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Artificial Intelligence and Machine Learning For aerospace application

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Abstract—Artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools in various industries, including aerospace. The application of AI and ML techniques in the aerospace sector has led to significant advancements in areas such as aircraft design, flight control, autonomous systems, and predictive maintenance. In aircraft design, AI and ML algorithms can assist engineers in optimizing the aerodynamic shape, reducing weight, and improving fuel efficiency. By analyzing vast amounts of data and simulating different scenarios, these techniques enable faster and more accurate design iterations, leading to the development of more efficient and advanced aircraft. Flight control systems also benefit from AI and ML. These technologies enable real-time data processing, allowing for precise control and decision-making during flight. By continuously analyzing sensor data and aircraft performance, AI algorithms can detect anomalies, predict potential failures, and initiate appropriate corrective actions, enhancing safety and reliability.

Keywords— *MACHINE LEARNING-BASED PREDICTION METHOD: GMM-BASED TRAJECTORY, LSTM-BASED TRAJECTORY, ESTIMATION-BASED TRAJECTORY.*

I. Introduction

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in aerospace applications has revolutionized the industry. AI and ML enable advancements in aircraft design, manufacturing, operations, and maintenance, enhancing safety, efficiency, and performance while reducing costs and environmental impact.

These technologies analyze vast amounts of data, provide real-time insights, and enable proactive decision-making. The development of predictive and health monitoring for space systems is one of the essential issues of aerospace engineering, which increases its efficiency, reliability, and safety based on the status of the resources and mission operations [1], [2]. Aerospace applications of AI and ML include flight control systems, autonomous navigation, predictive maintenance, aerodynamics optimization, and mission planning.

They enhance aircraft safety, optimize design and performance, enable autonomous flight systems, and facilitate predictive maintenance. The integration of AI and ML in aerospace represents a new era of intelligent, efficient, and sustainable aviation. In the aerospace industry, AI refers to the simulation of human intelligence in machines that can analyze and interpret vast amounts of data, make decisions, and perform tasks with minimal human intervention. ML, a subset of AI, focuses on the development of algorithms and models that enable computers to learn and improve from data inputs without explicit programming.

Aerospace applications of AI and ML encompass a wide range of areas, including flight control systems, autonomous navigation, predictive maintenance, anomaly detection, optimization of aerodynamics, and mission planning. These technologies can process immense amounts of data from sensors, flight data recorders, weather reports, and other sources, providing real-time insights and enabling proactive decision-making. One of the significant benefits of incorporating AI and ML into aerospace is the potential to enhance aircraft safety.

Intelligent systems can analyze data in real-time to detect anomalies, predict failures, and issue alerts, allowing for preventive measures and reducing the risk of accidents. Furthermore, AI and ML algorithms can aid in identifying patterns in complex flight data, leading to improved pilot training programs and decision support systems. Aerospace manufacturers also leverage AI and ML techniques to optimize aircraft design and performance. Through advanced simulations and data analysis, engineers can improve aerodynamic efficiency, reduce fuel consumption, and enhance overall aircraft performance.

Therefore, data-driven methods have been widely developed to address The associate editor coordinating the review of this manuscript and approving it for publication was Halil Ersin Soken . all aerospace applications' health prognostic and monitoring operations [3], [4].

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These technologies facilitate the development of innovative designs that push the boundaries of efficiency, durability, and environmental sustainability.

Additionally, AI and ML play a crucial role in the field of autonomous flight systems. Unmanned aerial vehicles (UAVs) and drones are rapidly evolving, with AI-powered algorithms enabling autonomous navigation, collision avoidance, and adaptive decision-making.

These advancements pave the way for applications such as package delivery, aerial inspections, and search and rescue operations. THE expansion of the aerospace industry has led to an increase in the number of aging aircraft which are still in service [5].

Novel composite materials have been developed, which possess high strength-to-weight ratio and are used in aircraft, space vehicles and in other industrial applications. These materials are usually exposed to high loads and climatic factors progressively causing dangerous defects. Even the smallest flaws in the structure can lead to catastrophic failures.

To ensure safety and airworthiness, it is necessary to employ new and innovative structural health assessment (SHA) techniques for fast and reliable inspection of aircraft parts [6].

Non-destructive testing (NDT) methods—e.g., based on acoustics, X-Rays, eddy current, or images—are capable of detecting defects during production as well as during usage.

A recent and extensive review of NDT methods for defect detection and characterization in composites in aircraft structures is given in One of the most common SHA methods in the aerospace industry is the ultrasonic non-destructive testing [7]–[10].

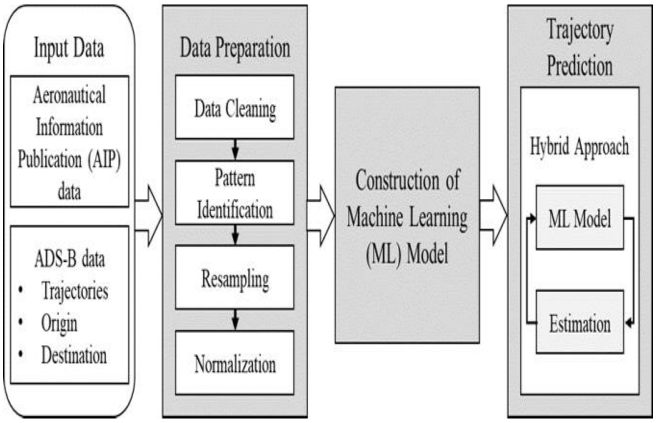

FIGURE 1. Overview of the proposed hybrid machine learning and estimation-based trajectory prediction framework.[17]

The use of machine learning for sensor signal interpretation in NDT reaches more than 25 years back. The application of support vector machines and neural networks has a long history in the automatic evaluation of ultrasonic data and showed promising results [11]–[15].

However, finding the optimal setup for a particular purpose is difficult due to the wealth of available methods and the large number of hyper-parameters to be tuned. The fault diagnosis based on data-driven methods can be seen as the classification problem, where the binary classification has to detect whether there is a fault or not.

Multiclassification is used to distinguish which type the fault belongs to. Multiple classifiers based on artificial intelligence (AI) techniques have been applied for fault diagnosis problem of aerospace systems, which include support vector machine, principal component analysis (PCA), Bayesian classifier [16], artificial neural network (ANN). Most recently, deep learning techniques have also been applied in aerospace for fault detection and diagnosis problems.

A. *Problem statement*

In the estimation-based methods, the expected future behaviors of an aircraft rely on the assumption that the

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aircraft follows its flight plan or an a priori known trajectory pattern.

In this paper, such information is extracted from historical data by using machine learning techniques that can represent the collective behavior (or pattern) of the aircraft which operated in terminal airspace.

Note that there could be some degree of errors in the trained model due to the assumed structure of the machine learning model, and the machine learning-based methods cannot explicitly account for the current motion of an aircraft. Hence, the machine learning model could generate inaccurate (possibly unfeasible) future states that violate the aircraft dynamics. To make up for it, we propose a flight trajectory prediction framework by combining the following two approaches:

The collective behavior of a set of similar flight trajectories is represented as a machine learning model trained from historical data; and for the aircraft's observed states until the current timestep, the machine learning model is then used to generate the expected states in the future timesteps, which are fed into an estimation-based method that combines the expected states from the data with the propagated states from the current state into the future timesteps based on the aircraft dynamics.

The framework of the proposed method is illustrated in Fig. 1 which consists of

(i) data preparation by using a pattern identification framework,
(ii) construction of a machine learning model with the identified trajectory patterns, and
(iii) the hybrid trajectory prediction method that combines the machine learning-based method and the estimation-based method. The main contributions of this paper are as follows:

- A novel method for trajectory prediction in complex terminal airspace is proposed, combining Gaussian Mixture Model (GMM) and Residual-Mean Interacting Multiple Models (RM-IMM) [16].
- GMM is utilized to extract future pseudo measurements based on past measurements up to the current timestep. RM-IMM is employed to estimate the current aircraft dynamics and predict the future trajectory. This approach represents the first integration of a machine learning-based method and an estimation-based method, aiming to improve the performance of aircraft trajectory prediction in intricate terminal airspace .
- The proposed method offers real-time trajectory prediction for a 2-minute look-ahead time, while the combined LSTM and RM-IMM method fails to achieve real-time predictions. This prediction horizon of 2 minutes is chosen considering the response time of Conflict Alerts (CAs) and Minimum Safe Altitude Warnings (MSAWs) as documented in the literature [17].
- The proposed trajectory prediction method generates a greatly improved prediction accuracy compared to the baseline algorithms such as LSTM.

B. Outline of the Paper

The rest of the paper is organised as follows. The following section describes literature survey.The Artificial intelligence and Machine learning, and compares and contrasts their advantages and disadvantages In Aerospace explained in Section III. The research methods are explained in Section IV. This is followed by Section 5, that contains the experimental results, followed by conclusion and suggestions for future research.

2. LITERATURE SURVEY

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Number	Author and Paper title	Parameters	Summary of the Paper
1.	Machine Learning For Anomaly Assessment In Sensor Networks For NDT In Aerospace [24]	Published in: IEEE Sensors Journal (Volume: 21, Issue: 9, 01 May 2021) Electronic ISSN: 1558-1748 DOI: 10.1109/JSEN.2021.3062941	investigated and compared various algorithms in machine learning for anomaly assessment with different feature analyses on ultrasonic signals recorded by sensor networks. The following methods were used and compared in anomaly detection modeling: hidden Markov models (HMM), support vector machines (SVM), isolation forest (IF), and reconstruction autoencoders (AEC).
2.	Multi-Objective Hybrid Artificial Intelligence Approach for Fault Diagnosis of Aerospace Systems [25]	Published in: IEEE Access (Volume: 9) Date of Publication: 9th March 2021 Electronic ISSN: 2169-3536 INSPEC Accession Number: 20657163 DOI: 10.1109/ACCESS.2021.3064976	This paper proposes a novel fault diagnosis approach using Deep Learning (DL) technique. The proposed approach consists of two main phases; the feature selection phase by Binary Grasshopper Optimization Algorithm (BGOA), and the learning and prediction phase by Artificial Neural Networks (ANNs) with voting ensemble method.
3.	Hybrid Machine Learning and Estimation-Based Flight Trajectory Prediction in Terminal Airspace [26]	Published in: IEEE Access (Volume: 9) Date of Publication: 08 November 2021 Electronic ISSN: 2169-3536 INSPEC Accession Number: 21417164 DOI: 10.1109/ACCESS.2021.3126117	This paper proposed a framework for trajectory prediction in terminal airspace by combining a machine learning-based method and a physics-based estimation method. The findings indicated that as the workload increased, MySQL exhibited a significant decline in performance compared to MongoDB. A trajectory prediction model based on machine learning is trained from historical surveillance data to represent the collective behavior of a set of flight trajectories, from which the data-driven prediction can be obtained as the expected future behavior of an incoming flight.
4.	How Can Artificial Intelligence Help With Space Missions - A Case Study: Computational Intelligence-Assisted Design of Space Tether for Payload Orbital Transfer Under Uncertainties [28]	Published in: IEEE Access (Volume: 7) Date of Publication: 04 November 2019 Electronic ISSN: 2169-3536 INSPEC Accession Number: 19124558 DOI: 10.1109/ACCESS.2019.2951136	this paper, a multi-objective optimal design for payload orbital transfer involving space tethers is proposed based on a computational intelligence-assisted design framework with the artificial wolf pack algorithm (AWPA). The proposed method effectively performs optimization tasks based on index of evolutionary pathway trends, has been defined to demonstrate the optimizing process.
5.	AdaptIDS: Adaptive Intrusion Detection for Mission-Critical Aerospace Vehicles [27]	Published in: IEEE Access (Volume: 23) Date of Publication: 25 October 2022 Electronic ISSN: 1558-0016 INSPEC Accession Number: 22360217 DOI: 10.1109/TITS.2022.3214095	This paper proposes, AdaptIDS, a novel adaptive intrusion detection system as a security analytics framework for the MIL-STD-1553 communication bus. AdaptIDS mainly adopts data science principles and leverages advanced deep learning techniques (i.e., the stacking ensemble) to boost its generalization capabilities for detecting unseen patterns of attacks.

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III. DATA PREPEARATION

The air traffic surveillance data utilized in this paper is sourced from the Automatic Dependent Surveillance-Broadcast (ADS-B) system. This dataset provides comprehensive information about the aircraft's states, including timestamp, position (longitude, latitude, altitude), and speed (horizontal and vertical), for each flight trajectory. The study focuses on the arrival and departure flights at Incheon International Airport (ICN), a major airport in South Korea, from January to August 2019. Figure 2 depicts the flight trajectories observed during a single month, specifically January 2019.

During the January to August 2019 period, the dataset consists of 130,110 arrival trajectories and 138,999 departure trajectories. Trajectories are recorded at one-minute intervals, although there may be occasional missing or repeated timestamps. Trajectories with significant missing points are excluded, and any repeated points are eliminated through data cleaning. After this process, the analysis specifically considers trajectories recorded within a 60-nautical-mile (nm) radius from the airport, encompassing the entire terminal airspace of ICN.

To effectively handle the trajectories, an algorithm for identifying trajectory patterns, developed by the authors, is employed. This algorithm groups trajectories with similar behaviors together. It begins by calculating the dissimilarity between trajectories using Dynamic Time Warping (DTW) and Euclidean distance. The trajectories are then linked using the Ward's linkage method, resulting in the creation of a dendrogram. This dendrogram allows for the selection of the desired number of trajectory patterns, ensuring that all trajectories within a pattern share the same set of waypoints.

As an illustrative example, Figure 3 showcases the resulting trajectory patterns, specifically presenting a set of arrival and departure trajectories along two distinct routes at ICN. Arrival flights pass through a fix called KARBU, serving as the entry point to the arrival route, before approaching ICN from the southeast for landing on Runway 33L/R or 34. Conversely, departure flights take off from Runway 15L/R and pass through a fix called EGOBA, which marks the final fix of the departure route.

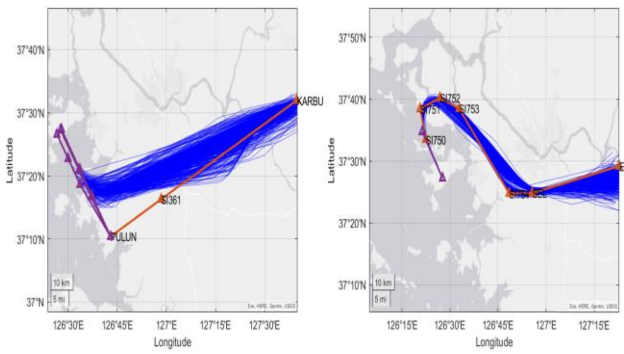

FIGURE 2. Illustrative examples of trajectory pattern identification.

IV. METHODOLOGY

In this section, we present the proposed algorithm for trajectory prediction in terminal airspace, that is, the hybrid machine learning and estimation-based trajectory prediction method. Two machine learning-based prediction methods are firstly explained as baseline algorithms: (i) conventional Gaussian Mixture Model (GMM) and (ii) Long Short-Term Memory (LSTM) which is a widely used deep learning method for time-series data. A Stochastic Linear Hybrid System (SLHS) is introduced and then the proposed hybrid approach for trajectory prediction is presented by combining a machine learning model and an estimation method.

A. MACHINE LEARNING-BASED PREDICTION METHODS

1. GMM-BASED TRAJECTORY PREDICTION METHOD

The air traffic surveillance data examined in this study consists of trajectory patterns that exhibit similarities in the spatial dimension. However, it is important to note that these patterns also display variability in both the spatial and temporal dimensions. To accurately represent and analyze this variability, a GMM is employed. The GMM is a statistical model that assumes the data points are generated from a mixture of multiple Gaussian distributions. Each Gaussian component in the mixture represents a distinct mode or cluster within the data. By modeling the data as a combination of these Gaussian distributions, the GMM can effectively capture the complex and diverse characteristics present in the air traffic surveillance data. In the context of trajectory prediction, the GMM allows for the modeling of the probability distribution of data points within each

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trajectory pattern. This distribution captures the inherent variability observed in both the spatial and temporal dimensions. It takes into account the different modes and patterns exhibited by the trajectories, allowing for a more accurate representation of their behavior.

By employing a GMM, the trajectory patterns can be analyzed more comprehensively. The GMM captures not only the mean and covariance of each Gaussian component but also the weights that determine the contribution of each component to the overall mixture. This provides a flexible and adaptive framework for modeling the variability in the data. The GMM-based approach enhances the understanding and prediction of trajectory patterns in air traffic surveillance. It enables the identification of different modes of behavior within each pattern, accommodating the variations in flight paths, speeds, altitudes, and other relevant parameters. This richer representation of the data improves the accuracy of trajectory predictions, contributing to more effective air traffic management and decision-making processes. the utilization of a GMM allows for the comprehensive modeling of the variability in the air traffic surveillance data. By capturing the spatial and temporal variations through a mixture of Gaussian distributions, the GMM-based method enhances the understanding and prediction of trajectory patterns, enabling more accurate and reliable analysis in the context of air traffic management.

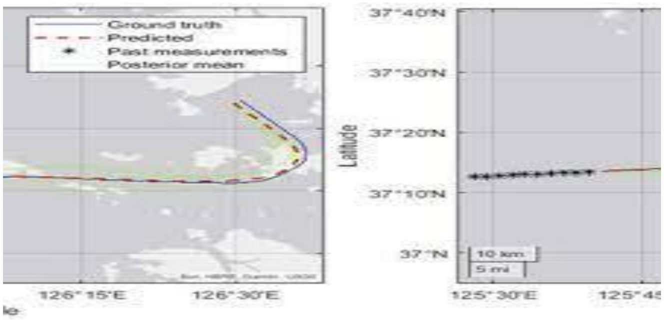

Figure 3. Measurement of posterior mean.

2. LSTM-BASED TRAJECTORY PREDICTION METHOD.

Trajectory prediction using the LSTM model in the aerospace industry involves several key steps. First, historical aircraft trajectory data, such as position, altitude, speed, and time information, is collected from sources like the Automatic Dependent Surveillance-Broadcast (ADS-B) system or radar systems. This data provides a comprehensive understanding of past aircraft movements and serves as the basis for training the LSTM model. The collected trajectory data is preprocessed to handle missing or redundant timestamps and remove any outliers or noisy data points. It is crucial to ensure data quality and consistency to achieve accurate predictions. Additionally, the trajectories are often grouped or segmented based on specific criteria, such as departure or arrival flights, routes, or airspace sectors, to capture distinct patterns and improve prediction performance.

The LSTM model is then trained on the preprocessed trajectory data. The training process involves feeding historical trajectory sequences to the LSTM network and adjusting the model's internal parameters (weights and biases) through backpropagation and gradient descent optimization. The objective is to minimize the prediction error and improve the model's ability to capture complex temporal patterns and dependencies in aircraft trajectories.

During training, the LSTM model learns to recognize and extract meaningful features from the input trajectory data. It can capture long-term dependencies and patterns that traditional machine learning methods may struggle to identify. The model's recurrent structure, with memory cells and gating mechanisms, enables it to retain important contextual information and make accurate predictions based on past trajectory states. Once the LSTM model is trained, it can be used for trajectory prediction. Given a sequence of historical trajectory points, the model sequentially processes the data, updating its internal states and generating predictions for future positions and movements. The model's ability to learn from past data allows it to make real-time predictions, providing estimates of aircraft positions and trajectories for a given time horizon. In the aerospace industry, LSTM-based trajectory prediction has numerous applications. It supports air traffic management by providing accurate forecasts of aircraft trajectories, assisting in airspace planning, traffic flow optimization, and conflict detection and resolution. It enables improved decision-making for air traffic controllers, helping them manage airspace congestion and ensure safe and efficient operations.

Moreover, LSTM trajectory prediction contributes to flight planning and optimization, aiding pilots and airlines in fuel efficiency, route planning, and time management. It can also enhance weather impact assessment by integrating real-time weather data into trajectory predictions, enabling airlines to make informed decisions and take appropriate measures to mitigate weather-related disruptions or hazards.

Overall, the LSTM trajectory prediction method offers a powerful tool for the aerospace industry, enabling accurate forecasting of aircraft trajectories. By leveraging the model's ability to capture temporal dependencies, it enhances air traffic management, supports safe and efficient operations, and contributes to improved decision-making in the dynamic and complex airspace environment.

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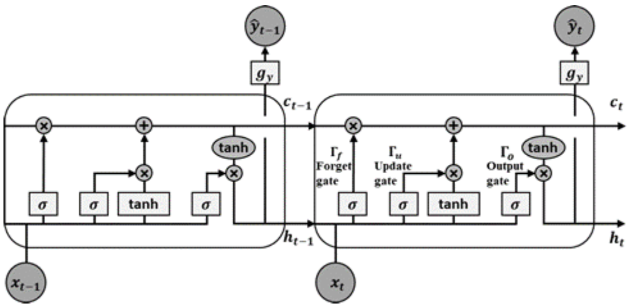

FIGURE 4. Structure of LSTM blocks.

B. HYBRID PREDICTION METHOD

1) ESTIMATION-BASED TRAJECTORY PREDICTION METHOD

Estimation-based trajectory prediction methods play a crucial role in the aerospace industry for accurately forecasting the future paths of aircraft in terminal airspace. These methods utilize mathematical models and estimation algorithms to account for the complex dynamics involved in aircraft motion, such as changes in flight modes and continuous state evolution.In the estimation-based approach, the aircraft's dynamics are typically modeled as a Stochastic Linear Hybrid System (SLHS)[18],[19]. This model incorporates both discrete dynamics, which describe transitions between flight modes, and continuous dynamics, which govern the evolution of the aircraft's continuous states (e.g., position and speed) over time within each mode. To make trajectory predictions, estimation algorithms like Residual-Mean Interacting Multiple Models (RM-IMM) are employed. These algorithms leverage measurements from air traffic surveillance systems and estimate the probabilities of different flight modes and the continuous state of the aircraft. By considering the measurements up to a specific timestep, these algorithms update the mode probabilities and continuous state estimates iteratively. The estimation-based trajectory prediction approach allows for accurate tracking and prediction of aircraft trajectories by considering the inherent variability in both spatial and temporal dimensions. By modeling the aircraft's motion as a hybrid system and utilizing estimation algorithms, these methods can handle the frequent changes in flight modes and provide real-time predictions.In the aerospace industry, accurate trajectory prediction is vital for air traffic management, collision avoidance, and efficient airspace utilization. It enables air traffic controllers to make informed decisions regarding routing, sequencing, and separation of aircraft, ensuring safe and efficient operations. Additionally, accurate trajectory prediction contributes to improving situational awareness, enabling proactive measures to mitigate potential conflicts and enhance overall airspace management.By combining mathematical modeling, estimation algorithms, and real-time data from air traffic surveillance systems, estimation-based trajectory prediction methods offer valuable insights and tools for decision-making in the aerospace industry, ultimately enhancing safety, efficiency, and overall air traffic management.

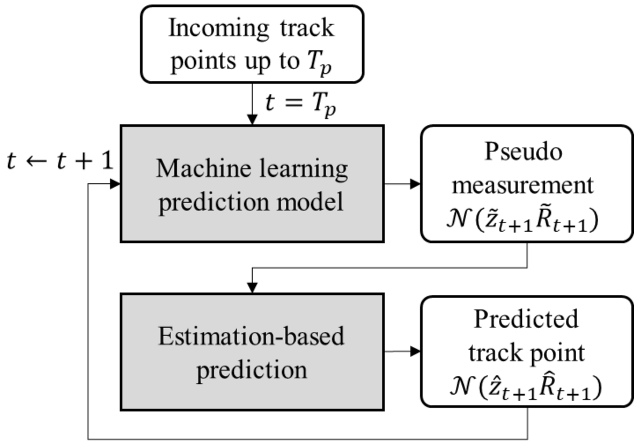

FIGURE 5. A hybrid approach to trajectory prediction.

2. INTEGRATION OF MACHINE LEARNING-BASED AND ESTIMATION-BASED METHODS

To combine the machine learning model with the estimation algorithm, our approach involves utilizing the machine learning prediction as a pseudo measurement within the estimation-based prediction using RM-IMM. This integration allows us to consider both the anticipated future behavior and the current motion of an aircraft. As depicted in Fig. 7, the trained model generates a pseudo measurement by leveraging the previous measurements up to timestep t. Subsequently, the estimation algorithm (RM-IMM) applies the aircraft dynamics to propagate the current state and then refines the propagated state by incorporating the pseudo measurement. The integration of machine learning-based and estimation-based methods in trajectory prediction involves combining the strengths of both approaches to enhance the accuracy and performance of predictions in the aerospace industry. This integration leverages the capabilities of machine learning models to capture complex patterns and trends in data, while also utilizing estimation algorithms to account for the dynamic nature of aircraft motion.At its core, the integration process begins with training a machine learning model using historical trajectory data. The model learns from the past behavior of aircraft, capturing

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relationships between various input features such as position, velocity, altitude, and time. The trained model is then used to generate predictions of future aircraft trajectories based on the current and past states.However, machine learning models alone may not fully account for the uncertainty and variability inherent in aircraft dynamics, especially in complex airspace environments. This is where estimation-based methods, such as the Residual-Mean Interacting Multiple Models (RM-IMM), come into play. Estimation algorithms utilize mathematical models to represent the aircraft's dynamics and incorporate real-time measurements to update and refine the predicted trajectories. The integration process involves using the machine learning prediction as a pseudo measurement within the estimation algorithm. The pseudo measurement is generated based on the machine learning model's output, considering the previous measurements up to the current timestep. The estimation algorithm then integrates this pseudo measurement into its prediction process, combining it with the propagated state obtained from the aircraft dynamics model.

By integrating the machine learning prediction as a pseudo measurement, the estimation algorithm can leverage the strengths of both approaches. The machine learning model captures long-term patterns and trends in the data, providing insights into the expected future behavior of aircraft. On the other hand, the estimation algorithm considers the immediate dynamics and current measurements to refine the predicted trajectories, ensuring accurate and up-to-date predictions.This integration approach offers several advantages. It enhances the prediction accuracy by combining the predictive power of machine learning models with the adaptability of estimation algorithms. It also improves the robustness of trajectory predictions by accounting for uncertainties and variations in aircraft motion. Furthermore, the integration enables real-time predictions, allowing for timely decision-making in air traffic management and airspace operations.Overall, the integration of machine learning-based and estimation-based methods in trajectory prediction provides a comprehensive and effective solution for the aerospace industry. It combines the strengths of both approaches to deliver accurate, adaptive, and real-time predictions, contributing to safer and more efficient air traffic management.

V. EXPERIMENTAL RESULTS

To measure the performance of the trajectory prediction methods in detail, we introduce four metrics that are widely used in trajectory prediction [20]–[22]. The horizontal error (HE) measures the difference between the actual and expected locations of an aircraft in the horizontal dimension. The along-track error (ATE) and cross-track error (CTE) measure the parallel and perpendicular difference to the actual course between the aircraft's actual and predicted posi- tions. The vertical error (VE) represents the altitude error in the vertical dimension. These metrics can also be computed by using Root Mean Square Error (RMSE) which is given by RMSE = " 1 n Xn t=1 (Pt − Rt) 2 #1 2 (25) where n is the number of data points. Pt represents the trajectory predicted by a model and Rt denotes the actual trajectory at timestep t. Since RMSE is always non-negative, the smaller the values of each metric, the closer the prediction is to the actual value, which means that the model's prediction is more accurate.

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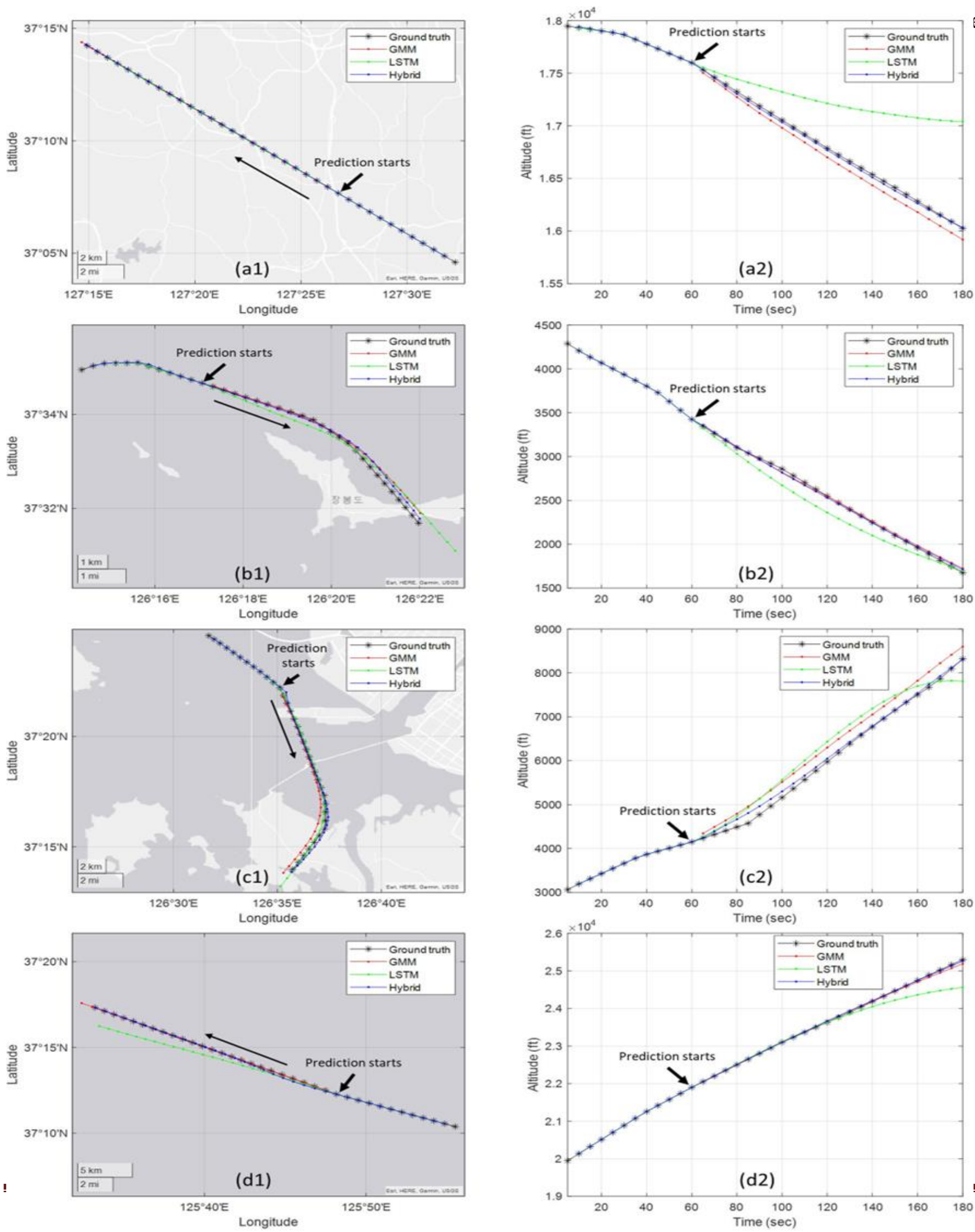

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A. COMPARATIVE ANALYSIS

The literature [23] has shown that the median response time (i.e., the time between the activation of an alert and the issue of a control instruction) following a Conflict Alerts (CAs) and a Minimum Safe Altitude Warnings (MSAWs) are 88 seconds and 38 seconds, respectively. In this regard, the 2-minutes- ahead prediction could help ATC's situational awareness that is important for safe and efficient air traffic operations. In the experimental tests, the predictions of each method are per- formed over the horizon of 24 timesteps (120 seconds with the time interval Δt 5 seconds).For the illustration, we first present representative trajectories for the arrivals and the departures around ICN. Figure 8 presents a total of 4 prediction results of two arrivals (a, b) and two departures (c, d). The actual and the predicted trajectories in the horizontal dimension and in the vertical dimension are plotted in the left and the right, respectively. As can be seen from Fig. 8 (a1 - d1), the horizontal prediction of the three methods shows the same trend with the actual trajectory, but the predicted trajectory of the LSTM model deviates signif- icantly, especially in the heading, from the actual trajectory compared with the other two methods. In Fig. 8 (a2 - d2), compared with the actual altitude, the predicted trajectory points of the LSTM model have large fluctuations at some timesteps. For all the plots in Fig. 8, it can generally be seen that the trajectories predicted by the proposed hybrid method are closest to the actual trajectory, with the smallest error, followed by GMM and LSTM.To evaluate the performance of the proposed hybrid trajec- tory prediction method, the four metrics of HE, ATE, CTE, and VE discussed in Section IV-A are first computed based on the predicted trajectories of arrival aircraft and ground truth. For the illustration, the histograms of the metrics are pre- sented in Fig. 9. The HE histogram of the proposed method is skewed to the left and the ATE, CTE, and VE histograms are concentrated on around zero, which means the proposed method outperforms the other methods in terms of the given evaluation metrics.We carried out the extensive trajectory prediction tests with all the available test dataset for the quantitative evalu- ation of the proposed method, and the RMSE of HE, ATE, CTE, and VE is used to measure prediction accuracy. The RMSE is computed using Eq. (25) and the results of arrival and departure flights are presented in Table 2 and Table 3, respectively. The comparison shows that the prediction errors, HE, ATE, CTE, and VE, of the proposed hybrid method for arrival flights are reduced by 46.8%, 48.6%, 24.2%, and 1.2% compared to the prediction errors of GMM on average and by 76.0%, 77.4%, 65.0%, and 55.8% compared to the prediction errors of the LSTM model on average. Similarly, the prediction errors of the hybrid method for departure flights also show significant performance improvements, that is, huge error reduction compared to the other two base- line algorithms, like the arrivals. Therefore, based on these quantitative analysis results, it is concluded that our hybrid trajectory prediction method outperforms the GMM and theLSTM model for the given time horizon. In other

words, the experimental results show that the GMM, as well as the proposed hybrid method, can predict the future position of the aircraft trajectories more accurately than the LSTM model in general. Interestingly, as shown in Fig. 10, while the LSTM model performs similarly to the hybrid trajectory prediction method and better than the GMM for one or two-step prediction (corresponding to 5 or 10 sec- onds), it is quickly outperformed by the other two methods as the prediction time grows. This is because for LSTM, as discussed in Section III-A2, only the future position in one-step ahead can be predicted at a time, to achieve real-time prediction. For a look-ahead time of 2 minutes, the LSTM model needs to be implemented multiple times, each time with a new one-step prediction appended to the original data. Therefore, the error from each step's prediction propagates, which causes the performance of the LSTM model to be worse than the proposed hybrid method and the GMM in multi-step trajectory prediction.The prediction errors of the hybrid method are lower than those of GMM in general. The difference is attributed to the current dynamics (or flight mode) of the aircraft that is explic- itly incorporated into the hybrid method, while the GMM generates future predictions based only on the learned model and past measurements. For the illustration, the prediction example by a single GMM that shows poor performance is presented in Fig. 11. The predicted trajectory of the GMM begins to slow down and turn as soon as the prediction starts, even though the aircraft maintains the Constant Velocity (CV) mode. This sudden change in the aircraft's motion cannot be explained by its dynamics because the current motion of the aircraft follows the CV mode with a high probability. Due to the interaction between the GMM and RM-IMM in Fig. 7, the pseudo measurement from the GMM has been corrected by RM-IMM step by step, and thus the prediction is kept closer to the ground truth, while the prediction by a single GMM significantly deviates from the ground truth after five steps.

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Therefore, we conclude that the proposed hybrid machine learning and an estimation-based method can contribute to enhancing the prediction accuracy by facilitating the benefitsof both methods.

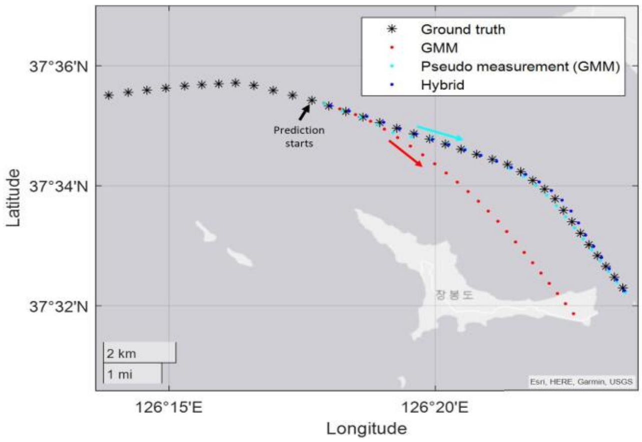

FIGURE 7. Interaction between machine learning and estimation-based method.

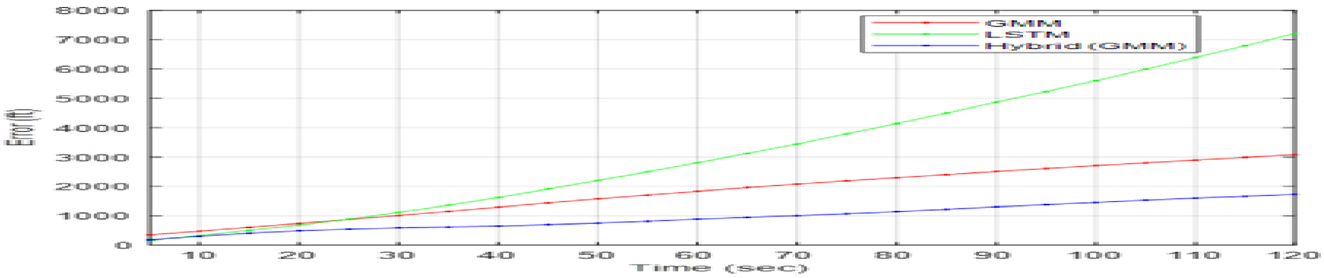

FIGURE 8. An example of prediction error of the three methods overtime.

VI. CONCLUSION

In this paper, we propose a framework that combines a machine learning-based method and an estimation-based method to improve trajectory prediction accuracy in terminal airspace. Our approach focuses on capturing the collective behavior of trajectory patterns using a Gaussian Mixture Model (GMM) as a machine learning model. The output of the GMM serves as a pseudo measurement for the Residual-Mean Interacting Multiple Models (RM-IMM), an estimation-based prediction method. We evaluate and demonstrate our proposed method using real air traffic surveillance data from Incheon International Airport (ICN) in South Korea, considering a total of 269,109 trajectories.

To assess the prediction accuracy, we utilize four metrics: horizontal error, along-track error, cross-track error, and vertical error. The quantitative comparison reveals that our proposed method outperforms both the GMM and LSTM models. This indicates that our approach can significantly enhance Air Traffic Control (ATC) situational awareness, thereby improving the safety and efficiency of air traffic operations in terminal airspace.However, our proposed method has certain limitations that should be addressed in future research. Firstly, we consider a look-ahead time of 2 minutes, based on existing literature [22]. Extending the prediction horizon to longer time intervals is an avenue for further investigation. Secondly, while our method focuses on data-driven trajectory prediction, we do not consider the reliability of the predictions or potential adversarial attacks that could lead to incorrect predictions. These aspects require attention in future studies. Lastly, we rely solely on surveillance data, specifically Automatic Dependent Surveillance-Broadcast (ADS-B) data, without incorporating additional features such as meteorological data (e.g., wind speed and direction) and operational information. Future work will explore incorporating these factors to achieve more accurate and reliable trajectory prediction for longer look-ahead times. Additionally, weaim to enhance prediction performance by conducting further clustering along the temporal dimension.By addressing these limitations and refining our approach, we can advance trajectory prediction capabilities, providing ATC with improved situational awareness and

contributing to the safety and efficiency of air traffic operations in terminal airspace.

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