Erciyes Üniversitesi
Fen Bilimleri Enstitüsü Dergisi
Cilt 40, Sayı 3, 2024

Erciyes University
Journal of Institue Of Science and Technology
Volume 40, Issue 3, 2024

Investigation of Pilot Reaction Time on Automatic Ground Collision Avoidance System

Birce Boga[*1], **Zeynep Seda Mor**[2], **Nida Kuşku**[3]

[*1] TUSAŞ, ANKARA
[2] TUSAŞ, ANKARA
[3] TUSAŞ, ANKARA

(Alınış / Received: 26.11.2024, Kabul / Accepted: 30.12.2024, Online Yayınlanma / Published Online: 30.12.2024)

Keywords
Ground collision,
Pilot interaction,
Reaction time,
Manual GCAS,
Automatic GCAS,
Flight test

Abstract: In this study it is aimed to compare manual pilot recovery behavior and automatic recovery in case of Controlled Flight into Terrain (CFIT) condition. Several test cases are conducted for random initial conditions in a fixed-based simulator environment and obtained test results are compared. Average pilot reaction time is determined from simulation results. Collected data is used to improve GCAS algorithm design for augmented pilot trust and comfort. The duration required to achieve situational awareness has been examined.

Otomatik Yer Çarpmasından Kaçınma Sistemi için Pilot Tepki Süresinin İncelenmesi

Anahtar Kelimeler
Pilot etkileşimi,
Reaksiyon süresi,
Manuel GCAS,
Otomatik GCAS,
Uçuş testi

Öz: Bu çalışmada Araziye Kontrollü Uçuş (CFIT) durumunda manuel pilot kurtarma davranışı ile otomatik kurtarma davranışının karşılaştırılması amaçlanmıştır. Sabit tabanlı bir simülatör ortamında rastgele başlangıç koşullarında çeşitli test senaryoları yürütülmüş ve elde edilen test sonuçları karşılaştırılmıştır. Ortalama pilot reaksiyon süresi simülasyon sonuçlarından belirlenmiştir. Toplanan veriler, pilotun güvenini ve konforunu artırmak amacıyla GCAS algoritma tasarımını geliştirmek için kullanılmıştır.

1. Introduction

The development of advanced aviation systems has significantly enhanced the safety and operational capabilities of modern fighter aircraft. Among these innovations, the Ground Collision Avoidance System (GCAS) stands out as a critical life-saving technology. GCAS is designed to prevent catastrophic accidents by warning pilots of potential ground collisions through aural and visual cues. CFIT occurs when a healthy aircraft collides with terrain because the pilot is unaware of or unable to avoid the danger due to his or her spatial disorientation (which is a cognitive precur-sor to CFIT) or because of g-force-induced loss of consciousness (G-LOC)[1]. GCAS's more advanced counterpart, the Automatic Ground Collision Avoidance System (AGCAS), takes safety a step further by autonomously intervening to execute recovery manoeuvres when a collision is imminent. These systems are indispensable for mitigating risks in high-performance flight scenarios, particularly in fourth, 4.5, and fifth-generation fighter aircraft. However, the design and implementation of such systems are complex and directly influence pilot interaction and mission success.

AGCAS primarily addresses collision scenarios caused by factors such as G-LOC , loss of situational awareness, and spatial disorientation. These factors are especially prevalent in high-G environments, where pilots may be unable to respond promptly or effectively to hazardous situations. AGCAS leverages predictive algorithms and a mathematical model of the aircraft's dynamics to calculate potential trajectories, including recovery manoeuvres. By intervening at the last possible moment, AGCAS ensures that the aircraft avoids terrain while minimizing disruption to the mission. Despite its proven effectiveness, the system's automation philosophy and interaction design are critical to its success. Poorly configured systems or inadequate pilot-system integration can lead to mistrust, reduced situational awareness, or even unintended mission risks.

The pilot's role remains central in the operation of AGCAS, even as automation levels increase. Unlike fully autonomous systems, AGCAS is designed to act as a safety net, complementing the pilot's actions rather than replacing them. Therefore, the effectiveness of AGCAS is closely tied to how pilots perceive and interact with the system under various operational conditions. Factors such as reaction time, situational awareness, and trust in the system play a pivotal role in determining its success. Understanding and optimizing this interaction is crucial to enhancing the system's performance and ensuring seamless integration into modern fighter aircraft.

This study aims to investigate pilot interactions with AGCAS and their impact on collision avoidance. By examining reaction times and behavioural responses across different simulated flight scenarios, the research seeks to identify design improvements that enhance both safety and usability. A fixed-based simulator environment provides a controlled setting for testing, enabling the collection of detailed feedback from pilots. Test cases are systematically organized using a flight test card, allowing for comprehensive evaluation of the system's algorithms and their effectiveness in real-world conditions.

The findings of this research will contribute to the ongoing development of AGCAS by addressing the critical balance between automation and pilot control. By optimizing design solutions based on pilot feedback, the study aims to reduce the risk of ground collisions while maintaining operational effectiveness. As fighter aircraft continue to evolve, ensuring the reliability and adaptability of collision avoidance systems will remain a cornerstone of aviation safety.

1.1. Literature review

Forward-Looking Terrain Avoidance (FLTA) algorithms aim to predict potential collisions by projecting the UAV's trajectory into the future and evaluating its interaction with terrain or obstacles. These algorithms are critical for UAVs operating in dynamic or unknown environments. Algorithms with different approaches are found in the literature and are used in air vehicles. These algorithms, which require different subsystems and sensors to function, are optimized with great precision for aircraft to be used in military operational environments, ensuring that they are highly classified.

There are four main approaches and methods for FLTA algorithms. Ray-Casting for Flight Path Simulation, Real-Time Terrain Matching, Potential Field-Based Navigation, and Genetic Algorithm-Enhanced Path Planning Ray-Casting for Flight Path Simulation algorithm, projects the UAV's future trajectory using simulated rays to identify potential obstacles along its path. This method is computationally efficient and allows real-time adjustments in navigation systems, making it suitable for low-altitude operations [8].

Real-Time Terrain Matching systems use onboard sensors to compare real-time terrain data with pre-stored Digital Elevation Models (DEMs). This approach is widely used in military-grade systems such as TERPROM, which matches terrain profiles to provide collision alerts and navigation support [9].

Potential Field-Based Navigation algorithms create virtual repulsion forces around obstacles and attraction forces toward targets, guiding UAVs dynamically through complex terrains. These systems are especially effective in avoiding local minima through advanced optimization techniques [10].

Genetic Algorithm-Enhanced Path Planning algorithms, when combined with geometric obstacle avoidance methods, optimize UAV paths while ensuring collision avoidance. These hybrid systems improve computational efficiency and adapt to dynamic flight scenarios [11].

Some FLTA algorithms have the advantage over others in that they do not require a map of the operational area. Therefore, they offer certain advantages in military UAV operations. FLTA algorithms are extensively used in UAV operations requiring real-time decision-making, such as low-altitude military reconnaissance and autonomous delivery drones. Systems like TERPROM are pivotal for enhancing UAV survivability in unknown terrains [8].

Despite their advantageous capabilities, some FLTA algorithms face limitations such as sensor inaccuracies, dependency on high-resolution DEMs, and computational constraints in real-time operations [7, 8]. Better hardware, higher processing capacity, etc., require detailed trade-off studies in aircraft system design, and typically, high capacities cannot be achieved.

There are six main models for collision risk assessment. These are; Monte Carlo Simulations, Bayesian Inference Models, Causal Network Analysis, Ground Risk Modeling, Mixed Integer Programming for Path Planning, Velocity Obstacle Approach. Collision risk assessment models estimate the likelihood of UAV collisions, considering operational uncertainties. These models are essential for high-risk zones and swarm operations, where multiple UAVs operate simultaneously.

Bayesian models incorporate prior probabilities and real-time sensor updates to calculate collision risks. These models effectively handle sensor uncertainties and provide dynamic risk assessments Bayesian modeling provides a strong probabilistic approach for collision avoidance systems in UAVs prior to a collision. It is especially useful in environmental situations with high uncertainty (e.g., movements of other aircraft). However, challenges such as complexity, computational cost, and data accuracy must also be considered. Therefore, an appropriate balance should be achieved in terms of applicability and efficiency. [13].

Monte Carlo simulations can be a powerful tool for automatic collision avoidance systems in UAVs. Its probability-based approach enhances resilience against environmental uncertainties and various scenarios.
Monte Carlo methods evaluate collision probabilities by running numerous simulations with stochastic variables. This approach is particularly beneficial in scenarios with uncertain terrain data or dynamic environmental conditions However, challenges such as high computational costs and sensitivity of simulation results should also be considered. This method can be effective in improving UAV safety with a proper control and optimization process, but careful balancing is required in the design for real-time, low-latency systems. [12].

Causal Network Analysis (CNA) can be a powerful tool for collision avoidance systems in UAVs. By using cause-and-effect relationships, it can assess the impact of environmental factors on collision risk, thus enabling the development of safer flight strategies.
Causal models analyze the interdependencies of variables influencing collision risks, identifying critical factors and enabling targeted risk mitigation strategies However, disadvantages such as complexity, computational costs, and the need for accurate data also exist. Therefore, careful control and optimization processes are necessary for CNA to be effectively applied in automatic collision avoidance systems for UAVs. [14].

Ground Risk Modeling (GRM) is an important tool in collision avoidance systems for UAVs, especially for low-altitude flights such as takeoff and landing, where it offers an effective method to minimize interactions with ground obstacles. Advantages include reducing ground collision risks, the ability to perform real-time analysis, and integrating complex environmental factors. Disadvantages include high computational costs and reliance on sensor accuracy.
Ground risk models evaluate potential hazards to people and property in the event of UAV crashes, guiding flight planning and operational safety Therefore, effective implementation of GRM requires high processing power, accurate sensor data, and careful modeling. [15].

Mixed Integer Programming (MIP) can be a powerful optimization tool for developing Automatic Collision Avoidance Systems (ACAS) for UAVs. It enables safe route planning while minimizing collision risks and adapting to environmental variables. Advantages include precise solutions, flexibility, and the simultaneous optimization of multiple objectives.
Mixed Integer Programming (MIP) techniques allow for the optimization of multi-vehicle path planning in dynamic environments. These methods are highly effective in ensuring collision-free trajectories in complex scenarios involving multiple UAVs However, disadvantages include high computational costs, solution time, and complexity. When used in dynamic, real-time systems for UAVs, appropriate optimization techniques or heuristic approaches may be needed to overcome these disadvantages. [16].

The Velocity Obstacle Approach (VOA) is an effective tool in the development of Automatic Collision Avoidance Systems for UAVs. By using real-time velocity obstacle analysis, it prevents collisions with moving obstacles in dynamic environments, ensuring the UAV follows a safe flight path. Advantages include real-time collision avoidance, adaptation to dynamic environments, interaction with multiple obstacles, and efficient computation. However, disadvantages such as limited geometric modeling, computational load, and challenges in complex environments must also be considered.

The velocity obstacle method predicts potential collisions by modeling the relative velocities of UAVs and obstacles. It is widely applied in dynamic environments where real-time adjustments are necessary for collision avoidance [16].

These models are used in UAV swarm management, urban air mobility, and risk mitigation in crowded airspace. They are also pivotal in compliance with regulatory standards for UAV safety [12].

The primary challenges in developing collision risk models include acquiring accurate data, computational resource demands, and integrating these systems into real-time operations [13]. These challenges were also felt within the scope of the study. Along with the relevant classification requirements, the high-security demands for accurate data collection, processing, and later simulation created difficult problems to solve in the study.

2. Material and Method

The development of the GCAS algorithm involves a combination of predictive modelling, real-time data analysis, and integration with the aircraft's control systems. The core of the GCAS algorithm is a mathematical model of the aircraft dynamics, which predicts future trajectories based on current flight parameters such as altitude, velocity, pitch, roll, and heading. These predictions consider terrain data, aircraft performance limits, and recovery manoeuvres to identify potential ground collision risks.

The algorithm is structured into two primary phases, the prediction phase and the action phase. In the prediction phase the aircraft's trajectory is continuously evaluated in real-time to detect if it intersects with the terrain. It uses terrain databases and on-board sensors to identify potential hazards. If a collision is imminent in the action phase, the system triggers a response. In manual GCAS, warnings are issued to alert the pilot, while in automatic GCAS (AGCAS), the system autonomously executes recovery manoeuvres.

There are two automation levels; manual GCAS and automatic GCAS (AGCAS). During manual GCAS; the system provides aural and visual warnings, leaving the recovery decision to the pilot. During automatic GCAS (AGCAS); the system assumes control to execute an automatic recovery manoeuvre at the last possible moment. This minimizes disruption to the mission while ensuring safety.

The three algorithm features are; G-LOC Detection, Dynamic Adaptation and Trajectory Recovery Planning. The G-LOC Detection; incorporates physiological monitoring to detect G-force-induced loss of consciousness and automatically activates recovery protocols. The Dynamic Adaptation; adjusts warning and recovery thresholds based on operational contexts, such as low-level flight or combat scenarios. The Trajectory Recovery Planning; computes a safe recovery path that avoids overstressing the aircraft while maximizing terrain clearance.

The algorithm undergoes iterative testing and validation in simulation environments to refine its accuracy, reliability, and interaction with pilots.

2.1. GCAS algorithm design

The manoeuvre type that is frequently used in GCAS design and is considered the optimum rescue manoeuvre is roll to wings level and 5g pull up [2].

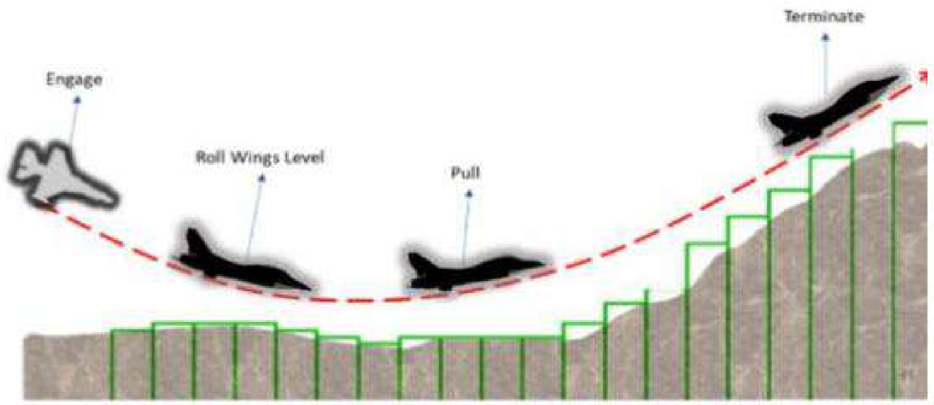

Figure-1. Automatic Ground Collision Avoidance Manoeuvre

The GCAS algorithm mainly uses navigation sensor data, navigation database, flight data computer and pilot control inputs. The algorithm creates a dynamic scan pattern using the velocity, turn rate and dive angle of the aircraft and calculates the estimated trajectory of the aircraft for a certain period of time at every moment.

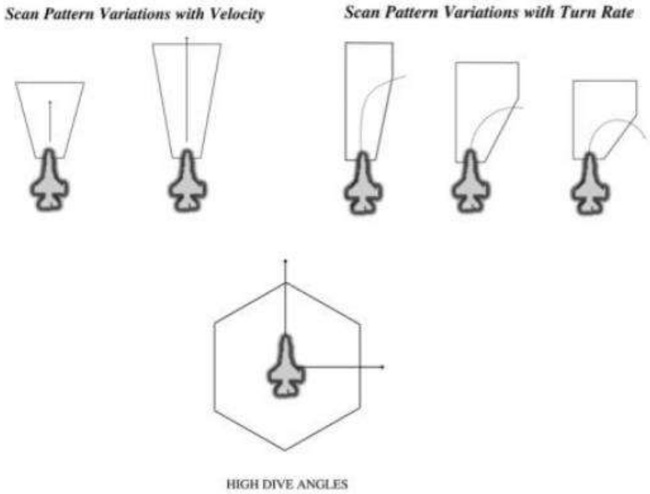

Figure-2. Dynamic Scan Pattern

The region that the relevant sensors will scan and process, depending on the manoeuvre performed by the UAV, is illustrated in Figure-2. In cases of linear flight, scanning is performed only by the forward-facing sensors, and only these data are processed. The scanning distance dynamically increases or decreases based on the vehicle's speed. For manoeuvres made to the sides, the lateral scanning distance of the vehicle dynamically increases according to the radius of the manoeuvre, and sensor data from the relevant areas are processed. In the case of a high dive, sensor data used during the aircraft's downward manoeuvres are processed.

2.2. Automatic and manual GCAS scenarios

To evaluate the system's performance and pilot interaction, specific manual and automatic GCAS scenarios are designed. Each scenario replicates realistic operational conditions where ground collision risks may arise.

Manual GCAS algorithm does not initiate any automatic manoeuvre. The algorithm initiates aural and visual alerts to the pilot on various displays according to cockpit avionics design. Manual GCAS test campaign aims to test visual and aural warnings timing to prevent nuisance alerts based on the test pilots' comments and define the exact manual recovery point for the pilot guidance [3].

There are two manual GCAS scenarios. In Scenario 1; The terrain avoidance in Low-Level Flight is simulated, simulation goes on with a high-speed, and low-altitude navigation over uneven terrain. The system provides visual and aural alerts for upcoming terrain. The pilot must respond with a corrective manoeuvre. In Scenario 2; there is a sudden Loss of Situational Awareness. Scenario introduces distractions, such as simulated system malfunctions, while approaching a ridge. The system warns the pilot, testing reaction time and situational awareness. [4].

AGCAS algorithm initiates the recovery manoeuvre automatically when recovery condition occurs depending on the design criteria. However; initiation time, type of recovery manoeuvre, pilot control criteria and termination of the automatic recovery manoeuvre depend on the design criteria. The main purposes of AGCAS algorithm flight test are; to measure the success of the algorithm in recovering both aircraft and pilot and how closely automatic system converged to the pilot reactions. The main purpose here is to keep pilot comfort at the highest level during the automatic manoeuvring [5].

In Scenario 1; G-LOC Recovery the pilot undergoes simulated high-G turns to induce temporary loss of consciousness. AGCAS autonomously detects the condition and executes a recovery manoeuvre. In Scenario 2; there is a steep dive interception simulates a combat scenario where the aircraft is in a steep dive. AGCAS intervenes when the trajectory intersects with the terrain, recovering the aircraft with minimal impact on mission parameters.

2.3. Manoeuvres

The GCAS algorithm's effectiveness depends on its ability to execute a range of recovery manoeuvres tailored to different flight scenarios. The manoeuvres are preprogramed and optimized to ensure both safety and performance.

Pull-Up Manoeuvre is a rapid increase in pitch to climb and avoid terrain. It is designed to prevent aerodynamic stall by considering aircraft speed and angle of attack. Roll and Pull Manoeuvre combines a roll to level the wings with a pull-up manoeuvre. It is ideal for situations where the aircraft is in an inverted or steep bank position. Throttle Adjustment Manoeuvre commands an increase or decrease in thrust during recovery. Ensures energy management without exceeding performance limits. Split-S Recovery Manoeuvre is a combination of roll, pitch, and descent used to reverse course when climbing is not feasible. Primarily used in combat scenarios where upward recovery may expose the aircraft to threats [6, 7].

Each manoeuvre is validated in simulation environments to ensure seamless execution under various conditions, including aerodynamic limits and pilot input overrides.

Moreover, this study does not focus on the rescue manoeuvres performed by the AGCAS. After ensuring the system's situational awareness, rescue manoeuvres should be decided by evaluating both the terrain and environmental conditions, as well as potential threats, collectively.

2.4. Flight test cards

Flight test cards are used to organize and standardize the evaluation process for GCAS and AGCAS algorithms. Each test card defines the parameters, objectives, and success criteria for a given test.

The structure of a flight test card contains; objective, flight parameters, test scenario, success criteria, and data collection. Objective, clearly states the purpose of the test (e.g., evaluate pilot reaction to manual GCAS warnings).

Table 1. An example test card for AGCAS

Objective:	Test AGCAS recovery from a steep dive.
Parameters:	a, b, c
Altitude:	500 feet AGL (Above Ground Level).
Airspeed:	450 knots.
Descent Angle:	30 degrees.
Scenario:	The pilot simulates a dive toward a mountain. AGCAS must detect the collision risk and autonomously recover.
Success Criteria:	Recovery occurs before terrain impact. Post-recovery altitude is above 800 feet. Minimal loss of airspeed and mission capability.

Flight Parameters specifies conditions such as altitude, airspeed, and manoeuvres to be performed. Test Scenario describes the simulated situation (e.g., low-level flight, steep dive). Success Criteria defines the metrics for success, such as reaction time, recovery trajectory, and pilot feedback. Data Collection outlines the instruments and methods for recording flight data, including cockpit video, telemetry, and pilot physiological monitoring.

2.5. Flight test scenarios

The flight test campaign to be prepared for such a system is also quite challenging. Main scope of the flight test campaign is to test the algorithm for both manual and automatic manoeuvring cases. Another scope is collecting pilot reaction time data to improve both manual and automatic algorithms. The evaluation campaign involves a series of flight test scenarios in a fixed-based simulator environment. Each scenario is designed to replicate real-world conditions while allowing controlled data collection and analysis.

Test scenarios are determined based on different initial conditions consisting of flight parameters such as speed, altitude, Flight Path Angle (FPA), roll angle, etc.

In Low-Level Terrain Navigation; pilots navigate a simulated low-altitude route with varying terrain features. GCAS and AGCAS responses are evaluated under manual and automatic modes.

In Combat Engagement Simulation, involves high-G manoeuvres during a simulated dogfight. Tests AGCAS performance in detecting and recovering from unsafe trajectories.

In Weather-Induced Disorientation, simulates poor visibility and turbulence to assess pilot reliance on GCAS.

The G-LOC and Recovery, subjects' pilots to high-G scenarios to evaluate AGCAS's ability to detect and recover from G-LOC events.

Multiple System Failures, simulates scenarios with partial system failures to evaluate GCAS reliability and redundancy.

2.6. Data collection and analysis

The data collected during flight tests include; Pilot Reaction Time, System Response Metrics, Pilot Feedback, and Physiological Data. Pilot Reaction Time is measured from the time a warning is issued to the initiation of a corrective action. System Response Metrics includes time to recovery, trajectory deviations, and altitude gain. Pilot Feedback is gathered through surveys and debriefing sessions capture subjective evaluations of system usability and trustworthiness. Physiological Data, includes tracks of heart rate, G-tolerance, and cognitive load to understand pilot stress and performance.

The collected data are analysed to identify patterns and areas for improvement in GCAS and AGCAS design. The findings inform iterative refinements to algorithms and interface design, ensuring optimal integration into operational aircraft. By systematically evaluating scenarios, manoeuvres, and algorithms, this study provides a comprehensive assessment of GCAS and AGCAS capabilities, contributing to safer and more effective aviation systems.

GCAS processes data received from relevant sensors (such as GPS, altitude, speed, etc.) according to the selected algorithm and provides the pilot with a warning of a potential terrain collision. On the other hand, AGCAS must also collect data from additional sensors (such as terrain maps, etc.) and internal systems (such as avionics systems, etc.) in order to perform rescue manoeuvres. To execute these manoeuvres, AGCAS collects data from all control sensors as well.

3. Results

Aircraft configuration and test cases are defined in the test card for each different test case. In Figure 3 below, Test Points (TP) are defined with different initial conditions to determine the pilot reactions based on the practicability of each manoeuvre.

These TP's are conducted in a fixed-based simulator environment. Test pilots' comments and data collected during flight test campaign assist to compare manual pilot recovery behaviour with automatic recovery manoeuvre in case of CFIT. Furthermore, collected pilot reaction time during flight tests is another valuable parameter to improve GCAS algorithm design. Improved algorithm according to test results and pilot feedbacks, will increase pilot trust and comfort.

The success criterion for the AGCAS, as evaluated in this study, is how closely the system's response time aligns with that of expert pilots. In this context, the system's performance will be considered better the faster its response time is in comparison to human tests.

This study focuses on both the developed AGCAS and the measurement of the pilots' reaction times and situational awareness response times under varying flight conditions. Therefore, the specific rescue manoeuvre executed by either the pilot or the system is outside the scope of this study.

The graph presented here illustrates the response time of pilots solely based on auditory and visual cues in scenarios where situational awareness is absent. To conduct this analysis, 30 different random cases were generated and tested. Randomization was essential to eliminate any cognitive bias that may have influenced response times in previous tests where pilots were aware of the initial cases presented to them. By sending the initial cases randomly, it was ensured that pilots were not mentally prepared for any specific scenario, thus providing a more accurate representation of true response times. The resulting graph was obtained through repeated testing with randomized initial cases, enabling a comprehensive assessment of pilot reaction times.

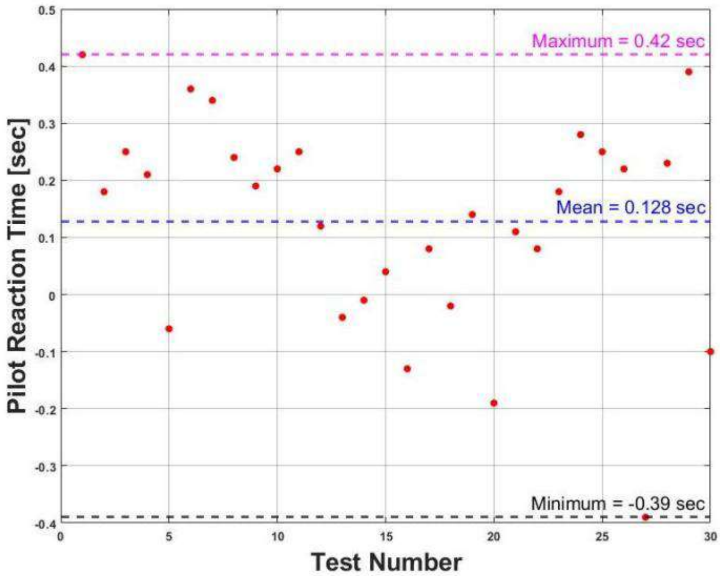

Figure-3. Pilot Reaction Time Test Demo Graphic

It appears that the reaction times of the pilots range from 0.42s to -0.39s. The mean value of the distribution is 0.128s. The pilots' reactions were positive in 17 tests and negative in 13 tests.

It was observed that in 43.3% of the TP's, the pilots' reaction times were below zero.

4. Discussion and Conclusion

In some tests, it was observed that the pilots' reaction times were below zero. These negative reaction times represent the pilot responses recorded before the system issued a warning. It is believed that this situation is a result of the pilots' years of training, which allows them to almost reflexively recognize and respond to potential emergency situations.

The reflexive responses given by pilots in stressful situations have demonstrated that pilots are able to provide more predictive responses compared to the system. After evaluating this, the safety coefficient in the GCAS was recalibrated according to the data in the table, bringing the system's behavior even closer to that of the pilot. The developed algorithm was thus better aligned with pilot behaviour.

Testing plan with suitable flight test card is as significant as the design and development activities of the systems with high pilot interaction. These activities require an iterative process and as each step is completed, next iteration is proceeded by applying improvements and updates achieved by the previous step, considering the lessons learned. As these iterations are repeated, the design of AGCAS is improved and step by step progress towards the perfect design, which can never be achieved. Thus, the pilots' comments and understanding of their interactions with autonomous functions are critical.

Forward-looking terrain avoidance algorithms and collision risk assessment models play a vital role in advancing UAV safety and reliability. While these systems have significantly improved operational capabilities, challenges such as sensor limitations and computational demands persist. Future research should focus on enhancing data quality, optimizing algorithms for real-time applications, and integrating these systems into broader UAV operational frameworks.

Rescue maneuvers that could be performed are not included wthin the scope of this study. Therefore, the selection and execution of applicable rescue manoeuvres involve interdisciplinary studies that could be the subject of future research.

Future developments in artificial intelligence, machine learning and reinforcement learning will directly contribute to the improvement of AGCAS algorithms. While examining pilot behaviour models, future studies should be updated considering the changing new generation of pilot behaviours.

References

[1] Lyons, Joseph & Ho, Nhut & Abel, Anna & Hoffmann, Lauren & Sadler, Garrett & Fergueson, William & Grigsby, Michelle & Wilkins, Mark. (2017). Comparing Trust in Auto-GCAS between Experienced and Novice Air Force Pilots. Ergonomics in Design: The Quarterly of Human Factors Applications. 25. 106480461771661. 10.1177/1064804617716612.

[2] D. E. Swiharta, A. F. (2011). Design, Integration and Flight Test of an Autonomous Ground. Gyroscopy and Navigation, 84–91.

[3] R. Huffman Jr., M. S. (1998). Application of Ground Collision Avoidance System Nuisance Criteria. ICAS and AIAA, 76-85.

[4] Dr. William B. Albery, C. M. (2003). Differences in Pilot Automation Philosophies in the US and Russian Air Forces Ground Collision Avoidance Systems. OH: Defence Technical Information Center.

[5] Hoffmann, Lauren. (2019). Assisting the Improvement of a Military Safety System: An Application of Rapid Assessment Procedures to the Automatic Ground Collision Avoidance System. Human organization. 78. 241-252. 10.17730/0018-7259.78.3.241.

[6] Kirkendoll, Zack & Hook, Loyd. (2021). Automatic Ground Collision Avoidance System Trajectory Prediction and Control for General Aviation. 1-10. 10.1109/DASC52595.2021.9594506.

[7] Lyons, Joseph & Ho, Nhut & Fergueson, William & Sadler, Garrett & Cals, Samantha & Richardson, Casey & Wilkins, Mark. (2016). Trust of an Automatic Ground Collision Avoidance Technology: A Fighter Pilot Perspective. Military Psychology. 28. 10.1037/mil0000124.

[8] Griffiths, S., Saunders, J., Curtis, A., McLain, T. W., & Beard, R. W. (2005). Obstacle and terrain avoidance for miniature aerial vehicles. Advances in Unmanned Aerial Vehicles, 213–244.

[9] Curry, I., & Phipps, D. (1997). TERPROM: The terrain referenced navigation, flight path optimisation and mission planning system. The Aeronautical Journal, 101(1008), 189–195.

[10] Sun, J., Tang, J., & Lao, S. (2017). Collision avoidance for cooperative UAVs with optimized artificial potential field algorithm. IEEE Access, 5, 18382–18390.

[11] Zhou, B., & Zhang, H. (2020). An integrated geometric obstacle avoidance and genetic algorithm TSP solution for UAV path planning. Drones, 4(3), 42.

[12] Kuchar, J. K., & Drumm, A. C. (2005). The traffic alert and collision avoidance system. Lincoln Laboratory Journal, 16(2), 277–296.

[13] Banerjee, A., & Gorospe, G. (2020). Risk assessment of obstacle collision for UAVs under off-nominal conditions. In Proceedings of the Annual Conference of the Prognostics and Health Management Society.

[14] Chen, L., & Tomlin, C. J. (2018). Probabilistic collision avoidance for UAVs using Gaussian mixture models. IEEE Transactions on Robotics, 34(3), 828–841.

[15] Zhang, Y., & Zhang, H. (2021). Safety risk modelling and assessment of civil unmanned aircraft system operations: A literature review. Drones, 5(1), 1.

[16] Schouwenaars, T., De Moor, B., Feron, E., & How, J. P. (2001). Mixed integer programming for multi-vehicle path planning. In Proceedings of the IEEE European Control Conference (pp. 2603–2608).

[17] Fiorini, P., & Shiller, Z. (1998). Motion planning in dynamic environments using velocity obstacles. The International Journal of Robotics Research, 17(7), 760–772.