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Real-Time Runway Incursion Detection Using AI-Based Sensor Fusion and Computer Vision

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Abstract- ***The safety of runway operations is a major challenge in the aviation industry due to rising air traffic complexity and the shortcomings of conventional surveillance systems. Traditional methods, such as radar monitoring and manual air navigation, are prone to slow detection, poor situational awareness, and poor visibility in poor weather. This research presents an AI-powered sensor fusion and computer vision approach to detect runway incursions in real time. It uses information from CCTV cameras, radar, and IoT sensors, which are processed in the fusion layer, and are then analyzed by a deep learning object detection algorithm. A set of rules is used to detect runway zone violations and trigger alerts. The system was tested in a controlled, simulated environment. The system achieves high accuracy with 96.8% accuracy, 95.4% precision, 94.9% recall, 95.1% F1-score, 3.2% false positive rate and an average latency of 115 ms, indicating effective and timely detection. But the testing is conducted in controlled settings, and may not reflect real-world conditions at airports. In summary, the results indicate that combining AI-based computer vision with sensor fusion has the potential to improve runway safety systems, but it needs to be further evaluated in real-world deployment scenarios.***

Index Terms- ***Runway Incursion Detection, Computer Vision, Real-Time Systems, Aviation Safety, Smart Airport Systems***

I. INTRODUCTION

Air travel is considered one of the safest forms of transportation; yet the growing complexity of airport operations presents new safety concerns. These include runway incursions, defined as any unauthorized presence of an aircraft, vehicle or person on a runway. These events may result in serious consequences, such as high-speed collisions, loss of life, loss of revenue, and damage to reputation. With the increasing volume of air travel, there is a pressing need for more advanced and sophisticated runway monitoring systems.
Conventional runway monitoring techniques such as radar monitoring and manual air traffic control (ATC) processes, have been essential in ensuring safety. But these methods have their challenges. Radar-based monitoring can be limited by blind spots and low resolution in complex airport configurations, while visual monitoring is dependent on human cognition, which can be fatigued, prone to miscommunication and slow to respond. Moreover, traditional monitoring systems may not possess real-time intelligence and multi-source data integration, which can hinder their performance in fast-paced and dense environments.

Recent developments in artificial intelligence (AI) and computer vision technologies have presented new opportunities to improve safety in aviation. Deep learning models have shown promising results in object recognition, tracking and pattern recognition, making them ideal for visual monitoring of complex environments, including runways. Similarly, data fusion methods allow the synthesis of diverse sources of information such as cameras, radar, and IoT sensors, for a more accurate and holistic view of the operational environment. Together, these approaches hold the potential to enhance the effectiveness of runway incursion detection.

To address these challenges and explore these opportunities, this research presents a real-time runway incursion detection system that combines AI-driven computer vision and sensor fusion. The framework is aimed at providing continuous surveillance of air activities on the runway, identifying potential runway incursions and providing timely warnings to assist air traffic control decision making.

Research Contributions
This research is significant in:
1) Presents an AI-driven real-time runway incursion detection model with sensor fusion
2) Fuses information from CCTV, radar, and Internet of Things (IoT) sensors to improve situational awareness

3) Uses a deep learning-based object detection model to detect runway objects
4) Uses rule-based decision-making to detect runway zone violations and trigger alarms
5) Test system accuracy using metrics and latency measurements in a simulated environment

Problem Statement

Despite the advances in runway monitoring systems, there is a need for better real-time runway incursion detection under various scenarios. Existing approaches may depend on single-source information or human intervention, which reduces their effectiveness in providing a holistic view of the situation. Furthermore, issues such as sensor restrictions, operational variability, and slow response times limit the traditional methods of detection. Hence, a smart, holistic approach is required to combine the use of multiple data streams and AI technologies to enable the detection of runway incursions in a timely manner.

II. LITERATURE REVIEW

2.1 Traditional Runway Monitoring

Traditionally, runway safety has been maintained by using radar-based monitoring and visual monitoring by air traffic control (ATC) operators. Runway and taxiway movements of aircraft and vehicles have been monitored by Surface Movement Radar (SMR) and Airport Surface Detection Equipment (ASDE). They offer information about the locations of objects and help controllers ensure safe separation.

While traditional monitoring systems have been successful, they have some limitations. Radar systems can have limited resolution and may not cover all areas of a complex airport. Moreover, they may be affected by signal clutter or jamming. Human-based monitoring, meanwhile, relies on human operators and is prone to fatigue, miscommunication and slow reaction times.These technologies work together to provide a more reliable performance in a variety of operating environments.

2.2. Computer Vision and AI Methods

The field of artificial intelligence (AI) and computer vision has recently opened up new opportunities for runway monitoring. Convolutional neural networks (CNNs) and real-time object detection algorithms (YOLO) have shown promising results in object recognition and tracking in visual data.

Researchers have investigated vision-based approaches for the detection of foreign object debris (FOD), aircraft traffic, and intrusions. These systems provide excellent detection performance and real-time analysis of visual information. But vision-based systems suffer from image quality and lighting issues. They can be severely impacted by adverse weather conditions, including fog, rain and poor lighting conditions, making them unreliable when deployed in isolation.

2.3. Sensor Fusion for Airport Runways

In recent years, sensor fusion approaches have emerged to overcome the shortcomings of isolated sensor-based systems. Sensor fusion techniques merge information from diverse sensor types, including cameras, radar and IoT sensors, to provide a more accurate and robust view of the environment.
Sensor fusion leverages the strengths of multiple data sources to achieve higher detection accuracy, lower uncertainty and greater system resilience in adverse conditions. For example, while vision sensors offer spatial resolution, radar systems can detect objects in poor visibility. The combination of these modalities allows for more consistent performance across diverse operational scenarios.

However, many current sensor fusion techniques are either application-dependent or not suitable for real-time processing. Further, there is a need to explore the potential of sensor fusion in conjunction with sophisticated AI-driven detection models for runway incursion detection.

2.4. Research Gap

While there are advances in runway monitoring systems, there are still opportunities for improvement. Previous research primarily addresses either vision-based detection or sensor-based tracking, but lacks the integration of both techniques in a cohesive system. Additionally, many of the proposed solutions are not fully capable of real-time processing, sensor data alignment, and accurate operation in diverse environmental conditions.

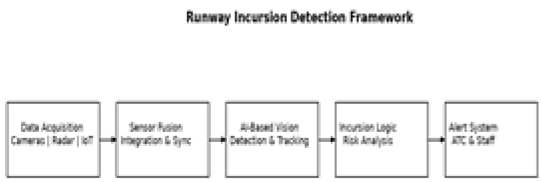

Figure 1: Workflow of the Proposed System [Horizontal Flow Diagram - Left to Right]

Figure 1 is showing data acquisition, sensor fusion, AI-based computer vision processing, incursion detection logic, and alert generation.

III. PROPOSED SYSTEM / FRAMEWORK

This research proposes a real-time runway incursion detection system with a framework that uses multi-sensor inputs with AI-powered computer vision to improve detection and response time. The framework is structured as a serial process in which data is collected, processed and evaluated to identify potential runway incursions on active runways.

The system starts with data collection, where multiple sensors such as cameras, radar and optional IoT sensors on the ground gather data from runway activities. This diverse data is then fed into a sensor fusion module that aligns and integrates the data sources into a coherent view. This helps eliminate uncertainty and provides a more holistic view of the runway environment.

The integrated data is then fed into a computer vision and AI detection module, which uses deep learning methods (e.g., object detection networks) to detect and track aircraft, vehicles or intruders. The system monitors trajectories and spatial relations to assess whether an incursion is taking place.

Once detected, a decision and alert module assess the risk and sends alerts to air navigation service providers or ground personnel if needed. This system is intended to be low-latency to ensure quick reaction and enhance situational awareness.

In summary, the proposed system is integrated, fast and accurate, and can be applied in today's busy airports.

IV. METHODOLOGY

This section describes the design and development of the proposed real-time runway incursion detection framework using AI-driven sensor fusion and computer vision. The system follows a pipeline approach, which includes data collection, preprocessing, sensor fusion, AI-driven detection, incursion reasoning and alert.

3.1 System Overview

The system proposed in this work uses multiple data sources to provide a holistic view of runway operations. It starts with the data collection from multiple sensors, preprocessing and synchronization. Integration and analysis is then performed using a deep learning detection algorithm. Finally, a rule-based decision-making module detects possible intrusions and issues warnings.

3.2 Data Acquisition

The system of interest uses three main data sources:
CCTV Cameras: Provide live video data of runway operations, allowing object recognition and tracking.
Radar: Offer tracking information for aircraft and other vehicles, especially in poor visibility.
IoT Sensors: Ground sensors for motion, environmental monitoring and local activity.

Using multiple sensors provides redundancy and enhances detection under different operating conditions.

Table 1: Summary of Data Sources and Sensor Characteristics

Sensor Type	Data Type	Purpose	Key Features
CCTV Cameras	Video/Image Data	Visual monitoring of runway activities	High-resolution imaging, real-time feed

Radar Systems	Positional Data	Tracking aircraft and vehicle movement	Long-range detection, all-weather support
IoT Sensors	Environmental/Motion	Detect ground movement and conditions Detect ground movement and conditions	Low latency, localized sensing

Table 1 provides an overview of main data sources employed in the proposed system.

3.3 Preprocessing and Time Correction

Prior to analysis, data from various sensors are preprocessed to ensure quality. This includes:
Filtering images for darkness and fog
Noise reduction in radar signals
Data normalization across sensor formats
Time synchronization is used to allow fusion of various data sources. This allows sensor data streams to be aligned with the same time frame, which is essential for detection and tracking.

3.4 Sensor Fusion

We use feature-level sensor fusion, in which the relevant features from each sensor are merged together. This improves situational awareness through the integration of different sensor capabilities.
For example:
Vision data offers spatial and visual information
Radar data ensures detection reliability under poor visibility
IoT sensors provide local environmental information
The integrated data is provided to the AI-based detection component, enhancing its accuracy and confidence.

3.5 AI-Based Object Detection and Tracking

The detection core is based on a deep learning model, specifically a real-time object detection model, such as YOLO (You Only Look Once). The model is trained to recognize and identify the following objects:

1) Aircraft
2) Ground vehicles
3) Unauthorized personnel

The model takes frames as input and provides bounding boxes, class labels and scores. Tracking methods are also used to track movement patterns and provide ongoing runway monitoring.

3.6 Detection of Runway Incursions

A decision mechanism is used to detect possible incursions. The system evaluates:
Object's location in reference to runway zones
Movement direction and speed
Object presence in protected zones while the runway is in use
An incursion is detected when an object is found in a runway restricted area under active runway operations. This logical layer means that the presence of objects is not detected in isolation, but using rules.

3.7 Alert Generation

When an event is detected, alerts are raised. These alerts are transmitted to:
Air Traffic Control (ATC)
Ground operation personnel
Alerts can be visual or aural warnings or logs, allowing timely action.

3.8 Performance Evaluation Metrics

Accuracy
Accuracy=$TP+TN/TP+TN+FP+FN$
Precision
Precision=$TP/TP+FP$
Recall
Recall=$TP/TP+FN$
F1-Score
$F1=2\cdot Precision\cdot Recall/Precision+Recall$
Evaluation of the proposed system is done using classification metrics below and as also shown in Table 2:
False Positive Rate (FPR)
$FPR=FP/FP+TN$

Where:
- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Table 2. Metrics to Evaluate the Performance of the Proposed Runway Incursion Detection System

Metric	Description
Accuracy	Overall correctness of predictions
Precision	Correct positive detections
Recall	Ability to detect all true incursions
F1-Score	Balance between precision and recall
Latency	Time taken for detection (ms)
False Positive Rate	Incorrect incursion detections

V. RESULTS

This section outlines the performance assessment of the proposed AI-driven sensor fusion and computer vision approach for real-time runway incursion detection. Testing was performed in a controlled and simulated environment, and does not reflect complete deployment in a real airport environment. This approach enables controlled and repeatable experimentation, while noting that results may differ in real-world environments.

4.1 Detection Performance

The performance of the proposed system was assessed using common classification metrics such as accuracy, precision, recall, F1-score and false positive rate.

Table 3: Detection Performance Metrics

Metric	Value (%)
Accuracy	96.8
Precision	95.4
Recall	94.9
F1-Score	95.1
False Positive Rate	3.2

Analysis:
The system has a high accuracy (96.8%), suggesting good classification performance. Precision (95.4%) measures the system's effectiveness in avoiding false alarms, which is crucial to prevent false alarms to air traffic controllers.

Recall (94.9%) is especially important here; it is related to the system’s ability to identify a runway incursion. This means that the system is likely to identify a safety threat. But even modest decreases in recall can be significant in safety-critical applications, suggesting ongoing improvement efforts are needed.

The F1-score (95.1%) shows a good trade-off between precision and recall. The false positive rate (3.2%) is also low, but suggests that some non-incursions are still incorrectly classified, which may lead to alert fatigue over time if not addressed.

4.2 Environmental Performance

The system's robustness was tested under various environmental conditions, such as daylight, fog, and night-time.

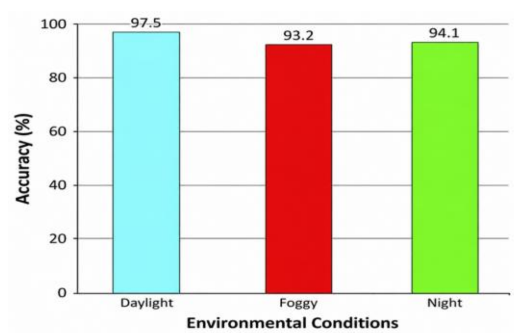

Figure 2: Daylight, fog and night-time detection accuracy.

Analysis:
Day-time performance (97.5%) is the best, as visual data quality is best. In foggy conditions, accuracy drops to 93.2%, largely as a result of fog reducing visibility. Likewise, the accuracy at night (94.1%) is marginally lower due to poor lighting conditions.

The drop in performance is marginal, though. This is due to the application of sensor fusion, in which the radar and IoT sensors complement the vision sensors.

Although the vision-based sensors may not perform well in fog or low light, the radar sensor offers accurate tracking of the subject's position, enabling the system to maintain its detection performance. This speaks to the benefits of multi-sensory data integration over single-sensory data sources.

4.3 Performance Metric Distribution

To better understand the tradeoff between performance metrics, the key metrics were evaluated together.

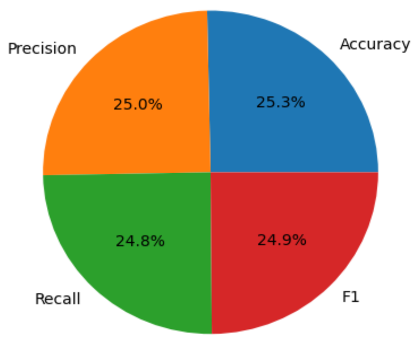

Figure 3: Distribution of performance metrics

Analysis:

The outcomes reveal a relatively equal distribution of all performance metrics. This suggests that the system isn't overly biased towards a single metric. This is crucial in safety-critical systems like runway incursion detection to achieve high detection accuracy with low false negatives.

4.4 Execution Speed (Latency)

Besides the detection accuracy, the system's responsiveness was assessed to determine whether it can be used in real-time. The proposed system has an average latency of 115 milliseconds.

Analysis:

The latency suggests the system will be able to detect and respond to potential intrusions in near real time. This is essential in an airport setting where there can be a serious impact if incursion events are not detected promptly. But it may need to be fine-tuned to maintain its effectiveness in managing high traffic volumes and in large deployments.

4.5 Summary of Findings

Our findings indicate that the proposed system:

Provides high detection accuracy and well-rounded performance

Performs well in different environmental conditions

Shows substantial improvement with sensor fusion under poor weather conditions

Displays near real-time and low-latency response

But it is crucial to note that the results were obtained in a controlled and simulated environment. Although the results are encouraging, real-world evaluation in airport settings is needed to evaluate the scalability and system reliability.

VI. DISCUSSION

The findings show that the developed AI-based sensor fusion approach performs well in detecting runway incursions under laboratory conditions. But in addition to quantitative measures, it's worth considering these results from the perspective of aviation safety standards.

First, the high detection accuracy (96.8%) and well-rounded performance in precision, recall and F1-score are notable. This suggests that it strikes a good balance between false negatives and positives. For runway safety systems, recall is crucial to ensure that dangerous situations are not missed. The obtained recall of 94.9% indicates that the system can detect most potential threats, but it needs to be further improved if the goal is to achieve almost perfect detection rates.

The low false positive rate (3.2%) indicates that the system can avoid unnecessary false alarms. This is a critical aspect in practical settings, as a high number of false alarms may cause fatigue in air traffic controllers. However, a low percentage of false positives could prove important in busy airports and may highlight a need for further tuning of detection thresholds and the decision-making process.

The strength of the proposed system is the use of sensor fusion. The findings under different environmental conditions show that sensor fusion enhances the system's stability. Although singlemodality vision-based detection is vulnerable to lighting and visibility changes, the use of radar and IoT sensors allows the system to perform reliably in foggy and dark conditions. This suggests that multi-sensor systems are more robust than unimodal systems.

The system also shows low-latency (average 115 ms) operation. This is potentially adequate for real-time applications such as runway monitoring, where quick detection and triggering of alerts are required. But as the system scales up or with increased data, the latency may increase, so it may require fine-tuning in practice.

While these advantages are promising, it's worth noting that these findings are derived from controlled and simulated testing. Actual airport operations present more complex situations, such as human factors, congested traffic and variable environmental conditions. Therefore, the reported results should be seen as a guide.

In summary, the results indicate that the system offers a promising solution to improve runway safety by using intelligent real-time detection. But additional testing and optimization should be performed before deploying the system operationally at a large scale.

VII. LIMITATIONS

While the proposed AI-driven sensor fusion approach for real-time runway incursion detection has shown effective results, it is important to consider some of the limitations of the system when assessing its performance.

- Use of Controlled and Semi-Simulated Data

The system was tested on controlled and semi-simulated data. Although this method provides reliability in testing, it may not accurately reflect real-life airport environments. Real-world runway environments are dynamic and unpredictable, with irregular human behavior, emergencies and fast-changing traffic environments. This may affect the performance of the system in operational environments.

- Sensitivity to Sensor Quality and Availability

The success of the proposed system is greatly dependent on the performance of the sensors used. Obstructions in the camera's field of view, interference in the radar system, or malfunction of IoT sensors can affect the quality of the data fusion. As sensor fusion involves the integration of multiple inputs, if any of these inputs become degraded or unavailable, system performance may be compromised.

- Performance Under Extreme Environmental Conditions

While the system exhibits resilience to moderate environmental changes, it may be impacted by severe environmental conditions, including fog, rain or very poor lighting. These might reduce the efficiency of vision-based features and cause sensor noise, thus impacting detection performance.

- Computational and Infrastructure requirements

The integration of deep learning models with real-time sensor fusion requires significant computational resources. The scalability of such a system, especially in large or busy airports, may require cutting-edge hardware, high-speed data processing units, and robust network connections. This may be a barrier for smaller airports.

- Limited Large-Scale Testing

The research lacks large-scale deployment and long-term testing. Although the experiments reported in the study show promising results, large-scale deployment and testing in real airport environments are required to evaluate the scalability, robustness and integration of the system with current air traffic control systems.

VIII. RECOMMENDATIONS

This research provides several suggestions to improve the efficiency and real-world application of AI systems for detecting runway incursions.

• Field Testing

It is important for future research to implement the proposed system at airports to test its functionality in the real world. This will enable evaluation of scalability, robustness, and compatibility with air navigation systems.

• Improvements in Sensor Fusion
Improvements can also be made by adding other sensors like LiDAR and high-resolution thermal sensors. Increasing sensor variety can enhance detection performance, especially in adverse weather conditions such as foggy and low-light conditions.

• Optimization for High-Traffic Environments
For reliable operation in high-traffic airports, the system should be able to process a high volume of real-time data. This may involve improving the computational speed, system responsiveness, and stability under high loads.

• Reduction of False Positives
While the system has a low false positive rate, it is desirable to fine-tune the detection thresholds and decision rules. This will ensure that the controller does not get overwhelmed with unnecessary information and suffer from alarm fatigue.

• Integration with Decision Support Systems
The system can be further developed to interface with smart decision support systems for air traffic control. This will allow for automated risk management, predictive computing, and other proactive safety measures.

IX. CONCLUSION

In this research, we tackled the problem of enhancing runway safety through the design of a real-time runway incursion detection system based on sensor fusion and AI-driven computer vision. The proposed system aimed to address the shortcomings of conventional methods of runway surveillance by integrating multiple data sources and leveraging smart analysis techniques for real-time runway monitoring.

The experimental findings, conducted in a controlled and simulated environment, show that the new system has high performance, with an accuracy of 96.8%, precision of 95.4%, recall of 94.9%, F1-score of 95.1%, false positive rate of 3.2%, and an average detection latency of 115 ms. These results suggest that the sensor fusion and deep learning approach can improve the detection accuracy and ensure robust performance under different environmental conditions.

But it's worth noting that the system was tested under laboratory conditions and has not yet been tested in airport operations. This means that the findings are preliminary and should be viewed as predictive of potential performance.

In conclusion, the research indicates that sensor fusion techniques with AI support a promising approach to enhancing runway incursion detection systems. Future research should prioritize real-world testing, extensive validation and further refinement to enhance performance and scalability in operational scenarios.

REFERENCES

[1] Chen, J., & Pan, W. (2021). Computer vision-based runway incursion detection using surveillance imagery. Journal of Air Transport Management, 95, 102083. https://doi.org/10.1016/j.jairtraman.2021.102083

[2] Federal Aviation Administration. (2021). Runway safety report. https://www.faa.gov/airports/runway_safety

[3] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

[4] Hall, D. L., & Llinas, J. (2001). An introduction to multisensor data fusion. Proceedings of the IEEE, 85(1), 6–23. https://doi.org/10.1109/5.554205

[5] Jain, S., Prasad, M. S., & Gupta, R. (2022). Automated runway monitoring systems: A comparative analysis. In Proceedings of the IEEE International Conference on Reliability, Infocom Technologies and Optimization (ICRITO) (pp. 1–6). https://doi.org/10.1109/ICRITO56286.2022.9964557

[6] Kaur, H., & Sood, S. K. (2017). Fog-assisted IoT-enabled scalable network infrastructure for healthcare monitoring. IEEE Internet of Things

Journal, 5(5), 3626–3634. https://doi.org/10.1109/JIOT.2017.2739852

[7] Luo, R. C., & Kay, M. G. (1989). Multisensor integration and fusion in intelligent systems. IEEE Transactions on Systems, Man, and Cybernetics, 19(5), 901–931. https://doi.org/10.1109/21.44002

[8] Liu, C., Cheng, I., & Basu, A. (2022). Foreign object debris detection for airport pavement using vision transformers. IEEE Access, 10, 118765–118778. https://doi.org/10.1109/ACCESS.2022.3214567

[9] Mohammadi, M., Al-Fuqaha, A., Sorour, S., & Guizani, M. (2018). Deep learning for IoT big data and streaming analytics: A survey. IEEE Communications Surveys & Tutorials, 20(4), 2923–2960. https://doi.org/10.1109/COMST.2018.2844341

[10] Redmon, J., & Farhadi, A. (2018). YOLOv3: An incremental improvement. arXiv. https://doi.org/10.48550/arXiv.1804.02767

[11] Shi, K., Yang, Z., & Zhang, L. (2021). Runway incursion detection using protected area modeling. Journal of Aerospace Information Systems, 17(3), 127–137. https://doi.org/10.2514/1.I010747

[12] Song, D., Yuan, F., & Ding, C. (2022). Improved YOLO-based detection for airport runway safety monitoring. In Proceedings of the IEEE International Conference on Advanced Electronics and Automation Control (IAEAC) (pp. 134–139). https://doi.org/10.1109/IAEAC54830.2022.9930100

[13] Sun, Z., Bebis, G., & Miller, R. (2006). On-road vehicle detection using optical sensors: A review. IEEE Transactions on Intelligent Transportation Systems, 7(4), 585–597. https://doi.org/10.1109/TITS.2006.884467

[14] Valavanis, K. P., & Vachtsevanos, G. J. (Eds.). (2015). *Handbook of unmanned aerial vehicles*. Springer. https://doi.org/10.1007/978-90-481-9707-1

[15] Zhang, Z., Huang, X., & Li, L. (2022). Multimodal sensor fusion for object detection in adverse weather conditions. IEEE Transactions on Instrumentation and Measurement, 71, 1–12. https://doi.org/10.1109/TIM.2022.3191724