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Modeling the situation awareness by the analysis of cognitive process

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Abstract. To predict changes of situation awareness (SA) for pilot operating with different display interfaces and tasks, a qualitative analysis and quantitative calculation joint SA model was proposed. Based on the situational awareness model according to the attention allocation built previously, the pilot cognitive process for the situation elements was analyzed according to the ACT-R (Adaptive Control of Thought, Rational) theory, which explained how the SA was produced. To verify the validity of this model, 28 subjects performed an instrument supervision task under different experiment conditions. Situation Awareness Global Assessment Technique (SAGAT), 10-dimensional Situational Awareness Rating Technique (10-D SART), performance measure and eye movement measure were adopted for evaluating SAs under different conditions. Statistical analysis demonstrated that the changing trend of SA calculated by this model was highly correlated with the experimental results. Therefore the situational awareness model can provide a reference for designing new cockpit display interfaces and help reducing human errors.

Keywords: Situation awareness, ACT-R, analysis model, mathematical model, ergonomics

1. Introduction

Safe and efficient task performance within complex systems relied on operators acquiring and maintaining appropriate levels of Situation Awareness (SA). Therefore, a critical issue was how well the flight deck could support pilots to acquire and maintain SA of relevant information in the environment [1]. Endsley defined SA as the perception of the elements in the environment (level 1 SA, SA1), the comprehension of their meaning (level 2 SA, SA2), and the projection of their status in the near future (level 3 SA, SA3). The higher level SA depended on the lower level SA. Within this taxonomy framework of SA, a prior study showed that 71% of aviation accidents involved human errors, and 88% of these accidents involved the SA problems [2]. Such study suggested that pilot SA modeling could help predicting how pilot SA would respond to different encountered situations, which could ultimately improve flight safe and performance.

Recently, the issue of SA modeling was getting more important in the field of ergonomics and human factors studies. For qualitative analysis, Endsley proposed an information processing model, Neisse developed a perception/action loop model, and Flach analyzed the SA model from phenomeno-

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logical standpoint [2]. While for quantitative analysis, Wickens developed an attention-situation awareness (A-SA) model [3], Entin discussed a performance sensitivity model [4], and Hooney improved a man–machine integration design and analysis SA model [1]. Although these studies offered a variety of ideas and methods for investigating SA, the combined application of qualitative analysis and quantitative calculation were inadequate. In the present study, considering the three levels of SA, a joint qualitative and quantitative model was established based on a previous SA model [5] that incorporating the ACT-R theory for analyzing pilot cognitive process for the situation elements (SEs), and explaining how the SA was obtained.

2. Modeling situation awareness by ACT-R theory

2.1. Qualitative analysis model of SA

The relationship between how cognition was produced by the ACT–R theory and how the pilot obtained three levels of SA was analyzed, as shown in the Figure 1 [6].

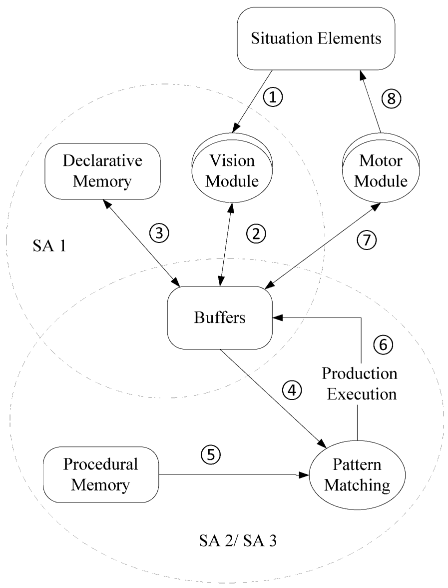

Fig. 1. Relationship between the ACT–R and SA.ACT-R =Adaptive Control of Thought-Rational theory. SA=Situation Awareness; SA1=Level 1 of SA, perception; SA2=Level 2 of SA, understanding the present; SA3=Level 3 of SA, understanding the future; ①Determine what and where to see (Event a_i) ②Obtain the visual information of situation element ③Retrieve the chunk (If successfully, Event b_i) ④Match the IF side ⑤Select the Rule (If the Optimal rule, Event c_i) ⑥Execute the THEN side ⑦Prepare for movement ⑧Act movement .

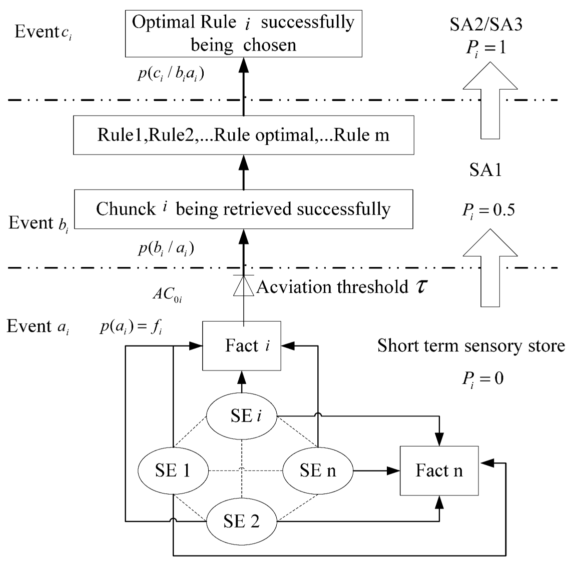

Fig. 2. Qualitative analysis model of pilot SA.SE=Situation Element; Fact = Fact of recognizing SE; $p(a_i)$= Probability of paying attention to SE; f_i =Attention allocation proportion; $p(b_i / a_i)$ = probability of chunk being retrieved successfully; $p(c_i / b_i a_i)$ =probability of Optimal rule being selected; AC_{0i}=Activation level of chunk; P_i=Cognitive level.

The vision module was used to determine what or where the ACT-R to "see" so that certain SEs could be registered into the short term sensory store after being filtered by the selective attention. Then the buffers obtained the visual information from SEs through the visual module and visited the declarative memory to retrieve corresponding knowledge. Only when the level of activation of the chunk was greater than a certain threshold, could the retrieval succeed and the perception been produced (SA1, perception), which corresponded to Wickens' attention module in the A-SA model [3]. In addition, the procedural memory was production rules (IF–THEN Rules).When the condition (IF) was matched against a set of buffers, the pattern matching would select the corresponding rule to fire from it to execute the THEN side. With regard to the recognizing status generated by the production execution, there was a fuzzy boundary between understanding the present meaning (SA 2, understanding) and understanding the future meaning (SA3, prediction) of the SE, since the former generally had direct implications for the latter and both of them were equally relevant for the task, which corresponded to belief module in the A-SA model [3]. The specifics of the pilot SA qualitative analysis model were presented in Figure 2, with more descriptions in Section 2.2.

2.2. Quantitative calculation model of SA

In a certain environment, the situation related to the current operation could be broken down into several SEs. Assuming the attention resources obtained by the n SEs were $A=(A_1, A_2, ..., A_i, ...A_n)$, and allocation to the SE i was A_i, which could be defined as $A_i=\beta_i V_i Sa_i E_i^{-1}$. For a certain SE i, β_i indicated the occurring frequency, Sa_i was the salient, V_i meant the information priority, $V_i=\partial_i u_i$, where ∂_i was the possibility of which potential cognitive status would be available, u_i was the importance, and thus the attention allocation proportion f_i of the SE i could be structured as $f_i = A_i \Big/ \sum_{i=1}^{n} A_i$ [5].

When the visual module determined to "see" the SE i as event a_i, the occurrence probability of a_i should be equal to the attention allocation proportion, so

$$p(a_i) = f_i \tag{1}$$

If the event a_i had occurred, the buffers would have activated corresponding chunk i to the SE i in the declarative memory, and the activation level of chunk i (AC_{0i}) could be defined as

$$AC_i = AC_{0i} + \sum_{j}^{n} W_j S_{ji} \tag{2}$$

Where AC_{0i} was base-level activation of the chunk i, reflecting its general usefulness in the past, usually $AC_{0i} \approx c + 0.5\ln t$, indicating the fact that recognizing SE i (Fact i) had been presented for t times, and $c = 0$ was chosen. W_j was the attention weighting of the SE j at the current Fact i ($W_j = f_j$); S_{ji} represented the strength of association from the current Fact i to the relational

SE j ; fan_j was the number of facts associated to the SE j , with $S_{ji} = S - \ln(fan_j)$ and S was estimated to be 2 [6,7].

Only if the level of activation was over a threshold, could the chunk be retrieved successfully to possess the perception of the SE (SA1), as event b_i ,

$$p(b_i / a_i) = 1/1 + e^{-(AC_i - \tau)/s} \tag{3}$$

Here s controlled the noise in the activation levels typically set to 0.4, and τ was set to 1.0 [7].

The key idea in ACT-R is that at any point in time multiple production rules (IF THEN) might be executed, only one could be selected. As for Fact i, if the optimal Rule i production with the highest utility U_i was chosen, the SE i would be fully comprehended either in the form of its current meaning (SA2) or the future one (SA3), which could be recorded as event c_i ,

$$p(c_i / b_i a_i) = e^{U_i/\theta} \Big/ \sum_l^m e^{U_l/\theta} \tag{4}$$

According to the previous work, the cognitive level P_i of SE i could be set as three values to reflect three cognition stages [1]. At a certain moment, if the level of activation was lower than the threshold, it wouldn't be perceived (short term sensory store) at $P_i = 0$ with $p(a_i \overline{b_i}) = p(a_i) p(\overline{b_i} / a_i)$. If the level of activation was greater than the threshold, it would be perceived (SA1) at $P_i = 0.5$ with $p(a_i b_i) = p(a_i) p(b_i / a_i)$. And even if the optimal rule was selected, it would be understood (SA2 or SA3) at $P_i = 1.0$, along with $p(a_i b_i c_i) = p(c_i / b_i a_i) p(b_i / a_i) p(a_i)$ .Therefore, the mathematical expectancy of cognitive level $\overline{P_i}$ for the SE i could be calculated by $\overline{P_i} = p(a_i b_i) \times 0.5 + p(a_i b_i c_i) \times 1 + (1 - p(a_i)) \times 0$, and the level of SA could be stated as

$$SA = e_1 \overline{p_1} + e_2 \overline{p_2} + \ldots + e_n \overline{p_n} = \sum_{i=1}^n ((\sum_l^m e^{U_l/\theta})^{-1} e^{U_i/\theta} + 0.5)\ (1 + e^{-(AC_i - \tau)/s})^{-1} f_i u_i \tag{5}$$

Where e_i indicated the influence of the SE i on SA and u_i meant the importance of SE i ($u_i = e_i$) [5].

3. Experimental method

3.1. Materials and participants

The experiment display interfaces were designed referring to two typical of primary flight display (PFD) interface formats with proper simplification and abstraction for the research needs, as shown in Figure 3. In addition, the GL studio from DiSTI was used as the tool to develop the graphical model for PFD and generate virtual instrumentation simulation procedure for the experiment in Microsoft

Visual Studio platform. The experiment interfaces were presented on a 19-inch Lenovo Monitor with resolution of 1280×1024, and the average illumination was about 600Lx in the experiment environment. Smart Eye Pro 4.5 was used to track eye movements in a natural way.

3.2. Design and procedure

In this experiment, an indicator monitoring and identifying task was simulated, and 4 flight SEs were set as the monitoring targets representing the optimal targets for human attention allocation, including the rolling angle (SE1), indicated airspeed (SE2), barometric altitude (SE3) and heading angle (SE4) [5]. A two-factor completely within-subjects design was adopted in which factor 1 was the abnormal probability with two levels set by the frequency at which the SE was questioned randomly, and factor 2 was the display interface with two levels shown in Figure 3. Task order was counterbalanced across the subjects according to the Latin square design.

Prior to the experiment, all participants were guided through the requirements and instructions for the procedure. In each monitoring task, a total of 32 questions with three types representing three levels of SAGAT were presented at random orders for a random time limit in a single choice format. The participants should answer within the time limit using the mouse to get the corresponding scores. As soon as the monitoring task finished, the 10-D SART self-rating scale was required to be accomplished. The eye tracker was monitoring in real-time tracking state throughout the whole task.

4. Results

The attribute values of 4 SEs as monitoring targets on the two display interfaces were calculated respectively, as shown in Table 1. To be precise, the effort values were determined by the relative normalized distances between SEs, and the salience value for SE i was determined by color matching c_i, indicator size s_i and type of indicator t_i, expressed as $Sa_i = (c_i + s_i + t_i)/3$ [5].

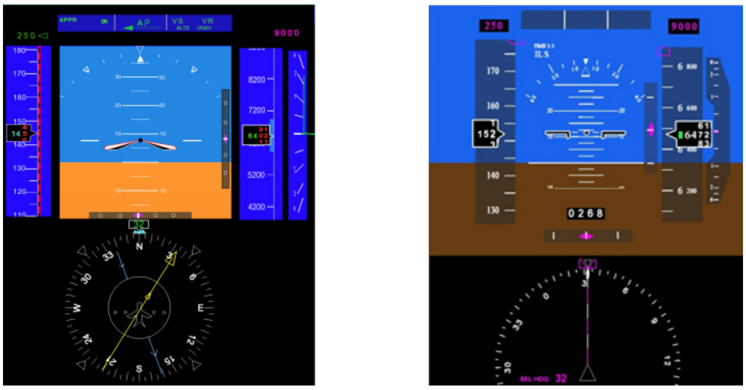

Fig. 3. Experiment display interfaces including the Display A (Left) and Display B (Right).The display interfaces were designed referring to typical of primary flight display (PFD) interface formats with proper simplification and abstraction.28 participants (20 males, 8 females, and mean age 23±0.99 year) from Beihang University were recruited in this study. All participants were right-handed with normal or correct to normal vision, and were familiar with the basic computer operations and aeronautics knowledge.

Table 1

Attribute values of the SEs

	Rolling Angle (SE1)		Indicated Airspeed (SE2)		Barometric Altitude (SE3)		Heading Angle (SE4)	
Display format	A	B	A	B	A	B	A	B
Indicator size	0.1559	0.3341	0.0719	0.0717	0.0719	0.0717	0.1329	0.0900
Type of indicator	0.0833	0.0833	0.1667	0.1667	0.1667	0.1667	0.1250	0.0417
Color matching	0.1304	0.1304	0.0874	0.1387	0.0957	0.1387	0.1401	0.1387
Salience	0.1232	0.1826	0.1087	0.1257	0.1114	0.1257	0.1327	0.0901
Effort	0.1264	0.1001	0.1429	0.1120	0.1429	0.1120	0.1539	0.1096

Note: SE=Situation Element; A and B were two formats of experiment display interfaces; Attribute values in the table were normalized to be dimensionless values.

Table 2

Modeling and measuring results under two display formats and two task types

	Display A		Display B	
	Task 1	Task 2	Task 1	Task 2
Prediction of SA model:	0.3364	0.3860	0.3508	0.4077
SAGAT:				
Level 1 correct rate	0.60±0.17	0.65±0.20	0.68±0.23	0.67±0.19
Level 2 correct rate	0.73±0.10	0.74±0.10	0.70±0.09	0.75±0.11
Level 3 correct rate	0.79±0.17	0.76±0.17	0.83±0.13	0.81±0.18
Level 1 &2 correct rate	0.67±0.09	0.70±0.12	0.69±0.13	0.71±0.12
Overall correct rate	0.71±0.08	0.73±0.08	0.72±0.09	0.74±0.09
Correct response time (s)	2.73±0.39	2.63±0.45	2.68±0.36	2.57±0.43
Performance:				
Operation score(point)	72.23±8.43	72.26±8.83	73.67±9.37	75.79±10.27
SART:				
Demand (point)	11.07±2.27	10.82±1.96	11.20±1.66	10.86±1.97
Supply (point)	17.14±2.30	17.92±3.05	17.39±3.04	16.93±3.66
Understanding (point)	13.46±2.91	13.82±2.55	13.32±2.93	15.07±2.43
Overall (point)	19.54±5.05	20.93±5.49	19.50±4.90	20.79±5.50
Eye movement:				
Pupil diameter (mm)	3.60±0.46	3.53±0.60	3.59±0.55	3.96±1.80
Blink frequency (times/s)	0.32±0.21	0.34±0.21	0.32±0.21	0.36±0.23
Ratio of saccades (times/s)	0.21±0.02	0.21±0.03	0.21±0.02	0.21±0.02

Note: SA=Situation Awareness; SAGAT=Situation Awareness Global Assessment Technique, with six indices; one index was analyzed by the measure of Performance; SART=Situational Awareness Rating Technique, with four indices; three indices were recorded by the measure of Eye movement. The measuring results in the table were shown as Mean±SD.

SA model predictions as well as the experiment results under the factors of two display interfaces and two tasks are presented in Table 2.

To validate the SA model, Wickens used a protocol modeling the average pilot to analyze the correlation between the predictions and the measurement indices [3,8]. This protocol was used in this study for model validation purpose.

For SAGAT, SA model prediction was correlated with the correct rate for the sum of level 1& level2 SAGAT correct rate (r=0.94), and was also higher than any other SAGAT indices, such as the overall (r=0.93), the level 1 (r=0.61), and the level 2 (r=0.57), but no correlation with the level 3 correct rate (r=-0.08) was found. Moreover, the SA model prediction showed a strongly negative correlation with correct response time (r=-0.89). For performance measures, the operation score was weakly correlated with the prediction (r=0.65). For 10-D SART, the prediction was highly correlated with both overall SART rating (r=0.91) and understanding rating(r=0.88), as well as negatively correlated with the demand rating (r=-0.81), but not correlated with supply rating (r=-0.007). For psychophysiological measures, eye movements were recorded. Model prediction results demonstrated a strong correlation with the blink frequency (r=0.98), and weak correlation with pupil diameter(r=0.648). However, no correlation was found with the ratio of mean number of saccades (r=-0.15).

5. Discussion and conclusion

In this study, four types of approaches with series of indices were applied to verify the SA model, and were analyzed according to the results shown in the Section 4.

Previous studies reported that the SAGAT had some limitations on measuring the SA3 [9], and there was a fuzzy boundary between SA2 and SA3 in the model. Therefore, it was reasonable to see that in this study level 3 SAGAT was not correlated with the prediction. It was clear that the two factors (display and task) both had significant influence on the correct response time ($p<0.05$, paired samples). And the results were strongly correlated with the model prediction, suggesting that correct response time might be better in measuring the SA changes under different conditions than correct rate. A possible explanation for this finding could be that increase in speed of the cognitive processing could decrease response time, which is in an agreement with previous findings [10,11].

For performance measures, the participants should be instructed to maximize operation scores with the appropriate attention allocation depending on the conditions. However, it was hard to avoid the situation that some participants might misunderstand the requirements and focused only on acquiring higher correct rate rather than higher performance score, which might lead to performances that could not yield a high correlation with SA model. For 10D-SART, the self estimation of SA could be computed by the algorithm SA=Understanding-(Demand -Supply), where the three indices were estimated by self rating respectively. However, no correlation between the performance and the overall SART (r=0.29) were found, since some subjects' misunderstanding existed during the assessments due to the overconfidence or excessive self-esteem [12].

For psychophysiological measurement, very few studies used this approach to investigate SA，because it not clear that psychophysiological measure can directly tap the high level cognitive processes involved in SA Therefore it was worth examining and exploring psychophysiological indices to reflect SA for the relationship between SA and attention [12].

With regard to blink frequency, it was suggested to measure the SAs under different displays or tasks, which was obviously influenced by the two factors ($p<0.05$, paired samples t test) and had a strong correlation with prediction. This result was also consistent with previous finding [5]. As a sensitive index for mental workload, pupil diameter was positive correlated with the model calculation but not consistent with the previous result [5]. Since the previous study didn't include SA3 in both the SA model and the experiment, when the experiment task was more difficult they could not improve the cognitive level but to obtain lower SA level, even if they put more effort to monitor the SEs with the pupil diameter increasing. However in this study, with SA3 considered, the more effort they put in the operation with pupil diameter increasing, the higher the cognitive level they could achieve. Therefore, further studies were required as the relationship between pupil diameter and the SA was complicated and uncertain, similarly to the relationship between the mental workload and the SA [13]. However the results of the ratio of mean number of saccades indicated that it was not sensitive for measuring SAs and more researches are needed.

In conclusion, the current study introduced a qualitative analysis model to explain how the three levels of SA produced with the ACT-R theory. Based on this model, the corresponding quantitative mathematical model was built and its validation was verified by a comprehensive experiment. The experimental results suggested that correct response time in SAGAT performed better than the correct rate in measuring SAs and blink frequency could assist SA measurement as well. Overall, this model could be applied to forecast SA changes during multi-tasking on one display interface or during different types of display interfaces in one task. Such application may also contribute to the evaluation and optimization design of human-machine interface as well as ergonomics studies in reducing and preventing human errors.

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