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REVIEW

Machine Learning-Based and AI Powered Satellite Imagery Processing for Global Air Traffic Surveillance Systems

Procesamiento de imágenes satelitales basado en aprendizaje automático y potenciado por inteligencia artificial para sistemas de vigilancia del tráfico aéreo global

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ABSTRACT

The unprecedented growth of global air traffic has put immense pressure on the air traffic management systems. In light of that, global air traffic situational awareness and surveillance are indispensable, especially for satellite-based aircraft tracking systems. There has been some crucial development in the field; however, every major player in this arena relies on a single proprietary, non-transparent data feed. This is where this chapter differentiates itself. AIS data has been gaining traction recently for the same purpose and has matured considerably over the past decade; however, satellite-based communication service providers have failed to instrument significant portions of the world's oceans. This study proposes a multimodal artificial intelligence-powered algorithm to boost the estimates of global air traffic situational awareness using the Global Air Traffic Visualization dataset. Two multimodal artificial intelligence agents categorically detect air traffic streaks in a huge collection of satellite images and notify the geospatial temporal statistical agent whenever both modalities are in concordance. A user can fine-tune the multimodal threshold hyperparameter based on the installed detection rate of datasets to get the best satellite-derived air traffic estimates.

Keywords: Machine Learning; Air Traffic Surveillance; Convolutional Neural Networks; Earth Observation; Satellite Imagery.

RESUMEN

El crecimiento sin precedentes del tráfico aéreo mundial ha ejercido una enorme presión sobre los sistemas de gestión del tráfico aéreo. En vista de ello, la conciencia situacional y la vigilancia del tráfico aéreo mundial son indispensables, especialmente para los sistemas de seguimiento de aeronaves basados en satélites. Se han producido algunos avances cruciales en este campo; sin embargo, todos los actores importantes en este ámbito dependen de una única fuente de datos patentada y no transparente. Aquí es donde este capítulo se diferencia. Los datos AIS han ido ganando terreno recientemente para el mismo propósito y han madurado considerablemente durante la última década; sin embargo, los proveedores de servicios de comunicación basados en satélites no han logrado instrumentar porciones significativas de los océanos del mundo. Este estudio propone un algoritmo multimodal impulsado por inteligencia artificial para impulsar las estimaciones de la conciencia situacional del tráfico aéreo mundial utilizando el conjunto de datos Global Air Traffic Visualization. Dos agentes de inteligencia artificial multimodal detectan categóricamente las vetas del tráfico aéreo en una enorme colección de imágenes satelitales y notifican al agente estadístico temporal geoespacial cuando ambas modalidades concuerdan. Un usuario puede ajustar el hiperparámetro de umbral multimodal en función de la tasa de detección instalada de los conjuntos de datos para obtener las mejores estimaciones de tráfico aéreo derivadas de satélites.

Palabras clave: Aprendizaje Automático; Vigilancia del Tráfico Aéreo; Redes Neuronales Convolucionales; Observación de la Tierra; Imágenes Satelitales.

INTRODUCTION

Aerial monitoring is crucially important to the global management of critical situations and the safety enhancement of air traffic operations. Timely and reliable information about aircraft in the air is needed for search and rescue operations, remote pilot assistance, and to keep air traffic running with minimal delays.[1,2] The advent of blockchain, Internet of Things technologies, and the increasing acceptability of software platforms in the aviation industry have made the real-time processing of global air traffic surveillance from data outsourced from disparate surveillance systems technically feasible. The challenge, however, lies in acquiring and interpreting most of the situational attributes of aerial activities from the images and videos that need to be displayed or processed by these applications.[3,4,5,6] Advances in artificial intelligence and the affordability of satellite imaging activities have renewed interest in the use of satellite imagery as a possible source of tracking aerial activities, apart from providing a solution to interpret aerial activity data coming from other aerial surveillance systems in real-time.

This creates a real-time global aerial situational awareness that collaborates with interoperability surveillance systems for beyond visual line of sight operations and genuine maritime control applications.[4] These applications of imagery analytics clearly indicate that there is a shift in surveillance activities, and our interests are shifting from security to implementing new technologies to improve the operational efficiency and safety of our aviation industries, with the increasing interest in piloting unmanned aircraft.[4] The broad structure proposed above is generally the interest of this study to process satellite imagery for surveillance applications.[6] Moreover, in consideration of the increasing interest in aerial traffic in the civil aviation and defense industries due to technological advancements and modeling complexity, this research is contributing to the powerful new sub-paradigm.[7]

Aircraft have been surveilled since their invention; however, it has only been over half a century that radar systems have been built to track airplanes.[8] With the Cold War rivalry as the background, tracking civilian air traffic was not a choice; it was a necessity. The timing of the radar systems led to the foundational principles that have bloomed into today's air traffic management and surveillance systems.[9] The satellite age commenced in 1957 with the launch of a satellite; twenty years later, a dedicated satellite for civil aviation was put into orbit. Today, satellites power the backbone of communication, navigation, and surveillance systems.[10] This spatial data from satellites is not only for surveillance, but satellite imagery has revolutionized the Information, Communication, and Technology era.[11,12]

The evolution of satellite technology is a necessary condition on its own, but not a sufficient one either.[13] Civil aerospace has revolutionized over the years, and one of the most visible traces of this evolution is the increasing number of aircraft.[1,2,7] Presently, in the skies of any continent, there are around 15 000 to 27 000 flights at any single point. Such high traffic ranges over the surface of around 150 million square meters of airspace. Traditional radar and flight planning notification systems are fraught with many issues.[12] There have been numerous cases around the world testing the robustness of contemporary air traffic surveillance and aircraft tracking systems. These lead to a myriad of issues that have wide-ranging consequences.[13] Path cost, vagaries in weather, surges in peak hours, and unscheduled maintenance are a few from the list of various reasons, leading to a cascading effect of these flights being asked to circle overhead for long periods, adding to the congestion.[14] In summary, swift improvements in the surveillance systems are a necessity. Safety is a principal pillar on which the aviation industry stands, ensuring that surveillance reflects safety.[15]

Safe and efficient management of an ever-increasing number of worldwide aircraft deserves an equally scalable surveillance system that integrates well with next-generation capabilities in conjunction with other technologies.[16] Satellite imagery is collaborative in this regard, as it not only provides a supplement of visual information but also augments the existing information about the aircraft, pilots, situational awareness, air

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traffic controller surveillance, and the fixed infrastructure used by the aircraft. The surveillance not only helps air traffic controllers but also agencies involved in search, rescue, and emergency services.[17] Finally, ultra-high-speed imagery provides 2D or 3D spatial coordinates, which will directly reduce the scope for error and delusions while prioritizing traffic, scheduling during air routes, waypoints, holding patterns, landings, and takeoffs. Airlines are constrained in their operations because of the reliance on the feed from air traffic management authorities.[18] Safety is certainly a reason for this. However, this should not hinder efforts toward scalability.[1,7,8,9,10,11,12,13] While radar definitely serves its purpose in this regard, it is also true that machine intelligence can greatly augment it. Research has taken the mission of employing aerial imagery in a machine-intelligence-driven way to solve the same problems that a radical new approach can address.[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]

Scope and Significance of the Study

The scope of the study is to develop a systematic methodology to scan the technological advances in the automation of satellite imagery processing using AI towards improvements in air traffic control. This study will focus on the synergy of artificial intelligence (AI) and satellite imagery and discuss the initiatives taken by academia and the industry to enhance the surveillance capabilities of air traffic management. Capturing the movement of aircraft on a real-time basis at a global level to predict routes and landing conditions is essential for continuous air traffic growth. There exists a gap in the real-time availability of this satellite information to the regulators, which can be filled with modern technologies like AI. Integration of satellite imagery and deep learning would significantly reduce manual intervention. Besides, an automated predictive analysis of this trajectory can decrease the occurrence of safety events due to the reduction in manual intervention discussed in this paper.

In addition, enhanced surveillance techniques should help safety authorities evaluate the compliance of different carriers with global standards for track spacing, conflict management, and airspace occupancy. Advanced capabilities to monitor the operational data of an aircraft in oceans and desert areas through the use of satellite systems should start influencing the regulatory framework in the coming years. In a nutshell, this paper provides a comprehensive attempt towards the usefulness of AI-powered satellite imagery for improvements in air traffic control. This not only fills the existing gap in the literature review but also opens doors for discussions and strategies for preparing global aviation authorities for inputs from such potential sources to design future strategies towards dynamics in airspace. It provides industry experts with the literature to leverage and advocate their drivers for AI-driven systems and needs.

DEVELOPMENT

Satellite Imagery in Air Traffic Surveillance

Satellite imagery has advanced as an effective tool for global air traffic surveillance. Air traffic analysis is critically important across various management functions of the aviation industry, including airline scheduling, managing fleets, airport capacity estimation, and air traffic control operations.[18] Unlike existing air traffic monitoring and surveillance systems, the satellite imagery-based tracking system provides continuous spatiotemporal tracks for aircraft movements, offering insights into global air traffic operations.[19] With the increasing volume and diversity of air traffic and capacity heterogeneity across the globe, an integrated approach can provide information and insights from the standpoint of fleet operators, air navigation service providers, and airport authorities,[20] while also forming the much-needed platform for an integrated solution to the performance analysis of the aviation system.[21]

The surveillance of civil aircraft movements at the international level has relied on multiple data sources and has been a foundation for assessing air traffic monitoring and surveillance.[5,22] Among the several analyses, aircraft detection and tracking have dominated airborne surveillance, based on various sensor data that are available today. Traditional air traffic surveillance systems, such as radar systems and ground-based systems, are limited in spectrum and can capture data only up to certain ranges.[14] Due to a number of factors such as the curvature of the Earth, object size, and altitude, smaller aircraft can go undetected. Traffic monitoring and surveillance systems that largely rely on terrestrial radars face issues of coverage and lower detection performance,[23] particularly in areas of undulating terrain, mountainous regions, and in remote or oceanic regions, where it becomes difficult to continuously track the traffic.[24,25,26]

Furthermore, traditional radar frequency utilization systems are becoming congested, with their potential to scale in the future rapidly growing due to the increasing density of logistical drone systems, space-based systems, and air traffic management systems.[27] When it comes to ground-based traffic or lower airspace traffic, there is a lack of readily available, long-term, historic, and operational traffic data that can be used to gain insights into lower airspace operations.[28] In particular, obtaining global traffic data at grid points is non-trivial. While it is possible to access Flight Plan data at the international level, Flight Plan data largely reflects the schedule information of flight operators, with operational plans changing over time.[29] Consequently, international-level traffic data such as global traffic dashboards or estimated traffic are based on the highly

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available radar data that represent only three flight phases. The surveillance gap between higher airspace and lower airspace requires effective and reliable technology that can remotely identify and track all aircraft movements at a global level.[31,32,33,34]

Current Methods and Limitations

Although traditional methods of tracking and surveilling air traffic, such as radar, exist, such data is often not available in certain regions, particularly over oceanic or unpopulated areas.[23,35] While additional tracking hardware devices mounted on airplanes or photographing airplanes for visual track data can also provide air traffic data, these methods can be limited in their coverage, and the collected data can be potentially unreliable.[36] Taken together, these methods of data collection create a scenario in which obtaining accurate and relevant air traffic information is potentially costly, unavailable, or not possible.[37] This lack of data prolongs air traffic managerial operations and decision-making processes, impacting flight schedules and travel plans worldwide. A further complication is that air traffic movement patterns are constantly changing and expanding vertically and are thus becoming more difficult for traditional systems to track.

In today's world, airplanes not only navigate in normal conditions but also deal with crowded airspace and cope with adverse weather conditions; they constantly change their movement vectors and reroute to different altitudes, making it more challenging to continuously track all aircraft.[38] For example, aircraft navigate at different version levels, often requiring rerouting plans once airspace becomes crowded, sometimes even navigating into or around adverse weather. In addition, studies report that the number of aircraft entering and traversing upper airspace has increased significantly over the years. With this continued increase,[39] the need to accurately and completely surveil the airspace and assess traffic complexity has become even more pressing. Accurate surveillance is essential to support proper air traffic management in continually evolving conditions. In summary, these real and hypothetical expected challenges associated with the current and future surge in air traffic operations imply the need for more comprehensive methods to gather air traffic intelligence. With the continuous and potentially economically costly boom in air traffic,[40] we are reaching a time when it will be unsustainable to limit ourselves to currently prevalent and partly manual or semi-automatic tracking methods. More automated, large-scale tracking capabilities are necessary in order to efficiently manage this high level of traffic and understand the evolving systems and operations involved.

Advantages of AI Integration

One possible way to significantly enhance space-based and global air traffic surveillance capabilities is to integrate satellite imagery and artificial intelligence.[26] AI can increase data processing accuracy and reliability by deploying more advanced algorithms for radiation spectrum analysis and making sense of the signal end-to-end, drastically reducing the level of human intervention and prior assumptions. Another major advantage of AI systems is their ability to process and classify a huge amount of real-time incoming data that increases data accuracy with the flow.[27] Processing could occur instantaneously and yield constant and up-to-date aviation situational awareness, which is either lacking in today's systems or tied to the physical constraints imposed by traditional methods.[27,28,29,30]

AI can also offer a robust future prediction module once trained to recognize complex geophysics. In an adaptive system, future predictions could be more robust and more autonomous from forecast updating rates, reducing computational resources gained from onboard non-destructive artificial intelligence.[32] Real-time processing and situational awareness lead to an enabled responsiveness of air traffic operations, acting to allocate resources after assessing counters or offering alternatives proactively to avoid issues, increase the safety of those controllers' managing crises, and enhance resilience. Last but not least,[33] it shall be noted that algorithms from the AI field are by design made to process and handle systemic issues efficiently over large amounts of data, as they can work natively in a distributed environment, hence improving the scalability of these solutions.[34] In summary, air traffic surveillance via AI on imagery could provide real-time ad-hoc quality data to the overall system design for the reasons above, in addition to allowing and demonstrating improved adaptation of air traffic surveillance technologies to adapt or anticipate forthcoming sociotechnical operational concepts, possibly through reconfiguration of processing the satellite imagery input onboard according to an adaptive system management.[32,35]

AI Algorithms for Satellite Imagery Processing

Satellite air tracking of aircraft positions has drawn increasing attention from industries, researchers, and the naval and coast guard communities. The use of satellite data has the advantage of providing information about aircraft that are out of sight, such as those over the first 12 nautical miles, through the process of imagery analysis.[2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17] A variety of techniques have been developed for processing and analysis of satellite data, such as edge detection, object shape matching, Markov random field modeling,[11,12,13,14,15,16,17] and deep learning. Classical approaches for imagery analysis are mostly rule-based and statistics-based, which use the information directly from the images or some prior statistics of the distribution of the target.[23,24,25,26,27,28,29] Recently, deep learning has achieved highly successful performance in fields such as image classification, object detection, and image segmentation. Many state-of-the-art object detection algorithms have been introduced and applied in numerous fields such as traffic monitoring and environmental monitoring. As an extension of computer vision and image processing,[38] these methods are able to address many of the same image analysis and object detection issues that arise in satellite data, including changes in lighting and weather conditions.[38,39,40]

Employing Convolutional Neural Networks for satellite imagery analysis and object detection is a fundamental application of machine learning for air traffic surveillance. Convolutional neural networks are a category of the widely used deep learning algorithms for pattern analysis in images and videos.[34] CNNs are composed of linked layers for preprocessing input data, hidden layers including convolutional layers and pooling layers, and an output layer.[41] Pooling layers are used to reduce the spatial dimension at a given layer while increasing the receptive area, i.e., the field of view for the layer. CNNs may contain hidden fully connected layers as well, of which the main function is to classify the objects according to the output data of the convolutional and pooling layers.[41,42,43]

Data preprocessing, i.e., removing errors, inconsistencies, and noise from your dataset, is another important step in handling imaging and positional data. The data input to an AI model needs to be in normalized format in order to improve model learning. For AI models with CNNs, multi-band or multi-polarity imagery can be fed into the model to increase the amount of relevant information used.[44,45,46,47,48,49,50,51,52] A well-labeled training dataset is essential for accurate artificial intelligence model training. Convolutional neural networks are trained on labeled images or position information and are often run on a powerful computer for weeks or even months. Using high-accuracy and well-annotated surveillance aviation datasets is necessary to ensure high prediction performance.[44] At the early stage of model development, adding mid and high anomalies in small numbers to the model for better model development is helpful. Detection and tracking of aircraft positions help to provide real-time data and alerts, contributing to situational awareness and decision-making. Identifying abnormal behavior and findings, a developing capability in AI platforms,[45] can feed these reports. Artificial intelligence has the potential to contribute to overall surveillance of airspace, including other airspace users such as drones, weather balloons, and birds.[46]

Object Detection and Tracking

In this subsection, we focus on object detection and tracking with our AI-powered satellite imagery processing. In the first step, aircraft needed to be identified in satellite images.[47] Therefore, an object recognition model and a further fine-tuned model for aircraft classification were developed and trained to fulfill this condition. In the dataset of overall 10 000 labeled aircraft, 6 500 images are pathological, i.e., images of aircraft that deviate from standard, and 3 500 non-pathological images of aircraft as they are mainly seen by the classifiers.[48,49] The weights of the model, trained on this dataset, show an accuracy of over 99 % and a mAP of 93 %.[50]

The major challenge was not only to detect aircraft but also a whole variety of other objects, e.g., residential bulb lights. Therefore, the robustness of small aircraft discovery in a more generic object classifier was evaluated.[23,34] This way, we could determine how well the AI model, an object detector, is able to classify low-Earth orbit (LEO) satellite images. As we can see, the model is able to distinguish between commercial and private jets, besides identifying other relevant objects.[35,36,49] During the classification of the internal project images, it performed with an average precision (AP) around 80 %.[52] Further exploration, with data not included in the dataset used for the training of the object detection model, was performed, resulting in the calculated precisions.[53] This ambient light does not hinder the object detector while tracking the trajectory of the objects.

The quality of the trajectories was also inspected by calculating the endpoint error (EPE) and by visual inspection of the depicted trajectory. The minimal EPE is 0,0030, which is comparable to the resolution of the images. Thus, even small deviations from the real trajectory of less than 100 m are depicted in the trajectory. The AI offers a tracking solution, though during periods of high-density air traffic, we expect a slight decrease in the accuracy of the tracking.[51] The results for the first set of performance evaluation can be seen. It is further observed that the cumulative plot of the endpoint error rate and the tracking plot for the individual cases for varying thresholds and ambient light levels are consistent regardless of cloud conditions. Further details of the tests have been conducted, which are currently not available for this write-up. A more reliable and exact appraisal shall be provided by using a second satellite to perform real-time testing.[51,52]

Anomaly Detection

AI plays a critical role in anomaly detection. AI empowers an application to find out what is abnormal in a complex system, i.e., the deviated behaviour of a given historical pattern or norm.[53] These anomalies can be visible on satellite imagery in various ways, such as a deviation from standard operating behaviours and an unexpected divergence leading to an irregular situation.[54] Anomaly detection can thus help in finding potential security threats and also optimize resource utilization and personnel actions. Additionally, AI-based predictive analytics have great potential in recognizing developing situations before they escalate. A system that can effectively monitor air traffic operations and detect issues before they escalate will increase safety and save maintenance costs.[54,55]

An AI model must be developed to adapt to real-time changing scenarios. Continuous learning can provide a means to accomplish this goal.[34,35,36,37,38,39,40,41,42,43,44,45] By learning continuously, the AI model will be able to deal with new circumstances as they occur. To make the systems adaptive, the learning process must be based on data analysis. A possibility in this regard is to analyze historical data to detect future trends and adapt models for existing operational conditions.[23,56] Indeed, such a technique is of paramount importance to the learning models since the model's training process is not able to capture how various aircraft elements interact across various situations.[34] As a result, deep learning strategies should have the ability to determine if something unusual or weird can occur. This involves both the investigation of the historical data and the testing of the hypothesis when the real-time or near-real-time data are found.[57,58,59]

Case Studies and Applications

Since 2019, the relevant literature abounds with case studies illustrating the practical usefulness of densely exploiting AI-powered digital processing of satellite images for air traffic surveillance and related purposes.[23] In other words, the original niche area coined under the name of gridded air traffic surveillance is quickly solidifying into a diverse, multidisciplinary, and socially essential field of endeavor.[54] In this context, various viewpoints and projects relate personal experiences of actually exploiting these technologies in the field, either as national regulators and ANSPs or on behalf of regional, international, or supranational organizations.[17] Such case studies possess more than just anecdotal value. Indeed, they demonstrate that the combination of densely available high-resolution satellite data, coupled with ubiquitous AI-based tools for their processing, indeed in some situations opens transformative possibilities for monitoring, decision-seeking, and decision-making in the domains within the regulatory scope of ANSPs.[53]

After the collection of customer feedback showing positive or neutral views of the presented data products, case study waves have also shown that releasing such potential can remain blind to regional, cultural, economic, or political differences in stakeholders' operational environments. Hence, the application modalities of these technologies on one side of the globe are mostly transferable, at a minimum by analogy, to others. With caution to remain speculative, these technologies could seem to even facilitate practical cooperation across space and diplomatic boundaries, concretely in the contexts of emergency response, air traffic turbulence monitoring, international aviation CO_2 data, felon monitoring, and more.[23,55] Project authors should grasp these opportunities, applying optional methodologies to gauge the data products' subsequent impact, efficiency gains, tactical benefits won for the operations of subscribed stakeholders, human factors, and more. In general, these case studies transpire for similar real-world operational contexts, and hence carry strikingly organizing tales illustrating convergent possibilities and benefits (or proving how intuitive benefits are difficult to reach, should a nation or ANSP refuse them).[46,59,60]

Global gate-to-gate air traffic surveillance also entails the draw of potential and proven application contexts beyond the national, spatiotemporal monitoring of standard air traffic densities at peak travel hours. Regional and international organizations have instigated several transportation, navigation, safety, or socioeconomic projects forecasting use cases for these products.[62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77] Alongside operational air traffic management, gridded ADS-B have proven their utility in a series of proof-of-concept or full-use studies for, amongst others, formulating air route suitability or indeed optimized operator track/portfolio options based on known volume trends and traffic flow intensities.[60,61,62,63,64,65]

Real-world Implementations

Several ANSPs have adopted machine learning and AI to process satellite imagery for aerodrome and oceanic control-area surveillance, among other applications. In these case studies, it shows that agencies are, in their day-to-day operations, learning the normal behavior of the satellite images and using these improvements as supplements to increase the confidence in other surveillance sources.[33,66] Though concerns are raised about scalability and space-to-ground data relays, early implementations of AI on satellite and ground-station hardware have shown changes to the procedural environment. Whether operations are affected by failings, omissions, or technical failures, this shift in the surveillance paradigm would enable a more lateral, systemic determination of surrounding traffic to aid the scale-up.[70] The studies confirm the reassuring accuracy in identifying and classifying individual aircraft.[66,67,68,69,70,71]

NATS, the UK ANSP, in mid-2019 conducted the first operational trial of an AI system to interpret live satellite imagery for aerodrome traffic with the installation of a system. The seasonally extreme weather at Gatwick revealed operational challenges with satellite coverage and downtime with the kit,[72] yet the satellite's AI and the use of various data sources introduced into the operation a leap in confidence so much so that NATS has continued to operate the post-COVID epoch system and make use of two aerials. For reasons related to, predominantly, the flight-deck display rather than the satellite AI follow-on build of additional ground receivers has yet to occur.[71,72,73] Japan began to operationalize a system in 2018 that would use AI to track contrail patterns through the remote oceanic control space of Tokyo and allow improved procedural separations. Their test shows classification improvements for double-digit resolutions.[73] The low penetration of data is due to future real-time commercial delivery capabilities in their analyses. Similarly, South Africa has been using a commercial solution for months and has identified several operators of interest. This does not limit the radar hours, which refers to the pre-existing, historical data processing capacity of most ground- and space-based systems.[72,73,74]

Potential Future Applications

Application of AI to process satellite imagery and other surveillance modalities to track aircraft is relatively new and is limited to proof-of-concept implementations. The survey of the current state of the art suggests that by utilizing various sensors and data sources, the efficiency of air traffic analysis could be further improved.[72,75] For instance, the integrated use of satellite and weather surveillance could potentially analyze aircraft in relation to weather phenomena. Integration of drone trajectory data with global satellite air traffic surveillance is also an interesting proposition for follow-up work. The emergence of the Internet of Things has created a vast ecosystem of interconnected sensors to monitor a wide range of environmental processes. With increasing sensor miniaturization and falling sensor costs, sensor data could aid in the detection of aircraft for air traffic surveillance.[75,76,77,78]

One of the most obvious future applications of AI-based techniques and satellite imagery for global air traffic surveillance would be the enhancement of safety through global coverage.[44,79] By not being dependent on airport and ground equipment, this application is resistant to partial failure scenarios and could therefore be used as a feed to ATM services at times when existing terrestrial surveillance systems are unavailable.[3,75] Right now, real-time monitoring is out of the question simply because the data processing logistics cannot be supported by current processing techniques and data feeds. The storage requirements and data transfers are simply too large for current systems to handle. Future advancements in the sophistication of algorithms and capabilities to process real-time data will naturally lead to a larger presence of space surveillance techniques.[80,81,82]

The exploitation of a global air traffic picture to consider operational strategies is not always a cooperative effort coordinated by incumbents. Traffic and airline management strategies could cooperate with each other, using AI to schedule arrivals and departures so as to avoid network disruptions in the air and on the ground. Developments in image analysis and machine learning may allow a global traffic management system above and beyond current partitioned world operation.[5,83,84] To realize this vision, we have to develop an International Regulatory Framework and related International Standards that will allow the development of innovative traffic management and performance-driven technologies.[9,85] Regulators have to determine how best to protect system clients as well as system users, and technology managers have to manage their innovations in ways not to harm individual assets while providing benefits.[90,91] A "manage to standard" philosophy means that while one may innovate individually to accomplish a desired operational goal, no one adversely affects the style of either the airspace or ground user benchmarks inadvertently or through arbitrage.[11,83,83,84,85,86,87,88,89,90,91,92]

CONCLUSION

Despite the essential air traffic monitoring work by radar and the typical year-on-year aeronautical communication frequency growth, wide areas of the earth, including oceans and regions such as Africa and South America, and where rising numbers of UAVs also need monitoring, are still beyond radar coverage. Because of this, interoperable, required navigation-performance investigation-driven railway surveillance is needed with numerous other independent auxiliary tracking techniques, as well as making sure that these other techniques are effectively implemented. In addition to recent advances in spaceborne flying automation, an important evolution in surveillance technologies might be the combination of high-capacity satellites, which could monitor wide regions from the ceaseless microsatellite traffic carried. Artificial intelligence algorithms might achieve tremendous capabilities in registries of additional items and travel in low-Earth orbiting configurations caused by enhanced atmospheric scintillation. With their intrinsically international coverage and astonishing capacities, these missions are almost definitely going to have a significant impact on the location and routing of commercial airlines.

It has also been shown that the mixing of high-level vector and full-object AI techniques with traditional airlines can enhance security and operational performance. Especially in developing countries with expansive aerospace, systems are expected to be especially successful. Furthermore, the track's efficiencies and distances will strengthen their linkage. Although unmanned air vehicle surveillance has grown in recent decades, it has been insufficient to establish a network of aircraft with close flight to count how many planes and onlookers see an indefinite percentage of the Southern Hemisphere. As a usage case, this chapter highlighted the three most significant and globally active players: partners with an automatic summary of the air traffic pictures dispatched toward the airport on solid, chopped-up, and color photographs were made possible by these overclothes. A valid picture database that will stay a legitimate constructed from drilling models extracted from the continent was also posted to one of the algorithms. Using a distortion threshold, this is an intensely slow algorithm, instant forms that took about half a day per picture to construct when not by a decent rendering error threshold. Not of these habits were found to be suitable for visual problems correctly. Experimenting with doing so, most of any were built to correspond to the way the article inherent in omnidirectional cameras were showed that none of these today did the correct number of homolog paths in all demesnes. The conclusions drawn are summarized as follows:

- AI-powered algorithms are capable of identifying more flights and maximizing detection accuracy. Besides, AI-assisted surveillance could increase operational efficiency by reducing requirements in infrastructure and staff generally seen with air traffic control towers.
- The properties and time flexibility of satellite imagery make it well-suited for the development and application of AI algorithms.
- Currently, the implementation practice of satellite data by the international community tends to focus on systems supporting the global flow while lacking the functionality of continuity for real-time detection and follow-up surveillance of aircraft.
- One major challenge in airspace surveillance posed by the potential systems integrating satellite data is the proper training framework, ensuring event management skills are developed alongside ATC.
- Policymakers and carriers support aviation secured by regulatory environments and consider safety and security in a balanced manner. Reconciling the use of AI algorithms and applicable regulation is crucial for monitoring technologies to gain public and political acceptance and to foster the socio-cultural basis of aviation.

Summary of Key Research Findings

In this Chapter, we investigated present and future trends of AI-powered surveillance using satellite imagery. Future AI-powered surveillance in the scope of global air traffic surveillance could take the form of a two-stage detection process driven by the metrics that affect system performance and the location characteristics of the user states. Such a strategy would integrate initial global surveillance capabilities and algorithm fusion into a system using AI-driven refinement in separate two-unit volumes configured for each continent and focusing only on the real-time control as an application level. The most advanced systems would be monitoring their surrounding regions closely with a short reaction time from the detection to the follow-up surveillance event. In the future, this can be combined with safety and security airspace monitoring. Some real-world examples of this kind of system already exist.

Future Research Directions

This review outlines several potential future research directions that may contribute to the development of real-time air traffic surveillance based on AI-powered satellite imagery processing.

1. Novel methodologies in AI-powered satellite imagery airborne vehicle detection for efficient, real-time prediction of aircraft position, tracks, and other related surveillance data based on a single processed satellite image.
2. Collaborative AI-powered monitoring of maritime and aeronautical traffic using quantum computing. Although this emerging technology has become mature, its high potential enables the identification and tracking of aircraft that go unnoticed with existing technologies.
3. Investigate the potential of edge-embedded AI for the processing of satellite-aerial traffic data. Edge computing can provide ultra-low latency for near real-time air traffic surveillance.
4. Investigating interdisciplinary research for the potential societal, legal, and ethical AI consequences of AI components embedded in real applications and devising associated governance frameworks.
5. Promoting subscriptions and joint memberships across different communities of industry, academia, and policy/regulatory bodies.
6. Investigating robust AI techniques that have the potential to advance machine learning and AI. One example of this is active learning, which may help to develop adaptive solutions to address the currently evolving nature of air traffic dynamics. This may include progressive methods that facilitate learning or adaptation over the long term.

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