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A Predictive Model of Situation Awareness with ACT-R

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Objective: The aim of this study is to model all levels of situation awareness (SA), which would be able to predict situation awareness quantitatively.

Background: When measuring situation awareness, directly measuring SA methods such as SAGAT and SART have been utilized. Several approaches (cognitive modeling approaches) were introduced to model SA but level 3 SA was not completed. For real-life situation, however, it is necessary to detect the problematic level of SA rather than overall SA. Therefore, we proposed a new model of all levels of SA in this study.

Method: In order to model all levels of SA, this study chose factors in ACT-R architecture through literature review. ATC (Air Traffic Control)-related simulation task was video-taped to analyze human behaviors in order to model all levels of SA including level 3.

Results: As a result, regression analyses show that cognitive activities (neural activations) represented for all levels of SA were highly correlated with SAGAT.

Conclusion: In conclusion, neural activations in ACT-R could be proved to be effective to model all levels of SA.

Application: Our SA model could be used to predict all levels of SA quantitatively without directly measuring the SA of operators.

Keywords: Situation awareness (SA), Cognitive architecture, Neural activations, SAGAT, ACT-R

1. Introduction

Situation awareness (SA) has been regarded as an important concept for understanding dynamic situation and decision making for dozens of years. The area that emerged as the research background of SA is aviation system. As the area of dynamic system was expanded as time went on, studies have been carried out in various areas including automobile (Ma and Kaber, 2005), submarine (Loft et al., 2013) and army land battle situations (Riley et al., 2006), as well as airplane. Researches to measure SA in various situations from full-manual system in which humans perform all jobs to full-automation in which systems carry out all functions have been conducted, as researches on automation system are actively performed recently (Ma and Kaber, 2005; Kaber et al., 2006). The three-level SA model of Endsley (1995) is the most representative model representing SA. According to the model, level 1 SA is defined as perceiving the color, size, speed and location of the factors consisting of a situation.

Level 2 SA is defined as understanding factors as a whole one picture, based on factors perception. Level 3 SA is defined as predicting the near future state.

The most well-known and widely used techniques among the techniques to measure SA are as follows: Situation Awareness Global Assessment Technique (SAGAT) (Endsley, 1988; Endley et al., 1998), which freezes an experiment temporarily during the experiment, and measures SA by level through problem solving, based on Endsley's three-level SA theory; Situation Awareness Rating Technique (SART) (Salmon et al., 2009), which comprehensively measures an experiment subject's subjective feeling level through multidimensional approach, after the experiment is finished, as a technique measuring SA that appeared prior to the three-level SA theory.

According to recent research results, 71% of aviation accidents are human-causing problems, and 88% of those are associated with the error of SA (Yang and Zhang, 2004), and 78% of car accidents occur due to human's SA errors (Klauer et al., 2006). In view of such statistical result, the SA prediction to prevent accident occurrence in advance will be more important than to measure SA, which is difficult to immediately cope with in human's use of dynamic system. The following existing SA prediction models have been carried out: a research using dTank, a JAVA-based tool (Ritter et al., 2007), a research using CoJACK, one of the cognitive architectures (Evertsz et al., 2008), and MIDAS (Man-Machine Integration Design and Analysis) (Hooey et al., 2011) predicting with quantitative values by dividing the environment with situation elements in explaining SA. However, such existing prediction methods could not explain all three levels of SA. The researches using dTank and CoJACK just could predict level 1 SA, and MIDAS could be able to predict only level 1 SA and level 2 SA. Therefore, it was inappropriate to explain by connecting with the existing evaluation techniques measuring SA, because a limitation that they could partially explain the three-level SA theory. In relation with this, Liu et al. (2014) explained the process in which Endsley's three-level SA is formed through the algorithm provided from the ACT-R (Adaptive Control of Thought-Rational, Anderson et al., 2004) theory, and predicted SA with quantitatively values. Furthermore, he verified it through SA values acquired through the existing measuring techniques by using an experiment. However, his research explained by applying the existing algorithm, and therefore there was a limitation that clear distinction between level 2 SA and level 3 SA was not made. For this reason, Liu's study calculated with overall SA values in predicting SA. As such, there was no research that clearly classified three levels of SA, and thus a study on new SA modeling that can represent all three levels of SA is needed.

This study aims to propose a new model for three levels of SA to quantitatively predict all levels of SA. That SA can be represented with quantitative numeric values is different from the SA explanation of Endsley (1995), who explained with a general structure applicable to various environments and systems. This study conducted modeling of each level's SA by selecting the factors associated with Endsley's SA by each level, and using those factors, based on the ACT-R theory which can explain human's cognitive processing process in order to predict SA quantitatively. To acquire SA values through existing SA measuring methods, this study designed a simulation task related with ATC (Air Traffic Control) similar to an experiment performed in a study of Kaber et al. (2006), and measured the experiment subjects' SAGAT result values. The factors selected as associated with SA by level in the ACT-R cognitive architecture are indicated as quantitative values. This study calculated the values quantitatively indicating each level's SA through cognitive behavior analysis so that those factors can be indicated quantitatively in the actual experiment (x_{level1}, x_{level2}, x_{level3}). This study showed that the validity of the SA model proposed in this study by using and verifying the experiment subjects' SA values measured through an experiment.

1.1 ACT-R architecture

ACT-R is the cognitive architecture that is explained with several modules, and it explains how human's perception is formed through those modules. Each module is associated with each different information processing process. Those modules are as follows: visual module related with distinction by looking at visual objects, response module (segmented with manual and vocal modules) that interacts with the external world, goal module related to things that continue to remember the current goal and declarative module associated with storing and retrieving human's knowledge (memory). Information is stored and retrieved in a specific form, which is called chunk. These several modules are processed and integrated by procedural memory. When a specific condition is met by IF-THEN algorithm, human's behavior is represented in a mode to be connected with the next behavior.

Each chunk within the declarative module has the numeric value of activation level. Change to activation level is caused as the result of storing and retrieving of knowledge and information, and therefore the activation level in ACT-R can be used to predict how much a human remembers the information within each chunk (Baumann and Krems, 2009). A high activation level means that the person concerned has enough information on a specific factor. The activation level in ACT-R is defined as follows:

$$A_i = B_i + \sum_j W_j S_{ji}$$ (activation equation) (1),

where B_i shows initial stage activation level of a specific chunk, and it can be defined as follows:

$$B_i = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right)$$ (base-level learning equation) (2),

where n indicates the number of chunk i is appeared. t_i refers to time since the appearance of chunk i's jth appearance. D is the decay constant, and is set as 0.5 in almost all the cases. W is the weighted value corresponding to detailed goal in carrying out work, and has the value of 1/n according to the number of slots, n, as shown in Figure 1. S indicates how much correlation the chunks formed in the course of performing work on the goal have, and it is allocated in proportion to each chunk's correlation, and is called source spreading.

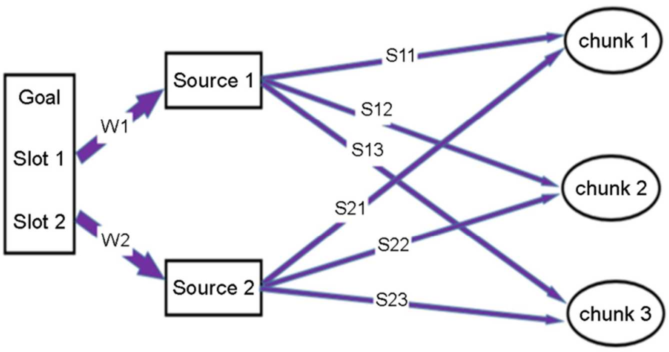

Figure 1. Spreading activation of ACT-R

2. Method

2.1 Modeling of level 1 SA

According to Kaber et al. (2006), level 1 SA increases in proportion to how much information is acquired for set time. The first process of a person's perceiving an object and inputting it in the memory system is referred to as encoding, and the time spent is called encoding time. That lots of information was acquired means that encoding time was spent so much. Prediction will be possible with percentage of the encoding time spent through information acquisition related with the goal to the total encoding time spent. Level 1 SA can be indicated like equation (3). In ACT-R, the time spent per encoding is defined as 85ms. According to Endsley (1995), the factors causing the failure of level 1 SA can be he following cases: The experiment subjects are difficult to acquire proper information through system design failure, and detection possibility is reduced, due to a visual barrier or auditory masking. The model in this study assumes that such a system problem does not exist, and encoding errors do not occur, due to given information is easy to perceive and understand.

$$\text{Level 1 SA}: \frac{\sum Encoding\ time(goal)}{\sum Encoding\ time(total)} \qquad (3)$$

2.2 Modeling of level 2 SA

In case that a mental model is not sufficiently formed to properly accept and understand received information, as an experiment subject carries out work, level 2 SA should be formed within working memory (Endsley, 1995). If an experiment subject is equipped with professional level of situation awareness, and the mental model is sufficiently formed, and he/she can make a more effective decision than a novice, even though information lacks. In measuring SA using SAGAT, an exceptional situation of three-level SA model in which level 3 SA is indicated high, is revealed without sufficient formation of level 1 SA. A possibility that cognitive bias can be shown in the selection and interpretation of information by the mental model also exists (Endsley et al., 2003). The model in this study assumes the experiment subjects whose professional level mental model is not formed regarding work. According to Anderson et al. (2004), activation level in ACT-R is the value changing in real time by reflecting how often the inputted information was used, or how much it was recently used. The ACT-R cognitive architecture shows person's actual information processing process well that is re-used, after the inputted information is formed through working memory and is stored in the long-term memory, based on these two, through the real time-changing activation level of a chunk. According to Endsley (2015), SA is represented as a dynamic concept that continuously changes, as time goes on, and this study additionally assumes that the understanding on changing situation according to the elapse of time can be indicated with the sum of activation level on chunk information. Therefore, level 2 SA can be indicated like equation (4).

$$\text{Level 2 SA}: \frac{\sum base - level\ activation(goal)}{\sum base - level\ activation(total)} \qquad (4)$$

2.3 Modeling of level 3 SA

Sulistyawati et al. (2011) measured experiment subjects' SA through SAGAT in an experiment, and simultaneously performed a cognitive experiment based on Education Testing Service Kit of Factor-Referenced Cognitive Test (Ekstrom et al., 1976), and showed that level 3 SA is greatly associated with general reasoning ability. A general reasoning ability is the upper level cognitive ability related with prediction, and is related with an ability to collect and integrate the relevant information in solving a problem (Sulistyawati et al., 2011). The reasoning ability of a general person represented through ACT-R cognitive architecture is fixed, and thus level 3 SA can be highly formed, since information integration is easier, as the person has the information with higher correlation with the task goal. This study assumed level 3 SA can be predicted additionally considering source spreading that reveals the level of correlation between the information concerned and goal in ACR-R in addition to the chunk and activation level presented above as the factor related with level 2 SA formation. Equation (5) shows level 3 SA.

$$\text{Level 3 SA}: \frac{\sum base - level\ activation * source\ spreading(goal)}{\sum base - level\ activation * source\ spreading(total)} \quad (5)$$

2.4 Experiment

This study proposed the new modeling of SA using ACT-R cognitive architecture, and designed a similar experiment using Allegro Common Lisp based on ATC-related simulation task, which was carried out in a study of Kaber et al. (2006) (see Figure 2). The study of Kaber is concerned with SA change of experiment subjects according to automation level change in carrying out ATC-related task, and it comparatively analyzed the results by performing the same task under various automation levels. This study aims to propose a new model that can quantitatively check and verify SA, and measured SA under only one condition of manual operation, unlike the study of Kaber. Because, the proposed model assumed beginning level experiment subjects, difference existed from existing experiments in terms of training level. Other factors consisting of the experiment environment (Number of airplanes, airport and runway), experiment process and interface were designed as the same. The experiment targeted 15 subjects aged 21~29 without aviation traffic control experience to make them suitable for the assumptions of the proposed model. The 15 subjects performed a task ordering to safely land seven airplanes slowly approaching the two runways existing in two airports, respectively. All airplanes have the destination airport and runway upon the beginning of the experiment. The goal of the experiment is to make all airplanes safely arrive finally by changing adequate destination so that the airplanes' predicted potential collision can be avoided, based on the understanding of overall aviation situation. The subjects can make necessary orders by airplane in consideration of distance left to the airport, current airplane speed and destination by receiving the airplane information through the query button. The information that can be acquired through the query button includes the name of an airplane, current speed (nautical miles), destination airport and destination runway. According to Gibson et al. (1997), time pressure and mental workload highly affect SA errors among the factors of SA error causes. To prevent SA error occurrence due to temporal and mental pressure on approaching airplane, training time to be accustomed to the experiment environment for about 5~10 minutes was offered. In the actual experiment, seven minutes of experiment time were awarded on the basis of quick understanding on overall aviation situation, and a task to order to one airplane per minute was executed. During the experiment, the subjects answered the questions for SAGAT measurement by moving to a place where they could not see the experiment screen, after halting work by making the pause button appear at random time. Two times of this were carried out in the experiment. According to existing research result that at least two minutes should be offered for a subject to re-form SA from one time SAGAT measurement to the next SAGAT measurement concerning measurement interval (Endsley, 1995), two minutes and more of time interval was set. As a result of

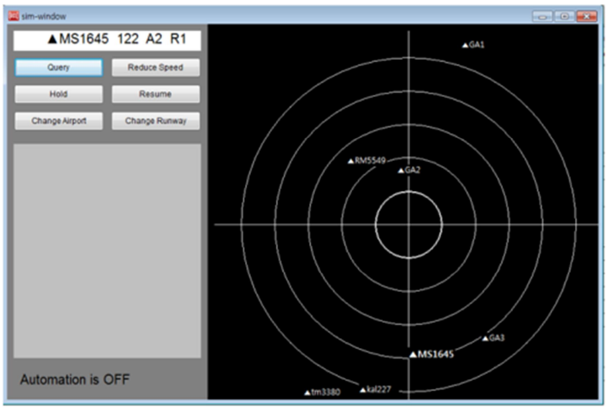

Figure 2. ATC (Air Traffic Control)-related simulation task

actual experiment and pilot test, the experiment was set to be carried out once, since the subjects tend to focus more on behaviors to answer the questions, rather than to carry out work suitable for goal, since they already know the SAGAT questions in case two times of experiment were carried out.

3. Results

As a result of measuring 15 subjects' SA through an experiment, average SAGAT scores were shown in Figure 3. SA by each level was relatively shown evenly (Level 1 SA: 59.26%, level 2 SA: 62.97% and level 3 SA: 54.07%). The experiment process of 15 subjects was video-taped for the analysis through subjects' cognitive processing process in the future. Because this study assumed the beginning level of subjects in the basic assumption of the proposed model in this study, there was difference in training level from the research of Kaber. Consequently, it was confirmed that SA by each level was lower overall than the existing experiment.

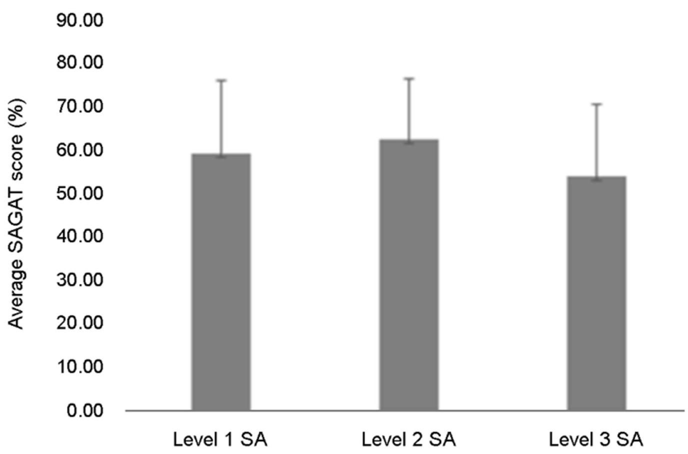

Figure 3. Average SAGAT scores (Level 1 SA, Level 2 SA, Level 3 SA)

3.1 Prediction result of level 1 SA

Level 1 SA was indicated using the encoding time based on the ACT-R theory, and this study calculated quantitative values by analyzing the corresponding part in the actual experiment, and predicted level 1 SA. Specifically, level 1 SA was predicted with the percentage of the number of looking at the objects related with the goal to order the number of the subjects' looking at the entire objects during the experiment. Furthermore, this study verified the level 1 SA values predicted in this study and the SA values measured through actual experiment using a cross validation technique. The results of 11 subjects among the results of 15 subjects were verified using a regression analysis, and verification was conducted through the remaining four subjects' results, and this study ascertained the error rate. Actually, $F(1, 9) = 32.02$, p-value < 0.001, $r^2 = 0.78$, and error rate was 4.49%, and this study confirmed that SA was relatively precisely predicted (see Figure 4).

3.2 Prediction result of level 2 SA

Level 2 SA was represented using base-level activation based on the ACT-R theory. This study calculated quantitative values and predicted level 2 SA through the analysis of cognitive and mental processing process that can simultaneously consider frequency indicating how often information was used, and recency indicating how much information was used recently in the actual experiment.

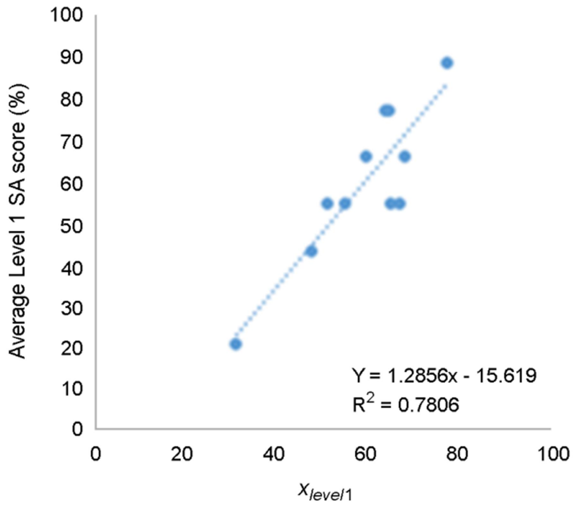

Figure 4. Scatter plot of Xlevel 1 vs average Level 1 SA score

Specifically, this study awarded relative weighted values on the information decay in consideration of how goal performing point in time is far away from the selected point with regard to the goals existing before, when level 2 SA is predicted at random point. By reflecting the relative weighted values, this study predicted through indication of how much information related with the goal corresponding to each section was viewed as percentage. In the experiment, the random points concerned were designated as the point in time of two times SAGAT measurement for the subjects, and level 2 SA was predicted. Furthermore, this study verified the level 2 SA values predicted in this study and the SA values measured through actual experiment using the cross validation technique. The results of 11 subjects among the results of 15 subjects were verified using a regression analysis, and verification was conducted through the remaining four subjects' results, and this study ascertained the error rate. Actually, $F(1, 9) = 26.78$, p-value < 0.001, $r^2 = 0.71$, and the error rate was 12.6%, and this study confirmed that SA was relatively precisely predicted (see Figure 5).

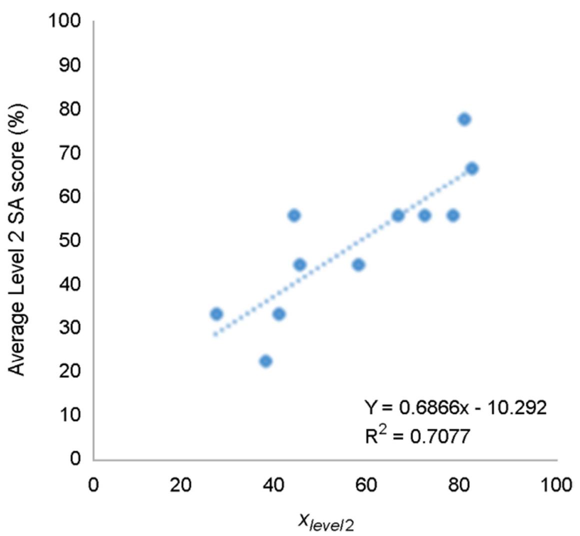

Figure 5. Scatter plot of Xlevel 2 vs average Level 2 SA score

3.3 Prediction result of level 3 SA

Level 3 SA was represented, based on the two factors, base-level activation and source spreading on the basis of ACT-R theory. Using the research result of Sulistyawati et al. (2011) that future prediction ability is higher through information integration, as reasoning ability is higher, this study predicted level 3 SA with percentage in the case of proper comparison of two airplanes having actual potential collision possibility to the comparison process of two airplanes that were conducted by the subjects in the actual experiment. Likewise, this study verified the level 3 SA values predicted in this study and the SA values measured through actual experiment using the cross validation technique. The results of 11 subjects among the results of 15 subjects were verified using a regression analysis, and verification was conducted through the remaining four subjects' results, and this study ascertained the error rate. Actually, $F(1, 9) = 25.03$, p-value < 0.001, $r^2 = 0.74$, and the error rate was 4.81%, and this study confirmed that SA was relatively precisely predicted (see Figure 6).

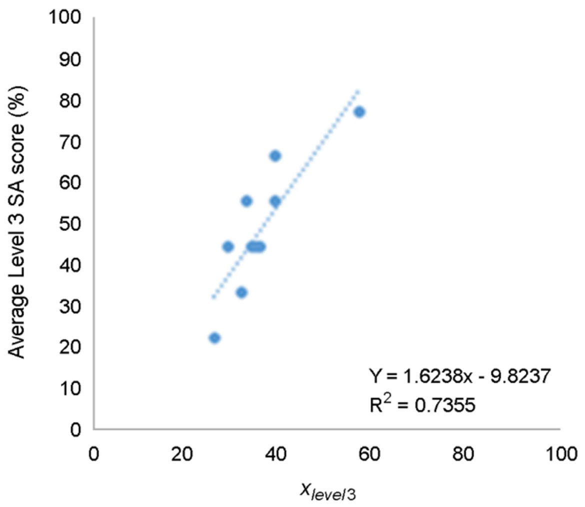

Figure 6. Scatter plot of Xlevel 3 vs average Level 3 SA score

4. Conclusion

This study predicted situation awareness (SA) by modeling each level SA based on the ACT-R theory, and by analyzing the cognitive processing process of a person carrying out actual experiment. This study showed the validity of SA modeling proposed in this study by verifying with the measured SA values by each level acquired in the actual experiment through SAGAT, an existing SA measuring technique.

5. Discussion

ACT-R is a theory that can represent human's cognitive processing process, and that can explain how SA is formed. Therefore, ACT-R is an appropriate theory suitable for measuring SA (Liu et al., 2014). In a study of Liu et al. (2014), the formation level of each level SA was explained using the computational algorithm offered by the ACT-R theory. However, there was a limitation that distinction between the level 2 and level 3 was not clear, as a result of explaining the level 2 and level 3 SA based on existing algorithm indicating the probability for optimum behavior to be selected suitable for the current situation on the basis of perceived information. Consequently, SA values were predicted with only overall SA values indicating level 1, level 2 and level 3, instead of calculating SA's quantitative values by level. In human's using a dynamic system, however, the system becomes more and more complex, and the risk of momentary SA failure can be linked with huge casualties increases, due to the advent of various additional functions, as time goes on. In this regard, it is important to immediately identify the level concerned, offer feedback, and improve it, if a problem is judged to occur through SA prediction, rather than simply judging high and low overall SA. This study clearly discriminated the factors greatly associated with SA in ACT-R by level, and selected them, and then conducted new modeling of SA in order for quantitative prediction of SA by level, rather than predicting simply overall SA values. This study successfully predicted the values corresponding to each level SA by quantitatively calculating the corresponding values through actual experiment performing human's mental and cognitive processing process analysis. This study has huge significance in the practical aspect in that a possibility to prevent casualties that can occur in a dynamic system in advance can be presented through the method presented in this study.

Because some errors existed in verifying the SA values predicted in this study through a regression analysis via the SA values measured through SAGAT, the predicted values were higher or lower than the measured values. Indeed, the external factors having a possibility to affect each level SA existed as follows: The dwell time that occurred in looking at an object can be regarded as the first factor. The confirmed information in predicting level 1 SA is concerned with how much encoding time was spent. This study did not consider how long a subject's vision dwelled, after encoding on an object was conducted. When lots of dwell time occurred on several objects during the experiment, it may work as a reduction factor from the aspect of losing time to look at other objects. During the simulation task, additional information was acquired, due to peripheral vision, which was reflected in the measurement of SA, and the information could work as an increasing factor of subject's SA, in addition to acquisition of just one piece of information upon moving vision each time. There is the name of an airplane that must be fully familiarized in conducting an experiment, and measuring SA through SAGAT. As the airplane names consisting of the combination of English alphabets and numbers were awarded to seven airplanes, a possibility that a memory error may occur existed upon measurement, due to similar or complex airplane name. SAGAT measurement, one of the existing SA measurement techniques, consisted of multiple choice questions, and the subjects answered all the questions. There was a possibility that SA could be evaluated highly existed, since random answers to the questions without conviction were selected as correct answers. The experiment carried out in this study was designed similarly with the experiment carried out in a study of Kaber et al. (2006). The experiment did not include altitude information in various information related with an airplane, and there is a limitation that differences exist from the aspect of difficulty in terms of the task performed by a controller in the actual ATC situation. According to Tsang and Vidulich (2006), human's cognitive resources are limited, which may affect SA formation, when high workload is imposed. According to Endsley (1995), a novice is affected more by workload. This study carried out an experiment with beginning level subjects according to the basic assumption of the proposed model in this study. Therefore, altitude information was omitted as in the Kaber's experiment to minimize the effects of workload on beginning level subjects' SA formation.

This study proposed a new model of SA to quantitatively predict SA by level using the ACT-R theory, and showed that the model was valid through human's cognitive behavior analysis in the actual experiment. In a further study, there is a need to check what differences exist between the professional level subjects and beginning level subjects by additionally considering the former whose mental model is sufficiently formed to carry out a task. Furthermore, real time SA prediction can be conducted without the use of existing SA techniques or subjects' behavioral analysis through a study on ACT-R cognitive modeling.

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