System Architecture and Evaluation Method of Human-machine Collaboration in Flight Control System

Jun CHE[1,2], Xiaolong CHEN[1,2], Shiqi CHE[3], Jia LI[1,2], Zhangjun SUN[1,2]

[1]Flight Automatic Control Research Institute, AVIC, Xi'an, Shaanxi, China
[2]Science and Technology on Aircraft Control Laboratory, FACRI, Xi'an, Shaanxi, China
[3]Northwestern Polytechnical University, Xi'an, Shaanxi, China

Abstract

The application of artificial intelligence makes the collaboration between machine and human closer in the future. How to build the architecture of human and machine collaboration and evaluate the profit of human and machine collaboration is the premise of promoting the effective application of artificial intelligence in flight control system. The paper proposes an architecture of human and machine collaboration, focusing on the method based on human-machine cognition and behavioral ability evaluation, and how to make task allocation between human and machine through the analysis of man-machine ability expertise and collaboration efficiency. Using NASA-TLX scale and objective metrics, an example of allocating the human and machine tasks during the design process of the flight control system using this architecture is proposed in the paper, showing the effectiveness of the architecture.

Keywords: Human and Machine Collaboration, Cognition Model, NASA-TLX Scale, Flight Control System

1. General Introduction

In the process of performing complex tasks, the pilot needs to observe the environment, read a large amount of information displaying on the screen and decide how to react in a short time. Reducing the pressure of the pilot will increase the rate of correct decision and making it easier to pay attention to items related to the task, not to the flight operation. Application of artificial intelligence system is such an obvious way, but currently most of the AI systems developed today is aimless. Some of the AI is trying to replace all the tasks assigned to human, or some AI just spit out lots of information, wasting the time human doesn't really have.

Previous research shows that it is possible to match the attributes of the tasks between human and machine and by identifying the status of human being, some of the tasks will be assigned to human while the left will be handled by machine. The usage of AI will improve the assisting decision-making ability of the flight control system, and it is possible for the AI-enabled control system handling tasks from conventional control to decision-making and management, so as to realize the perception, evaluation, decision-making and control for different tasks. Machine vision, gaming and speech recognition are already in use in flight control system. LLMs are also a potential way, with a possibility of increasing the awareness ability and knowledge base of the AI system.

1.1 Different style of human-machine collaboration

Human-robot collaborative technology is currently the most deeply researched field within robotics. Researchers have designed various human-robot collaboration models based on different robotic functionalities. Currently, the primary six modes of collaboration between humans and robots include guided control, supervisory control, traded control, direct shared control, indirect shared control, and allocation control [1].

Guided Control: This mode facilitates task completion in unknown environments by providing haptic and motion feedback from the robot to the human operator. The primary form of feedback involves force feedback transmitted to the operator, enabling them to avoid excessive robot operation in environments with limited sensory perception [2].

Supervisory Control: A human operator oversees the robot's performance and intervenes with direct manipulation or program adjustments when necessary. For example, during pesticide spraying operations, the ground handler manually controls the robot when autonomous program function irregularly.

Traded Control: Both humans and robots can possess full control at any given moment and transfer control to the other party under specific circumstances. In remote-controlled robots, the default behavior when communication signals are lost, such as returning to base, is pre-programmed. Alternatively, control between direct brain-machine interface control by a human and autonomous visual control by the machine could switch based on factors like distance to the target, where visual control handles all the control within closer ranges [3].

Shared Control: Control of the system is jointly held by humans and robots. It is divided into direct shared control, where both entities act as independent sources of commands, and indirect shared control, converting high-level human inputs into low-level robot commands through a controller, which is always used in surgical robots.

Allocation Control: Humans and robots have distinct task assignments. Industrial robots on production lines primarily fall under this category, responsible for tasks such as assembly, welding, and gluing.

Complex interaction and task allocation become even more intricate in scenarios involving sophisticated manned aircraft cockpits or ground stations for medium to large unmanned aerial vehicles (UAVs), leading to hybrid styles combining allocation control and direct shared control, among others.

For instance, the need for single-pilot operations in commercial airlines implies that part of the flight control tasks is automated [4-6]. MITRE Corporation's assistive system integrates pilot voice or keyboard inputs, airspace surveillance, weather forecasts, and runway information to provide cognitive assistance and alerts via auditory and visual notifications [7]. However, the widespread adoption of such systems is hindered by unresolved technical issues, including a high rate of false positives for rare risks, decreased safety awareness among pilots due to new systems leading to riskier maneuvers, and imperfect intent inference.

In the UAV sector, the focus is on manned-unmanned teaming. Depending on the level of autonomy, the division of control and functionality between manned aircraft and UAVs varies, with different organizational structure and operation procedure [8]. As AI capabilities advance, manned aircraft pilots prefer more direct control over their aircraft but are more concerned with the UAV's ability to support their mission rather than its flight control [9].

Most commonly applied human-robot collaborative technologies are control augmentation, human-robot authority allocation, and human-autonomous system formations.

1.2 Control Compensation

In indirect shared control, the machine must be capable of recognizing the operator's intentions and utilizing its superior sensors and actuators compared to humans to accomplish tasks. Where operational procedures are well-defined, future human behaviors can be predicted to a certain extent [10], although this approach often proves less effective in complex scenarios. Alternatively, instead of direct prediction, the focus can be on optimizing the overall performance of the human-robot system [11]. This involves compensating for human control under predefined criteria for evaluating operational effectiveness [12], necessitating an internal motion model (Internal Vehicle Model). This model integrates human input commands and outputs a fused human-robot action. The internal motion model functions by incorporating the human's control signals, enhancing the overall system response by adjusting for potential inadequacies or limitations in human reaction time or precision. Through this integration, the combined system can leverage the strengths of both human decision-making and machine execution, thereby improving task efficiency and accuracy even in dynamically changing environments.

With the advancement of machine learning techniques, particularly deep learning, Long Short-Term

Memory (LSTM) networks and Deep Reinforcement Learning (DRL) [13, 14] have further expanded the representation of state spaces, thereby expanding the capability of predictive and global optimization methods. These advancements have found applications in simpler scenarios such as robotic grasping and quadcopter landing [14], demonstrating improved performance.

1.3 Human-Machine Task Allocation

Allocation control regards humans and machines as parallel entities operating an aircraft, with the primary approach to human-machine cooperative control centering on the rational distribution of control authority between humans and machines. Methods for human-machine authority allocation can be categorized into those based on theoretical analysis and those grounded in learning approaches.

Theoretical analysis-based methods involve modeling both humans and tasks separately to assess the compatibility between human cognition and machine capabilities. Human modeling techniques, such as those based on cognitive process modeling like ACT-R (Adaptive Control of Thought-Rational) [15], are employed, alongside task modeling methodologies like IMPRINT (Improved Performance Research Integration Tool) [16] and SNA (Social Network Analysis), which are based on network analysis.

ACT-R [17], initially proposed by John R. Anderson, comprehensively models cognitive processes through modules dedicated to memory, perception, and action, among others. These modules interact via a shared buffer, with decision mechanisms governing concurrent access. This model has evolved through multiple versions and can integrate with EEG measurements to account for individual differences [15].

IMPRINT, developed by the U.S. Army Research Laboratory, deconstructs tasks into subtasks and actions, connecting them in a network through action relationships [18]. By examining network structure and node interactions, it evaluates task performance and workload.

SNA represents social relationships among multiple agents using undirected graphs, analyzing network metrics to evaluate structure and performance. It identifies nodes or edges prone to overload [19], applicable to modeling roles and tasks within a cockpit and pinpointing weak links in human-machine interaction [20].

While modeling allows for a degree of analysis into the human-machine collaborative process, the accuracy of authority allocation conclusions depends heavily on modeling sophistication and analytical methods. Zhang [19] constructed an evolutionary game model incorporating pilots and intelligent decision systems, employing game theory to analyze a strategy space defined by machine intervention or non-intervention and crew trust or distrust in machine decisions. This yielded evolutionarily stable strategies under varying conditions of human error probability and task load change rates.

Currently, online learning methods in human-machine authority allocation remain underexplored due to uncertainties involved [21], with prevailing research leaning towards offline theoretical analyses that are more subjective and require case-by-case examination.

1.4 Human-Machine Interaction

The rapid development of artificial intelligence technologies has significantly enhanced comprehension abilities of machines, shifting the recent research focus onto another approach for tackling complex human-machine collaborations: shared control, specifically in designing Human-Autonomy Teaming (HAT) systems [22]. Direct shared control not only encounters issues of human-machine authority allocation but also hinges critically on human-machine interaction.

In the context of flight control, human-machine interactions demand swift response times and high reliability, resulting in a cautious adoption of new technologies, especially AI, with many pilots concerned about added complexity [23]. But traditional control methods, such as button, joysticks, and pedals, alongside screen-based character and icon outputs for conveying information, still dominate aircraft control systems.

Natural language interfaces are mostly confined to limited voice command inputs and alarm sounds [24]. Prada et al. addressed human-robot interaction challenges by employing a gesture-voice system (GSM) in mixed reality to expedite communication [25]. Using HoloLens for mixed reality and Baxter robot for execution, their study with 20 participants revealed a 21.33% speed increase in grab-and-place tasks with the gesture-voice system over gestures alone.

To overcome difficulties in control input using joystick and keyboard faced by astronauts in bulky spacesuits, Fu et al. proposed a voice-based human-machine interaction solution for space exploration [26]. They developed the CO-Sense Reasoning Prediction (Co-SRP) framework for human-robot dialogues, emphasizing knowledge sharing and joint spatial cognition. This framework enables object localization and pathfinding tasks, with robots interpreting astronauts' spatial descriptions to determine paths, measurements, and attributes, bypassing traditional directional controls. Tests using task completion time as a metric showed that voice-aided human-robot dialogue, especially in visually obstructed scenarios, reduced task duration.

COMBI [22], a concept system by Thales, enhances interaction between humans and autonomous intelligent systems. It translates human intentions into low-level semantics for the AI system via a downlink translator and converts AI's low-level outputs into high-level operational intent through an uplink translator. The conversion model is built using Genetic Fuzzy Trees (GFT), a process involving expert knowledge acquisition, fuzzy inference system construction, and optimization through genetic algorithms to refine the translation model.

Ye et al. demonstrated, through a case where a robotic arm was manipulated to assist operators in tool pick-and-place tasks [26], that leveraging large language models like ChatGPT can enhance semantic understanding and communication between humans and robots. They initiated this by constructing RoboGPT and designed an experiment employing trust questionnaires and the NASA-TLX scale as metrics for quantifying trust and task completion time as an indicator of task quality. Fifteen participants were involved in the trial, validating that ChatGPT can indeed elevate the level of human-robot collaboration. However, the authors pointed out that ChatGPT's understanding and responses might be based on erroneous communication cues, potentially leading to misoperations. They further suggested that integrating text-based interactions with image inputs could potentially improve outcomes. Given the current immaturity of multimodal large models, an alternative approach involves employing image interpretation models to generate text, which can then be combined with large language models. For instance, TypeFly utilizes YOLO as an object detector to generate object names and position coordinates, which are then relayed to the large language model [27].

1.5 Human-Machine Collaboration Architecture

Human strengths lie in their possession of knowledge and cognitive abilities, coupled with a strong adaptability to uncertain environments. Machines, on the other hand, excel in performing repetitive tasks according to fixed patterns, with no emotional fluctuations. Consequently, it is advisable to minimize involvement of human in repetitive operational patterns, freeing up their time and mental resources to focus on addressing uncertain, unscripted scenarios. Human should handle tasks that require manipulation of knowledge and rules, while machines should be tasked with handling activities that involve rules and skills. Based on the allocations derived from the research, we proposed a task assignment structure for human-machine collaboration based on cognitive model as Fig.1 in [28].

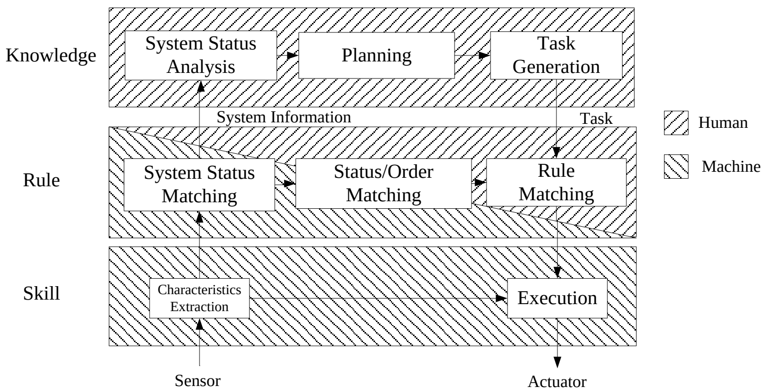

Figure 1 – Authority allocation principle based on the general cognitive model [28]

Specially, for spin recovery scenarios, we have a task assignment in Fig.2.

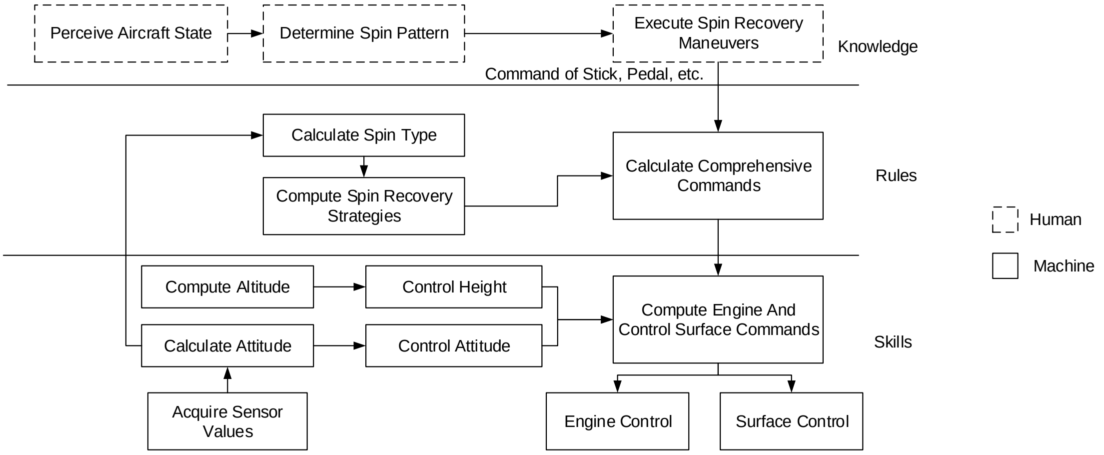

Figure 2 – Task Assignment in Spin Recovery Scenario

On the basis of the architecture of authority allocation based on the general cognitive model, it is necessary to further evaluate the efficiency of the human-machine collaboration system. It is common to evaluate probability of winning or accuracy during flying along the specified trajectory. Most previous methods do not consider the possibility of reducing of mental pressure that people may obtain in the human-machine collaboration system as it is not easy to be quantified. This part of the work is often carried out by man-machine efficacy related studies through physiological characteristics such as eye tracker and pulse measurement, but at the same time, there are problems in the interference of the test results caused by the tester wearing the device.

Currently, some experiments are already carried out. Using NASA-TLX, we interviewed 5 trained UAV pilots, and calculating the coefficients used by the scale. After using a weighted human and control algorithm using predetermined control coefficient, we found that the pressure scores decreased, and the wining rate of aircraft recover from spinning increases. We are also trying to evaluating the architecture presented in the paper, trying to show different task allocation with different intelligent level of AI.

We presented in this paper a human-machine collaboration system architecture based on cognitive model. Using mixed evaluation method combing improved NASA-TLX scale and operation performance, we try to evaluate the performance of the system, considering human manipulation pressure. Different scenarios are tested with different level of assistance. Comparing to just using wining rate, our method is more conducive to the evaluating the performance of artificial intelligence algorithm.

2. Simulation Environment Construction

2.1 Model Preparation

The accuracy of flight control and flight dynamics model is very important in the experiment. To simulate the flight characteristic of high attack angle, we carried out wind tunnel tests to obtain the model. Building upon existing aircraft models, we focus on enhancing the fidelity of post-stall maneuver modelling. Wind tunnel tests and flight tests are conducted to establish baseline models, with particular emphasis on modelling high angle-of-attack conditions. A series of spin wind tunnel tests were carried out based on a specific aircraft configuration, yielding static three-axis force and moment data for the aircraft at designated points across an angle of attack range from -90 degrees to +90 degrees. Dynamic data of the aircraft was further obtained through the use of derivative motion analyses and rotating balance tests.

By analyzing this data and constructing aircraft models, predictions were made regarding the angle of attack at which spins occur and the characteristics of the spin rate. This comprehensive approach not only advances our understanding of post-stall behaviors but also contributes to enhancing flight safety by improving simulation accuracy for these critical flight regimes.

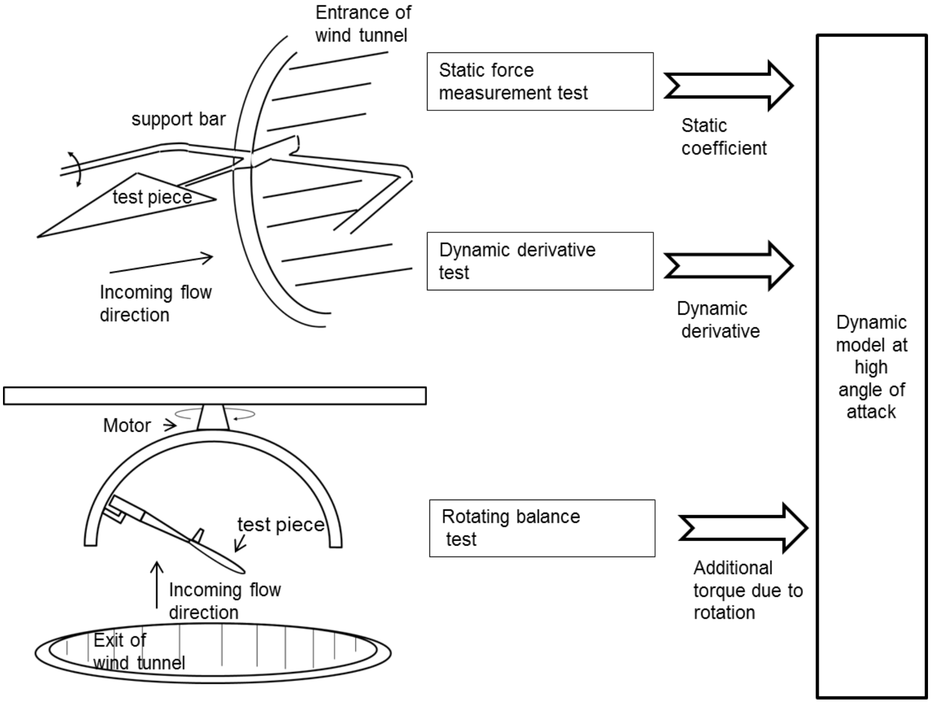

Figure 2 – Flow chart of dynamic model construction based on wind tunnel test

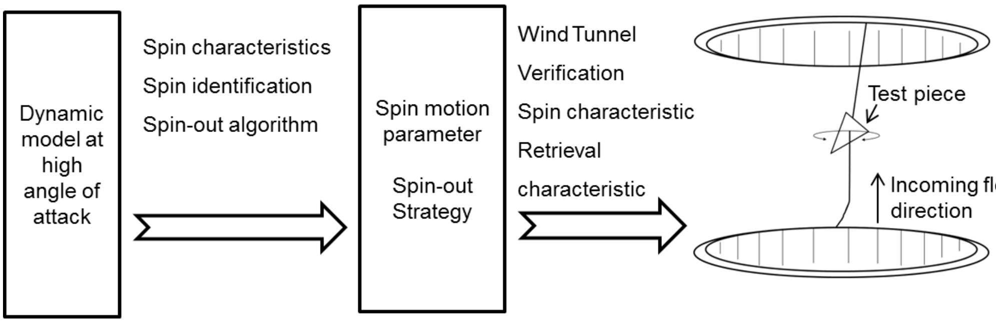

Figure 3 –Verification of Modeling Accuracy Based on Wind Tunnel Test of Tail Rotation

2.2 Simulation Environment

The simulation system is a combination of task environment simulation, unmanned aerial vehicle (UAV) simulation, manned aircraft simulation, human-machine environment simulation, and an agent design and verification platform tailored for research application.

Task Environment Simulation: Primarily, this component provides simulations of terrain, electromagnetic environments, and weather conditions, furnishing information such as communication conditions, air density, and temperature within the scenario to enhance the realism of simulation. Simplified simulation of other aircraft and ground units within the environment, offers simplified dynamic states of moving objects and a highly integrated control interface. Additionally, it simulates interactions among different entities involved in mission execution, including visibility determinations, payload trajectory calculation, collision assessment, and integrity evaluation.

Manned Aircraft Simulation: Comprised of aerodynamic models, electromechanical models, sensor models, flight control and management simulation, and cockpit simulation, this module ensures a level of complexity and fidelity in modeling. The dynamic, electromechanical, and sensor models can be replaced with newer ones and are capable of introducing faults, changes in center of gravity, mass, and configurations. The flight control/management simulation mimics the real-time behavior of onboard systems, capable of executing given flight control/logic management algorithms.

Unmanned Aerial Vehicle Simulation: Similar in composition to manned aircraft simulation but including ground station simulation, this module focuses on UAV-specific aspects. The aerodynamic, electromechanical, and sensor models also exhibit a realistic degree of complexity and can be easily swapped out, with capabilities to simulate failures, variations in center of gravity, mass, and configurations. The flight control and management aspect mirrors the real-time responsiveness of

onboard systems, processing predefined control logic.
Human-Machine Interaction Simulation: This component is designed to gather and transmit information related to human-machine interactions during system operations. It captures pilot inputs such as stick, pedal, switch and button manipulations for use as control commands in manned and unmanned aircraft simulations. Integrated voice recognition and synthesis systems are set up to capture and process verbal communications between manned aircraft pilots, UAV operators, and air traffic controllers. The manned aircraft cockpit simulation replicates the pilot's operational interface, emulating the information observed by a pilot during actual flight and enabling simulated operational inputs.

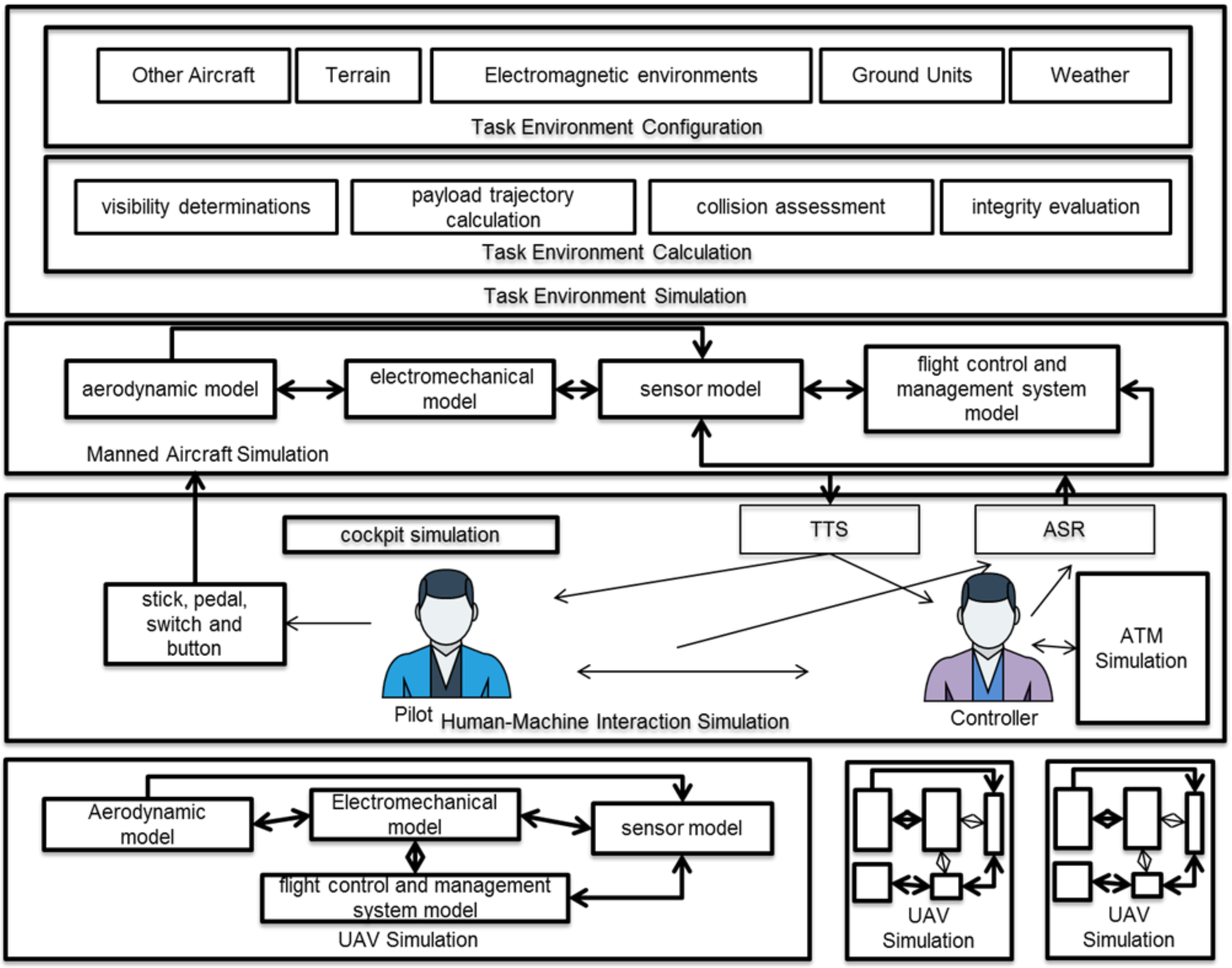

Figure 4 –Architecture of Simulation Environment

3. Experiment Design

3.1 Experiment scale design

The NASA-TLX scale was developed by NASA as a multidimensional mental load evaluation scale. The scale consists of six items (or dimensions), namely mental demand (Mental Demand, MD), physical demand (Physical Demand, PhD), time demand (Temporal Demand, TD), effort (Effort, EF), performance level (Performance, PER), and degree of frustration (Frustration Level, FR). The scale is mainly based on the subjective scores given by the participants. The paper proposes a mixed test method combining NASA-TLX test scale and objective performance of flying, taking the spin recovery as an example to verify the effective degree of human efficiency improvement under different AI-assisted circumstances. Objective manipulation performance indicators, including state quantity evaluation in manipulation cases, are static difference, average variance, maximum minimum, and arrival time and arrival ball error in the designated landing site or target point. The modified NASA-TLX scale is used, and spin recovery is evaluated as an example to verify the rationality of the human-machine collaboration system architecture proposed in this paper. 5 trained UAV pilots are tested under the scenario of getting out of the situation of UAV spinning. They are tested with different level of AI-assisted, such as:

- TC1: Screen display, no voice prompts
- TC2: Weighted human and control algorithm using predetermined control coefficient

3.2 Experiment steps design

The test flow includes introduction of test subjects, adaptation of test environment, operator manipulation test, operator evaluation, data processing and analysis, etc.

The introduction of test subjects is to explain the operation, display position and possible display settings of the test environment to the subjects participating in the test, so as to make the operators familiar with the test environment.

The adaptation link of test environment is that the subjects participating in the test perform 3 flight manipulations, and are familiar with the flight conditions that may occur in the test flow and the operations that can be involved.

The flight test is as follows: when the operator is on the pilot's seat, when the test starts, the aircraft is kept in the flat flight state, randomly select a time point within 1 ~ 5 minutes to start the stall state, that is, the angle of attack of the aircraft is greater than the stall angle of attack under the influence of instantaneous disturbance. The operator shall operate according to the prompts on the screen. The tests will repeat for 4 times for each participant.

Operator manipulation test is to conduct manipulation test in sequence according to test subjects, record process data, and decide whether to adjust test scheme or terminate test according to abnormal conditions.

Operator evaluation is based on subjective evaluation questionnaire to evaluate the mental pressure and operating difficulty of operators in different scenarios.

Data processing and analysis is to calculate the score of subjective evaluation questionnaire, and evaluate the flight performance of man-machine cooperation system with objective control index, and get the output result of human-machine cooperation system.

3.3 Experiment Result

In the course of flight, the tail spin is put into operation, the flight test subjects are carried out, and the subjective psychological indexes and objective maneuvering indexes are calculated and evaluated for the operators after the test. Five operators conducted a questionnaire after the test, and the scores are shown below. TC stands for test case 1 and test case 2, P1 to P5 stands for participants 1 to 5.

Table 1 – Test result of 5 participants

	P1	P2	P3	P4	P5
TC1	82.33	79.67	66.67	77.33	71
TC2	59.33	59.16	56.33	10	52.67

From objective point of view, the probability of participants successfully getting out of spinning is as Table 2.

Table 1 – Probability of participants getting out of spining

	P1	P2	P3	P4	P5
TC1	0	0	25%	0	0
TC2	75%	100%	100%	100%	100%

4. Conclusion

We mainly discuss in this paper the application of a framework of human-machine task assignment in spin recovery, and designs a verification method of human-machine authority assignment, which consists of precise modeling, design of test flow and evaluation of test results. 5 pilots were interviewed with NASA-TLX scale after the test. The results of interview and objective manipulation effect evaluation showed that spin recovery assistance method could effectively reduce pilot's manipulation pressure and increase manipulation efficiency.

However, the research of this paper still has the following contents to be studied:

1. Though spin recovery scenario of flight control is proved to be effective for this method, it is necessary to prove that this method can be expanded to more complex scenarios with higher level of task, such as rescue search, which can further enrich the changes of the scene and make the rules more complete;

2. At present, this method is only applicable to the comparison between two methods, and the analytic hierarchy process can be considered, which can be used to solve the multi-choice evaluation problem.

5. Contact Author Email Address

mailto: xackc8@163.com

6. Copyright Statement

References

[1] Yang C, Zhu Y, Chen Y: A Review of Human-Machine Cooperation in the Robotics Domain. IEEE Transactions on Human-Machine Systems.52(1),12-25(2022).

[2] Zheng H: Research into Force Sensation based Shared Control for Haptic Device. Jining University,Changchun(2016).

[3] Xu Y, Ding C, Shu X, Gui K, Bezsudnova Y, Sheng X, Zhang D: Shared control of a robotic arm using non-invasive brain–computer interface and computer vision guidance. Robotics and Autonomous Systems.115,121-9(2019).

[4] Ho NT, Johnson WW, Panesar K, Wakeland K, Sadler GG, Wilson N, et al.: Application of human-autonomy teaming to an advanced ground station for reduced crew operations. 2017 IEEE/AIAA 36th Digital Avionics Systems Conference (DASC).1-4(2017).

[5] Tokadlı G, Dorneich MC: Comparison and synthesis of two aerospace case studies to develop human-autonomy teaming requirements. Frontiers in Aerospace Engineering.(2023).

[6] Wang M, Xiao g, Wang G: Single Pilot Operation Mode Technology. Acta Aeronautica et Astronautica Sinica.41(04),202-20(2020).

[7] Estes S, Helleberg J, Pollack M: Cognitive Assistance for Recreational Pilots. In: 2022 IEEE/AIAA 41st Digital Avionics Systems Conference (DASC). pp. 1-5.(2022).

[8] Wang X, Cao Y, Liao W: Modeling of MAV/UAV Collaborative Combat Network Based on UAV Autonomous Level. In., pp. 2990-9. Springer Singapore, Singapore(2022).

[9] Xie L, Chen J, Jiao L, Li H, Wang P, Chen S: Research on All-Domain Fire Field in Future Air Combat. Acta Aeronautica et Astronautica Sinica.1-18(2023).

[10] Jain S, Argall B: Probabilistic Human Intent Recognition for Shared Autonomy in Assistive Robotics. J Hum-Robot Interact.9(1),Article 2(2019).

[11] Javdani S, Admoni H, Pellegrinelli S, Srinivasa SS, Bagnell JA: Shared autonomy via hindsight optimization for teleoperation and teaming. The International Journal of Robotics Research.37(7),717-42(2018).

[12] Dai A, Xu Y: Hidden Markov Model Based Control Augmentation Design for a Class of Human-in-the-Loop Systems. IEEE Transactions on Intelligent Transportation Systems.23(10),18876-88(2022).

[13] Gao J, Reddy S, Berseth G, Dragan AD, Levine S: Bootstrapping Adaptive Human-Machine Interfaces with Offline Reinforcement Learning. 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).7523-30(2023).

[14] Reddy S, Levine S, Dragan AD: Shared Autonomy via Deep Reinforcement Learning. ArXiv.abs/1802.01744(2018).

[15] Klaproth OW, Halbrügge M, Krol LR, Vernaleken C, Zander TO, Russwinkel N: A Neuroadaptive Cognitive Model for Dealing With Uncertainty in Tracing Pilots' Cognitive State. Topics in Cognitive Science.12(3),1012-29(2020).

[16] Lebiere C, Archer R, Warwick W, Schunk DW: Integrating Modeling and Simulation into a General-Purpose Tool. In:(2005).

[17] Ritter FE, Tehranchi F, Oury JD: ACT-R: A cognitive architecture for modeling cognition. Wiley interdisciplinary reviews Cognitive science.10 3,e1488(2018).

[18] Anderson JR, Bothell D, Byrne MD, Douglass S, Lebiere C, Qin Y: An integrated theory of the mind. Psychological review.111 4,1036-60(2004).

[19] Zhang X, Sun Y, Zhang Y: Evolutionary Game and Collaboration Mechanism of Human-Computer Interaction for Future Intelligent Aircraft Cockpit Based on System Dynamics. IEEE Transactions on Human-Machine Systems.52(1),87-98(2022).

[20] Stanton NA, Harris D, Starr A: The future flight deck: Modelling dual, single and distributed crewing options. Applied Ergonomics.53,331-42(2016).

[21] Zhang R, Torabi F, Warnell G, Stone P: Recent advances in leveraging human guidance for sequential decision-making tasks. Autonomous Agents and Multi-Agent Systems.35(2),31(2021).

[22] Hourlier S, Diaz-Pineda J, Gatti M, Thiriet A, Hauret D: Enhanced dialog for Human-Autonomy Teaming - A breakthrough approach. In: 2022 IEEE/AIAA 41st Digital Avionics Systems Conference (DASC). pp. 1-5.(2022).

[23] Zhang ZT, Liu Y, Hußmann H: Pilot Attitudes Toward AI in the Cockpit: Implications for Design. In: 2021 IEEE 2nd International Conference on Human-Machine Systems (ICHMS). pp. 1-6.(2021).

[24] Ruia V, Lee DH, Mancao TG, Feigh KM: Implementation of an Automated Voice-Checklist in General Aviation Aircraft. In: 2023 IEEE/AIAA 42nd Digital Avionics Systems Conference (DASC). pp. 1-9.(2023).

[25] Prada JDP, Lee MH, Song C: A Gaze-Speech System in Mixed Reality for Human-Robot Interaction. In: 2023 IEEE International Conference on Robotics and Automation (ICRA). pp. 7547-53.(2023).

[26] Fu Y, Wang H, Xue S, Zhang B, Cheng J, Gao Z: A New Paradigm of Human-robot Dialogue Facilitating Human and Robot Teaming in Sample Exploration. In: 2023 IEEE International Conference on Real-time Computing and Robotics (RCAR). pp. 805-10.(2023).

[27] Chen G, Yu X, Zhong L: TypeFly: Flying Drones with Large Language Model. ArXiv.abs/2312.14950(2023).

[28] Chen X, Zang X, Li J: Autonomous Flight Control System Design of UAV and Human-Machine Permission Allocation. In: Annual Conference of the China Aviation Industry Technology Equipment Engineering Association CATEA, Xi'an, China(2022).