Proceedings Paper

Developing AI-assisted Cognitive Load Approach for Improving Mission Aviators' Training†

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ABSTRACT: Trusted autonomy refers to confidence in the ability of autonomous systems to operate safely, reliably, and predictably without direct human intervention (Abbass et al., 2016). The use of such systems will require a new workforce capable to operate such systems. Training will require an intelligent training ecosystem that can monitor trainee performance and provide adaptive learning strategies to ensure progression to uniform competency standards with minimal attrition in training. This Defence Trailblazer project aims to develop artificial intelligence (AI)-based technology that will assist mission aviators in improved situation awareness and decision-making while operating under various levels of cognitive load. This research will combine an experimental part to understand participants' performance, with AI algorithms and machine learning techniques to assist in detecting various types of cognitive load and their situation awareness. This project addresses the Defence requirements to understand the training needs for operators of systems where there is the potential for high cognitive load and task performance risk.

KEYWORDS: cognitive load, artificial intelligence, human performance

1. INTRODUCTION

Trusted autonomy refers to the confidence in the ability of autonomous systems to operate safely, reliably, and predictably without direct human intervention (Abbass et al., 2016). A common uncrewed aerial system (UAS) control scheme among such applications is human supervisory control, where human operators remotely monitor and direct high-level tasks (Zhou et al., 2019). However, different levels of autonomy, control systems and operator training may affect operators' task performance and efficiency. As the management of complex information and sensor control on and between multiple platforms increases, the task loading on mission aviators has and will continue to increase.

The use of such systems will require a new workforce capable of operating such systems. Training will require an intelligent training ecosystem that can monitor trainee performance and provide adaptive learning strategies to ensure progression to uniform competency standards with minimal attrition in training.

As the management of complex information and sensor control on and between multiple platforms increases, the task loading on mission aviators has and will continue to increase. The operational paradigm is one of complex and dynamic systems that require high order operating cognitive capabilities from the mission crews. Implicit in this operational requirement is the need to measure mission-critical high order cognitive constructs automatically to improve the rate and efficacy of training complex skills required for operational effectiveness.

Current approaches to training provide a set curricula and rate of delivery for all trainees regardless of experience, aptitude, and ability. These approaches require the most able trainees to learn and gain experience at the pace of the whole cohort while the least able are forced to keep pace. As a result, the best potential of trainees can go undeveloped, and those requiring remedial training are often not offered a tailored curriculum to enable them to meet the required standard.

Understanding the relationship between cognitive load (CL) and its effects on mission aviators is vital for enhancing aviation safety and optimising mission outcomes. Cognitive load – as the mental effort required to process information and perform tasks – can significantly impact an aviators' decision making and performance.

In high-stakes environments such as aviation, healthcare, and defence, the ability to monitor CL in real time is critical. Real-time monitoring allows systems to detect periods of high CL. The periods of high CL may impair decision-making, reaction time, and situational awareness, especially in complex and time-sensitive tasks. High CL can lead to poorer decision-making performance, as evidenced by increased errors and slower task completion times in complex environments (Smith, 2017; Nicholson and O'Hare, 2014; Borrag´an et al., 2017; Paas and Merri¨enboer, 1994), and negatively impact situational awareness, particularly in dynamic decision-making environments where quick and accurate assessments are crucial (Spivak et al., 2019; Nicholson and O'Hare, 2014). Increased CL is also consistently associated with longer reaction times across various tasks, including math problems, logic puzzles, and dynamic decision-making scenarios (Turcotte and Oddson, 2022; Fu et al., 2018; Deck et al., 2021).

Accurately assessing the cognitive load, the research community increasingly relies on physiological measures (i.e. heart rate variability [HRV]). These quantitative measures can act as a link and data source for CL modelling. However, the relationship between physiological measures and CL is complex and multifaceted, granting more advanced approaches.

The project addresses Defence requirements to understand the training needs for operators of systems where there is the potential for high cognitive load and task performance risk. The introduction of robotic and autonomous systems capability in defence is projected to play a key role in sovereign capability. The use of such systems will require a capable workforce to operate such systems and collect, interpret and make decisions on the data provided. To train those operators, a complementary and intelligent training eco system be required that has the ability to monitor trainee performance and provide adaptive learning strategies to ensure progression that suits the learner, results in uniform competency standards and minimal attrition in training.

AI and machine learning (ML) can automatically identify complex patterns in data to predict and classify different cognitive load states. Based on reviewed literature, multimodal data fusion (combining different kinds of data) and integrated models (combining the predictions of multiple models) usually achieve better classification CL results.

This Defence Trailblazer project aims to understand the relationships among CL, physiological measures and machine learning methods used within this context.

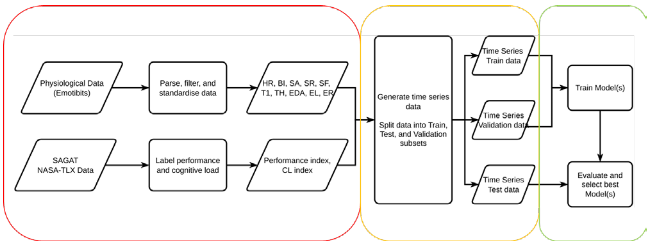
Specifically, understanding the relationship between these measures will assist in developing AI-based technology to monitor and predict CL. This research combines an experimental part to understand participants' performance, with AI algorithms and ML techniques to assist in detecting various types of CL and their situation awareness.

2. METHOD

The methodology followed a 3-step workflow (as shown in Table 1):

1. Data parsing and preparation
2. Time series and ML-ready data generation
3. Model training and best model selection.

Table 1 Summary of methodology.



Data preparation included parsing physiological data, data cleaning, trimming data to similar time windows, unification of data for participants, adding CL index column based on the experiment ID to the data, and adding performance and subjective measures to the data columns.

Time series and ML data generation included several steps. Forst data was converted to time series to create a dataset maintaining temporal relations in addition to generating a non-time series data. Then, data was split into subsets for the training purpose:

- Train: 60% of the data is used for training purposes.
- Validation: 30% of the data is used for validation within the training process.
- Testing: 10% of the data is used as the unseen data for performance testing the models.

Model training and model selection included temporal and non-temporal datasets version. Various models were tested and the best performing models were selected. Models were trained by splitting the data into training, validation, and test datasets using cross-validation. Then, model hyperparameters were tuned to find the best performing hyperparameter (i.e. epochs, learning, and batch size). Finally, model was evaluated based on accuracy and other parameters.

3. RESULTS

ML models employed the stages of code development, model architecture, and model performance. The results of merging several physiological variables (i.e. HRV, temperature) demonstrated that the ML model achieved 50% validation accuracy across 3 cognitive load classifications (i.e. low, medium, high; see Figure 1).

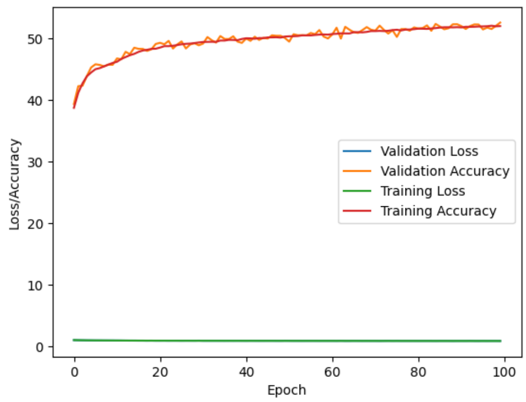


Figure 1 Advanced ML model performance.

While the classification model shows promise, further work is required to improve performance, particularly by incorporating additional physiological data and testing advanced architectures like long short-term memory networks and attention models.

The results of this project aim to contribute to better understanding of novice UAS operators' CL that can serve as background for developing effective training for Mission

Aviators. Blending advanced behavioral technology within an adaptive learning approach can improve performance, reduce time spent on training, and increase situational awareness under various levels of CL. This project addresses the Defence requirements to understand the training needs for operators of systems where there is the potential for high CL and task performance risk.

4. CONCLUSIONS

This project aims to contribute to better understanding of CL for mission air crew that can serve as background for developing effective training for Mission Aviators. Blending advanced behavioral technology within an adaptive learning approach can improve performance, reduce time spent on training, and decision-making under various levels of CL. This project addresses the Defence requirements to understand the training needs for operators of systems where there is the potential for high CL and task performance risk.

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