Neurologically Inspired Computational Cognitive Modelling of Situation Awareness

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Abstract. How information processes in the human brain relate to action formation is an interesting research question and with the latest development of brain imaging and recording techniques more and more interesting insights have been uncovered. In this paper a cognitive model is scrutinized which is based on cognitive, affective, and behavioural science evidences for situation awareness. Situation awareness has been recognized as an important phenomenon in almost all domains where safety is of highest importance and complex decision making is inevitable. This paper discusses analysis, modelling and simulation of three scenarios in the aviation domain where poor situation awareness plays a main role, and which have been explained by Endsley according to her three level situation awareness model. The computational model presented in this paper is driven by the interplay between bottom-up and top-down processes in action formation together with processes and states such as: perception, attention, intention, desires, feeling, action preparation, ownership, and communication. This type of cognitively and neurologically inspired computational models provide new directions for the artificial intelligence community to develop systems that are more aligning with realistic human mental processes and for designers of interfaces of complex systems.

Keywords: Situation Awareness, Perception, Attention, Intention, Bottom-Up, Top-Down, Cognitive Modelling and Simulation.

1 Introduction

Situation Awareness (SA) describes the subjective quality of awareness of a situation a person is engaged in. The construct of SA is a nontrivial challenge mainly because of poor understanding in the scientific area of human cognition and the associated complexity in practical areas where SA is relevant, for example: aviation, air traffic control, maintenance, healthcare, intelligence, power systems, transportation, etc. The latest findings from brain imaging and recording techniques in the last decade provide the opportunity to uplift the understanding of cognitive processes in the human brain and more specifically the interplay among those for action selection. It seems that most of the basic actions are pre-stored as habitual tasks through the effects of prior

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learning, and will activate unconsciously when a relevant stimulus is perceived [1]. Nevertheless, it is an innate ability of human beings to control in a conscious manner habitual actions adhering to a situation and/or to react in novel situations where no prior learning or experience exists. Conscious action formation turns out to be complicated; especially the complex interplay among bottom-up and top-down processes behind it has to be addressed to provide more insight in action selection [2–5]. Furthermore, there are various viewpoints about conscious awareness and it seems from the latest findings that we develop awareness of action selection related to a situation just before the action execution, and it may be the case that this awareness has a decisive effect on actually executing the action, but it may equally well be the case that the awareness state has no effect on whether the action is performed (cf. [2, 6, 7]). Therefore, from the current evidences from cognitive, affective, and behavioural sciences, the process behind SA in parallel to action formation can be reformed together with considering the factors explained in well known past SA models.

With the lessons learned from tragic events that have occurred in the aviation domain, more attention has been given to the importance of SA in the aviation domain (cf. [8, 9]). There are more than fifteen definitions for SA in the literature [10], and still it is debate over what SA actually is, what it comprises, what factors impact it. Mica R. Endsley in [11] put forward a working definition which became the most widely used definition among many researches. According to Endsley, SA is:

> "*the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*" ([12], pp. 36).

Based on this definition Endsley highlighted three elements 1) perception, 2) comprehension, and 3) projection, as the necessary conditions for SA which are three levels of which one is followed by the other to develop complete (subjective) awareness. Furthermore, it has been found that based on the safety reports in the aviation domain for the period of 1986 to 1992, 76% of errors related to SA were because of Level 1 (i.e., failure to correctly perceive information), 20.3% were Level 2 (i.e., failure to comprehend the situation), and 3.4% were Level 3 (i.e., failure to project situation into future) [8, 9]. Therefore, this statistical information provides an indication of the importance of those three factors on SA. Furthermore, Endsley has indicated how attention, goals, expectations, mental models, long-term memory, working memory and automaticity contribute to situation assessment as cognitive processes [12, 13]. To get a more detailed picture of such interplay, in this paper both the insights derived from Endsley's SA model and the latest neurocognitive findings have been utilized and brought together.

Research like this may have benefits especially for the artificial intelligence community to consider more natural computational models for complex systems where emergent behaviours need to be analyzed and simulated. Furthermore, through such simulations, system (or interface) designers can validate the quality of their designs and may come up with fine-tuned designs which are guaranteed with better action selection minimizing data related errors. Below, in Section 2 introduces the SA model by Endsley. Section 3 explains the proposed neurologically inspired cognitive model mainly by adapting the work in [14], and three simulation experiments are discussed in Section 4. Finally concludes the paper with a discussion.

2 Situation Awareness by Endsley

System automation has been rapidly improved, and has facilitated more robust systems. Therefore, obtaining information is not difficult though finding the relevant and most important information is more challenging due to information overloading [13]. Developing operator interfaces, automation concepts and training programs are important areas where theoretical SA models can contribute to minimize human errors in complex systems [12, 13]. As mentioned in the previous section, Endsley's model with three levels of SA has obtained the highest attention (though some are not fully accepting this definition (e.g., [15])). According to Endsley, Level 1 is the first step to achieve the SA which concerns to perceiving status, attributes, and dynamics of relevant elements in the environment [12, 13, 15]. It is the most important factor for better SA and having a wrong perception always ends up with poor SA. As reasons to have poor Level 1 SA are indicated: data not available, data hard to detect, failure to monitor/observe data, misperception of data, and memory loss [8, 9]. Level 2 takes the awareness beyond being sensitive to the perceptual information but to develop the understanding by binding the relevant perceptual information to ones goals through comprehension [12]. Incomplete or incorrect mental models and over-reliance on default values have been identified as reason for poor Level 2 SA [8, 9]. Level 3 further extends the awareness so that it will obtain the ability to project the future actions [12]. According to Endsley each higher level of SA depends on the success of the lower level [12, 13]. Incomplete/poor mental models and over-projection of current trends have been noted as the main reasons behind poor Level 3 SA [8, 9]. More descriptive information about each level with examples from the aviation domain can be found in [16]. Furthermore, this model includes more mechanisms behind information processing (based on information processing theory in [17]) that includes attention, goals, expectations, mental models, long-term memory, working memory and automaticity for situation assessment (cf. [13]). According to Endsley's view SA and situation assessment are different: product and process respectively [13]. The summary from Endsley in [12], p. 49 provides some useful indications of how this model can be related with neurocognitive literature (in Section 3):

3 Description of the Computational Model

This section presents a computational cognitive model for SA based on the latest findings and evidence from cognitive, affective, and behavioural sciences. The underlying research evidence behind this model has been separately explained in [14]; there also the role of cognitive control in action formation is illustrated in more detail. Therefore, here only a condensed summary will be provided as a theoretical basis.

3.1 Overview of the Model

Fig. 1 below highlights the adapted cognitive model for SA from [14] and in Table 1 listed abbreviations for the state labels in it. The model uses two world states WS(s) and WS(b) as inputs, for stimulus s and effect b. The stimulus s represents any external (or even internal) change that may lead to an action execution. To reduce the complexity of computations in this model it is assumed to be that stimulus s is a compound input (alternatively it is possible to use s as a vector s_k, k = 1, 2, … where k inputs are taken in parallel).

The effect b_i represents the effects of the execution of an action a_i. The input world states WS(s), and WS(b) lead to sensor states SS(s), and SS(b), and subsequently to sensory representation states SR(s), and SR(b), respectively. This model includes the aspects of both conscious (through a top-down process: internally guided based on prior knowledge, intentions, and long-term desires [5, 18]) and unconscious (through a bottom-up process: mainly driven by salient features of external stimuli [18]) processes behind action formation. Automaticity concerns the unconscious behaviour according to Endsley [13]. The unconscious process of action formation has been modelled in here in a causal manner by combining an as-if body loop (see Damasio [19]) and a body loop (see James [20]); for more details see [14]. According to

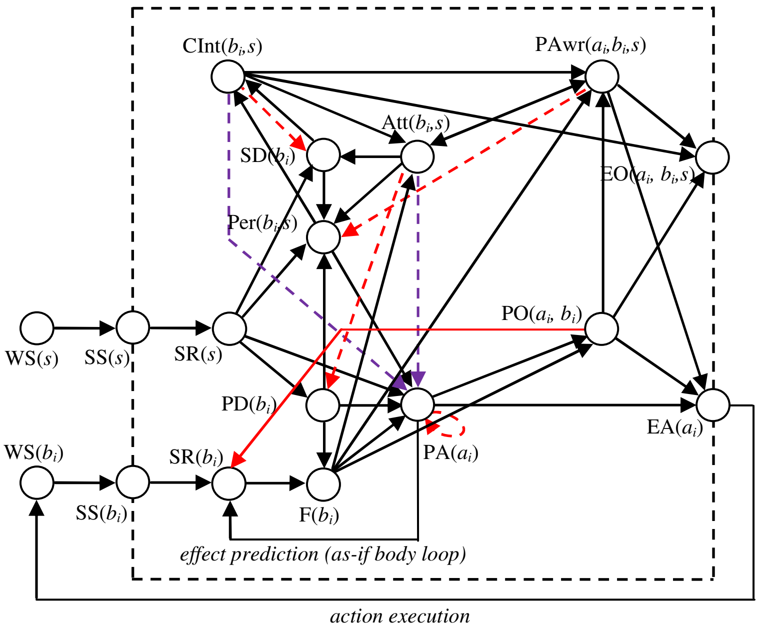

Fig. 1. Overview of the computational cognitive agent model. The arrow ➜ represent a direct activation to state B from state A, arrow ➜ represent a direct suppression to state B from state A, arrow ⇢ represent a suppression to all the complements of 'ith' state on B_i from state A_i (where 'i' presents an instance of a perticuler state), and ⇢ represent a direct activation to state B_i from state A_i while supressing all the complements of 'ith' state on B_i from state A_i.

Table 1. Nomenclature for Fig. 1

WS(W)	world state W (W can be either stimulus *s*, or effect *b*)	PAwr(*a,b,s*)	prior-awareness state for action *a* with *b* and *s*
SS(W)	sensor state for W	Att(*b,s*)	attention state for *s* on *b*
SR(W)	sensory representation of W	CInt(*b,s*)	conscious intention state for *s* on *b*
PD(*b*)	performative desires for *b*	EA(*a*)	execution of action *a*
SD(*b*)	subjective desires for *b*	Per(*s,b*)	perception state for *s* on *b*
PA(*a*)	preparation for action *a*	F(*b*)	feeling for action *a* and its effects *b*
PO(*a,b*)	prior ownership state for action *a* with *b*	EO(*a,b,s*)	communication of ownership of *a* with *b* and *s*

Damasio the cognitive process of action selection is based on an internal simulation process prior to the execution of an action. Effects of each relevant action option PA(a_i) (a stimulus *s* will have many options i=1..n) are evaluated (without actually executing them) by comparing the feeling-related valuations associated to their individual effects. Each option on PA(a_i) suppresses its complementary options on a_i for all PA(a_j) with j≠i (see Fig. 1), and therefore by a kind of winner takes it all principle naturally the option that has the highest valuated effect felt will execute through the body loop (for more details see [14]).

- as-if body loop: PA(a_i) → SR(b_i) → F(b_i)
- body loop: PA(a_i) → EA(a_i) → WS(b_i) → SS(b_i) → SR(b_i) → F(b_i)

In parallel to action preparation prior ownership (in how far does a person attribute an action to him or herself or to another person) of the action will be developed, as explained in [21]. Ownership and performative desires states also relate to the unconscious processes (for more details see [14]). PD(*b*) facilitates short-term desire effects on action execution. Furthermore, in this model Per(b_i,*s*) gets a direct effect from the stimulus *s* and therefore it will enable to develop bottom-up perception which further leads to strengthen action preparation (see Fig. 1) [22]. This phenomenon is particularly useful in a fight-or-flight situation. Therefore a suddenly developed very strong perception (due to salient features in a stimulus) may execute an action without enabling top-down control (cf. [14]).

In this model action formation is initiated through the as-if body loop and because of the limited capacity of the human brain to process all action options, bottom-up attention will play its role as described in [18] (see [14]). Due to this bottom-up attention, higher-order cognitive processes will enable and start to control current action formation. Here an important role is played by the internally activated subjective intentions on cognitive content [18, 23, 24]. This is in line with the idea of transforming Level 1 SA to Level 2 SA in Endsley's model in terms of a process. The prefrontal cortex (PFC) has a higher-order connectivity with other cortical and subcortical areas and therefore, when sensory inputs need more attention in top-down driven controlling, it plays a role of integrator [25, 26]. Furthermore, brain circuits related to cognitive control seem to consist of loops rather than linear chains (cf. [4]) and this can be clearly seen from the associations among states in Fig. 1. Posterior parietal cortex

(PPC) and PFC seem to be playing unique roles in bottom-up and top-down attentional systems respectively and a close interaction among these two has been observed when orienting the attention [18]. This explains the possible interplays among these two and how such an interaction will contribute to sophisticated cognitive control with suppression mechanisms (for more details see [14]). In Fig. 1 to model bottom-up attention an effect from F(*b*) to Att(*b,s*) is provided, and then top-down attention modulates PA(a_i) (i.e., increasing the activation of option a_i while suppressing all its complementary options PA(a_j) for all j≠i). This leads to a cyclic dependency and eventually with the other states (SD(*b*), CInt(*b,s*) and Per(*b,s*)) this will select an option from the competing set through a cognitive bias.

In literature intentional actions are related to a brain network that involves SMA proper and pre-SMA and further an increase of activation of pre-SMA has been observed when participants attend to their intention [4, 27]. Therefore, attention to intention has been hypothesized as one mechanism for control of actions and this has been modelled through a loop: Att(*b,s*), SD(*b*) and CInt(*b,s*). Subjective desires (or constitutive desires) SD(*b*) is essential in top-down control to facilitate alternative interpretations (or even to further extend the meaning) on performative desires [3].

Awareness is one of the challenging phenomena in human cognition, and as highlighted in the introduction there are various viewpoints related to this. Based on many evidences it is assumed to be that we develop awareness of action selection related to a situation just before the action execution [2, 6, 7]. Nevertheless, Moore and Haggard have highlighted that this awareness may have a decisive effect on actually executing the action [2] (therefore in Fig. 1 there is a direct relation between EA(*a*) and PAwr(*a,b,s*)). More importantly, the cognitive processes behind this development of awareness are important, which is why they have been given more weight in this model. Therefore, based on such recent research finding the choice was made to let the model deviate from the traditional idea of first developing a proper awareness before getting to decision making (as highlighted, for example, by Endsley). With this difference and by having cyclic loops, the model proposed here deviates from what Endsley proposed, and more attention has been given to the action selection as a wider process covering decision making. Furthermore, Moore and Haggard have highlighted the interplay between prior and retrospective (relative to action execution) awareness of action [2], but for the simplicity of this model retrospective awareness was not included. Finally through EO(*a,b,s*) the agent can communicate its information to the outside. In addition to the highlighted relations among states all the remaining dependencies (including suppression processes) have been explained in more detail in [14].

3.2 Dynamics of the Model

The computational model was mathematically compiled as proposed in [28] to simulate situations. Each connection between states have been given a weight value (ω_{ji}: weight of state j to i) that varies between +1 and -1. Weight values are non negative in general, except if it is a suppressive (or inhibiting) link (see Fig. 1 caption). To model the dynamics following the connections between the states as temporal–causal relations, a dynamical systems perspective is used as explained in [28]. Therefore, each state includes an additional parameter called speed factor γ_i, indicating the speed by which an activation level is updated upon received input from other states to the state 'i'. Two different speed factor values are used as fast and slow: fast value is for internal states and slow value is for external states (i.e., for WS(*W*), SS(*W*), EA(*a*), and EO(*a,b,s*)). Activation of a state is depending on multiple other states that are directly attached to it. Therefore incoming activation levels from other states are combined to some aggregated input and affect the activation level according to a differential equation as in (1). As the combination function for each state a continuous logistic threshold function is used as in equation (2), where σ is the steepness, and τ the threshold value. When the aggregated input is negative, (3) is used. To achieve the temporal behaviour of each state as a dynamical system, a difference equation is used in the form of equation (4) (where Δt is the time step size). More details about the dynamics of the model can be found in [14].

$$\frac{dy_i}{dt} = \gamma_i\left[f\left(\textstyle\sum_{j\in s(i)} \omega_{ji} y_j\right) - y_i\right] \tag{1}$$

$$f(X) = th(\sigma,\tau,X) = \left(\frac{1}{1+e^{-\sigma(X-\tau)}} - \frac{1}{1+e^{\sigma\tau}}\right)(1+e^{\sigma\tau})\ when\ X > 0 \tag{2}$$

$$f(x) = 0\ when\ X \leq 0 \tag{3}$$

$$y_i(t+\Delta t) = y_i(t) + \gamma_i\left[th\left(\sigma,\tau,\textstyle\sum_{j\in s(i)} \omega_{ji} y_j\right) - y_i(t)\right]\Delta t \tag{4}$$

4 Analysis of SA on the Proposed Model Based on Simulations

In this section by simulations it will be explained how situation awareness related incidents can be explained through this proposed model. For this, three situations were selected from the document 'Enhancing Situational Awareness[1]' in 'Flight Operations Briefing Notes' from the Airbus Company. They have provided 3 generic examples for each of the three levels of the SA described by Endsley:

- For Level 1 SA: '*Focusing on recapturing the LOC and not monitoring the G/S*'
- For Level 2 SA: '*Applying a fuel imbalance procedure without realizing it is an engine fuel leak*'
- For Level 3 SA: '*Expecting an approach on a particular runway after having received ATIS information and being surprised to be vectored for another runway*'

These three generic examples were modelled as an implementation in Java, based on the mathematical basis explained in the previous section. For each scenario, three different sets of input data were used in XML format with dedicated parameter values. All the input information and parameter values (step size (Δt), speed factor (γ), total time slots, steepness (σ), threshold (τ), and weight values) for each state can be found in an external appendix[2].

[1] http://www.airbus.com/fileadmin/media_gallery/files/safety_library_items/AirbusSafetyLib_-FLT_OPS-HUM_PER-SEQ06.pdf

[2] http://www.few.vu.nl/~dte220/BIH14Appendix.pdf

4.1 Simulation for a Level 1 SA Example Incident

The reason behind this example incident is poor SA due to a failure to monitor/observe data, as highlighted in Section 2. A pilot has observed only one device (LOC) though he/she was supposed to take into consideration data from two devices (LOC and G/S). Due to these missing data, the pilot has developed a strong perception related to action selection only based on LOC, while his perception should have been for action selection in line with the integrated reading of LOC and G/S. Due to this incomplete input the appropriate perception was unable to develop and as a consequence of that the pilot has not developed the 'right' situation awareness, but instead of an awareness based on incomplete situation information. For the sake of simplicity of the simulation it is assumed that the current stimulus includes salient features of the LOC device but not strong data from the G/S device. From that stimulus agent will prepare for two action options PA(a_1) and PA(a_2) where action a_1 is based on information from the device LOC and action a_2 is based on information from both devices. Fig. 2 provides simulation results for this scenario; more enlarged graphics can be found (for all simulations) in the previously mentioned external appendix. It can be clearly seen from these that from the given input stimulus the agent has obtained sufficiently large effects on SR(s_i) and PD(b_i) for both options (i.e. for i={1,2}). Nevertheless, it clearly shows that the agent has developed very strong PA(a_1) (with a max of 0.86) and Per(b_1,s) (with a max of 0.86). For action option a_2 it has a relatively weak Per(b_2,s) (max of 0.25) that contributes to develop a poor PA(a_2) (max of 0.17). Therefore, merely through this effect of incomplete perception (as Endsley highlighted) the agent has not developed the right situation awareness (in this case it would have been PAwr(a_2,b_2,s)) but the situation awareness PAwr(a_1,b_1,s) (max of 0.74) based on wrong perception; note that SA is a subjective term and always the agent will develop an awareness and the argument is whether that's the right

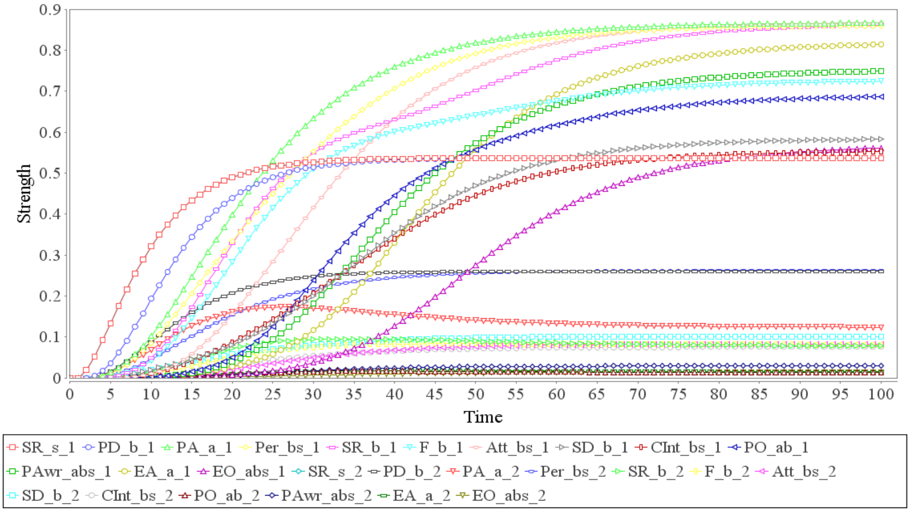

Fig. 2. Simulation details for Level 1 SA example

awareness for that situation. Subsequently the agent has shown sufficient strengths for all the other states related with option a_1, and finally has executed the action EA(a_1) (max of 0.81) with a PAwr(a_1,b_1,s) of max 0.74.

4.2 Simulation for a Level 2 SA Example Incident

In this situation the problem is with the Level 2 SA and according to the incident the reason may be due to an incorrect mental model. In this situation the pilot has observed all the necessary data with a correct and complete perception, and noted a problem with fuel usage. Nevertheless, the pilot was unable to realize that the reason was a fuel leak in the engine, and therefore he has decided to follow fuel imbalance procedure, whereas the recommendation is not to apply fuel imbalance procedure if fuel leak is suspected [29]. Fig. 3 provides the simulation information for this scenario. Here for the given stimulus the agent will internally prepare for two action options: a_1 is to execute the fuel imbalance procedure and a_2 is to deal with a fuel leak in the engine. For this simulation all the states involve identical parameter values for the action options 1 & 2 separately, except for SD(b_i) and CInt(b_i,s). This shows the impact of subjective desires and intention of top-down control on other states. The agent starts action formation with the input stimulus that triggers two action options as mentioned. At the beginning it clearly shows that the rate of activation for Per(b_1,s) and Per(b_2,s) are almost the same (similarly the other pairs: PA(a_i), SR(b_i), and F(b_i)), but the development of SD(b_1) and CInt(b_1,s), the rates of increase related to action option a_2 have been significantly declined. The states SD(b_2) and CInt(b_2,s) have not been activated with sufficient strength (which was assumed to be the relevant mental model to interpret the situation as an engine fuel leak) and therefore the state Att(b_1,s) has increased rapidly (with a max of 0.85) due to the cyclic dependency highlighted among SD(b_1), CInt(b_1,s) and Att(b_1,s). Therefore, naturally the agent has been led to

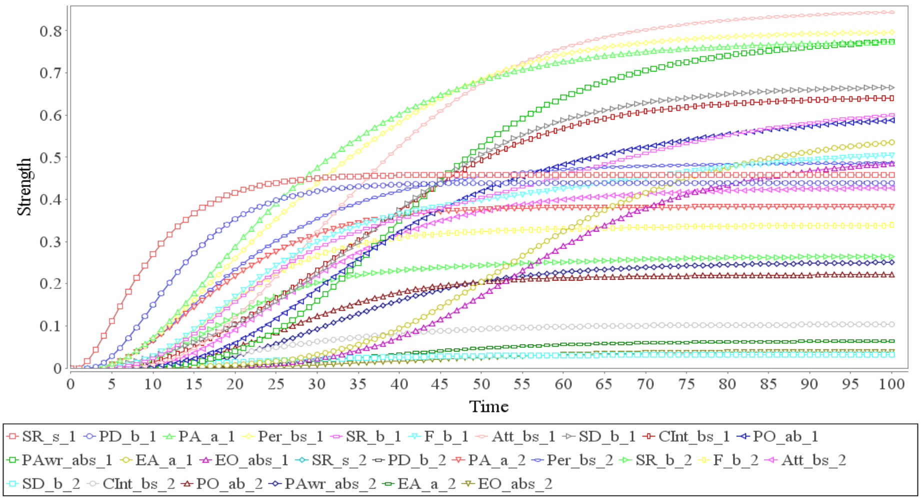

Fig. 3. Simulation details for Level 2 SA example

select option a_1: s/he developed a strong prior awareness PAwr(a_1,b_1,s) (with a max of 0.77) and has executed option a_1 (i.e., EA(a_1)) with a maximum activation value of 0.54. Having the same parameter values for each state on the respective action options but only different values for each option on SD(b_i), CInt(b_i,s) has sufficiently explained the behavior of SA in Level 2: inability of binding the perceptual information relevance to the subjective goals through comprehension.

4.3 Simulation for a Level 3 SA Example Incident

In this scenario a pilot was expecting an approach on a particular runway (let's say R14) and while he is preparing for that he gets an instruction from the air traffic controller (ATC) to be vectored for a different runway (let's say R35). Here it is assumed that landing on R14 is the most common action and therefore without getting a direct request from ATC the pilot was preparing for the habitual task. Due to this new ATC instruction now the pilot may be unable to immediately adjust for this new situation as he may have not loaded the necessary mental model to execute the new instruction. This may go together with the effect of 'over-projection of current trends' as mentioned in Section 2 as one of the possible reasons behind poor Level 3 SA. Therefore, it is assumed here that due to this over-projection of current trends, the pilot is unable to immediately project the necessary future actions. Therefore first s/he needs to internally suppress current action execution and needs to get ready for the relevant action choice for the new ATC instruction. Simulated behaviour of this situation is presented in Fig. 4. Two stimuli were used for this scenario but they occur at different time points: one at time t=0 and the other one at time t=100. More specifically, it has been assumed that at t=100 the agent is getting the ATC instruction and by that time the agent was already performing an action with the intention of approaching to R14 (labelled as action option a_1, whereas the new action after t=100 is labelled as a_2). From Fig. 4 it shows that the agent has initiated action formation for option a_1 and has

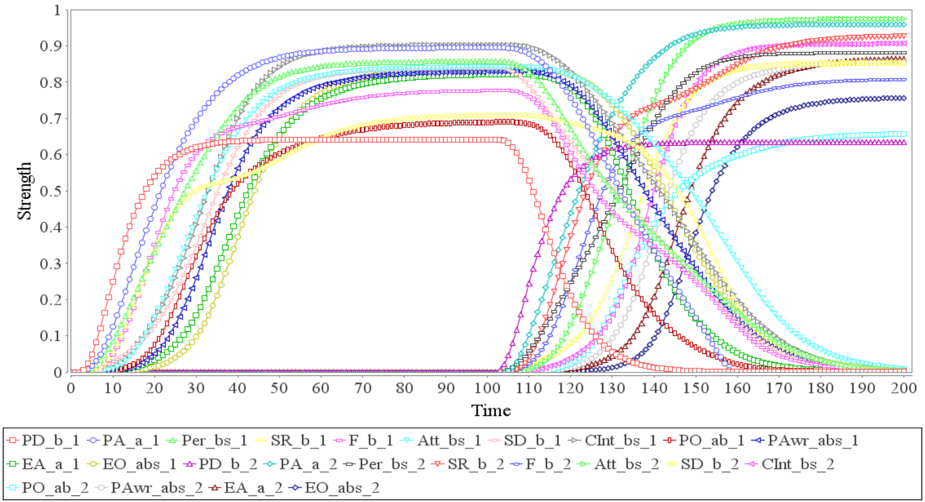

Fig. 4. Simulation details for Level 3 SA example

developed sufficiently high activation of PD(b_1) (max of 0.64), PA(a_1) (max of 0.89), Per(b_1,s) (max of 0.85), SR(b_1) (max of 0.70), F(b_1) (max of 0.77), Att(b_1,s) (max of 0.84), SD(b_1) (max of 0.82), CInt(b_1,s) (max of 0.90), PO(a_1,b_1) (max of 0.68), PAwr(a_1,b_1,s) (max of 0.82), EA(a_1) (max of 0.81), and EO(a_1,b_1,s) (max of 0.82) (in the order mentioned here). Nevertheless, having a new instruction at t=100, the agent has started to suspend its current action and enabling the relevant states to execute option a_2. Related to option a_2, the respective states have obtained slightly higher activation values in the same order as for option a_1. Furthermore, it can be clearly observed that to fully execute action a_1, the agent has taken roughly 60 time intervals but for a_2 to be fully activated it has taken more than 80 time intervals (due to the mental overload: to suppress the current action and to form the new action selection).

5 Discussion

This paper has presented a neurologically inspired cognitive model (which was adapted from [14]) and has provided simulation results for 3 incident examples where poor SA was expected as put forward by Endsley. The obtained results explain the different scenarios. The model has been designed according to the latest neurocognitive evidence, and therefore it deviates a bit from the somewhat linear model that Endsley proposed originally. More specifically, this research shows how models that were designed according to the earlier cognitive science tradition and often assume linear causal cascades from sensory input to behavioural output, can be refined and enriched by incorporating more recent evidence on actual brain processes in which cyclic processes play a major role. Such model refinement often leads to dynamic systems style models with cyclic causal cascades instead of linear ones, as is clearly shown here (see also [28]). This work can be further extended to explain more specific scenarios in the aviation domain and also to other areas that are applicable.

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