Adaptive Simulation of Monitoring Behavior: The Adaptive Information Expectancy Model

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***Abstract*—Human attention is a fundamental but limited resource. Especially when performing safety critical tasks a suitable distribution of attention is essential for safe operation. E.g., changes in task relevant information have to be recognized in time in order to react adequately. This paper presents the Adaptive Information Expectancy (AIE) model, which simulates the scheduling of attention within cognitive architectures. It can be used for model-based evaluations of interactive human-machine systems. Results of a first evaluation study are shown based on a simple laboratory monitoring task. An overview on the AIE model is given and it is shown how it was integrated in the Cognitive Architecture for Safety Critical Task Simulation (CASCaS). A formal model for the laboratory task was developed and then simulated using CASCaS. Several aspects of the AIE model are evaluated on the basis of the simulations of this agent in two main steps. The first step of the evaluation compares the agent behavior with results from the studies conducted by Senders. In this step two alternative AIE model variants are compared to participants' behavior. The second evaluation step explores parameter sensitivity and the convergence behavior of the model.**

***Keywords*-Event expectancy; cognitive model; attention allocation; monitoring behavior;**

I. Introduction

Detailed knowledge about human attention allocation is vital for designers of human-machine interaction, e.g., in cars or aircrafts. It has been acknowledged by many researchers that executable cognitive models have the potential to capture such knowledge and to make it readily available to designers (e.g., [1][2][3]). This paper presents the Adaptive Information Expectancy (AIE) model which is an extension of the seminal SEEV model introduced by Wickens et al. [4].

How humans distribute their attention depends on several factors. The SEEV model is a predictive model of attention distribution that relates the amount of attention allocated to a specific information source to four influencing factors. The abbreviations of these factors form the acronym SEEV: Saliency of information events, Effort required to perceive the information, Expectancy of new information events and Value of the task, that requires the information. The SEEV model can easily be applied to estimate percentage dwell times (PDTs) – the percentage of time a human operator spends looking at an information source, e.g., of a human-computer interface.

The AIE model is based on the two knowledge driven factors Expectancy and Value. Although it does not consider Saliency and Effort, it extends the SEEV model in two ways. (1) It relates the attention distribution to an executable task model, which can be simulated, e.g., in a cognitive architecture. Based on the simulation further measures like gaze frequencies or link values can be estimated, besides the mere prediction of PDTs as provided by the SEEV model. (2) The second extension is related to the operationalization of Expectancy. The SEEV model requires a system designer or Human Factors Expert (HFE) who applies the model to give an estimate of each of the influencing factors for all considered information sources. For this, Wickens et al. [4] propose a lowest ordinal algorithm as an easy to use method, that orders the influencing factors by small integers according to their rank. Although this method has been proven simple and effective, it is only a very rough operationalization that is dependent on the subjective rating of the HFE. The AIE model strives to replace this by deriving the expectancy factor dynamically from a simulation of the task model in a dynamic environment. It is thus able to adapt its attention distribution automatically to the current situation, which is an enhancement over the SEEV model. It furthermore provides a much more detailed view because it integrates the simulation of task performance and the simulation of attention control in a tightly coupled way. The long term goal of this research is to use the AIE model to predict the allocation of attention dependent on design characteristics of human-machine interfaces and associated tasks in complex and safety critical environments.

The following shows results of a preparatory study that was used to evaluate the AIE model on the basis of a laboratory monitoring task, which was developed by John Senders in the 1960s [5]. The paper starts with an overview on the AIE model and its integration in the Cognitive Architecture for Safety Critical Task Simulation (CASCaS) [6][7]. Then an overview on Senders' task and the derived task formalization is given in Section III and IV. Section V is dedicated to the detailed evaluation of the AIE model.

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II. Adaptive Information Expectancy Model

The AIE model and its integration into CASCaS will be described here briefly on an abstract level to provide a basic understanding. For a more elaborated description see [7].

Cognitive architectures can be understood as engines that are intended to execute formal models of tasks in a psychological plausible way. CASCaS is a modular architecture consisting of components for perceptual, memory, knowledge processing and motor processes. The AIE model is a general model of attention allocation and thus is integrated in CASCaS as part of a general model of human cognition. In contrast, task models describe task specific aspects of human behavior. The interpretation of a task model by the cognitive architecture eventually simulates human-like behavior. In the following the term *(cognitive) agent* refers to the combination of task model and cognitive architecture.

A. Control of Attention

While the SEEV model is typically used to predict the visual attention allocation to multiple information sources, the AIE model intends to predict to which task an agent mentally attends. However there is typically a very strong relationship between visual and mental attention, which Just and Carpenter [8] named the eye-mind-assumptions. This assumption was adopted for the AIE model evaluation presented in Section V, where the gaze behavior of the participants in Senders' study is compared with the gaze behavior of the cognitive agent.

An assumption of the AIE model is, that human behavior is goal oriented and every task serves to achieve one specific goal. The AIE model is applicable to situations where multiple tasks have to be performed in parallel in a time-shared fashion, like e.g., a pilot that has to monitor a set of displays, while controlling the aircraft and communicating with the pilot non flying. Attention is a limited resource and often only one of the tasks can be processed consciously. Although in real situations it is often possible to execute some parts of tasks really in parallel, this aspect will not be discussed in this paper.

To instantiate a cognitive agent CASCaS loads a hierarchical task model. Each task seek to achieve a goal and is modeled by a set of rules. These rules represent the knowledge of the human operator about the task. For a driver model, for example, they describe how the driver interacts with the car and the surrounding traffic. The rule language is based on the well-known GOMS notation [9]. All rules consist of a left-hand side (IF) and a right-hand side (THEN). The left-hand side names the goal to be achieved and a Boolean condition that defines in which situations the rule shall be applied. The right-hand side defines the actions that are executed when applying the rule.

Multitasking situations in the task model have been handled in the past by a very simple mechanism that treats every task as equal and repetitively executes every task for a certain but short amount of time in a fixed sequence. This mechanism is now replaced by the AIE model. The AIE model assigns a weight to each goal g_i of all active tasks:

$$w(g_i) = U \cdot \frac{u_{g_i}}{\sum\limits_{g_j \in G} u_{g_j}} + V \cdot \frac{v_{g_i}}{\sum\limits_{g_j \in G} v_{g_j}}. \qquad (1)$$

In the above equation G is the set of goals for all active tasks, u_{g_i} is the expectancy coefficient that describes how much the agent expects new information for the task of goal g_i and v_{g_i} is the value or importance of goal g_i. Thus the weight $w(g_i)$ depends on the relative importance of a task compared to the importance of all tasks and the relative information expectancy of a task compared to all tasks. The factors U and V are used to adjust the overall influence of task importance and information expectancy.

CASCaS now selects the next goal to be executed in a probabilistic way. The probability of selecting goal g_i is defined by the relation of all weights:

$$P(g_i) = \frac{w(g_i)}{\sum\limits_{g_j \in G} w(g_j)} \qquad (2)$$

In Equation 1 the value and expectancy factors are linked by addition. However in applications of the SEEV model additive combinations (e.g., [10]) as well as multiplicative ones (e.g., [11]) can be found. Arguments can be found for both variants. This was discussed by Wickens et al. [12]. They achieved a better model fit with the additive formulation. But still there is no consensus about this issue. To shed further light on this matter, the AIE model was implemented in both variants. To explicitly distinguish between both variants the symbol AIE$^+$ is used for the additive formulation and AIE* for the multiplicative formulation.

B. Event functions

To use the AIE model the coefficients in equation 1 have to be defined for each task. For the value coefficients v_{g_i} it is suggested to employ the lowest ordinal algorithm that is typically used for the coefficients of the SEEV model [4]. But for the expectancy coefficients u_{g_i} an automatic operationalization is proposed.

Wickens et al. describe the expectancy factor as an *"information-related measure of event expectancy (e.g., bandwidth, event rate; [...])"* [4, p.3]. This view is adopted by the AIE model. The expectancy coefficients are operationalized on the basis of information events. An event is defined as follows:

If at time t information, which is relevant for a goal g is used to achieve g, then $e = (g, t)$ is called an event at time t for goal g. Let E be the set of all events that occurred during a simulation, then $E_g \subseteq E$ is denoted to be the set of all events for goal g. Events can be ordered and indexed by their time of arrival. With $e_{g,i}$ the i-th event in E_g is denoted.

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The identification of events in CASCaS is straight forward. CASCaS processes tasks using a rule engine similar to other rule based architectures like e.g., ACT-R. It provides four different rule types: regular, percept, waiting and reactive rules. When a task gets actively processed by a rule engine the process is typically as follows. If the task needs some information appropriate percept rules are executed that instruct CASCaS to direct its gaze to an information source, which provides the information. After the information has been perceived, it can be used by regular rules to achieve the task goal. If the perceived information is of no use for the agent, a waiting rule is fired, which signalizes, that another task should be executed. Hence the execution of a regular rule corresponds to the recognition of an information event for the goal, which is supported by that rule.

During the simulation of the task model CASCaS records the events of all goals and develops for each a cumulative frequency distribution function H_g of the distances between consecutive events $e_{g,i}$ and $e_{g,i+1}$. The value $H_g(\Delta t)$ can answer the question, how often an event occurred not later than Δt time units after the previous event. This is used to describe whether the agent can expect new events for a specific goal and thus the expectancy coefficients are defined by $u_g = H_g(t - t_{g,n})/d_g$, with t being the current time, n being the index of the last event for g and d_g being the amount of time that the agent was working on g. Thus u_g is a time dependent function which is called the event function of g. One effect of this operationalization is that the expectancy of new events continuously increases since the last event was observed.

Another effect is that the behavior of the agent changes over time. At the beginning of the simulation it has no knowledge about event distance. But the more events the agent detects the more stable the event functions get. Thus the behavior should change less the more time passes. The learning speed of the agent should correspond to the convergence speed of the event functions. According to the Berry-Esseen theorem [13] the pointwise convergence speed should be bounded by $\mathcal{O}(n^{-\frac{1}{2}})$, with n being the number of events which are recorded in H_g. If the distribution of event distances does not change over time, having a fixed average event rate, this can be expressed in a time-dependent way by $\mathcal{O}(t^{-\frac{1}{2}})$. Unfortunately the assumption that the distributions do not change over time is false, because there is always a feedback within the cognitive agent when using the AIE model: The event functions influence the selection of goals; the selection of goals determine, where the model looks at; where the model looks at influences the perception of events distances; finally, the perception of event distances influence the event functions. But assuming, that the effect of this feedback loop is small, at least a similar learning speed should be obtained. This was considered during model evaluation and will be addressed in Section V.

Table I
BANDWIDTHS OF THE GAUGES FOR THE THREE EXPERIMENT CONFIGURATIONS.

Configuration	Participants	Signal bandwidths per gauge (Hz.) 1	2	3	4	5	6
C1	5	0.08	0.16	0.32	0.64	-	-
C2	3	0.03	0.05	0.12	0.20	0.32	0.48
C3	2	0.02	0.04	0.08	0.16	0.32	0.64

III. SENDERS' MONITORING TASK

For a first evaluation of the AIE model a simple laboratory task was selected. It is the monitoring task developed by Senders [5]. A cognitive agent was developed that relies on the AIE model and is able to interact with this task. The model is evaluated in section V against data that Senders obtained in his studies on this task. In this section a short overview on the task and the setup he used in his studies is given. For more details see the original work [5].

In the Senders Task participants had to observe a set of gauges that displayed dynamic values of currents for fictitious devices. Every time one of the displayed signals fell below -45 μA or above 45 μA participants had to push a button. Senders investigated how bandwidths of the signals influence the gaze distribution of the participants. He used five different tasks configurations. Three of these are used for the evaluation and are denoted by C1, C2 and C3. The signal bandwidths of each configuration are listed in Table I. It must be said, that the configuration C1 belongs to a different study than configurations C2 and C3. It was conducted before the study involving C2 and C3.

C1 investigates the gaze behavior while monitoring four gauges. Five participants executed this task for 1 h per day over 30 days . Gaze behavior of the last three minutes of each day have been analyzed.

C2 was similar to C1, but six instead of four gauges were used. Participants executed the task for 1 h per day over 10 days. Gaze behavior of the last 11 minutes of the last day have been analyzed. This configuration is shown in Figure 1, which shows the geometrical layout of the six gauges (left side) and the viewing distance of the observer (right side).

C3 was similar to C2, but signal generation was changed, which resulted in a different set of signal bandwidths.

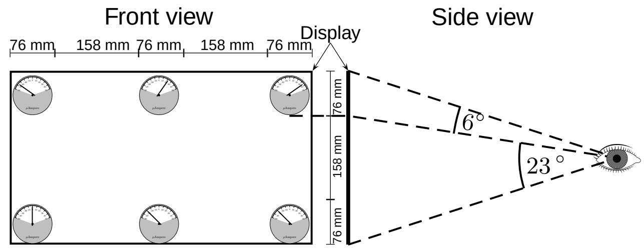

Figure 1. Task configuration with six gauges (reconstructed from [5]).

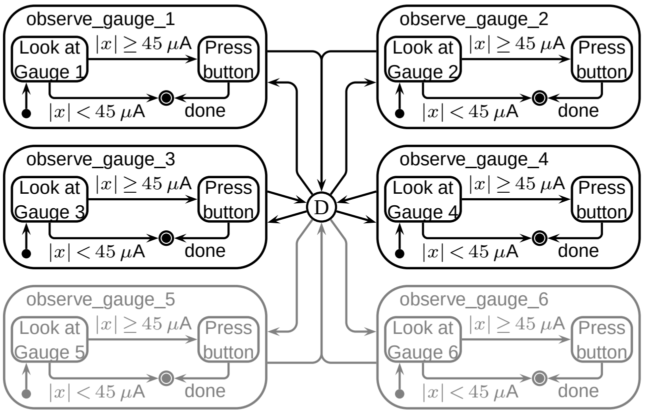

Figure 2. State diagram of the cognitive agent's task model. The states observe_gauge_5 and observe_gauge_6 are only active for C2 and C3.

IV. Cognitive Agent

Senders Task was modeled using the rule based language of CASCaS. Figure 2 shows the semantics of these rules in the form of a state chart. The overall goal is to observe all gauges. This is decomposed into one subgoal for the observation of each gauge. This results in four subgoals for C1 and six subgoals for C2 and C3. These subgoals are represented in Figure 2 by the top-level states. The task that is executed to achieve each goal is depicted within the top-level states by the process steps that have been mentioned in Section II-B. At the beginning of the task processing the agent executes a percept rule, which instructs CASCaS to look at the information source that provides information for the task. This is in this case the gauge for the specific task. If the perceived information demands a reaction of the agent a regular rule is fired. For Senders' task it happens when the signal is in the alarm region ($|x| \geq 45\,\mu$A). The response button is pressed as reaction by the execution of a regular rule. If the signal is not in the alarm region no reaction is required, the agent fires a waiting rule and the task is finished at least for the moment. In the condition that the signal is in the alarm region, the agent uses the perceived information to trigger an action by executing a regular rule. Thus these situations are the events for this task.

The AIE model comes into play at the decision point marked with a *D* in the figure. Here the agent selects which subgoal it will process next. According to the AIE model the agent will select to observe a gauge, where it highly expects an alarm, in order to detect as much alarms as possible. The expectancy coefficients u_i will be derived during the simulation. The task values v_i have to be assigned by the model developer. Because all tasks have the same priority, these coefficients have been selected to be 1 for each task. Expectancy and Value factors are weighted equally ($U = V = 1$).

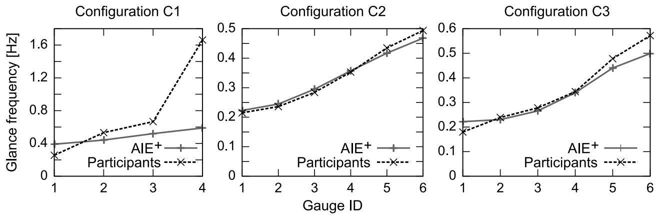

Figure 3. Glance frequencies of participants and AIE$^+$ agent for each gauge in each configuration.

V. Evaluation

To evaluate the AIE model CASCaS was connected to a simulation of the three configurations of Senders Task. The cognitive agent described in the last section was instantiated in CASCaS. CASCaS itself was connected to a simulation of the three configurations of Senders Task.

A. Additive Variant: AIE$^+$

The evaluation starts with an analysis about the model fit of the AIE$^+$ model to Senders' data. The agent was simulated 10 times for 3 h of simulation time in each of the three configurations. To avoid that the results are affected by learning effects, only the last 1 h from every 3 h simulation run was analyzed.

In [5] Senders presented the glance frequencies of the participants to each gauge. In Figure 3 this data is shown together with the glance frequencies that have been observed in the simulation of the AIE$^+$ agent. The figure shows, that the agent's behavior well matches the experimental data for C2 and C3 with very high trend correlation of $R^2 = 0.996$ for C2 and $R^2 = 0.984$ for C3. Also the absolute deviations measured by the root-mean-square error (RMSE) are small with RMSE = 0.04 Hz for C2 and RMSE = 0.09 Hz for C3. The situation is different for C1. Although the agent shows the general trend ($R^2 = 0.851$), the absolute deviation is quite high (RMSE = 1.1 Hz). Especially the overall frequency for C1 is with 3.1 Hz considerably greater than for C2 (2.0 Hz) and C3 (2.1 Hz). The cognitive agent is not able to reach the high glance frequencies in C1, because the model that is part of CASCaS and calculates the duration of saccades and fixations does not permit such small gaze durations, which are required to simulate these high gaze frequencies. For details on this model see [14]. The reason for the high frequencies in C1 compared to C2 and C3 are not known. It might be due to the additional 20 days of practice that participants had for C1, or just due to differences in the eye data processing, which was done by a frame-by-frame rating for videos of participants' eye movements.

However, Senders also calculated link values for C1. The link value probability according to ISO 15007-1:2002 describes for two information sources the relative frequency of gaze transitions between these information sources compared to all observed gaze transitions. The link values

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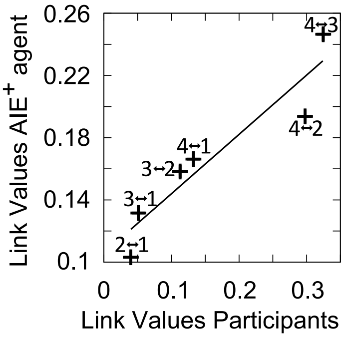

Figure 4. Correlation of link value probabilities for configuration C1. A data point i↔j represents the link value probability between gauge i and gauge j.

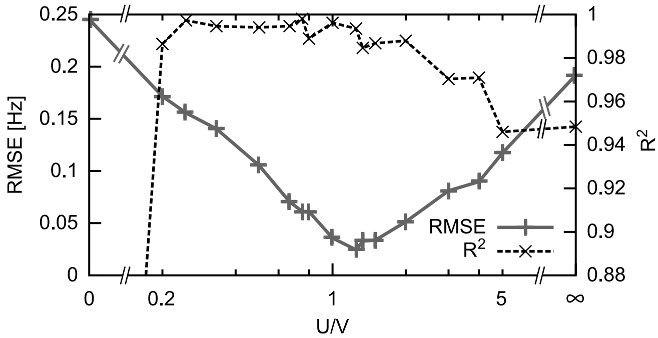

Figure 5. RMSE and R^2 values obtained from simulating the AIE$^+$ agent with different values of U/V.

obtained during the simulation of the AIE$^+$ agent correlate well with the ones observed by Senders for C1 (R^2 = 0.87) as can be seen in Figure 4.

B. Sensitivity Analysis

In equation 1 it can be seen, that there are quite a lot of coefficients that have to be determined before using the model. Compared to the SEEV model the AIE model already eliminates the need to define the expectancy coefficients u_i by expert knowledge.

But still the value coefficients v_i and the general weights U and V remain. A high number of parameters bears the danger that it allows, in principal, to fit the model predictions to any kind of data. Wickens addresses this issue by proposing the lowest ordinal algorithms to restrict the choice of coefficient for the application of the SEEV model. This approach is also proposed for the value coefficients of the AIE model. However, for the monitoring task discussed in this paper this is meaningless, because Senders did not instruct the participants to prioritize any of the gauges. Therefore the value coefficients are all equal and thus are not free parameters at least for this agent.

In applications of the SEEV model the issue of weighting the influence factors Expectancy and Value differently is typically not addressed and the factors are weighted equally. The same was done for the weights of the AIE$^+$ agent presented in the previous section ($U = V = 1$), which led to very good results for C2 and C3. Nevertheless these are free parameters, which have only the weak restriction that usually they are chosen equally. Although it seems that U and V are two parameters, it is effectively one parameter. Inserting equation 1 into equation 2 leads to:

$$P(g_i) = \frac{\frac{U}{V} \cdot \frac{u_{g_i}}{\sum\limits_{g_j \in G} u_{g_j}} + \frac{v_{g_i}}{\sum\limits_{g_j \in G} v_{g_j}}}{\frac{U}{V} + 1} \tag{3}$$

Note that this conversion is only valid for $V \neq 0$. As can be seen now U and V only occur as U/V and thus this is only one free parameter. A sensitivity analysis was conducted to estimate the effect of the relation U/V on the model fit. A set of selected relations were analyzed:

0⁄1, 1⁄5, 1⁄4, 1⁄3, 1⁄2, 2⁄3, 3⁄4, 4⁄5, 1⁄1, 5⁄4, 4⁄3, 3⁄2, 2⁄1, 3⁄1, 4⁄1, 5⁄1, ∞

For each relation 10 simulations with a duration of 3 h have been executed like described in Section V-A. The obtained RMSE and R^2 values are displayed in Figure 5. The highest correlation values have been obtained in the range from 0.2 to 2.0 with $R^2 > 0.98$, while the lowest absolute deviations have been found in the range between 1.0 and 1.5 with a RMSE < 0.04 Hz. So the popular choice of $U = V = 1$ was obviously also for this task an adequate one, although a slightly better fit has been observed with a slightly higher value of U. This is a satisfactory result. According to Pitt et al. [15] a model should be stable around a reasonable region of parameters. As an equal weighting of expectancy and value is a usual assumption, this property seems to be well met by the cognitive agent.

It should be noted that the considerations made in this section are only valid for the presented task model. For a more general view on the AIE model this work has to be repeated for a set of different task models in different application domains.

C. Multiplicative Variant: AIE*

In Section II it was mentioned, that there is no consensus about how expectancy and value are linked. In the following the simulation results are shown using the AIE* agent. In the multiplicative variant of equation 1 the weighting factors U an V are eliminated when the fraction in equation 2 is reduced. Thus there is no free parameter. Executing the simulation again in the way described in Section V-A using the AIE* formulation produces the glance frequencies shown in Figure 6.

It can be seen, that the model fit is worse than for the AIE$^+$ agent. The differences are clearly visible for C2 and C3 for which the AIE$^+$ agent showed a very good model fit. Here the AIE* agent especially underestimates the frequencies to the gauges with low signal bandwidths.

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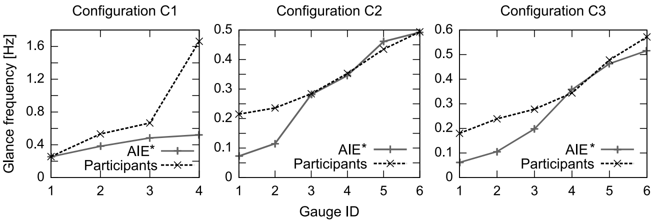


Figure 6. Glance frequencies of participants and AIE* agent for each gauge in each configuration.

Giving the data a closer look reveals that the obtained frequencies are almost identical to the frequencies of the AIE$^+$ agent using weights $U = 1$ and $V = 0$. And both models are in fact identical. The value coefficients of the AIE* model disappear when reducing equation 2, because they are all equal. This is equivalent to disabling the value factors in the AIE$^+$ model ($V = 0$).

D. Learning Convergence

In Section II-B it was assumed that the learning speed should be bound by $\mathcal{O}(t^{-\frac{1}{2}})$ if feedback effects can be neglected. To investigate this the same agent as in Section V-A was used. But now 20 simulation for C2, each with a duration of 9 h were made. Every 5 minutes the event functions of all 20 simulations were pairwise compared using the difference measure V from Kuiper's test, which describes the similarity of two frequency distributions u_1 and u_2. The symbol V^k is used to avoid a mix-up with the weight of the value factors. According to [16] V^k is calculated by:

$$V^k = \max_{0<\Delta t<\infty}(u_1(\Delta t) - u_2(\Delta t)) + \max_{0<\Delta t<\infty}(u_2(\Delta t) - u_1(\Delta t)) \quad (4)$$

This resulted in 190 comparisons every 5 minutes. It was expected that the event functions are getting more and more similar over time and thus the average V^k should converge

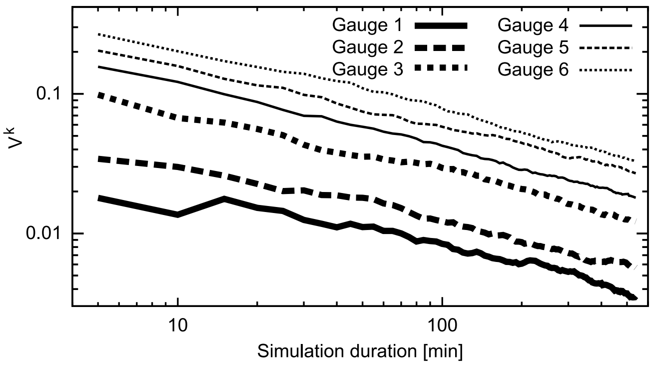
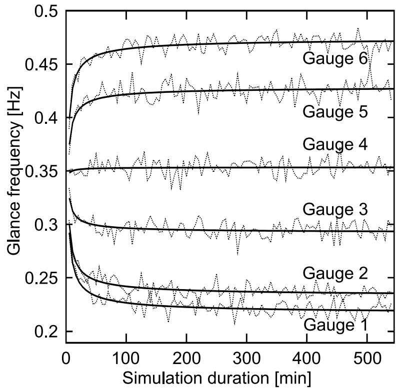


Figure 7. Convergence of event functions. Differences between event functions of different simulation runs measured by V^k are displayed on a log-log plot and asymptotically approach 0.



Gauge	a	c
1	-0.082	0.216
2	-0.072	0.233
3	-0.035	0.292
4	0.006	0.354
5	0.058	0.429
6	0.081	0.475
b	0.682	

Figure 8. Learning effect on glance frequencies. Frequencies over time are fitted to functions of the form $a \cdot t^b + c$. Fitted parameters are listed on the right side.

towards 0. The average V^k values are plotted on a log-log graph in Figure 7. It can be seen, that these values form straight lines for the event functions of each task. This strongly supports the initial assumption, that the learning speed can be expressed by a function of the form $a \cdot t^b$. It also supports the assumption that the event functions always converge against the same function.

In the same way the consequences of the learning process on the glance frequencies of the cognitive agent were analyzed. It turned out, that these reflect the learning process. They develop according to functions of the form $a \cdot t^b + c$. This knowledge now allows to fit the simulation data to such functions, and to estimate their asymptotical value. In Figure 8 this can be seen for C2. In the left graph the average glance frequencies are plotted over time by dotted lines. With solid lines functions of the form $a \cdot t^b + c$ are plotted that were fitted to the data using the method of least squares. In the table on the right side the fitted coefficient are listed. The c-coefficient is the estimation of the asymptotical glance frequency value. This graph helps to identify how much simulation time should be dedicated to learning the event distance distributions. For the AIE$^+$ agent a learning phase of at least 30-50 minutes should be used. After this time there is only little change in the glance frequencies.

The same analysis was conducted for the AIE* agent. It required a much longer learning time. The parameter b that determines the learning speed for the glance frequencies is for the AIE* agent only at $b = 0.432$.

VI. Conclusion and Future Work

The AIE model supports the simulation of task models within the cognitive architecture CASCaS, by providing a model of attention control. It was shown how the AIE model automatically derives expectancy for information events and uses this to guide its attention. A good model fit was achieved between the agents glance frequencies and results taken from studies conducted by Senders [5]. The issue of combining the Expectancy and Value factors additively or multiplicatively was addressed by evaluating both variants. The additive variant provided a better model fit. A sensitivity analysis for the free parameter revealed that the agents behavior is stable within a reasonable parameter region. It was analyzed how fast the agent is able to recognize the distribution of events. The hypothesized speed function $a \cdot t^b$ was successfully fitted against the observed simulation data.

The AIE model is strongly related to the SEEV model and extends it in some ways. However, it is more an alternative for the SEEV model than a replacement. The SEEV model provides a simple and fast way to estimate the distribution of attention. But its static way of application does not provide a detailed insight in the situation under investigation. This is provided by the AIE model, as it is integrated in a cognitive architecture as basic simulation framework. The AIE model additionally benefits from the simulation, because it dynamically derives expectancy values during simulation, which in contrast has to be done by human factors experts for the SEEV model. Thus from an application point of view the AIE model trades off simplicity for richness of detail.

It should although be noted, that the results presented in this paper are only valid for the investigated monitoring task and the transferability as well as scalability remains to be investigated. There are some aspects that reduce the representativeness of the study. Senders did not manipulate the information value for the gauges. Thus changes in the value coefficients are not addressed. However the expectancy coefficients are the main focus of the AIE model. In addition, the participants did not influence the displayed signals, which is unrealistic for most human-machine systems. This application served as a first evaluation step for the model. More and richer applications are required to ground the findings of this study. A subsequent step to this study is the application of the AIE model to a cognitive car driver model. In the long term, this work shall lead to a general evaluation method for human machine interaction that is based on virtual human-in-the-loop simulation.

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