Design for AI-enhanced operator information ergonomics in a time-critical environment

Jussi Okkonen^{1,*}, Jaakko Hakulinen¹, Matti Jalava², Heikki Mansikka^{3,}, Markku Turunen¹

¹ Tampere University, FIN-33014 Tampere University, Finland {jussi.okkonen, jaakko.hakulinen, tuuli.keskinen, markku.turunen}@tuni.fi

²lFinnish Defence Forces
{Matti.Jalava}@mil.fi

³National Defence University
{heikki.mansikka}@aalto.fi

Abstract. Maintaining situational awareness in time-critical operation control is an omni-dimensional optimisation problem. For excellent situational awareness, complete information with sufficient time to process it is prerequisite. Making sound judgement with limited time the flight controllers suffer poor information ergonomics as demanding situations cause cognitive load as well as incoming information is constipated. In this normative paper, design principles and main functionalities are presented for an artificial intelligence powered and extended reality decision support information system.

Keywords: information ergonomics \cdot situational awareness $\cdot 3D$ presentation \cdot artificial intelligence

1 Introduction

Decision-making depends on accurate information to enable good situational awareness (SA). Good SA is a state when an individual has all relevant information about what is going on when the full scope of the task is considered. It is about what is happening as well as what is, and is about to be, the status of factors considered, i.e., a perception of the factors within the environment and a comprehension of their meaning and a perception of their status in a near future. Taking the perspective of information ergonomics, the quality of information is more important than the quantity, i.e., only critical information is-should be presented as more excess information causes unwanted load to information processing [1]. Information related to decision making should be presented in the form of easily consumable information products in order to avoid distraction. The information-processing lag or additional processing cycles easily cause distraction. In an information driven operation management setting, the key issue is to concentrate on the most relevant information and to gain and maintain good SA. Adding time pressure as a factor presents an omnidimensional information processing optimisation problem. Optimisation is done according to the

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completeness of the information, the amount of the information and completeness of processing of the information. In traditional information management process models, such as those reported by Choo [2] or Savolainen [3], the mentioned factors are not discussed per se, but optimisation is seen as solved implicitly. However, literature on SA brings about the requirements for information, completeness of the information and processing of the information as discussed in Chen et al [4]. According to Franssila et al. [1], such conditions are a significant ergonomic issue. Enhancing information ergonomics promotes performance and lowers stress cognitive load in work settings [5].

Methodologically, this paper follows the principles of decision-orientated research as positioned in Kasanen et al. [6]. Striving to be both normative and theoretical, this paper aims to provide new information which is applicable in practice and sketch a test procedure to validate the construct. The context of this paper is SA where an operator's task is to monitor multiple aircraft engaged in air combat. The known information about the aircrafts location, altitude, heading and speed. Traditionally this information is presented as a 2-dimensional (2D) visualisation with symbols and rich information to provide all necessary information. In order to enhance the information ergonomics, a 3-dimensional (3D) visualisation is proposed for the monitoring task. In the 3D presentation, some information could be reduced as the three dimensions enable presenting relative position as well as location without numerical augmentation, thereby allowing a simpler visualisation. Clustering adds value to 3D presentation as the algorithm moderates how objects are presented, e.g., highlighted by certain criteria. In order to enhance the information ergonomics, the 3D presentation has less symbology than the 2D presentation and, in general, the notation is expected to be simpler and easier to comprehend with 3D. This means less objects to follow, less information to process, and more time to concentrate on relevant factors. Especially in time-critical decision making and operation management situations, artificial intelligence (AI) driven presentation of information could draw attention to noteworthy factors and reduce cognitive load. With lower cognitive load and less factors to pay attention to, the operator is likely to achieve a state of better information ergonomic state. The conclusions of this paper are the design principles for shifting from 2D presentation to 3D presentation as well as how to build the setting to operationalise it.

1.1. Measures of information ergonomics

Of all the possible measures of information ergonomics, this paper concentrates on those of SA and cognitive load. A variety of techniques are available to measure SA. These techniques can be broadly categorized as performance techniques [7], real-time probe techniques[8, 9], freeze-probe recall techniques [10,11,12,13,], post-trial self-rating techniques [14, 15, 16] and observer rating techniques[17, 18, 19]. Situation awareness global assessment technique (SAGAT) [20] is probably the most widely used freeze-probe recall technique. Before SAGAT can be used, a task of interest must be analysed to identify factors relevant to SA in that task. Then, probes about these factors are prepared. For example, in a piloting task an aircraft's altitude can be identified as a factor. A question: "What is the aircraft's altitude?" is a probe tapping the pilot's perception about that factor. When SAGAT is used, a participant engages in a simulated task. Then, at random intervals the simulation is paused, the visual of

the simulation is blanked and the audio is faded away. While the simulation is frozen, probes relevant to that phase of the simulation are introduced. The probes are selected such that they tap the participant's perception (SA level 1), comprehension (SA level 2) and projection (SA level 3) in the task. Once the participant has answered the probes, the simulation is continued until the next freeze-point is reached. The procedure is repeated until simulation is completed and participants' responses to all probes have been obtained. The participants' responses to probes are compared to correct answers to those probes and used as an index of overall SA and SA levels 1-3.

Cognitive load can be assessed using physiological, behavioral, and/or subjective measures – each with their own strengths and weaknesses [21]. Subjective measures, such as the NASA Task Load Index (NASA-TLX) [22] have been widely used mainly as they are non-intrusive and easy to implement (Mansikka, Harris & Virtanen, 2019). The NASA-TLX assesses cognitive load across six dimensions: mental demand (MD), physical demand (PD), temporal demand (TD), performance (OP), effort (EF) and frustration level (FR). When NASA-TLX is administered, two types of information about each dimension are obtained from the participants: weights and scores. The weights represent the subjective importance of each dimension as the source of cognitive load in the task of interest, whereas the scores express the subjectively sensed magnitude of cognitive load with respect to each dimension. According to Hart & Staveland [22], the weights are obtained by conducting pairwise comparison for every dimension pair. This procedure, however, is highly problematic and Mansikka et al. [24] provide several alternative, and more appropriate, methods for setting the weights. Once the weights have been set, the subjects engage in a task of interest and rate each load dimension based on their subjectively sensed cognitive load. A weighted cognitive load index for each dimension is calculated by multiplying each dimension's score by its weight. An overall load index is a weighted sum of the dimension scores, where weights have been normalized to the sum of one.

2 Information ergonomics in the context of situational awareness

Taking the definition of information ergonomics discussed in Franssila et al [1] and Okkonen et al [5], the load of information processing, the amount of information, and time pressure affect the ergonomic state of an operator. The foundation of sound judgement and decision-making is accurate, sufficient and targeted information about the key factors. SA is highly dependent on available time. Decision making under time pressure requires naturalistic decision making [24]. The SA model presented by Endsley [25, 26] identifies three hierarchical levels of SA: perception (level 1), comprehension (level 2), and projection (level 3). Perception is about recognising statuses, attributes and dynamics of the relevant factors within the environment- Comprehension is about combining information and building interpretation of the situation. Projection is about foreseeing the near-future states of the factors in the operating environment.

The role of AI in supporting SA links the OODA-loop (Observe, Orient, Decide, Act) and Endsley's SA levels AI supports the Observation and Orientation stages by improving perception and comprehension, i.e., SA levels 1 and 2. The quicker and

less cognitively demanding it is to reach the Observe and Orient stages, the more time and cognitive resources are available for projection, i.e., Decide and Act stages. As stated by Endsley [8], for naturalistic decision-making, it is most relevant to extract relevant information fast and to make quick yet well-justified decisions.

A human-technology interaction perspective views AI as an activity, which assists humans to filter, manage, analyse and refine information in order to gain and maintain SA. Crowder, Friess and Carbone underline the independent role of technology in assisting the operators [24]. In order to better utilise the human information processing capacity, the AI refined information should be presented in a form which minimises the cognitive load cf. [25]. This can be achieved as AI excels with speed and ability to process a large amount of information [26]. AI can support gaining and maintaining all three levels of SA and decision-making. However, these support functions require that characteristics, rules, and dependencies of the system elements have been identified and the AI has been taught and/or programmed accordingly.

For information ergonomics, the impact is still evident as AI curates the content, i.e. by the predesignated rules it, for example highlights the most noteworthy objects and keeps the attention on the relevant factors as discussed e.g. in.Crowder, Scally & Bonato [27]. On the other hand, the mode of the presentation has also an effect as some information is presented differently and no longer requires operator processing. Enhanced information ergonomics in the context of this paper is the product, not sum, of automated information processing combined with a more illustrative and natural presentation. Relating to the organisational intelligence cycle, the augmenting role of artificial intelligence are sensing, perception, interpretation, and memory cf. [2, 28]. Adaptive behaviour is dependent on human attributes such as creativity and trust in on the sound judgement of the operators, not the algorithm.

3 Using 3D modelling and AI driven clustering to enhance information ergonomics in time-critical activity

Enhancing information ergonomics is about a more balanced cognitive load and better SA. As discussed above, this could be achieved by shifting from 2D presentation to 3D presentation and/or representing AI driven information to the operator. A fighter controller (FC) is a military qualification given to a person trained to provide early warning (EW) and command and control (C2) services to military aircraft. As such, the FC is engaged in an operation control task. FC bases his/her control decisions mainly on aircraft position and speed. These are traditionally presented in2-dimensional visuals

ls. The user interface of the operation control software has been developed such that it supports the FC's SA and decision-making. However, when the complexity of the displayed air combat situation increases, the 2D visual can become cluttered, causing unbalanced cognitive load and reduced SA – and eventually degraded task performance (cf. e.g. [5, 23]).

This paper demonstrates an AI driven 3D presentation for the FC's simulated operation control task. Utilising the simulation environment features, most functionalities are developed by using open interfaces. The algorithm for clustering the objects follows certain standard operation procedure rules derived from the context.

The role of AI in the demonstration is twofold. Firstly, it is utilised to rank simulation entities and their relations. Ranking is done according to the entities' position, heading and altitude. Based on a certain set of rules, all objects are visible, yet only the high-ranking ones are highlighted. Moreover, different modalities for feeding alarm, e.g., sound or haptics, could be added if certain criticality criteria are met. Secondly, AI is utilized to calculate and display relative qualities of the entities. For example, the time it takes for one entity to reach another entity can be calculated and displayed when appropriate. Thirdly, AI enables automated switching of viewpoint, i.e., scenarios could be presented from alternative viewpoints based on AI rules. Table 1 summarises the key features.

Table 1. Expected outcomes of certain features

Feature	Function (Outcome
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3D	easier perception	less cognitive load and
		better SA
Clustering	automated analysis	less cognitive load and
		better SA
Relation information	automated analysis	less cognitive load and
	•	better SA
Different modalities	Attention	Attention at critical mo-
		ments
Automatically highlighted objects	easier perception	Attention to relevant items
Automated rendering	several viewpoints	Better understanding on
Automated rendering	severar viewpoints	relative positions
		relative positions

3.1 Use scenario

In real life, the FC relies on a recognized radar picture (RAP) to support the friendly, i.e., blue, aircraft. In this study, a RAP was generated using a Modern Air Combat Environment (MACE) simulation and threat environment https://www.bssim.us/mace/). Two alternative apparatus were used to represent RAP to the FC. One apparatus was a 2D visual and the other one was a virtual reality (VR) goggles, which provided the FC with a 3D view of the RAP. When the 2D visual is used, FC is limited to a viewpoint directly above the blue and red. However, the FC was able to zoom his viewpoint in and out and to move it to any compass point. The VR goggles were connected to a hand controller, which the FC could use to change his viewpoint freely and to 'move' around the simulated environment. The simulation did not include audio.

Two air combat test scenarios, both with eight blue and eight enemy, i.e., red, aircraft are programmed into the Modern Air Combat Environment (MACE) -simulation environment. All aircraft are constructive simulation entities and scripted to follow predetermined behaviours. As a result, there is no differences in the scenarios between the different simulation runs. The blue aircraft are programmed to intercept the red aircraft and vice versa. Both scenarios are designed similarly in terms of SA demands and mission complexity. In both scenarios, the blue and red aircraft were initialized 100 nautical miles apart.

Before the trials, the FCs are allowed to train with both the 2D and 3D displays and controls until they feel comfortable using them. In the air combat scenarios, FC's task is to observe the scenarios and to build and maintain SA such that he could provide EW and C2 services to the blue aircraft if needed. The scenarios are randomized between the types of apparatus used by the FCs. For each FC, one scenario was observed with 2D visuals and the other was observed with VR goggles. Based on the training session, FCs provide weights for the NASA-TLX dimensions.

As the FC observes the scenario, the simulation is paused, and the displays are blanked at predetermined intervals. While the simulation is paused, the FC's SA levels 1-3 about the scenario are probed using SAGAT. Each simulation run will be paused several times and a sufficient number of probes for each SA level are used to tap the FC's SA. Table 2 summarizes the SAGAT probes planned for tapping the FC's SA at each simulation pause. Once the scenario is completed, the FC evaluates the subjectively sensed cognitive load experienced during the scenario and scored the NASA-TLX dimensions accordingly.

Table 2. SAGAT probes used to probe FCs' SA levels 1-3

SA level 1	SA level 2	SA level 3
What is the formation of the blue aircraft?	What is the tactical status, i.e., winning/losing/tying of the blue aircraft?	How long will it take until the blue aircraft must defend against the red aircraft?
What is the formation of the red aircraft?	Is the blue aircraft still able to adhere to the directed tactics?	How long will it take until the blue can launch missiles against the red aircraft?
What is the altitude of the red aircraft?	Which red aircraft are being engaged?	If the red aircraft continues with this geometry, will the blue missiles hit them?
What is the altitude of the blue aircraft? What is the speed of the red aircraft?	Which blue aircraft are being engaged? Which blue aircraft have engaged which red aircraft?	
What is the speed of the blue aircraft?	Which red aircraft have engaged which blue aircraft?	

4 Concluding remarks

This paper further developed the way to augment humans for better SA. Future tests will provide a better understanding of acceptance of AI and trust in technology pertaining to its designated'effect on SA. The acceptance is especially critical when con-

sidering the role of AI. Above, the role of AI was set as an assistant enhances human information processing capability and augments knowledge related processes. Despite the augmenting role of the AI, human technology interaction perspective should be taken into account when implementing it [29]. Acceptance and trust are related to several factors such as motivation, user perception of the presence, and expectations on performance and utility [30]. Expectations of human-like behaviour and delivery of process virtues as well as the securing of operations also relate to acceptance [31]. This is also an important factor when assessing the performance effect as productive utilisation requires acceptance. If there is a lack of trust, there will be a high risk of cognitive dissonance and double checking, which leads to vicious cycle of increased cognitive load and poor information ergonomics. In future experiments, the issues of trust and acceptance should also be taken on the agenda. The first order condition for utilisation is delivering utility with key features or functionalities. The intention of this technology itself' is not solely sufficient as user's role in operating environment also has great significance.

The forthcoming user study will also provide important data on several knowledge-processing related issues. The increased accuracy of SA along better information ergonomics is the proposition for the test phase. Also, the subjective sense of workload while operating in different visual modalities is significant Cognitive dissonance, i.e. possible conflict between detected experienced and projected is an interesting issue to investigate as source for cognitive dissonance, i.e. is it caused by technology or mental factors.

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