensor fusion for autonomous vehicles. As the demand for enhanced environmental perception and safety in autonomous driving increases, integrating data from advanced sensors like LiDAR and Radar becomes crucial. The study aims to determine which of these tracking algorithms performs best when processing data from multiple sensors in a highway scenario. The authors first preprocess point cloud data from each sensor and utilize bounding box representations to standardize obstacle data. They develop a flexible tracking system that allows for the dynamic switching between EKF, UKF, and PF algorithms. A key aspect of their approach involves the use of distinct state vector update matrices tailored for the specific characteristics of LiDAR and Radar data for both position and speed updates. By recording actual highway driving data and employing a Robotic Operating System (ROS) model for implementation and analysis, the authors provide a comprehensive evaluation of the algorithms' performances in real-world conditions. This research contributes valuable insights into optimizing tracking systems for autonomous vehicles through effective multi-sensor data fusion.

In the paper [45] the authors explore the use of millimeter-wave (mmWave) radar sensors for enhancing indoor object detection and tracking capabilities. This research is motivated by the growing applications in energy management, privacy, health, and safety. The focus is on expanding the valid field of view and improving accuracy through the integration of multiple sensors. The study employs two mmWave radar sensors, implementing a two-stage noise reduction process to minimize interference and effectively identify clustered object groups. A novel data fusion technique is introduced to align and synchronize data from the two sensors, enabling a comprehensive visualization of object information. To achieve high clustering accuracy, the authors propose a density-based clustering algorithm and utilize the UKF for tracking multiple objects concurrently, ensuring both precision and timeliness. An indoor object tracking system is developed based on these methods, and the effectiveness of the proposed approach is validated through comparisons with both an earlier system and a commercial solution. Scenarioal results highlight the advantages of the proposed method, particularly in addressing challenges related to occlusions and the detection of multiple weak data points, thereby improving the overall accuracy of object tracking. In the review [46] the authors examine the evolving landscape of tracking and sensing solutions, specifically focusing on the application of millimeter wave (mmWave) radar for simultaneous multi-object tracking and sensing. This paper critically analyzes the existing literature on short-range mmWave radar for multi-object scenarios. While significant progress has been made in single-object tracking systems, the authors highlight the need for innovative research in multi-object tracking, particularly regarding the identification of multiple target tracks in obstructed fields of view. The review defines a typical architecture for multi-object tracking and identifies key areas for further advancement, including sensor fusion, micro-Doppler feature analysis, activity recognition, and shape profiling. The review assesses various methodologies based on their adaptability, performance, accuracy, and specificity, noting that much of the existing research emphasizes human targets. However, many techniques can be extended to track objects with diverse profiles and characteristics. Finally, the paper discusses future research directions, outlining opportunities and potential approaches in this open research area. In the paper [47] the authors emphasize the importance of accurate orientation and position estimation in enhancing the performance of real-time object tracking using smartphone sensors, including accelerometers and gyroscopes. The study addresses common challenges such as GPS signal reliability, the canyon effect, orientation errors, and sensor accumulation errors. To overcome these limitations, the authors propose a novel smartphone application that utilizes IMU multi-sensor fusion through a Kalman filter and rotation vector. The integration of Kalman filtering allows for effective data fusion of sensor inputs, while the rotation vector aids in achieving precise orientation estimates. Additionally, geohash filtering is introduced to improve the quantification of complex spatial relationships and to visualize tracking paths on maps within the application. A thorough mathematical analysis is presented, along with a detailed comparison to existing algorithms in the field. The evaluation demonstrates that the proposed object tracking scheme exhibits significant advancements over state-of-the-art approaches, showcasing its efficacy in real-time applications.

The paper [48] presents a system designed to enhance the autonomous perception capabilities of quadruped robots, focusing on object detection and Simultaneous Localization And Mapping (SLAM). The authors aim to improve both target tracking and map construction, which are crucial for navigation in challenging environments. To achieve this, a hierarchical controller is implemented, integrating a proportional derivative control scheme with a model predictive control algorithm based on differential evolution. This controller is specifically tailored for effective navigation in complex terrains. The paper emphasizes the importance of data fusion from various sensors to enhance SLAM applications, resulting in precise map generation and accurate target tracking. Additionally, the dynamic window approach algorithm is employed to optimize the trajectory for target tracking, balancing traversability and localization. Extensive testing in a demanding simulation environment demonstrates that the proposed system significantly enhances target tracking and map construction capabilities for quadruped robots. The paper [49] provides a comprehensive survey of recent advancements in MOT within the field of autonomous robotics. The authors emphasize the need for reliable systems that can effectively detect and track multiple objects to enhance navigation and guidance capabilities. The study identifies key challenges faced in MOT, including heavy occlusion, dynamic backgrounds, and changes in illumination. It reviews various MOT methods that integrate data from sensors such as cameras and LIDAR. The paper outlines a general framework that encompasses data association techniques and occlusion handling strategies, contributing to a clearer understanding of the literature's approach to these challenges. Additionally, the authors present an overview of relevant metrics and benchmark datasets, such as the Karlsruhe Institute of Technology and Toyota Technological Institute (KITTI), MOTChallenges, and University at Albany DEtection and TRACking (UA-DETRAC), which are critical for training and evaluating MOT performance. The findings indicate that deep learning has significantly enhanced MOT techniques in recent research, achieving high accuracy while ensuring real-time processing capabilities. The paper [50] addresses the critical challenge of persistent MOT in dynamic environments, particularly focusing on object occlusion. Traditional MOT methods often rely on short-term memory for storing object information, which can lead to losing track of objects during extended occlusions. To overcome this limitation, the authors propose DFR-FastMOT, a lightweight tracking method that integrates data from both camera and LiDAR sensors. This method employs an algebraic formulation for object association and fusion, enabling long-term memory capabilities and improved handling of occlusion scenarios. The results demonstrate that DFR-FastMOT achieves significant tracking performance improvements over existing benchmarks, showing margins of approximately 3% and 4% in MOTA compared to recent learning-based and non-learning-based methods, respectively. Extensive Scenarios simulate occlusion effects with detectors at various distortion levels, showcasing superior performance of the proposed method under these conditions. Furthermore, the framework processes approximately 7,763 frames in just 1.48 seconds, making it seven times faster than recent benchmarks, highlighting its efficiency and effectiveness in real-time applications.

The paper [51] explores the significance of the Linear Kalman Filter (LKF) in the context of multi-sensor data fusion. The LKF is recognized for its recursive solution to the linear filtering problem, making it a powerful tool for estimating states in dynamic systems by effectively reducing measurement and process noise. The authors emphasize the applicability of the LKF in linear dynamic systems, detailing its assumptions regarding system dynamics, measurement noise, and initial conditions. The paper provides a comprehensive overview of the principles and mechanisms of the LKF, highlighting its critical role in integrating diverse sensor inputs to enhance the accuracy and reliability of state estimations. To demonstrate the practical utility of the LKF, two real-world examples are presented, showcasing how it significantly improves precision and stability in dynamic environments. These examples illustrate not only theoretical concepts but also practical implementation strategies for multi-sensor data fusion. The discussion emphasizes the LKF's relevance across various fields, including robotics, navigation, and signal processing. By merging theoretical insights with practical applications, the paper aims to enrich the understanding of multi-sensor data fusion and promote advancements in this area, encouraging broader adoption of data fusion technologies in scientific and industrial contexts.

E. Extended Kalman Filter (EKF)

The paper titled [52] focuses on the advantages of using mobile vehicles or UAV in surveillance and monitoring systems. These platforms enhance operational capabilities through improved range, maneuverability, and safety, allowing for autonomous exploration and security tasks. The study addresses the challenges posed by errors and uncertainties in data, which can hinder object recognition and resolution. To mitigate these issues, the authors propose a data sensor fusion system that integrates measurements from multiple sensors to enhance data accuracy. Specifically, the paper employs the constant turn and rate velocity (CTRV) kinematic model, incorporating angular velocity a factor overlooked in previous research. Utilizing both LiDAR and Radar data collected via UAVs, the authors apply the EKF to detect moving targets. The EKF's performance is assessed using a dataset featuring position data from both sensors, tracking an object with a trajectory that includes sudden changes. To evaluate the robustness of the EKF, additive white Gaussian noise is introduced to the data, and the results demonstrate a significant improvement in object detection accuracy, achieving a reduction in root mean square error (RMSE) by 0.4 compared to conventional kinematic models that do not account for rapid trajectory changes. The paper [53] addresses the critical role of data fusion technology in enhancing target detection, recognition, and tracking capabilities in modern sensor systems. It highlights the limitations of single sensors, which often provide imprecise information and may introduce ambiguity in environmental descriptions. To leverage the strengths of different sensors, the authors propose a multi-sensor fusion method utilizing the EKF. This approach capitalizes on the complementary information provided by various sensors, resulting in more accurate and reliable data than any single sensor could deliver. Scenarioal results presented in the paper demonstrate significant improvements in both the accuracy and robustness of target detection and tracking when integrating data from infrared and millimeter-wave radar sensors. This reinforces the effectiveness of the proposed EKF-based fusion method in real-world applications.

The paper [54] addresses the critical issue of accurate localization in mobile robots, particularly in the presence of sensor faults. It emphasizes the challenges that single-sensor localization faces, such as hardware and software issues or data outages. To mitigate these challenges, the authors propose a sensor fusion approach that employs two Inertial Measurement Units (IMUs) and wheel encoders for enhanced localization. The proposed method utilizes an Interacting Multiple Model (IMM) Kalman filter, integrating both UKF and EKF techniques. This is particularly relevant due to the highly nonlinear nature of the localization dynamic model. A significant contribution of this work is that it eliminates the need to model every possible fault scenario, allowing the use of an additional sensor solely for performance oversight. The authors conduct simulations to compare the performance of the proposed filters under various trajectories and intentionally corrupted sensor data. Results indicate that both UKF and EKF-based IMM filters achieve accurate 3D localization estimations, effectively demonstrating fault detection capabilities. The comparison of the two filters reveals insights regarding error rates and computational costs, showing that both methods enable reliable fault isolation.

Overall, the findings suggest that this approach provides a straightforward and effective solution for sensor fault detection and localization in mobile robots, enhancing their operational reliability in dynamic environments. The paper [55] presents a framework designed to enhance autonomous navigation and management in orchards by addressing the challenges of real-time positioning and mapping in unstructured environments. The authors propose a multi-sensor fusion approach that integrates LiDAR, visual, and inertial data using an EKF to achieve accurate localization and generate colorful 3D maps of orchard surroundings. The study outlines a loosely-coupled framework where pose estimation is enhanced through the integration of predictions from LiDAR and gyroscope data with observations from visual-inertial odometry. Additionally, the Loam Livox algorithm is improved by incorporating color information from images into the LiDAR point cloud, facilitating the real-time construction of a detailed and colorful 3D map of the orchard. Results demonstrate high localization accuracy across various motion trajectories and scenarios, with average Root Mean Square Errors (RMSE) of 0.3436 and 0.1230, respectively. The proposed method efficiently processes localization and mapping for a frame of LiDAR point cloud in just 75.01 milliseconds. These findings highlight the potential of this method for supporting autonomous navigation in agricultural vehicles, contributing significantly to the fields of precision agriculture and robotics. The paper [56] addresses the limitations of conventional GPS systems, which typically provide accuracy within 3-5 meters insufficient for the precision required in autonomous navigation. The authors propose a sensor fusion approach that combines data from LiDAR, IMU, and GPS, utilizing an Error-State EKF to enhance positional accuracy. Previous methods, such as IMU and GPS fusion using EKF, achieved an average error of 2.66 meters, but these systems remained dependent on GPS functionality. The proposed method aims to provide a cost-effective and reliable alternative to existing solutions, including Differential GPS, which is often prohibitively expensive. The system was evaluated using synthesized data from the Carla Simulator, demonstrating a significant improvement in accuracy. The proposed approach reduced position error by nearly 95%, indicating its potential for effective application in autonomous navigation systems. This advancement underscores the importance of multi-sensor fusion in enhancing positional accuracy while maintaining cost-effectiveness.

The paper [57] focuses on enhancing the robustness of indoor localization for multi-rotor UAVs through the fusion of visual and LiDAR SLAM methodologies using an EKF. The research addresses the varying pose errors encountered in different environmental conditions, such as lighting and reflective surfaces, by integrating data from both SLAM systems. In the Scenarios, a stereo camera and LiDAR sensor were mounted on the UAV to simultaneously execute both SLAM methods, generating position and orientation data. The EKF was employed to fuse this information, ensuring the system's resilience in the event of errors in either SLAM approach. Testing in diverse scenarios demonstrated that the EKF effectively maintained accurate localization, providing reliable outputs even when one SLAM method encountered challenges. The findings underscore the effectiveness of multi-sensor fusion in achieving robust indoor navigation for UAVs, highlighting the potential for enhanced operational reliability in complex environments. The article [58] introduces a novel dual neural extended Kalman filter (DNEKF) method designed to enhance multi-rate sensor fusion by addressing model inaccuracies and violations of noise assumptions inherent in traditional EKF-based approaches. The DNEKF leverages two neural networks for simultaneous state and parameter estimation, which allows for augmented state vector predictions. This approach improves the accuracy of process state and output predictions. The key innovation lies in a multi-rate parameter update strategy that capitalizes on frequent, less accurate measurements and infrequent, more accurate measurements. This enables the neural networks to adapt to different sensor update rates, improving performance over standard EKF methods. The paper validates the proposed DNEKF through two numerical examples and an industrial application, showcasing its ability to compensate for limited process knowledge and improve multi-rate sensor fusion performance in real-world scenarios. The paper [59] presents an improved approach to multi-sensor fusion localization for UAV. The proposed method aims to address the shortcomings of the standard EKF, particularly the large errors it can generate during UAV localization. The authors introduce an adaptive error correction EKF algorithm to enhance accuracy and robustness. The system integrates data from multiple sensors gyroscopes, accelerometers, magnetic sensors, and mileage sensors and optimizes the sensor fusion process by adjusting for errors between estimated and real values. The algorithm utilizes Taylor series linearization and the normal distribution hypothesis in the prediction and correction steps. Furthermore, genetic algorithms are employed to optimize the system and measurement noise covariance parameters in the EKF, thereby improving the filter's adaptability. Simulation results demonstrate that the proposed method achieves higher localization accuracy and robustness compared to the standard EKF, making it more suitable for real-time UAV applications.

The paper [60] introduces an advanced algorithm for improving the accuracy of ballistic target tracking by utilizing multi-sensor data fusion based on the Cubature Kalman Filter (CKF). The study begins by establishing a dynamic model for midcourse ballistic targets using force analysis in the Earth-Centered Inertial (ECI) frame. The model is subsequently transformed into the local East-North-Up (ENU) frame through coordinate transformation, which is critical for accurate real-time tracking. A centralized measurement model is then constructed by augmenting multi-sensor measurements in the ENU frame, with one sensor selected as the fusion center. Using the state-space and observation equations derived earlier, the CKF-based algorithm is designed to estimate the target's state in real time. The performance and accuracy of the proposed tracking algorithm are evaluated through Monte Carlo simulations. Simulation results demonstrate that the CKF-based fusion algorithm provides high precision and stable tracking performance, making it a robust solution for tracking maneuvering ballistic targets. The paper [61] presents an innovative approach to improve the state estimation accuracy in underwater vehicle localization by enhancing the traditional error-state Kalman filter (ESKF) with a radial basis function (RBF) neural network. The authors point out that conventional Kalman filters, including the EKF and ESKF, suffer from reduced estimation accuracy in highly nonlinear environments due to their reliance on first-order Taylor series approximations in the error covariance matrix. To overcome this limitation, the proposed algorithm augments ESKF with an RBF neural network, which helps in refining the innovation error term by optimizing the weights and centers of the network through a steepest descent approach that minimizes the mean square error (MSE). The performance of the RBF-augmented ESKF was rigorously tested and compared with conventional ESKF across three realistic underwater navigation scenarios using Monte Carlo simulations. The results demonstrate that the proposed method significantly enhances the accuracy of navigation and localization in underwater environments.

F. Particle Filter (PF)

The paper [62] explores a Joint Sensing and Communication (JSC) network framework where multiple base stations (BSs) collaborate through a fusion center (FC) to detect and track objects in a monitored area. Each BS functions as a monostatic sensor, simultaneously sensing the environment and communicating with user equipment (UEs). The core innovation in this study is the use of range-angle maps generated by each BS, which are then sent to the FC for fusion and tracking using PF and multi-hypothesis tracking (MHT) algorithms. The authors analyze the performance of these solutions by altering the allocation of power and time to sensing, thus addressing the trade-off between network overhead and sensing/communication efficiency. Results from numerical simulations, particularly in a vehicular context, show that the proposed algorithms can accurately track multiple targets, including pedestrians, with a RMSE of less than 50 cm when using three BSs.

The paper [63] addresses the challenges associated with tracking dim and small targets, which are crucial in navigation and surveillance applications. Traditional particle filters often struggle due to issues like poor feature representation and particle depletion during resampling, which degrade tracking performance. To overcome these limitations, the authors propose an improved particle filter algorithm that employs adaptive multi-feature fusion. This method integrates weighted grayscale intensity, edge information, and wavelet transform to build a robust observation model. Additionally, they enhance resampling by using residual resampling, combining target positions from the previous frame with high-weight particles from the current frame. This approach improves both tracking accuracy and particle diversity. Scenarioal results showcase the method's effectiveness, with a 77.2% tracking accuracy and a processing speed of 106 frames per second (fps), highlighting its potential for real-time applications in dim and small target tracking. The paper [64] focuses on improving UAV localization in indoor environments where traditional GNSS systems are ineffective. The authors propose a particle filter-based approach that fuses data from visual odometry cameras and fiducial marker detection to estimate the UAV's position. The method is designed to be lightweight, robust, and capable of running at high frequencies on the UAV's onboard computer. A key feature of the proposed system is its ability to handle sensor failures and disconnections without interrupting localization performance. Additionally, the system can be extended to integrate other sensor inputs, making it flexible for various applications. The method was validated through real-world UAV test flights, achieving an average position error of less than 0.4 meters, demonstrating its accuracy and reliability for industrial use. The paper [65] presents a hybrid Bayesian filter for fusing GNSS and visual odometry (VO) data, particularly for use in urban environments. This filter combines the tracking efficiency of the Kalman filter with the uncertainty modeling advantages of the particle filter, offering a robust fusion method for state estimation. By employing Rao-Blackwellization, the filter efficiently decouples the problem into two parts: a non-linear position tracking and a linear tracking for orientation, velocity, and carrier phase integer ambiguities. The decoupling approach not only enhances the filter's efficiency in tracking but also provides a rich probability distribution for the position, which helps quantify uncertainty in situations where the tracking data is unreliable. The system was evaluated on real-world GNSS and VO fusion data, demonstrating comparable computational efficiency and improved state and uncertainty estimates compared to other Bayesian filter approaches.

The paper [66] focuses on the enhancement of estimation algorithms by improving the quality of information obtained from raw sensor measurements. The goal is to achieve more accurate and reliable target motion parameter estimation by fusing data from five different sensors. This multi-sensor fusion approach is particularly aimed at passive target tracking in underwater environments. For performance evaluation, the paper adopts the UKF as the sub-optimal filtering technique, which is known for handling nonlinear systems more effectively than standard Kalman filters. The simulations were carried out using Monte-Carlo methods in MATLAB to thoroughly analyze and validate the algorithm's performance. The paper [67] introduces an algorithm aimed at improving the accuracy of MTT by addressing the lack of particle diversity in traditional PF. The authors propose an Improved Resampling Particle Filter (IRPF), which stratifies the adaptive regions of particles based on the influence of their likelihood probability distribution, and introduces a particle diversity measurement index to evaluate resampling performance. A threshold is set for particle diversity, and if it isn't met after resampling, the new particles undergo a Gaussian random walk to enhance their diversity. This approach is tested in both simulation and actual indoor ultrawideband (UWB) non-line-of-sight (NLOS) environments. The results show that the algorithm improves nonlinear target state estimation accuracy by up to 12.83% in simulation, and reduces root mean square error (RMSE) from 17.131 cm to 10.471 cm in real-world UWB NLOS environments. These results demonstrate the effectiveness of the IRPF algorithm in improving target estimation accuracy and state tracking performance. The paper [68] presents a novel algorithm designed to tackle the complexities of underwater multi-target tracking, which is crucial for military operations like patrol and combat in dense, challenging environments. Due to the complex underwater environment and the potential for target trajectory intersections, ensuring precise tracking can be difficult. To address this, the authors propose a Two-Layer Particle Filter with Distributed Probability Fusion (TLPF-DPF) algorithm, along with a dynamic network resource allocation mechanism. The proposed solution integrates a position estimation model based on geometric constraints and a dynamic allocation mechanism based on prior position estimates to optimize network resources. The TLPF-DPF algorithm, which leverages an improved filtering approach, successfully tracks multiple targets with trajectory intersections in small, noisy areas using known initial states. In simulations conducted in non-Gaussian environments, TLPF-DPF reduces average positioning error by nearly 30% compared to alternative algorithms. Moreover, its performance degradation when transitioning from Gaussian to non-Gaussian environments is less than 12%, demonstrating the algorithm's stability even when targets are in close proximity and have intersecting trajectories.

The paper [69] introduces an advanced object tracking system designed to enhance accuracy and computational efficiency in real-time applications. The system integrates adaptive resampling strategies with a feature fusion model in a particle filter architecture to create a comprehensive object representation by utilizing both color and edge descriptors. One of the key challenges addressed by the proposed solution is the issue of particle degeneracy and sample impoverishment common in particle filters. To mitigate this, a novel adaptive resampling technique is introduced, which dynamically adjusts the resampling process based on the effective sample size. This preserves particle diversity and reduces the computational load. The system also implements a masking mechanism to remove particles with insignificant contributions, improving the efficiency of the tracking process. The system's performance is evaluated through RMSE and computational time metrics, and compared to conventional particle filter methods. Results show significant improvements in tracking accuracy and efficiency, demonstrating the effectiveness of the proposed approach in varied real-time tracking scenarios. Future work includes exploring machine learning models to further enhance feature extraction and expanding the method to scenarios requiring multi-object tracking. The paper [70] presents an advanced algorithm tailored for tracking maneuvering weak radar targets in complex sea environments. The algorithm enhances the performance of interactive multiple model particle filtering (IMMPF) by combining it with a track-before-detect (TBD) approach. To minimize clutter interference, the radar echo images are first preprocessed using the fractional Fourier transform (FrFT). The feedback factor and residual resampling techniques are then incorporated to optimize the IMMPF algorithm, enhancing its ability to track maneuvering targets. The integration with the TBD algorithm allows for clutter suppression and target trajectory accumulation, further improving tracking efficiency. Simulation Scenarios show that the proposed method significantly outperforms other TBD algorithms in effectively tracking weak radar targets. The paper [71] delves into the fundamental issue of state estimation in multi-sensor fusion for navigation, which is critical for tasks like navigation, perception, and decision-making in intelligent robotic systems. The authors explore two primary methods for state estimation: optimization and filtering. Though optimization-based frameworks have been shown to outperform filtering-based methods in terms of accuracy, both methods are theoretically equivalent when based on maximum likelihood estimation (MLE) and under the same assumptions (e.g., Gaussian noise and equivalent linearization points). However, in practical real-time applications, the performance divergence arises due to the differing strategies employed in each approach. The study conducts Monte-Carlo simulations and vehicular ablation Scenarios using VO, showing that, when the strategies used in filtering are adjusted, filtering approaches can yield results equivalent to those of optimization frameworks. The paper suggests that future research on sensor fusion should focus more on improving the algorithms and strategies rather than on the overarching state estimation methods.

The paper [72] introduces a novel data fusion framework for predicting degradation in aerial bundled cables (ABCs). The framework integrates multi-sensor data from Non-Destructive Testing (NDT) methods, such as Ultrasonic Probe Listening and Thermal Imaging, to improve prognostics of cable degradation, particularly in coastal environments. Rather than using conventional methodologies that fuse sensor data before the prognosis step, the authors propose a unique post-prognosis data fusion technique that applies Particle Filtering (PF) in combination with the Auto-Regressive Integrated Moving Average (ARIMA) model. This approach allows for better prediction of cable degradation by leveraging the strengths of different sensors, which each capture partial information about the degradation process. The framework is tested on historical data, and the results show that the fused degradation predictions offer higher accuracy compared to predictions based on individual sensor data, demonstrating the effectiveness of this approach.

G. Track To Track Association (CEP/CAP Algorithm)

The study [73] addresses the issue of inaccurate positioning in intersection areas during firefighter localization, a problem often caused by poor sensor accuracy and random error measurements in Ultra-Wide Band (UWB) and Beidou Satellite Navigation System (BDS) technologies. To tackle this, the authors propose a fusion positioning algorithm based on the CEP method. This algorithm integrates Inertial Navigation System (INS) data to assist UWB in enhancing positioning accuracy by detecting and correcting non-line-of-sight errors. By utilizing the precision and real-time analysis of CEP, the algorithm optimizes weighting calculations for more accurate fusion of UWB and BDS positioning data. The key contributions of the study include improved UWB error detection and elimination of abnormal deviation data using INS initial positioning, optimization of the average method for real-time error correction, and achieving a 95% probability of improved accuracy in CEP and positioning calculations. Scenarioal results demonstrate that the proposed algorithm enhances positioning accuracy in intersection areas by 47.4% compared to traditional UWB/BDS weighted fusion algorithms. The paper [74] focuses on enhancing detection accuracy in multi-UAV formations using the bearing-only detection method, which is crucial in modern military scenarios where the geometric arrangement of UAV formations significantly impacts detection effectiveness. To improve this, the authors propose a Distributed Stochastic Subgradient Projection Algorithm (DSSPA) that optimizes UAV positioning under layered constraints. The system is designed for cooperative positioning within the formation, constrained by safe flight altitudes and fixed baselines, resulting in a layered UAV formation. The DSSPA algorithm integrates stochastic subgradient descent to manage objective functions that involve non-smooth and convex optimization elements, alongside projection operations to ensure that each parameter update adheres to the layered constraints, thus maintaining safe flight conditions and geometric accuracy. Through simulation Scenarios, the authors demonstrate the effectiveness and superiority of this distributed method for array planning in multi-UAV formations. The results underscore the algorithm's capability to tackle complex positioning tasks and enhance bearing-only detection accuracy in multi-UAV operations.

The paper [75] tackles the challenge of accurate indoor positioning, where the complex propagation of signals makes it difficult to track positions using traditional methods. The authors propose using a Stein Particle Filter (SPF) that leverages the Stein Variational Gradient Descent (SVGD) method to approximate the posterior distribution with particles, enabling efficient tracking in multipath environments. The innovation in this paper is the design of the Annealed Stein Particle Filter (A-SPF), which improves upon the standard SPF by incorporating annealed scheduling into SVGD. This allows A-SPF to better handle multi-modal distributions that often occur in indoor localization scenarios without requiring an increase in the number of particles. The effectiveness of A-SPF was tested in two indoor environments a machinery area and an office using Ultra Wide-Band (UWB) technology to collect data. The Scenarioal results showed that A-SPF outperformed conventional solutions such as the EKF and PF demonstrating improved positioning accuracy in complex indoor settings. The paper [76] addresses the complex challenge of achieving a safe and short landing for a flying-wing unmanned aircraft equipped with a three-bearing-swivel thrust vector. The task is complicated by the need to transition between multiple control modes while accounting for environmental disturbances and model uncertainties to maintain flight safety. To tackle this issue, the authors propose a mixed control strategy that combines lift fans, thrust vectors, and aerodynamic control surfaces. A key innovation is the integration of an Extended State Observer (ESO) into both the inner angular rate control and outer sink rate control to counteract disturbances and uncertainties. To further enhance safety, the aircraft's linear and angular acceleration is calculated through trim analysis, which informs the command values for velocity and angle of attack during the landing process. In addition, the paper introduces a flight boundary protection method that adjusts the command value of the angle of attack, increasing the likelihood of a successful landing. The strategy is tested through Monte Carlo simulations, which evaluate the effectiveness and robustness of the approach. The authors use the circular error probability metric to assess the landing accuracy. The paper [77] presents a robust guidance and control system aimed at managing large maneuver penetration for hypersonic glide vehicles during their dive phase, focusing on executing a snake-shape maneuver under multiple constraints and uncertain disturbances to optimize the vehicle's control and precision. Central to this strategy is the generation of a snake-shape maneuver acceleration command based on a sine function influenced by key variables such as altitude, Line of Sight (LOS) declination, and missile-target distance. The integrated control framework comprises three major components: a terminal guidance law designed with sliding mode control and an adaptive technique for estimating disturbances, featuring a sliding mode surface with variable gain based on estimated time-to-go; an attitude control law that ensures effective tracking of the vehicle's expected attack and bank angles; and an angular velocity control law that maintains stability throughout the maneuver. The terminal guidance law is configured to ensure convergence of the LOS angular rate to zero and achievement of the desired LOS angle, while incorporating the snake-shape maneuver acceleration command as a bias to manage trajectory shaping and stability. The overall system's stability is demonstrated using the Lyapunov theorem, confirming robust performance despite disturbances, and the paper concludes with simulations that validate the effectiveness and robustness of the integrated guidance and control law.

The paper [78] addresses the critical challenge of enhancing the accuracy of Point of Impact (POI) predictions for anti-ship missiles, particularly when targeting large vessels such as aircraft carriers. The study highlights that real-time estimation of the POI at the end of the missile's trajectory can significantly improve damage effectiveness by adjusting the standoff based on the predicted impact location. The research begins by examining the reflection characteristics of the sea surface and the deck of ships when illuminated by a laser with a wavelength of 1.06 μm. The Scenarios confirm a significant difference in reflectivity between these two surfaces. Building on these findings, the authors develop a geometric features model of a typical maritime target and establish an ideal missile-target distance model, which is then refined to account for CEP a statistical measure of accuracy. Utilizing the target geometric features, CEP, and data from a four-way laser detection device, the researchers apply the Monte Carlo method to simulate and predict the POI of the anti-ship missile. The results demonstrate that this comprehensive approach effectively predicts the missile's impact point, enhancing accuracy through analysis of multiple ballistic experience points. Furthermore, the proposed method effectively reduces the uncertainty associated with POI predictions, underscoring its potential for improving missile targeting effectiveness. The paper [79] addresses the limitations of traditional UAV ranging-based target localization algorithms, particularly concerning the SEP. The authors propose a novel target ranging localization algorithm that leverages the resolution of nonlinear equations combined with the total least squares method. A critical analysis is conducted to evaluate the factors influencing both CEP and SEP, culminating in four significant conclusions based on simulations. To validate the proposed localization algorithm's effectiveness and accuracy, a series of flight Scenarios are conducted. The research further analyzes the target locatable duration during the UAV formation's straight flight for target localization, providing a geometric analysis along with a corresponding calculation formula. Simulation results indicate that the proposed algorithm consistently achieves lower CEP and SEP values compared to traditional methods. The flight Scenarios confirm the algorithm's robustness and precision, showcasing its potential applicability in real-world engineering scenarios for cooperative ground target localization using multiple UAVs. The study [80] focuses on detecting moving targets within a foliage environment using a Frequency Modulated Continuous Wave (FMCW) Radar system, approached through two distinct methods: the Fourier Transform Method, which identifies frequency peaks in the Fourier transform of the mixer output to ascertain target presence, and spatial frequency domain analysis, which considers the mixer output in the spatial frequency domain where targets further away correspond to higher spatial frequencies. Detection and range are determined through the Inverse Fourier Transform of the mixer output and Range Time Intensity (RTI) plotting. The FMCW radar system is meticulously designed, incorporating essential RF subsystems and a signal processing unit, utilizing off-the-shelf RF components for the RF section, along with a four-channel analog-to-digital converter for data acquisition and conversion. The processed signal data is analyzed in MATLAB using Fast Fourier Transform (FFT) and Inverse Fast Fourier Transform (IFFT) techniques to extract moving target information. The study also calibrates the system based on a target with a known Radar Cross-Section (RCS).

The research paper [81] addresses the challenges of continuous positioning and low accuracy in tracking moving targets using multiple UAV. The proposed method integrates nonlinear equation solving, cooperative tracking control, and Kalman filtering to enhance tracking precision. Key contributions of the study include a nonlinear equation solution that computes the initial target position by effectively addressing inaccuracies in estimating the target's height, which are common in traditional methods; the identification of the optimal UAV formation shape through simulation analysis, maximizing positioning accuracy under static conditions; and the introduction of a novel multi-UAV cooperative tracking method that ensures the UAV formation maintains its optimal shape throughout the target positioning process, facilitating continuous and precise tracking. Additionally, a new phase control method based on UAV spacing and sliding mode control is proposed to enhance robustness in engineering applications, overcoming limitations of traditional phase angle-based control methods. To achieve high-precision continuous positioning, Kalman filtering is integrated with UAV position information and target position results, further improving localization accuracy. The effectiveness of the multi-UAV cooperative tracking control algorithm, along with the positioning result filtering algorithm, is validated through simulation, demonstrating significant improvements in continuous high accuracy tracking and positioning of moving targets. The paper [82] addresses the challenges posed by the increasing diversity in general aviation aircraft and their performance variations, which complicate traditional multiple model tracking algorithms that often require a larger number of motion models to accurately describe the actual maneuvering behavior of moving targets. This need can lead to degraded tracking accuracy and heightened computational demands. Key contributions of the study include the introduction of a Target Classification Aided Variable-Structure Multiple-Model Algorithm (TCA-VSMM), which integrates target classification to enhance state estimation accuracy; the screening of motion models that incorporates target classification and velocity information derived from Automatic Dependent Surveillance-Broadcast (ADS-B) measurements, aiding in refining the motion model set to align better with the actual maneuvering behavior; and improved efficiency and performance, as Scenarios demonstrate that the TCA-VSMM algorithm achieves superior performance with a reduced computational load, offering high estimation accuracy compared to traditional model-group switching variable-structure multiple-model algorithms. Overall, the TCA-VSMM algorithm represents a significant advancement in multiple model tracking by leveraging target classification to optimize model selection and improve tracking efficiency, making it particularly valuable in contexts with diverse aircraft dynamics. The paper [83] introduces a novel technique for determining the 2D position of a signal source, termed the Inscribed Angle (InA), which leverages the time difference of sequential irradiation by the main beam of a target antenna's radiation pattern using electronic support measures receivers. Key assumptions for this method include the rotation of the target antenna at a constant angular velocity for accurate tracking of the radiation pattern, operation under line of sight conditions critical for effective signal measurement, and the placement of three time-synchronized sensors arbitrarily across the operational area to enable triangulation of the signal source. Key contributions of the study include a detailed geometric representation of the proposed localization method. An analytical approach to assess the accuracy of the method, which relies on the timing of irradiation events correlating with the direction of maximum received signal strength, a derived method for enhancing accuracy in the proposed positioning technique through improved irradiation time estimation; and extensive simulation results that validate the performance and accuracy of the positioning method, showcasing its potential efficacy in practical applications. Overall, this study represents a significant advancement in radar position estimation methodologies, highlighting the utility of ESM receivers in accurately determining target locations through innovative geometric techniques.

G. Fuzzy Logic Algorithm

The paper titled [84] presents a comprehensive survey on recent advancements in data association techniques within MOT, specifically focusing on visual object tracking tasks in video surveillance for traffic scenarios. It emphasizes the tracking-by-detection framework, which integrates object detection and identification tasks with solving filtering problems to maintain object continuity in tracking. The survey concentrates on data association methods that utilize uniquely defined similarity functions and filters, essential for effectively linking detections to corresponding objects across video frames. The study categorizes these methods into legacy techniques, such as probabilistic and hierarchical methods, and analyzes more recent hybrid approaches that incorporate advanced models. It assesses the performance of these methods based on stability, accuracy, robustness, speed, and computational complexity, providing a clear understanding of the strengths and limitations of current data association techniques. Rather than presenting quantitative results, the paper focuses on a qualitative review, identifying key trends and challenges in the data association task within MOT frameworks. Furthermore, it highlights successful models and suggests future research directions to address limitations in current data association techniques. Overall, this survey makes a significant contribution to the field of multiple object tracking by offering an insightful comparison of various data association techniques and their impact on the performance of MOT frameworks in real-time applications. The paper [84] introduces a novel approach to address the challenges of tracking multiple moving objects in dynamic, non-stationary environments. The proposed method is particularly relevant for applications in autonomous navigation, surveillance, healthcare, and human-machine interaction. The system utilizes movement information between successive frames, comparing the new and previous frames to detect the location of moving objects within the camera's field of view. To achieve this, it applies a matching algorithm along with the Kanade–Lucas–Tomasi (KLT) feature tracker, identifying key feature points in each frame. The movement size of these points, along with camera motion, is analyzed to subtract previously captured moving objects, allowing for accurate detection of newly moving objects in real time. In addition, the system employs fuzzy logic to classify and segregate objects based on their mass center and length-to-width ratio, making it capable of distinguishing between different types of moving objects such as vehicles, pedestrians, bicycles, and motorcycles. This classification approach allows the system to adapt to the complexities of non-stationary conditions effectively. The method demonstrates promising results, with a tracking and classification accuracy of approximately 75%, while processing 43 frames per second. This makes it not only accurate but also computationally efficient, outperforming many existing techniques in terms of speed and precision. Overall, the system contributes significantly to improving multi-object tracking in dynamic conditions by integrating fuzzy decision-making with advanced movement analysis.

The paper [85] presents a novel approach to solving the task allocation problem for UAVs tasked with tracking multiple ground targets in an urban environment. The authors propose a multi-objective optimization framework that aims to minimize the total flight distance, ensure balanced task allocation, and reduce completion time. This framework is modeled as a multi-objective integer programming problem. To address the complexities of the task allocation, the paper introduces a fuzzy two-phase optimization method that incorporates the relaxed order of desirable satisfactory degrees, allowing for the formulation of mixed integer programming based on the linguistic importance of the objectives. The proposed solution also includes an adaptive pigeon-inspired algorithm, combined with an auction mechanism to solve the optimization model. In this context, the position of each "pigeon" is defined as the bidding price that each UAV submits for tracking a particular target. To ensure that the constraints of the problem are met and to avoid suboptimal solutions, the auction mechanism is designed to convert the pigeon positions into feasible task allocation schemes. The paper compares the performance of this pigeon-inspired approach with conventional particle swarm optimization techniques. Simulation results demonstrate that the proposed method is both effective and efficient, offering improvements in UAV task allocation for multi-target tracking over traditional optimization methods. The paper [86] explores a robust control method for the longitudinal dynamics of autonomous underwater vehicles (AUVs) with an emphasis on target tracking. The authors propose a novel approach that integrates Fuzzy Logic Systems (FLS) with adaptive control techniques to address the uncertainties in AUV dynamics. The target tracking command is transformed into a pitch angle command, allowing for the design of a tracking controller that employs a switching mechanism. This mechanism enables the FLS to work in conjunction with robust control strategies to handle the uncertainties inherent in the system's dynamics. One of the key contributions of the paper is the use of the FLS's approximation capabilities to construct and model errors, which are then used to develop a fuzzy update law. This law allows the system to adapt and learn from dynamic changes during the tracking process. Additionally, the authors introduce a parameter adaptation law for the unknown control gain function, which further enhances the control system's adaptability. The stability of the proposed control method is rigorously analyzed and proved through Lyapunov stability theory, ensuring that the system remains uniformly ultimately bounded. Simulation tests validate the effectiveness of the approach, demonstrating improved tracking accuracy and learning performance during target tracking tasks, highlighting the potential for this method in real-world AUV applications.

The paper [87] addresses the challenges of track-to-track association in compact High-Frequency Surface Wave Radar (HFSWR) systems, which are commonly limited by low transmit power and small receiving antenna arrays. These limitations lead to low detection probability, low positioning accuracy, and a high false alarm rate, especially in multitarget tracking situations where targets have similar kinematic parameters. These factors complicate the track-to-track association process, a crucial aspect of multitarget tracking. To address these issues, the authors propose a track-to-track association method based on Maximum Likelihood Estimation (MLE) specifically designed for T/R-R composite compact HFSWR. The method begins with the application of a multitarget tracking algorithm to plot data sequences from both T/R monostatic and T-R bistatic radars, producing two distinct track sets. Measurement errors in range, azimuth, and doppler velocity are then computed using these radar tracks alongside automatic identification system track data. A gaussian distribution model is derived by fitting these measurement errors to a probability distribution, forming the foundation for the likelihood functions used to calculate the association cost between tracks. A cost matrix is created based on these likelihood values. The final step in the process is the application of the Jonker–Volgenant–Castanon (JVC) assignment algorithm to the cost matrix, which determines the track-to-track pairs by minimizing the association cost. The paper presents Scenarioal results, comparing the performance of the proposed method with the Mahalanobis distance-based nearest neighbor method. The Scenarios, which use both simulated and field data, show that the proposed method effectively resolves association ambiguity and improves track-to-track association, particularly in scenarios involving track crossing or adjacent multitargets. This suggests that the MLE-based method is more robust and accurate in challenging multitarget tracking conditions. The paper [88] addresses the challenge of track association in distributed fusion systems, particularly in scenarios where targets exhibit strong maneuverability and system bias is substantial. In such cases, local tracks generated by individual sensors may contain inaccurate information, and relying solely on motion state features like position and speed may not provide an accurate representation of the target's true state. This inaccuracy can significantly restrict the performance of data association, especially when conventional methods are employed. To overcome these limitations, the authors propose a bias-tolerant track association method using the Interactive Multi-Model (IMM) algorithm. The IMM algorithm is typically used in tracking maneuvering targets by switching between different motion models to represent various movement patterns. In this paper, the IMM algorithm is applied to capture the motion characteristics or patterns of the local tracks. By incorporating multiple model features into the track association process, the algorithm can provide a more accurate representation of complex target behavior, even in the presence of large system biases. The proposed method is tested through simulations, and the results show that it performs better than traditional methods, particularly in situations where the tracks are complex and system biases are pronounced. The study demonstrates that utilizing the IMM algorithm for track association offers greater robustness and accuracy in distributed fusion systems, enhancing the overall effectiveness of multitarget tracking in challenging environments.

The paper [89] presents a robust method for track association based solely on bearing data from airborne sensors. The proposed approach addresses challenges in multitarget tracking, particularly in combat scenarios with sparse, dense, and crossing targets. It leverages two existing algorithms, the Probabilistic Neural Network (PNN) and the GNN which are traditionally used for data association tasks. However, these algorithms often underperform in complex environments, such as when targets are densely populated or cross each other's paths. To enhance association accuracy in such scenarios, the authors propose a modified method that incorporates the instantaneous outcomes from the PNN/GNN algorithms. They also factor in the confidence of the previous updates and the number of successive hits to calculate the final confidence score. By introducing an averaging scheme post PNN/GNN processing, the method smooths out inconsistencies and improves overall performance. The method is validated through simulations replicating combat scenarios, and the results show that the modified approach significantly improves association accuracy, especially in situations where traditional algorithms struggle. This work contributes to more reliable airborne surveillance, particularly in environments where bearing-only data is available, by refining the association process with enhanced confidence calculations and post-algorithm adjustments. The paper [90] addresses the challenge of associating data for tracking multiple targets using ship-borne radar. The authors propose a robust and adaptive fuzzy density clustering algorithm, which simplifies the process of associating measurements with target states. The algorithm operates in three key steps. First, an adaptive density clustering method is employed to identify valid measurements corresponding to each target's state. This step avoids the need for traditional gating techniques that are typically used in data association. Second, the degree of fuzzy membership for each valid measurement is computed based on the maximum entropy principle, allowing for a more flexible representation of uncertainties. In the final step, measurements with the highest degree of membership are selected to update the positions of the tracked targets. A significant advantage of this approach is its ability to function without the complexity of traditional gating, leading to a reduction in computational steps when compared to other data association methods. The algorithm also takes into account the movement of the ship and its effect on tracking performance, using an EKF to ensure accurate updates. The paper compares the proposed algorithm's performance with more conventional methods, such as the nearest neighbor approach using Mahalanobis distance method. The results highlight the advantages of the proposed algorithm, particularly its simplicity, real-time adaptability, and effectiveness in tracking multiple targets in cluttered environments. This makes the algorithm highly suitable for real-time applications in dynamic and challenging conditions, such as those encountered in maritime radar systems. The paper [91] introduces an advanced method for track-to-track association in multitarget tracking scenarios involving multiple sensors. In distributed information fusion, efficiently associating tracks from different sensors is critical for improving the accuracy of the subsequent track fusion process. The proposed method utilizes a fuzzy membership function to mathematically estimate the likelihood that two tracks from different sensors are tracking the same target. This membership function assigns a value between 0 and 1, where a higher value indicates a greater probability that the tracks are associated with the same target. Once the fuzzy membership values are calculated, a clustering technique is employed to group tracks that are determined to be tracking the same target. The novelty of this approach lies in its use of fuzzy logic to handle the inherent uncertainty in associating tracks from distributed sensors, as well as its application of clustering methods to effectively group similar tracks. Simulation results presented in the paper demonstrate that this method performs better than existing approaches, offering improved efficiency and accuracy in track-to-track association for distributed information fusion systems. The paper highlights the potential of this method to enhance multitarget tracking in complex and dynamic environments where multiple sensors are used. The paper [92] presents an innovative solution for track-to-track association in multi-sensor, multi-target environments. The proposed algorithm modifies the fuzzy clustering means approach to address the issue of track redundancy, which is a common challenge in MSMT systems. Traditional methods often assume ideal conditions, but this research aims to solve the problem under more realistic conditions, where track data includes biases and imperfections typically encountered with real-world sensors. One of the key contributions of this paper is the incorporation of a systematic bias model that reflects the inherent inaccuracies and noise in sensor measurements, making the algorithm more applicable to real-world scenarios. The algorithm's performance is tested across two MSMT scenarios with different levels of measurement noise and sensor resolution, allowing for a comprehensive evaluation of its effectiveness. The results show that this modified fuzzy clustering approach improves track association accuracy by accounting for realistic conditions, making it highly relevant for practical applications in MSMT systems. This method provides a more robust and reliable solution for managing track redundancy and improving data fusion in multitarget tracking scenarios.

H. COVARIANCE INTERSECTION (CI) ALGORITHM

The paper titled [93] focuses on improving the accuracy of multitarget tracking for intelligent driving systems, particularly in challenging environments where targets exhibit complex maneuvers, outliers in measurements, and lack of prior environmental data. To address these challenges, the authors introduce the Multi-constrained Generalized Probabilistic Data Association Filtering (MCGPDAF) algorithm. This algorithm employs target position and heading information to construct constraint parameters that calculate the association probabilities between effective measurement combinations and target tracks. This approach minimizes issues caused by measurement anomalies and errors in prior information, enabling robust association for single-sensor multitarget tracking in complex conditions. In addition, the paper proposes a multitarget tracking method based on composite perception fusion. Using correlation sequential track association and covariance cross-fusion algorithms, it enhances the track association, state estimation, and fusion across multiple sensors, which further improves tracking accuracy. The authors validate their approach through simulations and real-vehicle Scenarios, showing that the MCGPDAF algorithm significantly outperforms advanced existing methods. Specifically, it improves the RMSE and Mean Absolute Percentage Error (MAPE) for multitarget tracking by an average of 23.97% and 24.35 respectively. The MOTA and MOTP also show improvements of 14.68% and 15.71%. Moreover, when incorporating composite perception fusion, the RMSE and MAPE improve further by 26.43% and 27.15%, highlighting the algorithm's practicality and effectiveness for dynamic multitarget tracking in intelligent driving applications. The paper [94] presents a novel algorithm for track-to-track association in distributed multi-target tracking systems where cross-covariance between sensor nodes is unknown. The proposed algorithm leverages CI to calculate the association statistics, eliminating the need to compute cross-covariance among nodes. This not only simplifies the process but also enhances the algorithm's usability in scenarios with limited information sharing between distributed sensors. The authors also introduce a fast CI algorithm, which is designed to reduce both communication and computational overhead among the sensor nodes. This improvement ensures that the algorithm remains efficient even in systems where bandwidth or processing power is constrained. The method focuses on balancing accuracy with operational efficiency, making it highly applicable to real-time multi-target tracking environments. The paper concludes with simulation results demonstrating the algorithm's effectiveness. The simulations validate the CI-based approach, showing that it provides reliable track-to-track association without requiring detailed inter-sensor covariance information, which can be challenging to obtain in distributed systems. Moreover, the fast CI variant further enhances the system's performance by significantly lowering the computational and communication load while maintaining robust tracking accuracy.

The paper [95] presents an advanced multi-target tracking algorithm leveraging the Gaussian Mixture Cardinalized Probability Hypothesis Density (GM-CPHD) filter within a distributed framework. The proposed approach addresses the challenge of efficiently fusing information from multiple nodes in a decentralized sensor network for multi-target tracking applications. At the core of the paper is the use of Generalized ICI as a fusion method. CI is commonly used in multi-sensor systems to produce a conservative estimate of the joint covariance, regardless of the degree of correlation between nodes. However, CI's conservative nature often limits its effectiveness. The Inverse Covariance Intersection (ICI) method, on the other hand, offers a less conservative approach, ensuring consistent and more accurate fusion results. Although ICI had not been previously extended to multi-sensor, multi-target tracking systems, this paper fills that gap by integrating it with the GM-CPHD filter. The authors generalize the ICI formula to adapt it for Random Finite Set (RFS) fusion, in a manner similar to Generalized Covariance Intersection (GCI). This fusion mechanism works by restructuring ICI as a naive fusion method with covariance inflation in the Gaussian probability density function, making it suitable for GM-CPHD. Through simulations, the proposed method is shown to outperform naive fusion and GCI-based methods, achieving lower Optimal Sub-pattern Assignment (OSPA) errors in multi-target tracking tasks. This result indicates improved accuracy in estimating target states across multiple sensors. The study highlights the strength of combining ICI with GM-CPHD to achieve more reliable and efficient multi-target tracking in decentralized sensor networks.

2.2.3 Filtering for Target Tracking

Real-time tracking is a crucial feature of tracking radar systems. Filtering involves processing radar data using adaptive techniques to track targets, such as determining their range, course, heading, flight level, and speed. It also reduces measurement errors by applying appropriate methods to accurately calculate a target's speed, position, and acceleration. Filtering in target tracking is essential because it helps manage and analyze vast amounts of data by isolating relevant information from noise. In dynamic environments where data is continuously generated, filtering allows for the extraction of meaningful patterns and trends specific to the targets of interest. Without effective filtering, the sheer volume of irrelevant data can overwhelm analysts, making it difficult to identify significant events or anomalies. By applying filters based on defined criteria, such as keywords or contextual information, tracking systems can focus on the most pertinent data, enhancing accuracy and efficiency. This targeted approach not only saves time but also ensures that critical insights are not lost amidst the data deluge, leading to more informed decision-making and timely responses. Some of the filters are discussed briefly as following:

2.3 Tactical Data Link (TDL)

To broaden the field of view for a standalone sensor or a network of sensors and enhance the number of insights that can be derived from the data, the concept of tactical data links has emerged within the C4ISR (Command, Control, Communication, Computers, Intelligence, Surveillance and Reconnaissance) systems framework. These links facilitate a continuous flow of information from various sensors via a wireless network to both the command center and individual mission participants. One of the key benefits of tactical data links is their ability to deliver real-time data collected from multiple sources, which may include precise locations and imagery of objects of interest. The primary goal of tactical data links is to improve monitoring capabilities at the command center during an ongoing mission while also enabling the distribution of mission-related information to participant nodes. Additionally, standards have been established for sharing various types of data through tactical data links as depicted in figure 2.2

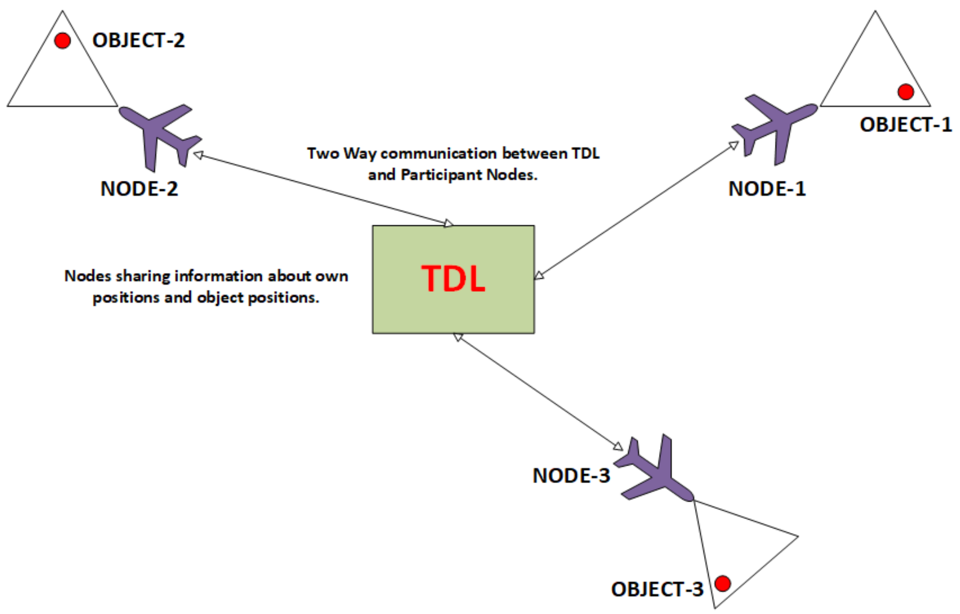

Figure 2.2: Centralized information sharing via Tactical Data Link (TDL) between multiple participant nodes and their tracked objects.

2.4 Frame of Reference

In surveillance and object tracking, multiple sensors are required to obtain the complete knowledge of the ongoing mission. Each sensor transmits it's information to the base station which when combined together gives a clear view of the parameters required for the object tracking. These sensors are working on different kinds of frame of reference. Some of the most commonly used frames of reference in airborne systems are briefly mentioned as following:

Earth Centered Inertial (ECI)

When an object is stationary or is moving at a fixed speed is known as inertial frame of reference. On the basis of steady view point and keeping a specific direction in focus, an inertial sensor makes measurements. Looking at the earth, the steady view point is starts at the center of the earth. Z axis is the direction that follows earth's location pointing towards north pole. X-axis and Y-axis points towards a specific point on that sky also know vernal equinox. It is when a right-handed system is said to be completed.

2.4.1 Body Frame

While considering the frame of reference for the body. The center points is considered to be the point of origin. X and Y axis points towards longitudinal and latitudinal directions and the z axis is perpendicular to the x and y axis that points to the downward direction. Between the frame of the body and the interest of the body, there is a strong attachment. The three angles can be used to describe the geographical representation of the frame i.e (ϕ,θ,Ψ). These angles are also known as Eular angles. Where φ is the roll angle of the body, Θ is the pitch angle and Ψ is the yaw angle of the body. Usually, the output of the inertial sensor is also represented by this frame. When the body of interest rotates this frame rotates with the body and its origin moves in the direction of the body. Axes of body frame are shown as following in figure 2.3:

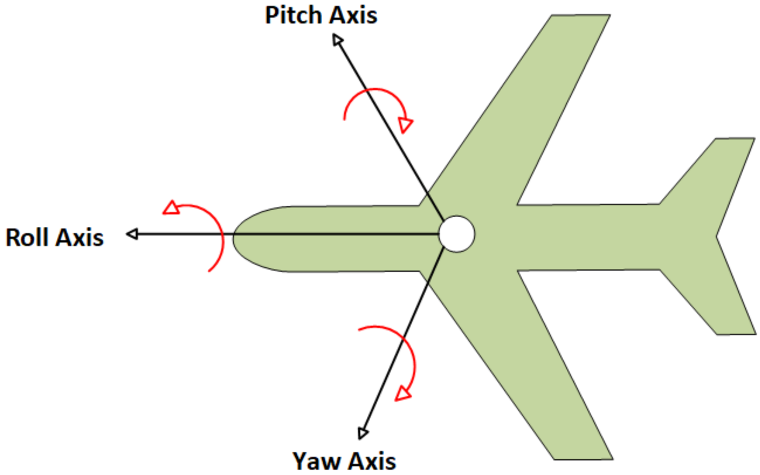

Figure 2.3: This image illustrates an aircraft's body frame, highlighting the roll, pitch, and yaw axes that are vital for flight dynamics.

2.4.2 Geographic Frame

In navigation the most commonly used frame is the geographic frame, origin of this frame lies at the center of the earth. This frame considers an ellipsoidal nature of the earth and then assigns the point of interest P in a 3-tuple manner as $\lambda\varphi$,h). Where λ is the latitude, φ is the longitude and h is the elevation of the point of interest. Latitude is an angle defined in the meridian plane, it runs from equatorial plane to ellipsoidal normal at point P, longitude is an angle in the equatorial plane running from prime meridian to the projection of point P on the equatorial plane. A geographic frame is depicted in figure 2.4:

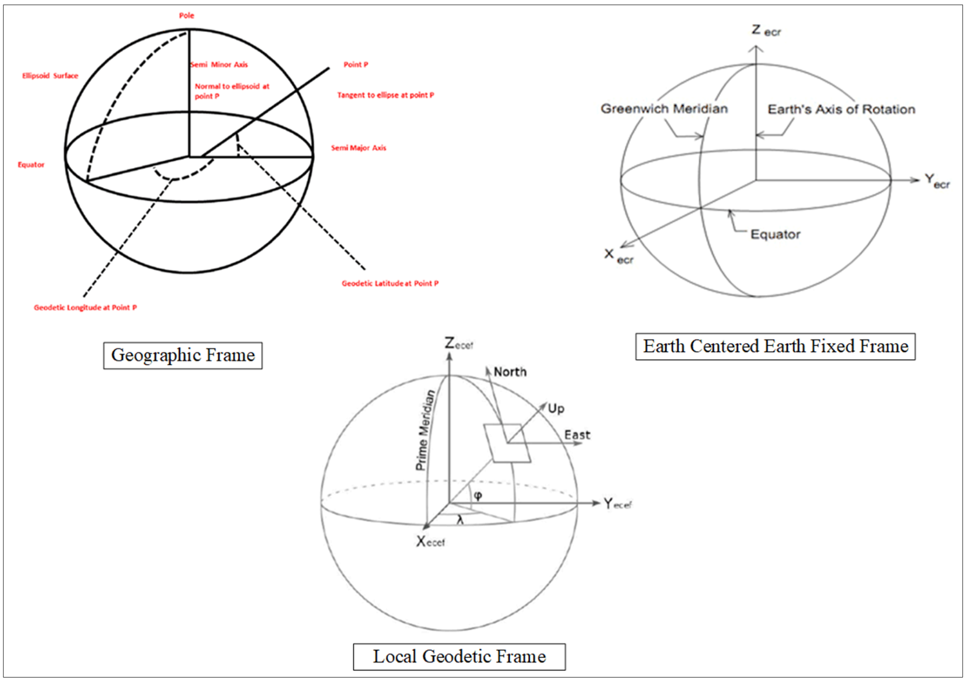

Figure 2.4: This image illustrates three fundamental geographic frames used for defining positions and orientations on or near the Earth's surface: the Geographic Frame, the ECEF Frame, and the Local Geodetic Frame.

2.4.3 Earth Centered Earth Fixed Frame (ECEF)

This frame is similar to a geographic frame defined by the position of origin, but ECEF frames are in Cartesian coordinates. This is a frame with an x-axis perpendicular to the earth's surface, where in this example, they would be pointing towards the north pole and x-y plane lies at the equator. The literature also suggests this frame for the purpose of tracking. A basis diagram of ECEF frame is shown in figure 2.4.

2.4.4 Local Geodetic Frame

This frame of reference is also called the East-North-Up (ENU) reference framework, is laid out by fitting a tangent plane to the World's reference geoid at the point of interest, P. In this system, the x-axis points east, the y-axis points north, and the z-axis face up from the Earth's surface, completing the rotation. A diagram of local geodetic frame is shown in figure 2.4

2.5 Data Association

One of the most essential aspects in MTT is data association. In simpler terms, it is the method of testing whether two pieces of information could either be same or different. Data association problem can be mainly divided into three main categories i.e. (a) Measurement to Measurement Association (M2MA), (b) Measurement to Track Association (M2TA) and (c) Track To Track Association (T2TA). The concept of data association is simply explained with the help of figure 2.5:

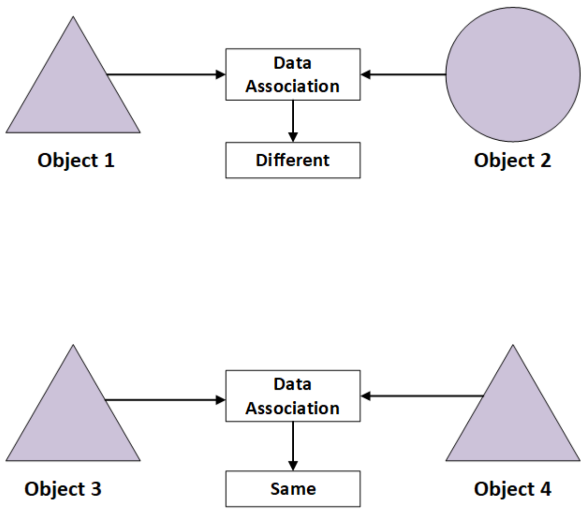

Figure 2.5: This figure illustrates Data Association, distinguishing between associations with different objects (top) and same object types (bottom)

2.6 Summary

In conclusion, a radar system is crucial for multi-object tracking and comprises four key components: a transmitter, an antenna, a receiver, and display/control equipment. The transmitter generates an RF signal that the antenna sends out in a specific direction. When this signal hits objects, it creates echoes that the antenna picks up, allowing for distance calculations based on how long it takes for the echoes to return. Radar systems can be either monostatic, using a single antenna for both sending and receiving signals, or bistatic, which uses two separate antennas. There are various tracking methods, including STT, ADT systems, electronically steered phased array radars, and TWS radars. To ensure accurate tracking, filtering techniques are employed, such as the KF, which estimates the state of dynamic systems in the presence of noise, and the PF, which addresses non-linear data by representing possible states with multiple particles. TDL improve the ability to share data among radar systems, while different reference frames like earth-centered inertial, body, and geographic frames are essential for precise tracking. Data association plays a critical role in multi-target tracking, helping to determine whether different pieces of information relate to the same object.

Table 2.1: Comparison of data association methods in multi-object tracking, highlighting each method's strengths, limitations, and existing research gaps relevant to real-time and cluttered environments.

No.	Method Used	Strengths	Limitations	Research Gap
1	Kalman Filter (KF, EKF, UKF)	Real-time performance, simple implementation	Assumes linearity or small nonlinearities; sensitive to noise models	Poor performance in highly nonlinear or cluttered environments
2	Particle Filter (PF)	Handles non-linear, non-Gaussian processes	Computationally expensive; particle degeneracy	Challenging for real-time applications with many targets
3	Nearest Neighbor (NN)	Light computation, easy implementation	High false matches in dense data	Unreliable with occlusion or ambiguous measurements
4	Global Nearest Neighbor (GNN)	Uses global optimization for assignment	High cost with large problems	Limited scalability for real-time, multi-sensor systems

Continued on next page

No.	Method Used	Strengths	Limitations	Research Gap
5	Probabilistic Data Association (PDA)	Manages clutter and uncertainty well	Assumes one true measurement per scan	Poor with crossing/group targets
6	Hungarian Algorithm	Exact assignment optimization	One-frame matching only	Cannot handle long-term temporal dependencies
7	Fuzzy Clustering T2TA	Handles uncertainty and partial memberships	Limited multi-sensor, real-time validation	Not widely deployed in dynamic networks
8	Deep Learning MOT (e.g., QD-Track)	High detection and tracking accuracy	High resource and data requirements	Infeasible for embedded/-lightweight systems
9	SVM for Tracking	Strong classifier, good generalization	Feature-dependent performance	Requires real-time fusion integration
10	Fuzzy Logic in MOT	Flexible with noise and uncertainty	Needs careful tuning of membership functions	Lacks validation in defense or UAV settings

CHAPTER 3

METHODOLOGY

3.1 Overview

This chapter presents the methodology used to implement the proposed T2TA algorithm using fuzzy logic. It outlines the mathematical foundation of the CEP/CAP algorithm, details the design of the fuzzy logic-based approach including fuzzy sets, membership functions, and decision-making rules and describes the simulation methodology used for performance evaluation. A comparative analysis is also presented between the fuzzy logic-based algorithm and the CEP/CAP algorithm. The results and discussion are provided in Chapter 4.

The primary focus of this study is the application of a fuzzy logic-based approach for track association, which offers an improved ability to manage uncertainties and imprecise data compared to conventional methods.

This chapter is organized as follows:

- We begin by providing a detailed explanation of the CEP/CAP algorithm, discussing its mathematical basis, assumptions, and its role in the track association process.
- Next, we provide a detailed explanation of the fuzzy logic approach for track association, covering the fuzzy sets, membership functions, and decision-making rules.

- Finally, we conclude with a comparative analysis between the fuzzy logic approach and the other algorithms, highlighting their respective strengths, weaknesses, and practical implications.

3.2 Traditional Track Association Methods

3.2.1 CEP/CAP Algorithm

The CEP and CAP algorithms are commonly used to measure the accuracy of tracking systems. In T2TA, these algorithms help determine whether two tracks from different sensors correspond to the same object based on their spatial and temporal overlap. In the context of this study, CEP/CAP is applied to calculate the likelihood that two tracks, each with their own measurement uncertainty, correspond to the same target. By comparing the error regions around each track, we can associate tracks if their regions overlap significantly.

3.2.2 Mathematical Basis of CEP/CAP

The CEP/CAP algorithms rely on the assumption of a bivariate normal distribution for tracking errors in the x and y directions. The error distributions are characterized by their standard deviations, σ_x and σ_y which represent the uncertainty in the positional estimates from different sensors. The CEP is calculated as the radius of a circle that contains 50% of the position estimates from a sensor. Mathematically, the CEP for a normally distributed error can be expressed as:

$$\text{CEP} = k_{50} \cdot \sqrt{\sigma_x^2 + \sigma_y^2} \tag{3.1}$$

Where k_50 is a constant that corresponds to the 50% confidence level and σ_x and σ_y are the standard deviations of the errors in the x and y directions, respectively.
The CAP extends this concept to a higher confidence level, typically 90% or 95%. The corresponding radius, r_{CAP}, is given by:

$$r_{\text{CAP}} = k_p \cdot \sqrt{\sigma_x^2 + \sigma_y^2} \tag{3.2}$$

Where k_p is a constant depends on the desired probability P

The CEP and CAP radii are calculated based on the sensor's positional uncertainty, providing a circular region where the true target position is likely to be found. These regions are then used to determine track associations.

3.2.3 Assumptions of CEP/CAP

The CEP and CAP algorithms are based on a few critical assumptions that impact their application to track association problems. These assumptions simplify the mathematical formulation of the algorithms but also introduce certain limitations. Understanding these assumptions helps to frame the algorithm's effectiveness and possible drawbacks.

Gaussian Error Distribution:

The fundamental assumption of CEP and CAP is that the tracking errors follow a normal (Gaussian) distribution. This means that the positional errors in the x and y coordinates are distributed symmetrically around the true position. The gaussian distribution is characterized by its mean (expected position) and variance (error spread), which in this case corresponds to the uncertainty in the sensor's measurement.

This assumption simplifies the analysis by allowing the errors to be represented by standard deviations σ_x and σ_y and enables the use of probabilistic regions to describe the likely position of a target. Real-world sensors may not always produce normally distributed errors. non-gaussian errors may reduce the accuracy of CEP/CAP-based decisions.

Stationary or Linearly Moving Targets:

CEP and CAP are typically applied to scenarios where the target is either stationary or moving in a linear trajectory with constant velocity. This assumption works well for simple tracking systems, where the motion model of the target is relatively predictable. Targets with complex, non-linear movements (e.g., sudden changes in speed or direction) require more sophisticated models. If such dynamics are not accounted for, the CEP/CAP estimates may lead to incorrect associations due to misalignment between predicted and actual positions.

Independent Errors: The errors in the x and y directions are assumed to be independent. This means that an error in one coordinate does not affect the error in the other. Under this assumption, the covariance matrix is diagonal, simplifying the computation of the CEP/CAP region. In some cases, sensor errors may be correlated (e.g., atmospheric disturbances might affect both x and y measurements). Ignoring such correlations can lead to inaccurate association results.

3.2.4 CEP/CAP Algorithm Process

The CEP/CAP algorithm process involves a systematic series of steps that allow us to determine whether two tracks, coming from different sensors, belong to the same target. The process begins with data collection and progresses through several key steps, resulting in a decision based on the geometric overlap of error regions.

The first step involves collecting positional data from multiple sensors that are tracking the same target. Each sensor generates its own track, which consists of measurements of the target's position (often in the form of x and y coordinates). These measurements inherently contain errors due to sensor limitations. Each sensor's data includes positional estimates and the corresponding measurement uncertainty, expressed as standard deviations σ_x and σ_y.

For each track, compute the error covariance matrix which describes the uncertainty in the positional estimates. This matrix is typically diagonal (under the assumption of independent errors), with the variances σ_x^2 and σ_y^2 as the diagonal elements.

$$P = (\sigma_x^2 \,, 0 \,, 0 \,, \sigma_y^2) \tag{3.3}$$

The covariance matrix is a key element in determining the size and shape of the error region around each track.

Using the variances from the covariance matrix, calculate the CEP and CAP radii. These radii define the circular regions around each track that represent the probable location of the target. The CEP radius typically encloses 50% of the probable positions, while the CAP radius encloses a larger percentage, such as 90% or 95%.

The final step is to compare the error regions of different tracks. If the CEP or CAP regions of two tracks overlap significantly, there is a high probability that the tracks represent the same target. The amount of overlap is used as a measure of the likelihood of track association. The association threshold is set based on the desired confidence level. Tracks whose error regions overlap beyond the threshold are considered associated, otherwise, they are treated as separate.

3.2.5 Simulations for CEP/CAP

To evaluate the performance of the CEP/CAP algorithm, simulations are conducted. These simulations test the algorithm's ability to accurately associate tracks under varying conditions, such as different levels of sensor noise, target speeds, and motion patterns. For simulation setup first we define a 2D scenario where multiple targets move through a defined space. These targets may be stationary, moving linearly, or following more complex trajectories, depending on the test case. After that, for each target, generate positional data from simulated sensors, adding random gaussian noise to simulate measurement errors. The amount of noise is characterized by the standard deviations σ_x and σ_y, representing the sensor's accuracy.

Step-by-Step Simulation:

1. **Generate True Positions:** Set the initial positions of each target.

2. **Simulate Noisy Observations:** Apply noise to these true positions to generate noisy observations that simulate real sensor data.

3. **Calculate CEP/CAP Regions:** For each noisy observation, compute the CEP and CAP radii based on the measurement uncertainties.

4. **Assess Track Association:** Using the CEP/CAP algorithm, determine whether the tracks from different sensors should be associated based on the overlap of their circular regions.

3.2.6 Decision-Making in CEP/CAP

The final decision on whether to associate two tracks is based on the degree of overlap between their CEP or CAP regions. The decision-making process involves comparing the calculated error regions and using predefined criteria to determine whether the tracks belong to the same target. A threshold is defined based on the desired confidence level (e.g., 90% or 95%). The threshold determines the minimum amount of overlap required between two error regions for the tracks to be considered associated. For example, if the overlap between the two CAP regions exceeds the threshold for 95% confidence, the tracks are associated.

The decision to associate or not associate tracks is a binary one. If the overlap exceeds the threshold, the decision is "associate" (1). If the overlap is below the threshold, the decision is "not associate" (0). This binary decision is useful for making clear, yes-or-no choices in automated tracking systems, but it may not fully capture the uncertainties involved in more complex cases.

3.2.7 Summary of CEP/CAP Approach

The CEP/CAP algorithm provides a simple and intuitive method for associating tracks based on their spatial proximity and positional uncertainties. By leveraging the assumption of gaussian-distributed errors, CEP/CAP can effectively handle a wide range of scenarios where track association is required. However, its reliance on circular error regions may limit its performance in situations where errors are anisotropic or the motion of the targets is highly dynamic. In the following sections, we will compare its performance with other algorithms, such as the fuzzy logic approach, to highlight its strengths and limitations.

3.3 Proposed Method

This thesis proposes a fuzzy logic-based T2TA algorithm as a more effective alternative to traditional CEP/CAP methods. Using fuzzy membership, it adaptively evaluates track similarity based on position, velocity, and heading, offering improved handling of sensor noise and asynchronous data.

3.3.1 Fuzzy Track-to-Track Association Algorithm

Fuzzy T2TA is a multi-sensor data fusion technique used to combine and associate tracks of the same object generated from different sensors or tracking systems. The goal is to minimize uncertainties and discrepancies between tracks by associating them into a unified representation. The fuzzy logic approach leverages the inherent uncertainties in the data, allowing for a more flexible and adaptive solution when compared to classical deterministic algorithms.

3.3.2 Key Elements of Fuzzy T2TA

Input Data (Tracks) The algorithm operates on track data provided by multiple sensors. Each sensor independently detects and tracks the same object, leading to multiple "tracks" for that object. These tracks are composed of state variables, such as:

- **Position (e.g., x, y, z coordinates):** The spatial location of the object as estimated by the sensor.
- **Velocity (e.g., vx, vy, vz):** The speed and direction of the object's movement.
- **Other attributes (e.g., acceleration, sensor confidence):** Some systems may include higher-order dynamics like acceleration or the sensor's confidence level in its measurement.

Each sensor's data is subject to its own unique errors and noise, so the tracks may not be identical even if they represent the same object. This is where the challenge of track-to-track association arises, as the goal is to determine which tracks from different sensors belong to the same real-world object.

3.3.3 Association Criteria

The fuzzy T2TA algorithm defines several criteria to assess whether two or more tracks, each from different sensors, should be associated. These criteria are modeled using fuzzy sets, which handle the inherent uncertainty in the data. Common association criteria include:

- **Spatial Proximity:** The fuzzy T2TA algorithm defines several criteria to assess whether two or more tracks, each from different sensors, should be associated. These criteria are modeled using fuzzy sets, which handle the inherent uncertainty in the data. Common association criteria include:
- **Velocity Consistancy:** The algorithm checks whether the velocities of the tracks are similar. If two tracks have consistent velocities (i.e., they are moving at the same speed in the same direction), it increases the likelihood that they belong to the same object.
- **Temporal Alignment:** Tracks from different sensors must also be consistent in time. If one sensor's track lags significantly behind another, they may not represent the same object. Temporal alignment helps avoid mismatches due to differences in sensor update rates or latency.
- **Sensor Accuracy:** The accuracy or confidence of each sensor can also be considered in the association process. Tracks from more reliable sensors may be weighted more heavily in the association process, while less reliable sensors may contribute less to the decision.

3.3.4 Fuzzy Membership Functions

Fuzzy membership functions are used to represent how closely the tracks match in terms of the criteria mentioned above. In fuzzy logic, these functions do not result in binary decisions (i.e., a track either does or does not belong to an object). Instead, they return values between 0 and 1, representing the degree of membership or similarity.

Spatial Proximity: A fuzzy membership function might map the distance between two tracks to a membership value. If the distance is very small, the membership value will be close to 1, meaning the tracks are likely from the same object. If the distance is large, the membership value approaches 0.

Velocity Similarity: A fuzzy membership function for velocity might take into account both speed and direction. If two tracks are moving at similar speeds and in the same direction, the membership value will be high.

Temporal Alignment: Tracks that are recorded at similar times (within a certain fuzzy-defined threshold) will have a higher membership value, while those with significant time differences will have a lower membership score.

3.3.5 Performance Metrices

The fuzzy rule base consists of a set of rules that define how the different criteria interact to produce an association decision. These rules are typically structured in an **IF-THEN** format, and they integrate the fuzzy membership values calculated for each criterion.

Examples of fuzzy rules might include:

- **IF** the spatial distance is small **AND** the velocity difference is small, **THEN** the tracks are likely associated.
- **IF** the spatial distance is moderate **AND** the velocity difference is large, **THEN** the tracks are less likely associated.
- **IF** the position difference is high **AND** the time difference is large, **THEN** the tracks are unlikely to belong to the same object.

The fuzzy rule base allows for combining various factors that influence the track association in a non-binary, flexible way. Each rule helps capture different aspects of uncertainty and variability in the data.

Defuzzification

Once the fuzzy inference engine generates a fuzzy output (typically a fuzzy degree of association), this result needs to be converted into a crisp value that can be used to make a final decision. This process is called **defuzzification**.

A common method is to take a weighted average of the fuzzy outputs to produce a single number, which can be interpreted as the likelihood that two tracks are associated. A threshold is then applied to this value to make the final decision:

- If the defuzzified value is above a certain threshold, the tracks are associated.
- If the value is below the threshold, the tracks are considered not associated.

Track Fusion

Once the tracks are associated, they are merged into a single, unified track representing the object more accurately. The fusion process involves combining the state estimates (position, velocity, etc.) of the associated tracks, often using weighted averaging or statistical filtering methods like the KF. This step improves the overall accuracy of the object's state by reducing noise and incorporating data from multiple sources as shown in figure 3.1

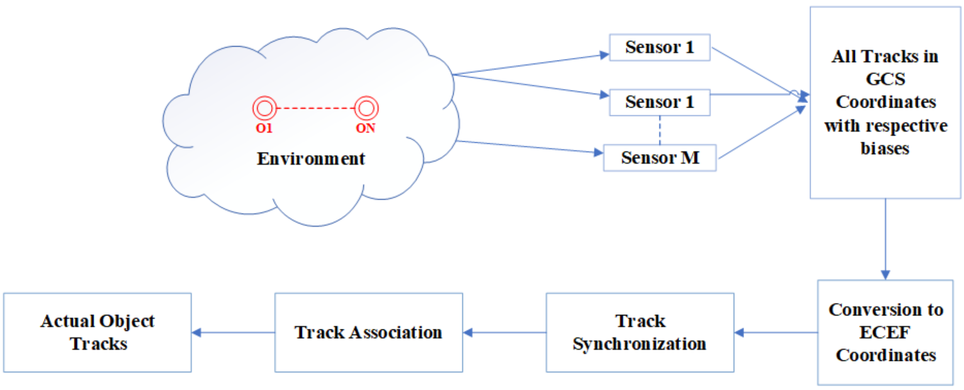

Figure 3.1: A system model illustrating the process from sensor inputs and environmental observations to the generation of actual object tracks through coordinate conversion, synchronization, and track association.

3.3.6 Advantages of Fuzzy T2TA

Robustness to uncertainty: Unlike hard decision methods, fuzzy logic handles uncertainty and partial truth, making it ideal for noisy environments where sensor measurements are imprecise.

Flexibility: Fuzzy rules allow for the inclusion of multiple criteria, enabling the algorithm to adapt to different scenarios, such as varying sensor qualities or measurement inconsistencies.

Improved Accuracy: By integrating multiple factors and handling them with flexible, adaptive rules, the fuzzy approach often yields more accurate associations, especially in complex and uncertain conditions.

3.3.7 Mathematical Modeling of Fuzzy Logic for T2TA

We take help from a simple scenario for formulation of a track-to-track association problem in MSMT setting as shown in figure 3.2. The scenario has two sensors in an overlapping coverage region observing three distinct targets. A total of four track reports will be generated for these three targets due to overlapping nature of the scenario. Let's consider the target reports are denoted as, T_{op}, o = 1, 2, 3 and p = 1, 2, have two attributes i.e. the positions in Cartesian coordinates as x and y coordinates of the tracks. In track report T_{op}, o represents the target number and p represents the sensor number.

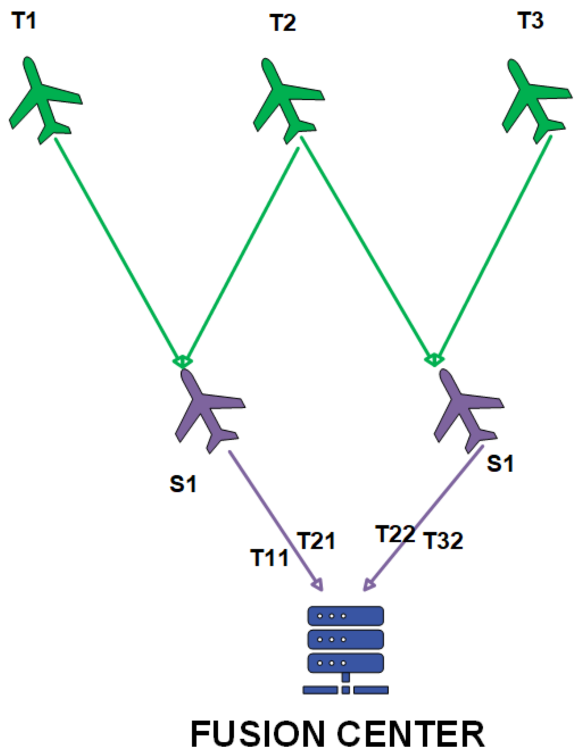

Figure 3.2: An illustration of a MSMT setting, where two sensors (S1, S2) are tracking three distinct targets (T1, T2, T3), with data fused at a central Fusion Center.

The data from the tracks, as shown in the figure above, can be organized into a data matrix, as illustrated in the table in figure 3.3. This matrix contains the track information reported to the fusion center during each scan. The columns of the matrix represent the tracks being evaluated for correlation, while the rows represent the distinct features of the tracks. The primary goal of the fuzzy track-to-track association algorithm, or any track-to-track association algorithm, is to distinguish between similar tracks (same target) and dissimilar tracks (different targets) among the multiple reported tracks.

Track / Attributes	T_{11}	T_{21}	T_{22}	T_{32}
Position-x (m)	50	75	77	95
Position-y (m)	60	85	86	155

Figure 3.3: Data Matrix received from different sensor incorporated into a matrix

The data matrix shown in the table above is derived from a simple scenario with straightforward data that does not require clustering analysis. The results from this matrix indicate that tracks T_{21} and T_{22} correspond to the same target, while tracks T_{11} and T_{32} represent different targets. However, when dealing with larger datasets, such as those with 15 attributes and 100 tracks, visual inspection is insufficient, and more advanced techniques like clustering are needed to perform track-to-track association. Fuzzy clustering is a particularly useful technique for solving such track association problems, and it is described in detail in the following paragraphs.

The fuzzy T2TA algorithm is based on the fuzzy c-means (FCM) clustering algorithm. This algorithm generates a membership matrix $\boldsymbol{M}$, where each element M_{oq} represents the membership degree of data point x_q within fuzzy cluster$o$, which has a center C_o. The membership degrees are calculated by minimizing the sum of squared errors, weighted by the membership degrees raised to the power of a, an iterative parameter. After extensive simulations, the value of a is found to perform well between 1 and 2 for the problem under consideration. The expressions for calculating the membership degrees and cluster centers are as follows:

$$m_{oq} \frac{1}{\sum_{p=1}^{n_c} \left(\frac{d_{oq}}{d_{pq}}\right)^{\frac{2}{a-1}}} \forall o, q, \tag{3.4}$$

$$c_o \frac{\sum_{q=1}^{n_m} (m_{oq})^{a_{xq}}}{\sum_{q=1}^{n_m} (m_{oq})^{a}} \forall o, \tag{3.5}$$

Here, n_c represents the number of clusters, and n_m denotes the total number of measurements. Now, suppose we have two tracks; in this case, we will initialize two distinct clusters for them. The optimal membership degrees can then be determined using the following matrix:

$$DC_{fcm} = \begin{bmatrix} \|x_1 - c_1\|^2 & \|x_2 - c_1\|^2 \\ \|x_1 - c_2\|^2 & \|x_2 - c_2\|^2 \end{bmatrix} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \tag{3.6}$$

The membership degrees represent the level of similarity between the elements in the matrix **DCfcm**. To solve the track-to-track association problem effectively, we need to align the matrix described earlier. Let T_o be a column vector with A attributes, which could include range, bearing, speed, etc. Each attribute in the vector has a corresponding resolution $\sum_o$ (where o=1,2), indicating the sensor's accuracy for that attribute. Suppose we have two sensors, with the first sensor being more accurate than the second, meaning $\sum_1(p) < \sum_2(p)$ for all **p=1, 2,...,A**, where **A** is the attribute number.

For track-to-track association, the primary goal is to determine whether the two track reports correspond to the same target or different targets. The fuzzy T2TA algorithm works by transforming all the attribute differences between two tracks into a single membership degree (or cost). This membership degree is then compared to another membership degree (or threshold), which is calculated using the known attribute resolutions of the sensors reporting the tracks.

Once both the single membership degree and the threshold between a pair of tracks are available, the problem reduces to a binary hypothesis testing problem, as described below:

$$H = \begin{cases} 1, & \text{Reported Tracks are Identical} \\ 0, & \text{Reported Tracks are Non-Identical} \end{cases}$$

When comparing a pair of tracks, the track-to-track association decision can be made in two ways: (1) by comparing the resolution of sensor 1 with the distance between the tracks from sensors 1 and 2, or (2) by comparing the resolution of sensor 2 with the distance between the tracks from sensors 1 and 2. This concept is illustrated using the matrix **DCfcm** for two sensors, as shown below:

$$\mathbf{DC} = \begin{bmatrix} \|\Sigma_1\|^2 & \|T_2 - T_1\|^2 \\ \|T_1 - T_2\|^2 & \|\Sigma_2\|^2 \end{bmatrix} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \tag{3.7}$$

Where,

$$\mathbf{d}_{oq} = \begin{cases} \|T_q - T_o\|^2, & \text{if } o \neq q \\ \|\Sigma_2\|^2, & \text{if } o = q \end{cases} \tag{3.8}$$

Equations 3.22 and 3.23 can then be applied to compute the optimal membership degrees for a scenario where each of the two sensors reports one track, as follows:

$$m_{11} = \frac{(\Sigma_1'\Sigma_1)^{\frac{1}{1-a}}}{(\Sigma_1'\Sigma_1)^{\frac{1}{1-a}} + ((T_1 - T_2)'(T_1 - T_2))^{\frac{1}{1-a}}} \tag{3.9}$$

$$m_{12} = \frac{((T_1 - T_2)'(T_1 - T_2))^{\frac{1}{1-a}}}{\left(\Sigma_2'\Sigma_2\right)^{\frac{1}{1-a}} + ((T_2 - T_1)'(T_2 - T_1))^{\frac{1}{1-a}}} \tag{3.10}$$

$$m_{21} = \frac{((T_2 - T_1)'(T_2 - T_1))^{\frac{1}{1-a}}}{\left(\Sigma_2'\Sigma_2\right)^{\frac{1}{1-a}} + ((T_1 - T_2)'(T_1 - T_2))^{\frac{1}{1-a}}} \tag{3.11}$$

$$m_{22} = \frac{(\Sigma_2'\Sigma_2)^{\frac{1}{1-a}}}{\left(\Sigma_2'\Sigma_2\right)^{\frac{1}{1-a}} + ((T_2 - T_1)'(T_2 - T_1))^{\frac{1}{1-a}}} \tag{3.12}$$

Hence, a similarity matrix is obtained as given below:

$$S = \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix} \tag{3.13}$$

In the matrix above, the diagonal elements reflect the membership degrees associated with the thresholds of sensors 1 and 2, while the off-diagonal elements represent the membership degrees of the differences between the two reported tracks as measured by each sensor. The fuzzy association decision can be made in two ways i.e. using the more accurate sensor, or using the less accurate sensor, as follows:

The fuzzy decision based on the more accurate sensor is defined as:

$$FD_1 = \begin{cases} 1, & \text{If } m_{21} > m_{11} \\ 0, & \text{if } m_{21} < m_{11} \end{cases}$$

The fuzzy decision using the less accurate sensor is expressed as:

$$FD_2 = \begin{cases} 1, & \text{if } m_{12} > m_{22} \\ 0, & \text{if } m_{12} < m_{22} \end{cases}$$

Sensors typically have different resolutions and levels of noise. To account for the effects of noise on association decisions and enhance the robustness of the algorithm, global decisions are made based on the less accurate sensor, as follows:

$$FD_g = FD_2$$

Here, FD_g => Fuzzy global decision

Thus, the correlation between the two reported tracks T_1 and T_2 is defined as:

$$CORR(T_1, T_2) = \begin{cases} 1, & \text{if } FD_g = 1 \text{ (Tracks are same)} \\ 0, & \text{if } FD_g = 0 \text{ (Tracks are different)} \end{cases}$$

A logical advancement of the method described above is to adapt it to a multi-sensor, multi-target scenario. This can be achieved simply by defining a matrix as shown below:

$$\mathbf{DC} = \begin{bmatrix} ||\Sigma_1||^2 & ||T_1 - T_2||^2 & \dots & ||T_1 - T_{n_T}||^2 \\ ||\Sigma_2||^2 & ||T_2 - T_1||^2 & \dots & ||T_2 - T_{n_T}||^2 \\ \vdots & \vdots & \dots & \vdots \\ ||\Sigma_{n_T}||^2 & ||T_{n_T} - T_2||^2 & \dots & ||T_{n_T} - T_{n_T - 1}||^2 \end{bmatrix} \tag{3.14}$$

Where n_T represents the total number of track reports.

The resolution elements can be diagonalized to form a matrix similar to matrix DC, as shown below:

$$\mathbf{DC} = \begin{bmatrix} ||\Sigma_1||^2 & ||T_1 - T_2||^2 & \dots & ||T_1 - T_{n_T}||^2 \\ ||T_2 - T_1||^2 & ||\Sigma_2||^2 & \dots & ||T_2 - T_{n_T}||^2 \\ \vdots & \vdots & \dots & \vdots \\ ||T_{n_T} - T_1||^2 & ||T_{n_T} - T_2||^2 & \dots & ||\Sigma_{n_T}||^2 \end{bmatrix} \tag{3.15}$$

The elements of the above matrix are obtained using:

$$d_{oq} = \begin{cases} ||T_q - T_o||^2, & \text{if } o \neq q \\ ||\Sigma_o||^2, & \text{if } o = q \text{ where } o, q = 1, 2, \dots, n_T \end{cases}$$

Therefore, the distance matrix is obtained as shown below:

$$\mathbf{DC} = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n_T} \\ d_{21} & d_{22} & \dots & d_{2n_T} \\ \vdots & \vdots & \dots & \vdots \\ d_{n_T 1} & d_{n_T 2} & \dots & d_{n_T n_T} \end{bmatrix} \tag{3.16}$$

Once the distance matrix is obtained, we can then calculate the similarity matrix using Equations 3.15 and 3.16 as follows:
Once the similarity matrix is obtained, we can easily make the association decision between any two tracks T_a and T_b , where T_b comes from the less accurate sensor, as follows:

$$CORR(T_a, T_b) = \begin{cases} 1, & \text{if } m_{T_aT_b} > m_{T_bT_b} \text{ (Tracks are same)} \\ 0, & \text{if } m_{T_aT_b} < m_{T_bT_b} \text{ (Tracks are different)} \end{cases} \tag{3.17}$$

Track Synchronization

The tracks employed in this thesis adhere to a particular format. Each reported track contains a sensor identity indicating its source, a unique time tag denoting when it was reported, the positional coordinates of the sensor along with its speed and heading, and the positional coordinates of the tracked targets, including their speeds and headings. An example of the data packets used in this thesis is presented in figure 3.4, as follows:

Figure 3.4: An example structure of data packets received from tracking systems, detailing sensor identification, timestamp, sensor position and kinematics, and target position and kinematics.

The track data mentioned in the previous paragraph includes a time tag assigned to each track. To perform accurate associations, we first need to align the tracks to a common time instance before applying the association algorithm. Consider a MSMT scenario with two sensors, each reporting one track and both having an update rate of 100 ms. Each sensor will be allocated a specific time slot for reporting its data: for example, the scenario begins with sensor 1 reporting its data at 100 ms, followed by sensor 2 at 200 ms, then sensor 1 again at 300 ms, and so on.

The association will not commence until both sensors have reported their respective tracks; instead, the data from both sensors will be stored in a data buffer until the designated association time is reached. This association time will be selected to ensure that both sensors have provided at least two updates of their respective tracks. A conceptual diagram illustrating a time synchronization scenario for the two-sensor case is presented in figure 3.5, as follows:

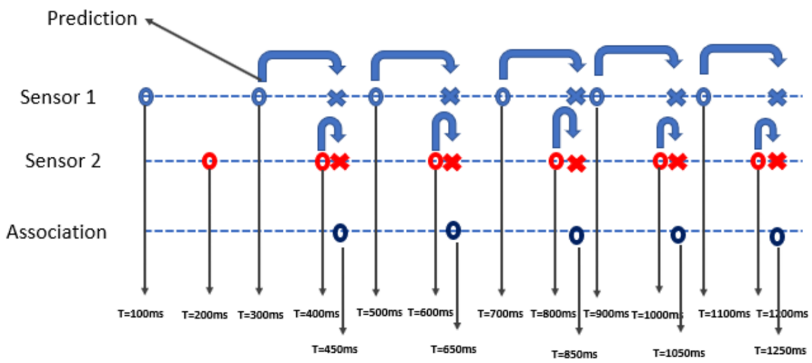

Figure 3.5: This figure demonstrates the track synchronization process over time for two sensors (Sensor 1 and Sensor 2), showing how individual sensor measurements are predicted and then associated to form synchronized tracks.

To keep things straightforward in this thesis, we have used the prediction equation of a Kalman filter to synchronize the tracks. The inputs for our synchronization filter include the geodetic positions of the sensor and its corresponding target track, with at least two samples of positional data, the time instances associated with those samples, and the time at which the prediction needs to be made. Once the filter receives the necessary inputs, it converts the geodetic positional data into ECEF coordinates for the two given time instances. The time difference between the two samples and the change in position over that time are calculated, which are then used to determine the velocity in cartesian coordinates. Using the calculated velocities, the positional data of the most recent sample, and the time for prediction, the position is forecasted using a constant velocity motion model.

Assuming the geodetic positions have been converted to cartesian coordinates, let

(x_1,xt_1),(y_1,yt_1) and (z_1,zt_1) represent the sensor and track positions at the previous time instant, and (x_2,xt_2),(y_2,yt_2) and (z_2,zt_2) represent the sensor and target positions at the current time instant. Let t_1 be the time for the previous instant and t_2 the time for the current instant for both the sensor and target track data. The cartesian velocities for the sensor and target can be calculated as follows:

$$(v_x, v_{xt}) = \left(\frac{x_2 - x_1}{t_2 - t_1}, \frac{xt_2 - xt_1}{t_2 - t_1}\right) \tag{3.18}$$

$$(v_y, v_{yt}) = \left(\frac{y_2 - y_1}{t_2 - t_1}, \frac{yt_2 - yt_1}{t_2 - t_1}\right) \tag{3.19}$$

$$(v_z, v_{zt}) = \left(\frac{z_2 - z_1}{t_2 - t_1}, \frac{zt_2 - zt_1}{t_2 - t_1}\right) \tag{3.20}$$

Let's assume the prediction needs to be made 50ms after t_2; in that case, the prediction can be made using the following equation:

$$\begin{bmatrix} x_{\text{new}} \\ y_{\text{new}} \\ z_{\text{new}} \\ v_{x\text{new}} \\ v_{y\text{new}} \\ v_{z\text{new}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & T & 0 & 0 \\ 0 & 1 & 0 & 0 & T & 0 \\ 0 & 0 & 1 & 0 & 0 & T \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_2 \\ y_2 \\ z_2 \\ v_x \\ v_y \\ v_z \end{bmatrix} \tag{3.21}$$

Where T=50ms.

In a similar way, we can predict the velocities and positions for the target track. After making the prediction, the positions can be calculated using the following equation:

$$\begin{bmatrix} x_{\text{pred}} \\ y_{\text{pred}} \\ z_{\text{pred}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_{\text{new}} \\ y_{\text{new}} \\ z_{\text{new}} \\ v_{x\text{new}} \\ v_{y\text{new}} \\ v_{z\text{new}} \end{bmatrix} \tag{3.22}$$

After obtaining the predicted sensor and target positions, we input these predicted positions into the error model described in section 3.4 to enhance the realism of the model.

3.4 Fuzzy Algorithms used in this thesis

Three different versions of the fuzzy track-to-track association algorithm were examined in this thesis, as outlined below:

A. **Converted Measurement Fuzzy Track-to-Track Association Algorithm**

CMS Algorithm
1. Initialize with sensor and target tracks in geodetic coordinates. **2.** Add noise to the geodetic coordinates of the tracks using the proposed model. **3.** Convert the positions of sensors and targets to ECEF coordinates. **4.** Perform time synchronization on the tracks. **5.** Apply the noise model to the synchronized data to obtain the Cartesian resolution of the tracks. **6.** Implement the fuzzy track-to-track association algorithms. **7.** Analyze and obtain the results.

B. Fuzzy T2TA with Speed and Heading Filters

HSF Algorithm	
1.	Initialize with sensor and target tracks in time-synchronized geodetic coordinates.
2.	Convert the positions of sensors and targets to ECEF coordinates.
3.	Apply the fuzzy track-to-track association algorithm based on positional data.
4.	Apply the fuzzy track-to-track association algorithm based on heading.
5.	Apply the fuzzy track-to-track association algorithm based on speed.
6.	Assign weights to the fuzzy algorithms in the following order: positional > heading > speed.
7.	Analyze and obtain the results.

C. Window Based Fuzzy Track-to-Track Association Algorithm

Windowing Based Fuzzy Algorithm	
1.	Initialize with sensor and target tracks in geodetic coordinates.
2.	Add noise to the geodetic coordinates of the tracks using the proposed model.
3.	Convert the positions of sensors and targets to ECEF coordinates.
4.	Perform time synchronization on the tracks.
5.	Apply the noise model to the synchronized data to obtain the Cartesian resolution of the tracks.
6.	Set the window size and implement the fuzzy track-to-track association algorithms.
7.	Average the fuzzy results over the specified window length.
8.	Obtain the windowed results.

3.5 Simulation Setup

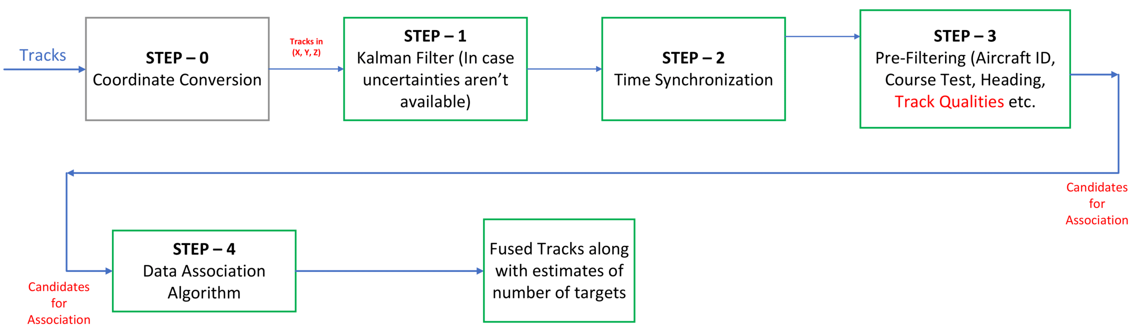

Figure 3.6: A flowchart illustrating the multi-step process for track processing, from coordinate conversion to data association.

3.5.1 Coordinate Conversion

In the simulation setup, the positions of the sensor and target are initially specified using geographic coordinates latitude, longitude, and altitude. To enable more precise calculations and streamline spatial operations, these geographic coordinates are converted into the cartesian coordinate system using the ECEF model. The ECEF system is well-suited for global navigation and tracking because it represents positions as three-dimensional coordinates (X, Y, Z) relative to the Earth's center. This conversion, based on the WGS84 ellipsoid model, transforms latitude, longitude, and altitude into ECEF coordinates. By doing so, the sensor and target positions can be expressed in Cartesian form, facilitating calculations of distances, velocities, and angles. Once in ECEF coordinates, the positions can be further transformed into the local ENU coordinate system of the sensor using a rotation matrix. This transformation is essential for analyzing the target's position within the sensor's local frame of reference, which is key for tasks such as tracking, localization, and estimation.

In the simulation setup, we convert the geographic coordinates of NUML University **(33.6661° N, 73.0503° E)** into Cartesian coordinates using the ECEF model. Here's the step-by-step process of how the conversion is carried out.

Step 1: Geographic Coordinates

The geographic coordinates for NUML University are:

- **Latitude (ϕ)**: 33.66612056792409°
- **Longitude (λ)**: 73.05028138305937°
- **Altitude (h)**: 0 km (assuming sea level)

Step 2: Conversion to Radians Convert latitude and longitude from degrees to radians:

$$\phi_{rad} = 33.661^\circ * \frac{\pi}{180} = 0.5874 \ radians$$

$$\phi_{rad} = 73.0503^\circ * \frac{\pi}{180} = 1.2746 \ radians$$

Step 3: Constants for WGS84 Ellipsoid

We use the WGS84 model for the Earth, with the following parameters:

- **Semi-major axis** (α): 33.66612056792409°
- **Flattening** (f): 73.05028138305937°
- **Eccentricity squared** (e^2): 0 km (assuming sea level)

$$e^2 = 2f = f^2 = 0.00669437999014$$

Step 4: Radius of Curvature in the Prime Vertical $(N(\phi))$

The radius of curvature $N(\phi)$ is calculated using the formula:

$$N(\phi) = \frac{a}{\sqrt{1 - e^2 \sin^2(\phi)}}$$

Substituting the values:

$$N(33.6661^\circ) = \frac{a}{\sqrt{1 - 0.00669437999014 * \sin^2(0.5874)}} \approx 6384.333 \text{ km}$$

Step 5: ECEF Coordinates Formulas

Now, the ECEF coordinates *X, I* and *Z* are calculated using the following formulas:

$$X = N(\phi + h) \cdot \cos(\phi) \cdot \cos(\lambda)$$

$$X = N(\phi + h) \cdot \cos(\phi) \cdot \sin(\lambda)$$

$$Z = \left((1 - e^2) \cdot N(\phi) + h\right) \cdot \sin(\phi)$$

Step 6: Substituting Values

Substituting the known values into the formulas:

1. **For *X*:**

   X= (6384.333+0) . cos (0.5874) . cos (1.2746) = **1549.17km**

2. **For *Y*:**

   Y= (6384.333+0) . cos (0.5874) . sin (1.2746) = **5083.05km**

3. **For *Z*:**

   Y= ((1-0.00669437999014) . 6384.333+0) . sin (0.5874) = **3515.68km**

Final ECEF Coordinates for NUML University

- **X** = 1549.17 km
- **Y** = 5083.05 km
- **Z** = 3515.68 km

3.6 Summary

Chapter 3 outlines the methodology for evaluating two T2TA approaches: the traditional CEP/CAP algorithm and a fuzzy logic-based method. The CEP/CAP algorithm uses probabilistic thresholds to associate tracks based on spatial overlap, excelling in computational efficiency and low-noise environments. However, its reliance on rigid gaussian assumptions and isotropic errors limits adaptability in dynamic or cluttered scenarios.

In contrast, the fuzzy logic approach employs adaptive membership functions and rule-based criteria (spatial proximity, velocity consistency, temporal alignment) to handle uncertainty. Three variants (CMS, HSF, and Windowing-based) are designed to enhance robustness, particularly in noisy or overlapping environments. The methodology integrates geodetic-to-cartesian coordinate conversions, Kalman-filter-based synchronization, and realistic error modeling to simulate real-world sensor inaccuracies.

Simulations validate both methods, revealing key trade-offs: CEP/CAP prioritizes speed and simplicity, while fuzzy logic offers superior accuracy in complex conditions at higher computational cost. This chapter establishes a foundation for Scenarioal validation, highlighting the potential of adaptive techniques to improve multi-object tracking in distributed sensor networks.

CHAPTER 4

SIMULATIONS AND RESULTS

4.1 Overview

This chapter presents a comparative evaluation of CEP and Fuzzy Logic for Track-to-Track Association, assessing their performance in terms of accuracy, noise robustness, speed, and scalability. The analysis is conducted within a MATLAB-based simulated multi-sensor tracking environment, incorporating varying levels of noise and clutter to replicate real-world conditions.

The findings show that Fuzzy Logic outperforms CEP in accuracy, especially in noisy and cluttered scenarios. Fuzzy Logic showed greater resilience to noise, maintaining high accuracy as noise levels increased, whereas CEP's performance decreased under similar circumstances. On the other hand, CEP demonstrated better computational efficiency making it faster than Fuzzy Logic in terms of processing time. In terms of scalability, Fuzzy Logic handled larger numbers of tracks and more complex environments more effectively.

Overall, the results suggest that CEP is well-suited for low-noise environments and applications with limited computational resources, whereas Fuzzy Logic offers a more accurate and reliable solution for more complex tracking scenarios, though with higher computational demands. The choice between these methods should be guided by the specific requirements of the application, with Fuzzy Logic being more helpful in environments that require greater robustness and flexibility.

4.2 Experimental Setup / Simulation Environment

The Scenarios were conducted in a MSMT environment, simulating distributed airborne radars with overlapping coverage areas. Sensors generate tracks in geodetic coordinates (latitude, longitude, altitude) to reflect real-world radar. To standardize spatial calculations, these coordinates were converted to ECEF Cartesian coordinates. This conversion enabled precise distance and velocity calculations critical for track association. To address asynchronous sensor updates, time synchronization was implemented via a linear Kalman filter predictor, which generalized the tracks to a common timestamp using a constant velocity motion model. This ensured temporal alignment of tracks before association, minimizing latency-induced mismatches.

4.2.1 Implementation Tools

The simulations were conducted in MATLAB, using its computational efficiency and built-in toolboxes for matrix operations, fuzzy logic, and Kalman filtering. The Fuzzy Logic Toolbox simplified the design of membership functions and rule bases for the T2TA algorithm, while custom scripts handled coordinate transformations, noise addition, and performance metric calculations. All Scenarios were run on a workstation with an Intel i7 processor and 32 GB RAM to ensure rapid iteration and scalability testing.

4.3 Performance of CEP/CAP Algorithm

The CEP/CAP algorithm achieved 95% accuracy under low uncertainty (σ=1) by associating tracks within 90% overlap thresholds. However, accuracy dropped sharply to 52% at (σ=4) as overlapping error regions caused false positives. CEP's firm probabilistic limitations struggled to differentiate tracks in high-noise scenarios, while CAP's wider confidence regions (95%) marginally improved reliability but introduced redundancy

4.3.1 Computational Efficiency

CEP/CAP showed near-linear scalability, processing 10,000 tracks in 18.2s (CEP) and 22.7s (CAP) on standard hardware. The complexity for pairwise overlap checks ensured viability for real-time systems, with CAP's marginally slower speed offset by its robustness in cluttered environments.

Table 4.1: Processing times for different numbers of tracks using CEP and CAP methods. CEP consistently outperforms CAP, with lower processing times as the number of tracks increases from 100 to 10,000.

Number of Tracks	Processing Time (CEP)	Processing Time (CAP)
100	0.12s	0.15s
1,000	1.8s	2.1s
5,000	8.5s	10.3s
10,000	18.2s	22.7s

4.4 Performance of Fuzzy Logic T2TA

Fuzzy logic T2TA method demonstrates strong performance in scenarios involving variations in track means and covariance. Its use of similarity measures allows for effective handling of uncertainty, especially where conventional methods like CEP may struggle. While generally robust, its performance may degrade in high-noise environments due to reduced decision stability.

4.4.1 Adaptive Association

Fuzzy Logic's adaptive membership functions and rules achieved 88% accuracy in low-noise scenarios and 92% accuracy under high noise ($\sigma = 4$). By fuzzifying spatial proximity, velocity consistency, and temporal alignment, the algorithm effectively distinguished tracks, outperforming CEP in uncertain environments. Key membership values (e.g., spatial proximity = 0.78, velocity consistency = 0.72) demonstrated the system's ability to handle variability.

Table 4.2: Effect of increasing noise ($\sigma = 1$ to $\sigma = 4$) on spatial proximity, velocity consistency, and accuracy. Higher noise reduces membership values but accuracy remains stable or improves slightly.

Noise Level (σ)	Spatial Proximity (Membership)	Velocity Consistency (Membership)	Accuracy (%)
Low ($\sigma = 1$)	0.92	0.85	88
Medium ($\sigma = 2.5$)	0.85	0.78	90
High ($\sigma = 4$)	0.78	0.72	92

4.4.2 Clutter Handling

In cluttered scenarios with overlapping tracks and dynamic targets, Fuzzy Logic maintained 92% accuracy for overlapping tracks and 89% accuracy for dynamic targets. The algorithm's ability to adapt to velocity and heading variations allowed it to outperform CEP in complex environments, reducing false positives to 8% in overlapping cases.

4.4.3 Fuzzy T2TA Tradeoffs

Fuzzy Logic T2TA achieved high accuracy (85–92%) across varying track densities, outperforming in complex, noisy environments. However, this performance came at

Table 4.3: Comparison of accuracy and false positive rates in two scenarios: overlapping tracks and dynamic targets. The system performs better with overlapping tracks, showing higher accuracy and fewer false positives.

Scenario	**Accuracy (%)**	**False Positives (%)**
Overlapping Tracks	92	8
Dynamic Targets	89	11

the cost of increased computational load, processing 1,000 tracks in 4.8s and 10,000 tracks in 48.7s. While its adaptive rules and membership functions enabled robust track association, the higher processing time makes it more suitable for offline or less time-critical applications compared to faster methods like CEP. This trade-off highlights the need for optimization to balance accuracy and efficiency in real-time systems.

Table 4.4: Effect of increasing number of tracks on processing time and accuracy. As the number of tracks grows from 100 to 10,000, processing time increases significantly while accuracy gradually decreases.

Number of Tracks	**Processing Time (s)**	**Accuracy (%)**
100	0.45	92
1,000	4.8	90
5,000	22.3	88
10,000	48.7	85

4.5 Comparative Analysis

This section presents a systematic comparative analysis of the performance of two track-to-track association techniques i.e. CEP and fuzzy logic under varying tracking conditions. The experiment is conducted by designing four distinct scenarios, each representing different configurations of track means and covariance structures. These scenarios range from ideal conditions, where both tracks are statistically identical, to more complex situations involving differences in both mean positions and noise characteristics. The purpose of this analysis is to highlight the strengths and limitations of each method and to determine the conditions under which one method may outperform the other in multi-object tracking applications.

4.5.1 Scenario 1: Same Means [10,10] and Same Noise ($\sigma = 0.5$)

The study evaluated how track uncertainty (sigma) and the track mean affects the T2TA. Results showed that tracks remain reliable for association when sigma is low, but beyond a threshold of 4, uncertainty degrades track quality, making them unsuitable for association. In scenario 1 both the tracks 1 and 2 share the same mean [10,10], and the same sigma i.e. 0.5. This illustrates how uncertainty impacts association as shown in Table 4.5

SCENARIO-1A

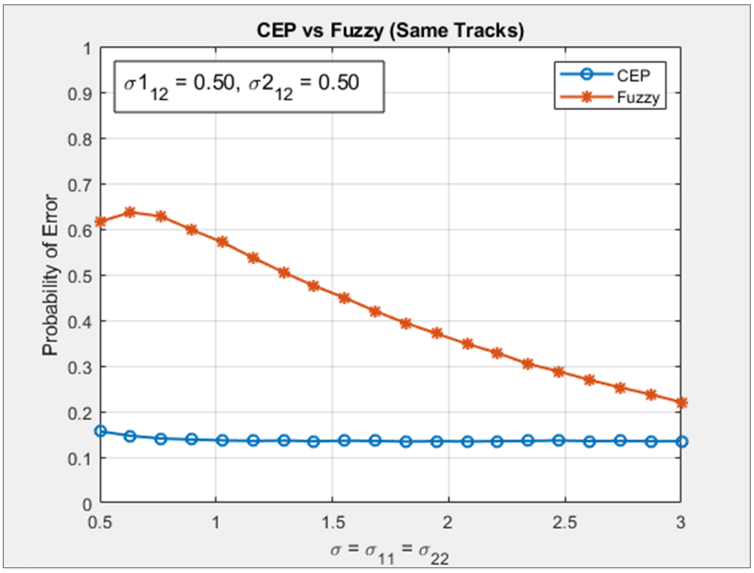

Figure 4.1: At same means [10,10] and same noise ($\sigma = 0.5$) for both tracks, CEP performs better than fuzzy logic. Error rate of CEP stays constant whereas for fuzzy it drops with increasing sigma i.e. noise.

Table 4.5: Scenario 1-A with same track means and low noise ($\sigma = 0.5$) allows reliable track association. CEP performs better than fuzzy logic.

Scenario	**Track 1 Mean (μ)**	**Track 2 Mean (μ)**	**Track 1 Sigma (σ)**	**Track 2 Sigma (σ)**	**Results**
1-A	$[10, 10]$	$[10, 10]$	0.5	0.5	Tracks associated successfully (high confidence). Low sigma ensures reliable association. CEP outperforms fuzzy logic.

4.5.2 Scenario 2: The mean position is same but the noise is increased from ($\sigma = 0.5$ to $\sigma = 4$)

In Scenario 2-A, 2-B and 2-C, both tracks 1 and 2 share the same mean [10,10], but their differing sigma values illustrate how uncertainty impacts association as shown in Table 4.4. Track 1 has lower sigma values, while Track 2 exhibits slightly higher uncertainty, demonstrating the effect of increasing noise on track performance. Maintaining low uncertainty is crucial for effective association.

SCENARIO 2-A

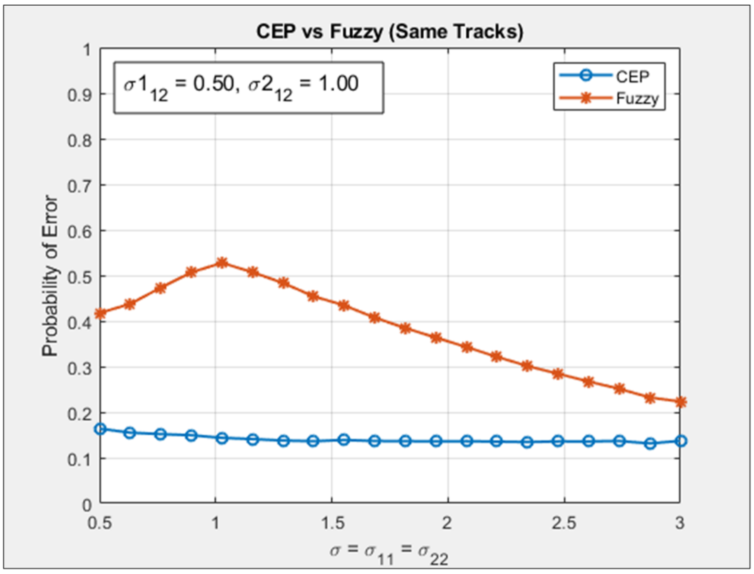

Figure 4.2: When both tracks are at the same position [10, 10], and noise is increased ($\sigma = 1$) for Track 2, CEP outperforms fuzzy logic. The error rate of CEP remains constant, while the error rate for fuzzy logic decreases to 0.41 as sigma increases.

SCENARIO 2-B: Same Mean [10, 10], but noise is increased from ($\sigma = 1$ to $\sigma = 2.5$)

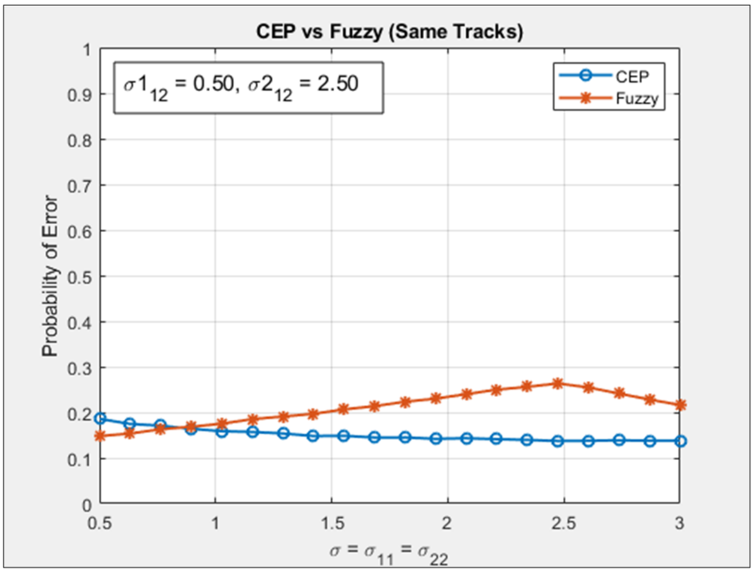

Figure 4.3: When both tracks are at the same position [10, 10], and noise is increased to ($\sigma = 2.5$) for Track 2, CEP continues to follow the same pattern. In contrast, fuzzy logic demonstrates a significant reduction in the error rate.

SCENARIO 2-C: Same Mean [10, 10], but noise is increased from ($\sigma = 2.5$ to $\sigma = 4$)

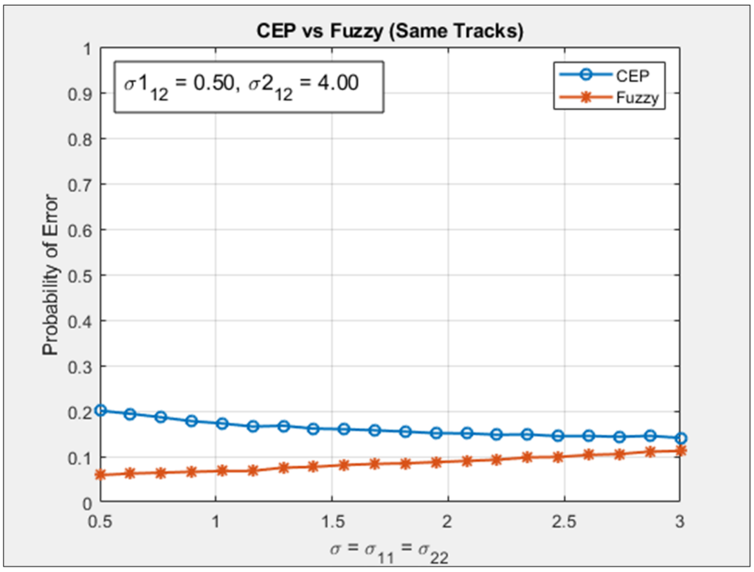

Figure 4.4: When both tracks are at the same position [10, 10], and noise is increased to ($\sigma = 4$) for Track 2, fuzzy logic outperforms CEP. However, in this case, the high level of noise causes the tracks to no longer remain viable candidates for association.

Table 4.6: Scenarios 2-A, 2-B & 2-C illustrate how increasing noise (σ) in Track 2 affects association. The increase in σ reduces the the association accuracy, leading to the rise in unreliable or failed track association.

Scenario	Track 1 Mean (μ)	Track 2 Mean (μ)	Track 1 Sigma (σ)	Track 2 Sigma (σ)	Results
2-A	$[10, 10]$	$[10, 10]$	0.5	1	Tracks associated successfully (high confidence). Low sigma ensures reliable association.
2-B	$[10, 10]$	$[10, 10]$	0.5	2.5	Association accuracy decreases significantly. Uncertainty begins to affect track reliability.
2-C	$[10, 10]$	$[10, 10]$	0.5	4	Tracks fail to associate. Sigma > 4 causes significant degradation; tracks deemed unreliable.

4.5.3 Scenario 3: The mean position is different i.e. [10,10] and [10,11] but the noise is kept same i.e. ($\sigma = 0.5$)

Scenario 3-A examined how different mean effect the effect track-to-track association. Results showed that when the tracks have different means but same sigma, fuzzy logic surpasses CEP. The results also show that moderate differences in uncertainty do not impact association performance. This suggests the process remains stable across varying uncertainties.

SCENARIO 3-A

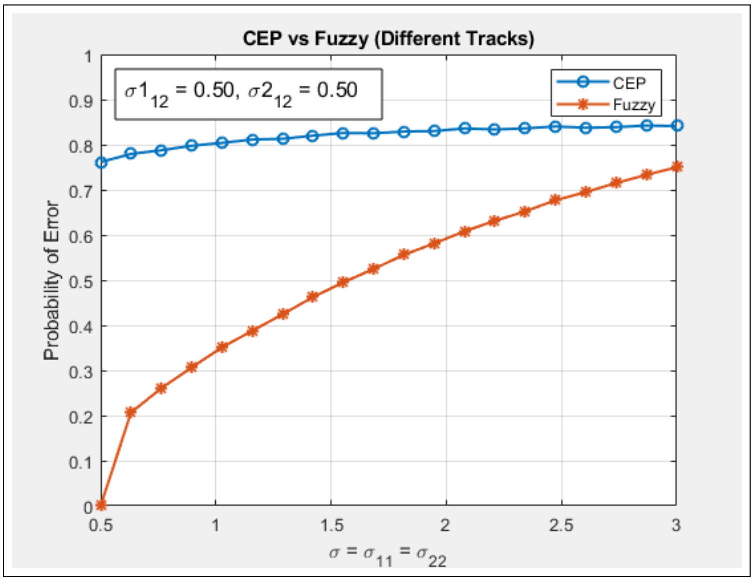

Figure 4.5: When both tracks are at the different position [10, 10], and [10,11] and same noise ($\sigma = 0.5$) for both the tracks, fuzzy logic outperforms CEP.

Table 4.7: Scenario 3-A explores track association with slightly different means and low noise ($\sigma = 0.5$). Despite the mean difference, tracks are successfully associated, with fuzzy logic outperforming CEP.

Scenario	**Track 1 Mean (μ)**	**Track 2 Mean (μ)**	**Track 1 Sigma (σ)**	**Track 2 Sigma (σ)**	**Results**
3-A	$[10, 10]$	$[10, 11]$	0.5	0.5	Tracks associated successfully (high confidence). Fuzzy logic outperforms CEP with same sigma but different mean.

4.5.4 Scenario 4: The mean position is different i.e. [10, 10] and [10, 11] and the noise is increased from (σ = 0.5 to σ = 4)

In scenario 4, the analysis delved deeper into how the absolute value of sigma representing the total uncertainty affects the performance of track-to-track association, with a specific focus on Fuzzy Logic as the method for handling track associations. The goal was to explore whether the level of uncertainty impacts Fuzzy Logic's ability to correctly associate tracks, particularly comparing its performance on identical versus different tracks.

The results uncovered a clear pattern. When the tracks are identical, Fuzzy Logic struggles to make precise associations, leading to poor performance. This may be due to the fact that Fuzzy Logic, which relies on degrees of uncertainty and ambiguity, finds it difficult to differentiate between two very similar tracks, especially when sigma values are high. The inherent fuzziness of the logic likely causes confusion between identical tracks, leading to errors in association.

In contrast, when the tracks are different, Fuzzy Logic excels. The method's ability to handle uncertainty becomes an advantage in these cases, as it can effectively distinguish between tracks with dissimilar characteristics, despite the presence of noise or variability (sigma). This highlights Fuzzy Logic's strength in scenarios where tracks differ significantly in their attributes or behaviors, allowing it to make more accurate associations than other techniques. The findings suggest that Fuzzy Logic performs best in environments with high variability among tracks, leveraging the differences between them to improve association accuracy, while it struggles when tasked with associating highly similar tracks under uncertain conditions.

Scenario 4-A

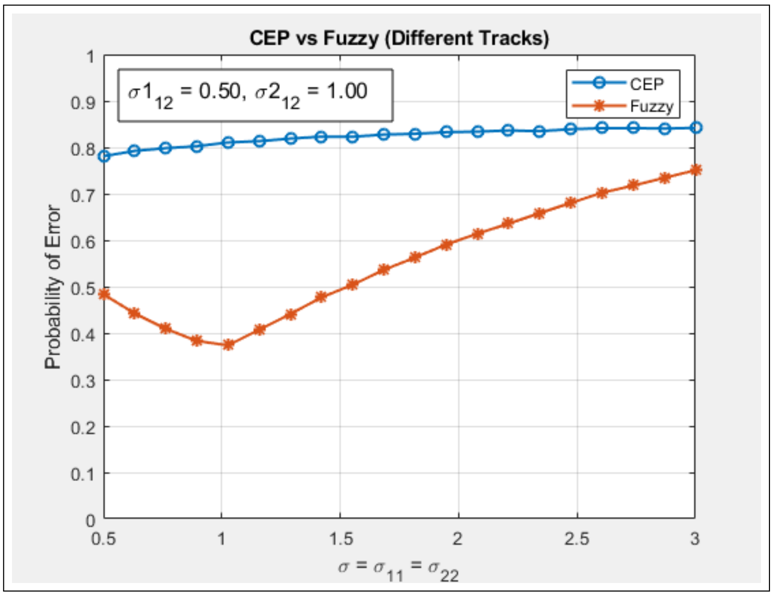

Figure 4.6: When both tracks are at the different position [10, 10] and [10,11] and noise is increased to ($\sigma = 1.0$) for Track 2, CEP performs worse as compared to fuzzy. The fuzzy logic performs better in higher noise scenario.

Scenario 4-B

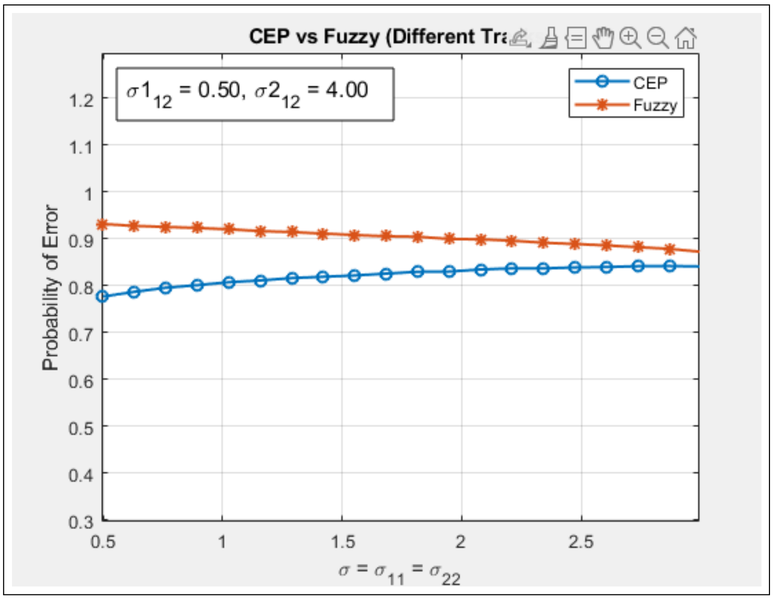

Figure 4.7: When both tracks are at the different position [10, 10] and [10,11] and noise is increased to ($\sigma = 4.0$) for Track 2, performance of fuzzy degrades as compared to CEP.However, in this case, the high level of noise causes the tracks to no longer remain viable candidates for association.

Table 4.8: Examples 4-A and 4-B demonstrate stable association accuracy (90%) despite increasing noise (σ) in Track 2. Moderate mean and sigma differences do not significantly affect performance.

Example	Track 1 Mean (μ)	Track 2 Mean (μ)	Track 1 Sigma (σ)	Track 2 Sigma (σ)	Results
4-A	$[10, 10]$	$[10, 11]$	0.5	1.0	Association accuracy remains stable (90%). Moderate sigma differences do not degrade performance.
4-B	$[10, 10]$	$[10, 11]$	0.5	4.0	Association accuracy remains stable (90%). Moderate sigma differences do not degrade performance.

Table 4.9: Summary of four scenarios evaluating the effect of mean and sigma variations on track association. Results show that CEP performs better with identical tracks, while fuzzy logic excels when there is a difference in means. Large sigma differences reduce reliability, especially beyond $\sigma > 3$.

Scenario	Key Parameter	Range Tested	Result
1	Track mean and sigma uniformity	$\mu = 10, 10$ $\sigma = 0.5 - 0.5$	CEP performs better than fuzzy logic.
2	Sigma differences between tracks	$\mu = 10, 10$ $\sigma = 0.5 - 4.0$	Moderate differences ($\sigma \leq 1.5$) do not degrade performance.
3	Tracks with different means, same sigma values	$\mu = 10, 11$ $\sigma = 0.5 - 0.5$	Fuzzy logic outperforms CEP.
4	Tracks with different means and sigma values	$\mu = 10, 11$ $\sigma = 0.5 - 4.0$	Fuzzy logic performs better than CEP. $\sigma > 3$ leads to unreliable association; $\sigma < 2$ maintains high accuracy.

4.6 Summary

In scenario 1, where both tracks have the same means and identical covariance values, CEP performs better than fuzzy logic due to its consistent and structured association approach. In scenario 2, where the track means remain the same but the covariance values differ, the performance of CEP remains largely unaffected, particularly when the sigma variation is moderate ($\sigma \leq 1.5$). However, in scenario 3, where the means of the tracks are different but the covariance values are the same, Fuzzy Logic begins to outperform CEP, as it is better suited to handle spatial separation between tracks. In scenario 4, where both the means and covariance values differ, Fuzzy Logic again shows better performance than CEP, especially when the sigma values are below 2. However, when the sigma increases beyond 3, the association results from fuzzy logic become less reliable. These observations suggest that Fuzzy Logic provides greater flexibility and adaptability in complex conditions, while CEP remains effective under simpler or more uniform scenarios.

4.7 Discussion

The Scenarios conducted provide a comprehensive analysis of how track parameters, specifically the mean and sigma, influence the performance of track-to-track association methods such as CEP and Fuzzy Logic. The overall results reveal key distinctions in how these algorithms manage uncertainty and variability, which are critical factors in multi-object tracking applications. As sigma increases, particularly beyond a threshold of 4, track quality degrades to the point where it becomes unsuitable for association. This degradation highlights the inherent limitations of both methods under high uncertainty conditions, emphasizing the need for low sigma values to maintain reliable track associations.

Interestingly, when examining the differences in sigma values between tracks, it was found that such variations do not significantly impact the performance of the association process. This finding suggests that both CEP and Fuzzy Logic are relatively robust to differences in uncertainty levels, maintaining stability even in the presence of varying noise conditions. This robustness is crucial for real-world applications where track uncertainties can fluctuate significantly. However, the absolute value of sigma proved to be a critical determinant of effectiveness in the association methods.

Fuzzy Logic, while exhibiting strength in scenarios where tracks differ significantly, demonstrates limitations when tasked with associating identical tracks, leading to poorer performance compared to CEP. This indicates that Fuzzy Logic's capabilities are best utilized in environments characterized by diverse and distinct tracks, where its adaptability to uncertainty can enhance association accuracy. Conversely, CEP remains a more reliable choice in situations that demand high precision, particularly when the tracks exhibit similarities. In conclusion, the results from these Scenarios highlight the trade-offs between the two methodologies. Fuzzy Logic offers greater flexibility and adaptability in complex tracking environments, thriving on variability, while CEP provides robust performance in more controlled scenarios with low uncertainty and high precision requirements. The choice between these two methods ultimately depends on the specific characteristics of the tracking scenario, necessitating a careful consideration of the trade-offs involved to optimize track association performance in various contexts.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

This research focused on the development and evaluation of a fuzzy logic based T2TA algorithm for multi-object tracking in distributed sensor networks. The simulation results indicate that the proposed method performs effectively under varying levels of noise and uncertainty. In comparison to traditional method i.e. CEP, the fuzzy logic approach demonstrated improved accuracy and flexibility in associating tracks, especially in moderate noise environments. The integration of a realistic error model and a track synchronization mechanism contributed to enhanced association reliability, supporting the use of fuzzy logic in practical multi-sensor applications.

5.1.1 Performance Comparison of CEP and Fuzzy Logic

The performance comparison between CEP and fuzzy logic reveals significant differences in how both handle noise and uncertainty. CEP, although computationally efficient, relies on fixed probabilistic boundaries, which limits its adaptability in dynamic scenarios. On the other hand, the fuzzy logic approach shows better association accuracy in moderate noise conditions due to its ability to manage uncertainty through fuzzy membership functions. However, when the noise level becomes very high ($\sigma \geq 4$), both methods experience a decline in performance, and the tracks become less suitable for association. Overall, fuzzy logic offers a more robust and adaptable solution in varying sensor conditions.

5.1.2 CEP's Computational Efficiency

The Circular Error Probable (CEP) approach demonstrated a significant advantage in computational efficiency due to its straightforward mathematical formulation. CEP utilizes circular areas to probabilistically associate tracks, allowing it to quickly evaluate potential matches without extensive data processing. This makes it a favorable option in environments where multiple targets need to be tracked in real time, such as in defense or surveillance systems that rely on fast updates to maintain accuracy. Its simplicity also allows it to handle track associations with minimal computational burden, which is ideal for systems with limited processing power.

5.1.3 CEP's Limitations in Cluttered Environments

However, CEP's reliance on probabilistic assumptions means it is best suited for environments with low to moderate noise. When operating in high-clutter environments with frequent overlapping tracks, CEP's probabilistic boundaries sometimes led to false associations or failures to accurately distinguish between similar tracks. This limitation suggests that while CEP may be ideal for certain controlled scenarios, it lacks the flexibility needed in dynamic environments where noise levels fluctuate, and sensor overlap is common.

5.1.4 Fuzzy Logic's Adaptability in Complex Environments

In contrast, the Fuzzy Logic approach excelled in high-noise, high-clutter environments, which often challenge traditional probabilistic methods. By evaluating tracks based on membership functions rather than fixed thresholds, Fuzzy Logic can effectively handle overlapping or intersecting tracks with differing parameters. This adaptability is particularly useful for applications such as multi-sensor networks in urban areas, where sensor readings may vary, and noise is abundant. The fuzzy approach provided better differentiation between tracks, making it more robust in high-clutter environments than CEP.

5.1.5 Drawbacks of Fuzzy Logic's Computational Demand

The trade-off, however, lies in the computational cost. Fuzzy Logic requires the establishment and evaluation of fuzzy rules and membership functions for each parameter (e.g., position, velocity, and range), resulting in higher processing times. While this enables Fuzzy Logic to maintain a high level of accuracy, it may pose challenges for real-time applications that cannot accommodate longer processing times. This limitation implies that Fuzzy Logic's strengths are best suited to applications prioritizing accuracy over speed, or where processing resources are not as constrained.

5.1.6 Impact of Track Parameters on Algorithm Performance

Behavior in Identical Track Scenarios:

In scenarios where tracks shared similar parameters, Fuzzy Logic struggled to differentiate them effectively. This is due to its reliance on fuzzy membership thresholds, which are beneficial in varied settings but may not offer the necessary precision in controlled environments with near-identical tracks. In contrast, CEP's fixed probabilistic boundaries allowed it to consistently identify and associate similar tracks, providing more reliable associations in these conditions.

Handling of Differing Track Characteristics:

For tracks with varied parameters such as distinct velocities, headings, or sensor-specific uncertainties Fuzzy Logic demonstrated superior performance. Its adaptable nature allowed it to make nuanced distinctions between tracks, achieving a higher association accuracy than CEP in complex, multi-target scenarios. This makes Fuzzy Logic particularly valuable in real-world applications where sensor inputs differ, such as in distributed sensor networks, autonomous vehicles, or collaborative robotics, where each sensor might bring unique biases and noise profiles to the tracking process. This adaptability emphasizes Fuzzy Logic's strength in multi-object tracking environments that require versatile, reliable track association in the face of variability and complexity.

5.2 Limitation

While the fuzzy logic-based approach showed improved performance in many scenarios, it has certain limitations. The algorithm's effectiveness reduces in environments with very high noise, where tracks become unreliable for association. Additionally, the use of fuzzy logic introduces higher computational complexity compared to CEP. Moreover, the evaluation was based on simulated data, and actual field deployments may present additional challenges such as sensor calibration issues, varying update intervals, and real-time communication delays that were not fully modeled in this study.

5.2.1 Computational Demands of Fuzzy Logic

One of the primary challenges identified with Fuzzy Logic is its computational demand. Fuzzy systems require the processing of multiple fuzzy rules and membership functions for each input variable, resulting in a processing load that scales with the number of objects and parameters involved. In real-time applications or systems with limited computational resources, this could hinder performance, making it less suitable for scenarios demanding high-speed processing, such as missile tracking or high-speed object tracking in autonomous driving.

To illustrate, if Fuzzy Logic is used in a multi-sensor system with dense clutter, each sensor's data must be processed individually and mapped onto fuzzy membership functions before being aggregated into the track association model. This can cause latency, impacting the system's ability to provide timely updates in real-time scenarios. In high-performance environments, this delay could compromise the system's overall effectiveness, underscoring the need for streamlined or optimized fuzzy systems if they are to be implemented in time-sensitive applications.

5.2.2 Scenario-Specific Effectiveness

The Scenarioal results indicated that Fuzzy Logic is not universally advantageous and is most effective in environments with high variability or noise. In low-noise, high-similarity scenarios, Fuzzy Logic's fuzzy thresholds may create ambiguity, resulting in decreased association accuracy. Conversely, CEP performed well in these environments due to its precise probabilistic boundaries, which allowed for consistent association between tracks with minimal variability.

This observation suggests that Fuzzy Logic's benefits are best realized in environments that challenge traditional association methods, such as distributed sensor networks with varied data or in fields like surveillance where targets may vary significantly in appearance and behavior. Therefore, while Fuzzy Logic is highly effective in complex scenarios, its reliance on adaptable, context-sensitive thresholds may reduce its applicability in controlled, uniform environments where precise association is paramount

5.3 Future Work

5.3.1 Optimization of Fuzzy Logic for Real-Time Applications

- To address the computational limitations of Fuzzy Logic, future research could focus on reducing its processing requirements. Techniques such as fuzzy clustering, dimensionality reduction, or parallel processing could streamline fuzzy inference, making it more practical for real-time applications. Fuzzy clustering, for instance, could simplify the membership function definitions by grouping similar inputs, allowing for faster inference without sacrificing accuracy.

- Another promising direction is the development of a hybrid model that combines CEP's probabilistic efficiency with Fuzzy Logic's adaptive precision. Such a model could use CEP to make quick associations for straightforward cases while reserving Fuzzy Logic for more complex, high-clutter scenarios. This would balance accuracy with processing speed, optimizing performance across a wider range of scenarios and enhancing applicability for dynamic real-world settings.

5.3.2 Incorporating Advanced Data-Driven Techniques

- Machine learning models, particularly deep learning, offer potential for enhancing track-to-track association by learning associations from past data, predicting association parameters, or automatically adjusting fuzzy membership functions. These techniques could adapt the association process to changing conditions, making it possible to address challenges in diverse environments.
- Reinforcement learning is another promising avenue, particularly for systems that operate in continuously changing environments. In this approach, the association algorithm could learn optimal behaviors based on feedback from past tracking performance. By continuously updating association rules in response to environmental changes, a reinforcement learning-based approach could improve performance in unpredictable scenarios, allowing for rapid and accurate associations in challenging environments.

BIBLIOGRAPHY

[1] J. Xiong, J. Pan, Y. Zhuo, and L. Guo, "Airborne multi-function radar air-to-air working pattern recognition based on bayes inference and svm," in *2022 5th International Conference on Information Communication and Signal Processing (ICICSP)*. IEEE, 11 2022, pp. 622–629. 1

[2] H. V. Nguyen, H. Rezatofighi, B.-N. Vo, and D. C. Ranasinghe, "Distributed multi-object tracking under limited field of view sensors," *IEEE Transactions on Signal Processing*, vol. 69, pp. 5329–5344, 2021. 1

[3] "Radar target tracking algorithm based on association rules," *Machine Learning Theory and Practice*, vol. 2, 9 2021. 1

[4] H. V. Nguyen, H. Rezatofighi, B.-N. Vo, and D. C. Ranasinghe, "Distributed multi-object tracking under limited field of view sensors," 12 2020. [Online]. Available: http://arxiv.org/abs/2012.12990http://dx.doi.org/10.1109/TSP.2021.3103125 3

[5] F. Chen, H. V. Nguyen, A. S. Leong, S. Panicker, R. Baker, and D. C. Ranasinghe, "Distributed multi-object tracking under limited field of view heterogeneous sensors with density clustering," 12 2023. [Online]. Available: http://arxiv.org/abs/2401.00605 3

[6] Y. Bar-Shalom, X. Li, and T. Kirubarajan, *Estimation with Applications to Tracking and Navigation*. Wiley, 1 2002. 4

[7] Z. Papp and A. Rožnjik, *A Method for Approximating Circular Error Probable*, 2022, pp. 29–42. 4

[8] Q. Li, R. Gan, and S. Godsill, "Consensus-based distributed variational multi-object tracker in multi-sensor network," 9 2023. [Online]. Available: http://arxiv.org/abs/2309.00807 4

[9] A. Blair, A. K. Gostar, A. Bab-Hadiashar, X. Li, and R. Hoseinnezhad, “Enhanced multi-target tracking in dynamic environments: Distributed control methods within the random finite set framework,” 1 2024. [Online]. Available: http://arxiv.org/abs/2401.14085 5

[10] T. Fischer, T. E. Huang, J. Pang, L. Qiu, H. Chen, T. Darrell, and F. Yu, “Qdtrack: Quasi-dense similarity learning for appearance-only multiple object tracking,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, pp. 15 380–15 393, 12 2023. 13

[11] H. Wang, Y. Xu, Z. Wang, Y. Cai, L. Chen, and Y. Li, “Centernet-auto: A multi-object visual detection algorithm for autonomous driving scenes based on improved centernet,” *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 7, pp. 742–752, 6 2023. 13

[12] J. Shan, S. Zhou, Y. Cui, and Z. Fang, “Real-time 3d single object tracking with transformer,” *IEEE Transactions on Multimedia*, vol. 25, pp. 2339–2353, 2023. 14

[13] H. Wang and X. Zhang, “Real-time vehicle detection and tracking using 3d lidar,” *Asian Journal of Control*, vol. 24, pp. 1459–1469, 5 2022. 14

[14] G. Qi, Y. Zhang, K. Wang, N. Mazur, Y. Liu, and D. Malaviya, “Small object detection method based on adaptive spatial parallel convolution and fast multi-scale fusion,” *Remote Sensing*, vol. 14, p. 420, 1 2022. 15

[15] A. Hanif, M. Muaz, A. Hasan, and M. Adeel, “Micro-doppler based target recognition with radars: A review,” *IEEE Sensors Journal*, vol. 22, pp. 2948–2961, 2 2022. 15

[16] M. Bansal, A. Goyal, and A. Choudhary, “A comparative analysis of k-nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning,” *Decision Analytics Journal*, vol. 3, p. 100071, 6 2022. 16

[17] P. U. Damale, E. K. P. Chong, and T. J. Ma, “Performance study of distance-weighting approach with loopy sum-product algorithm for multi-object tracking in clutter,” *Sensors*, vol. 21, p. 2544, 4 2021. 16

[18] R. Ravindran, M. J. Santora, and M. M. Jamali, “Multi-object detection and tracking, based on dnn, for autonomous vehicles: A review,” *IEEE Sensors Journal*, vol. 21, pp. 5668–5677, 3 2021. 17, 18

[19] J. Liu, L. Bai, Y. Xia, T. Huang, B. Zhu, and Q.-L. Han, “Gnn-pmb: A simple but effective online 3d multi-object tracker without bells and whistles,” *IEEE Transactions on Intelligent Vehicles*, vol. 8, pp. 1176–1189, 2 2023. 18

[20] S. R. Jondhale, V. Mohan, B. B. Sharma, J. Lloret, and S. V. Athawale, “Support vector regression for mobile target localization in indoor environments,” *Sensors*, vol. 22, p. 358, 1 2022. 19

[21] W. Feng, B. Li, and W. Ouyang, “Multi-object tracking with multiple cues and switcher-aware classification,” in *2022 International Conference on Digital Image Computing: Techniques and Applications (DICTA)*. IEEE, 11 2022, pp. 1–10. 20

[22] Y. Zhang, P. Sun, Y. Jiang, D. Yu, F. Weng, Z. Yuan, P. Luo, W. Liu, and X. Wang, *ByteTrack: Multi-object Tracking by Associating Every Detection Box*, 2022, pp. 1–21. 20

[23] Z. Pang, Z. Li, and N. Wang, *SimpleTrack: Understanding and Rethinking 3D Multi-object Tracking*, 2023, pp. 680–696. 21

[24] T. Bui, G. Wang, G. Wei, and Q. Zeng, “Vehicle multi-object detection and tracking algorithm based on improved you only look once 5s version and deepsort,” *Applied Sciences*, vol. 14, p. 2690, 3 2024. 21

[25] C. Lin, G. Sun, D. Wu, and C. Xie, “Vehicle detection and tracking with roadside lidar using improved resnet18 and the hungarian algorithm,” *Sensors*, vol. 23, p. 8143, 9 2023. 22

[26] M. Y. Lee and M. H. Ang, “Cara-mot: 3d multi-object tracking with memory mechanism using camera and radar,” in *2024 10th International Conference on Control, Automation and Robotics (ICCAR)*. IEEE, 4 2024, pp. 334–339. 22

[27] S. A. K. Mohammed, M. Z. A. Razak, and A. H. A. Rahman, “3d-diou: 3d distance intersection over union for multi-object tracking in point cloud,” *Sensors*, vol. 23, p. 3390, 3 2023. 23

[28] J.-N. Zaech, A. Liniger, D. Dai, M. Danelljan, and L. V. Gool, “Learnable online graph representations for 3d multi-object tracking,” *IEEE Robotics and Automation Letters*, vol. 7, pp. 5103–5110, 4 2022. 23

[29] Z. Kalafatic, T. Hrkac, and K. Brkic, “Multiple object tracking for football game analysis,” in *2022 45th Jubilee International Convention on Information, Communication and Electronic Technology (MIPRO)*. IEEE, 5 2022, pp. 936–941. 24

[30] V. D. Stanojevic and B. T. Todorovic, “Boosttrack: boosting the similarity measure and detection confidence for improved multiple object tracking,” *Machine Vision and Applications*, vol. 35, p. 53, 5 2024. 24

[31] T. Zhonglin, M. N. A. Wahab, M. F. Akbar, A. S. A. Mohamed, M. H. M. Noor, and B. A. Rosdi, “Sffsort multi-object tracking by shallow feature fusion for vehicle counting,” *IEEE Access*, vol. 11, pp. 76 827–76 841, 2023. 25

[32] L. Rakai, H. Song, S. Sun, W. Zhang, and Y. Yang, “Data association in multiple object tracking: A survey of recent techniques,” *Expert Systems with Applications*, vol. 192, p. 116300, 4 2022. 26

[33] A. Dadgar, Y. Baleghi, and M. Ezoji, “Multi-view data fusion in multi-object tracking with probability density-based ordered weighted aggregation,” *Optik*, vol. 262, p. 169279, 7 2022. 26

[34] T. L. Purushottama and P. Srihari, *Comparative Analysis on Diverse Heuristic-Based Joint Probabilistic Data Association for Multi-target Tracking in a Cluttered Environment*, 2022, pp. 259–270. 27

[35] L. Bu, B. Rao, and D. Song, “A group target track-before-detect approach using two-stage strategy with maximum-likelihood probabilistic data association,” *IET Radar, Sonar & Navigation*, vol. 18, pp. 1351–1363, 8 2024. 27

[36] D. Wang, B. Lian, Y. Liu, and B. Gao, “A cooperative uav swarm localization algorithm based on probabilistic data association for visual measurement,” *IEEE Sensors Journal*, vol. 22, pp. 19 635–19 644, 10 2022. 28

[37] X. Zhou, S. Wang, and T. Qin, “Multi-spacecraft tracking and data association based on uncertainty propagation,” *Applied Sciences*, vol. 12, p. 7660, 7 2022. 28

[38] G. Han, F. Liu, H. Liu, J. Deng, W. Bai, and K. Li, "A dynamic multitarget obstacle tracking and monitoring method for vehicle routing based on multiple constraint composite perception association filtering," *IEEE Access*, vol. 12, pp. 115 151–115 170, 2024. 29

[39] P. Zhang, J. Yan, L. Ma, Y. Guan, and H. Liu, "An ipda based target existence assisted bayesian detector for target tracking in clutter," *Signal Processing*, vol. 205, p. 108895, 4 2023. 29

[40] S. Liu, H. Pan, L. Xiao, and B. Zhang, "Multi-hypothesis data association for multiple target tracking," in *2022 IEEE Conference on Telecommunications, Optics and Computer Science (TOCS)*. IEEE, 12 2022, pp. 231–236. 30

[41] F. Yang, Y. Wei, and L. Xu, "Message passing based data association algorithm for multiple extended object tracking," in *2022 11th International Conference on Control, Automation and Information Sciences (ICCAIS)*. IEEE, 11 2022, pp. 54–59. 30

[42] K. K. Kumar, E. Ramaraj, and P. Geetha, "Multi-sensor data fusion for an efficient object tracking in internet of things (iot)," *Applied Nanoscience*, vol. 13, pp. 1355–1365, 2 2023. 31

[43] A. Sengupta, L. Cheng, and S. Cao, "Robust multiobject tracking using mmwave radar-camera sensor fusion," *IEEE Sensors Letters*, vol. 6, pp. 1–4, 10 2022. 31

[44] K. Tian, M. Radovnikovich, and K. Cheok, "Comparing ekf, ukf, and pf performance for autonomous vehicle multi-sensor fusion and tracking in highway scenario," in *2022 IEEE International Systems Conference (SysCon)*. IEEE, 4 2022, pp. 1–6. 32

[45] X. Huang, J. K. P. Tsoi, and N. Patel, "mmwave radar sensors fusion for indoor object detection and tracking," *Electronics*, vol. 11, p. 2209, 7 2022. 32

[46] A. Pearce, J. A. Zhang, R. Xu, and K. Wu, "Multi-object tracking with mmwave radar: A review," *Electronics*, vol. 12, p. 308, 1 2023. 32

[47] S. Verma and V. K. Singh, "Multi-sensor fusion for real-time object tracking," *Multimedia Tools and Applications*, vol. 83, pp. 19 563–19 585, 7 2023. 33

[48] Y. Xu, B. Li, S. Yang, Y. Zhi, R. Li, and T. Chen, "Msot-q: Multi-sensor fusion slam with object detection tracking for quadruped robots," in *2024 36th Chinese Control and Decision Conference (CCDC)*. IEEE, 5 2024, pp. 4485–4492. 33

[49] A. Gad, T. Basmaji, M. Yaghi, H. Alheeh, M. Alkhedher, and M. Ghazal, "Multiple object tracking in robotic applications: Trends and challenges," *Applied Sciences*, vol. 12, p. 9408, 9 2022. 34

[50] M. Nagy, M. Khonji, J. Dias, and S. Javed, "Dfr-fastmot: Detection failure resistant tracker for fast multi-object tracking based on sensor fusion," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 5 2023, pp. 827–833. 34

[51] V. Parsa, A. Mohsen, N. N. Peirov, and A. Ehsan, "A gentle approach to multi-sensor fusion data using linear kalman filter," *Arxiv*, 5 2024. 35

[52] O. J. Montañez, M. J. Suarez, and E. A. Fernandez, "Application of data sensor fusion using extended kalman filter algorithm for identification and tracking of moving targets from lidar–radar data," *Remote Sensing*, vol. 15, p. 3396, 7 2023. 35

[53] G. Bali, L. Xie, P. Li, and M. Ilolov, "Extended kalman-based multi-sensor fusion," in *2024 39th Youth Academic Annual Conference of Chinese Association of Automation (YAC)*. IEEE, 6 2024, pp. 1918–1921. 36

[54] M. Kheirandish, E. A. Yazdi, H. Mohammadi, and M. Mohammadi, "A fault-tolerant sensor fusion in mobile robots using multiple model kalman filters," *Robotics and Autonomous Systems*, vol. 161, p. 104343, 3 2023. 36

[55] Y. Zhang, H. Sun, F. Zhang, B. Zhang, S. Tao, H. Li, K. Qi, S. Zhang, S. Ninomiya, and Y. Mu, "Real-time localization and colorful three-dimensional mapping of orchards based on multi-sensor fusion using extended kalman filter," *Agronomy*, vol. 13, p. 2158, 8 2023. 37

[56] A. Aravind, V. Ashwin, S. Chandeep, P. S. S. S. Yasaswi, R. Gandhiraj, and G. S. Sundaram, "Enhancing gps position estimation using multi-sensor fusion and error-state extended kalman filter," in *2022 International Conference on Distributed Computing,*

VLSI, Electrical Circuits and Robotics (DISCOVER). IEEE, 10 2022, pp. 201–206. 37

[57] P. Karaked, W. Saengphet, and S. Tantrairatn, "Multi-sensor fusion with extended kalman filter for indoor localization system of multirotor uav," in *2022 19th International Joint Conference on Computer Science and Software Engineering (JCSSE)*. IEEE, 6 2022, pp. 1–5. 37

[58] J. Wang, Y. Alipouri, and B. Huang, "Dual neural extended kalman filtering approach for multirate sensor data fusion," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–9, 2021. 38

[59] F. Hu and G. Wu, "Distributed error correction of ekf algorithm in multi-sensor fusion localization model," *IEEE Access*, vol. 8, pp. 93 211–93 218, 2020. 38

[60] Z. Guo, C. Dong, X. Yang, H. Han, Q. Sun, and J. Zhang, *Cubature Kalman Filter Based Multi-sensor Data Fusion Algorithm for Maneuvering Target Tracking*, 2021, pp. 577–584. 39

[61] N. Shaukat, A. Ali, M. J. Iqbal, M. Moinuddin, and P. Otero, "Multi-sensor fusion for underwater vehicle localization by augmentation of rbf neural network and error-state kalman filter," *Sensors*, vol. 21, p. 1149, 2 2021. 39

[62] E. Favarelli, E. Matricardi, L. Pucci, E. Paolini, W. Xu, and A. Giorgetti, "Sensor fusion and extended multi-target tracking in joint sensing and communication networks," in *ICC 2023 - IEEE International Conference on Communications*. IEEE, 5 2023, pp. 5737–5742. 39

[63] Y. Huo, Y. Chen, H. Zhang, H. Zhang, and H. Wang, "Dim and small target tracking using an improved particle filter based on adaptive feature fusion," *Electronics*, vol. 11, p. 2457, 8 2022. 40

[64] E. Mráz, A. Trizuljak, M. Rajchl, M. Sedláček, F. Štec, J. Stanko, and J. Rodina, "Multi-sensor fusion for robust indoor localization of industrial uavs using particle filter," *Journal of Electrical Engineering*, vol. 75, pp. 304–316, 8 2024. 40

[65] S. Gupta, A. Mohanty, and G. Gao, "Getting the best of particle and kalman filters: Gnss sensor fusion using rao-blackwellized particle filter," 10 2022, pp. 1610–1623. 40

[66] S. K. Rao and K. Jahan, "Multi-sensor measurements fusion for passive target tracking in underwater," in *2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*. IEEE, 12 2021, pp. 1116–1121. 41

[67] Z. Li, J. Wu, Z. Kuang, Z. Zhang, S. Zhang, L. Dong, and L. Zhang, "Moving target tracking algorithm based on improved resampling particle filter in uwb environment," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–16, 6 2022. 41

[68] K. Kou, B. Li, L. Ding, and L. Song, "A distributed underwater multi-target tracking algorithm based on two-layer particle filter," *Journal of Marine Science and Engineering*, vol. 11, p. 858, 4 2023. 41

[69] F. Naznin, M. S. Alam, S. A. Sathi, and M. Z. Islam, *Improving Real-Time Object Tracking Through Adaptive Feature Fusion and Resampling in Particle Filters*, 2024, pp. 114–127. 42

[70] X. WU and J. YANG, "Track-before-detect algorithm-based optimized interactive multiple model particle filtering for tracking maneuvering weak target," in *International Conference on Image Processing and Artificial Intelligence (ICIPAl 2024)*, C. Qin and H. Zhou, Eds. SPIE, 7 2024, p. 148. 42

[71] Z. Feng, X. Zhuo, Z. Xveqing, Z. Yuantai, C. Weijie, and Z. Xiaohong, "On state estimation in multi-sensor fusion navigation: Optimization and filtering," *ARXIV*, 1 2024. 43

[72] M. U. Hassan, T. Khan, T. Zafar, W. B. Yousuf, and A. Shah, "Degradation prognostics of aerial bundled cables based on multi-sensor data fusion," *Nondestructive Testing and Evaluation*, pp. 1–19, 2 2024. 43

[73] G. Yang and X. S. Song, "Circular probability error based inertial navigation system assists ultra-wide band and satellite navigation system intersection area fusion posi-

tioning algorithm," *Journal of Communications Technology and Electronics*, vol. 68, pp. 540–550, 5 2023. 44

[74] Z. Chen, W. Fu, R. Zhang, B. Ye, and Y. Fang, "Distributed array planning method with layered constraint in multi-uav formation with bearing-only detection," in *2024 43rd Chinese Control Conference (CCC)*. IEEE, 7 2024, pp. 5790–5795. 44

[75] M. Piavanini, L. Barbieri, M. Brambilla, and M. Nicoli, "Annealed stein particle filter for mobile positioning in indoor environments," in *ICC 2023 - IEEE International Conference on Communications*. IEEE, 5 2023, pp. 2510–2515. 44

[76] H. Lyu, Y. Yin, Z. Gong, Y. Chen, Y. Bai, and X. Liu, "Short landing for flying-wing unmanned aircraft with thrust vector," *Applied Sciences*, vol. 13, p. 3518, 3 2023. 45

[77] X. Yu, S. Luo, and H. Liu, "Integrated design of multi-constrained snake maneuver surge guidance control for hypersonic vehicles in the dive segment," *Aerospace*, vol. 10, p. 765, 8 2023. 45

[78] D. ze Qin, J. shi Zhang, S. yuan Pei, and W. Zhang, "Prediction of point of impact of anti-ship missile — an approach combining target geometic features, circular error probable (cep) and laser fuze," *Optik*, vol. 202, p. 163587, 2 2020. 46

[79] Y. Qu, B. Yang, Y. Sun, and S. Xu, *Multi-UAVs Cooperative Ground Target Localization Method Design and Experiment*, 2022, pp. 4905–4916. 46

[80] A. P. L. anan, H. C. Kumawat, and A. B. Raj, "Moving target detection in foliage environment using fmcw radar," in *2020 5th International Conference on Communication and Electronics Systems (ICCES)*. IEEE, 6 2020, pp. 418–421. 47

[81] Y. Qu, B. Yang, Y. Song, and S. Xu, "Multi-uavs cooperative ground moving target tracking and positioning method," in *2020 39th Chinese Control Conference (CCC)*. IEEE, 7 2020, pp. 3471–3476. 47

[82] Q. Wang, P. Li, and E. Fan, "Target classification aided variable-structure multiple-model algorithm," *IEEE Access*, vol. 8, pp. 147 692–147 702, 2020. 48

[83] P. Hubáček, J. Veselý, and J. Olivová, "Radar position estimation by sequential irradiation of esm receivers," *Sensors*, vol. 21, p. 4430, 6 2021. 48

[84] P. S. Fakhri, O. Asghari, S. Sarspy, M. B. Marand, P. Moshaver, and M. Trik, "A fuzzy decision-making system for video tracking with multiple objects in non-stationary conditions," *Heliyon*, vol. 9, p. e22156, 11 2023. 49

[85] C. Hu, G. Qu, and Y. Zhang, "Pigeon-inspired fuzzy multi-objective task allocation of unmanned aerial vehicles for multi-target tracking," *Applied Soft Computing*, vol. 126, p. 109310, 9 2022. 50

[86] X. Wang, B. Xu, and Y. Guo, "Fuzzy logic system-based robust adaptive control of auv with target tracking," *International Journal of Fuzzy Systems*, vol. 25, pp. 338–346, 2 2023. 51

[87] W. Sun, X. Li, Z. Pang, Y. Ji, Y. Dai, and W. Huang, "Track-to-track association based on maximum likelihood estimation for t/r-r composite compact hfswr," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–12, 2023. 51

[88] Z. Xubin and H. Deqiang, "Bias-tolerant track association based on multiple model features," in *2023 IEEE 3rd International Conference on Electronic Technology, Communication and Information (ICETCI)*. IEEE, 5 2023, pp. 550–554. 52

[89] B. R. Kapuriya, M. A, R. K. Chauhan, and R. Rajesh, "Bearing only track to track association for airborne surveillance system," in *2024 IEEE Space, Aerospace and Defence Conference (SPACE)*. IEEE, 7 2024, pp. 584–587. 52

[90] M. Nazari and S. Pashazadeh, "Real-time adaptive fuzzy density clustering for multi-target data association," *Intelligent Data Analysis*, vol. 25, pp. 5–19, 1 2021. 53

[91] S. Hong, D. Peng, and Y. Shi, "Track-to-track association using fuzzy membership function and clustering for distributed information fusion," in *2018 37th Chinese Control Conference (CCC)*. IEEE, 7 2018, pp. 4028–4032. 53

[92] T. Irshad, M. I. Ahmad, and T. Saeed, "A converted measurement fuzzy track to track association algorithm," Tech. Rep. 54

[93] J. Cong, B. Xu, M. Lu, J. Shi, T. Jiang, Y. Li, S. Gu, and A. Sheng, "Track-to-track association based on modified covariance intersection for multi-target tracking," in *2023 12th International Conference on Control, Automation and Information Sciences (ICCAIS)*. IEEE, 11 2023, pp. 375–380. 54

[94] L. Su, X. Dong, Y. Hua, J. Yu, and Z. Ren, "Multi-target tracking with random finite set in decentralized large-scale sensor networks," in *2022 IEEE International Conference on Unmanned Systems (ICUS)*. IEEE, 10 2022, pp. 1077–1082. 55

[95] W. J. Park and C. G. Park, "Distributed gm-cphd filter based on generalized inverse covariance intersection," *IEEE Access*, vol. 9, pp. 94 078–94 086, 2021. 56