A Neurologically Inspired Model of the Dynamics of Situation Awareness Under Biased Perception

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Abstract. This paper presents a computational cognitive agent model of Situation Awareness (SA), which is inspired by neurocognitive evidences. The model integrates bottom-up and top-down cognitive processes, related to various cognitive states: perception, desires, attention, intention, awareness, ownership, feeling, and communication. The emphasis is on explaining the cognitive basis for biased perception in SA, which is considered to be the most frequent factor in poor SA (the reason for 76% of poor SA errors), through perceptual load. A model like this will be useful in applications which relay on complex simulations (e.g. aviation domain) that need computational agents to represent human action selection together with cognitive details. The validity of the model is illustrated based on simulations for the aviation domain, focusing on a particular situation where an agent has biased perception.

Keywords: Situation awareness · Perceptual load · Perception · Attention · Intention · Bottom-up · Top-down · Cognitive modeling · Simulation

1 Introduction

The relation between human awareness and action selection is a complex issue. Nevertheless; due to the developments in brain imaging and recording techniques, the insight in human brain processes is growing rapidly. Human cognitive processes are often grouped into conscious and unconscious processes. The understanding of the interplay between conscious and unconscious processes associated with action selection and related phenomena has improved a lot, especially thanks to the experimental framework proposed by Benjamin Libet and his colleagues [1] and later improvements made to it. In the literature, bottom-up cognitive processes have been mapped to unconscious action formation, whereas top-down processes have been related to conscious action formation (cf. [2]–[5]); it seems our action selection process initiates from unconscious phenomena, and that later we develop the conscious experience of this action selection. The unconscious neural activations in the brain seem to be a result of habitual tasks, through the effects of prior learning, which can be automatically activated when a relevant stimulus is perceived [6]. Nevertheless, conscious awareness of action selection also plays an important role (cf. [2]).

M. Ali et al. (Eds.): IEA/AIE 2015, LNAI 9101, pp. 84–94, 2015.
DOI: 10.1007/978-3-319-19066-2_9

Situation Awareness (SA) can be considered as a subjective quality or interpretation of the awareness of a situation a person is engaged in. When a person is engaged in a situation based on the information that he/she perceives, the attention that is allocated to that information based on his/her subjective desires will develop his/her subjective awareness of the situation. This is the reason why different individuals may have different interpretations of the same situation. The correctness of SA is always relative and its quality can be analyzed when a task is performed with an expert critiquing as a benchmark. Due to this complexity and subjective nature of SA, the concept has received many definitions in the literature (according to [7] there are more than fifteen definitions for SA); among those, the definition proposed by Endsley [8] became the most widely used. 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*" [9, p. 36]

Based on this definition, Endsley highlighted three elements as the necessary conditions for SA; these are three levels of which one is followed by the other, in order to develop complete (subjective) awareness namely: Level 1: perception, Level 2: comprehension, and Level 3: projection. Furthermore, it has been found that, based on safety reports in the aviation domain, 76% of the errors related to SA were because of Level 1 (i.e., failure to correctly perceive information), 20.3% were Level 2 errors (i.e., failure to comprehend the situation), and 3.4% were Level 3 errors (i.e., failure to project situation into future) [10], [11]. Hence, this statistical information provides an indication of the relative importance of these three aspects of SA. Therefore, the biased or poor perception addressed by Level 1 has received most attention, due to its high frequency among all errors (cf. [10]). Furthermore, Endsley has indicated how attention, goals, expectations, mental models, long-term memory, working memory and automaticity contribute to situation assessment in terms of cognitive processes [9], [12]. The summary from Endsley in [9] provides some useful indications of how this definition (through her model) can be related to the neurocognitive literature.

Though there is a positive analogy between Endsley's model and its psychological basis, from a dynamic perspective the model leaves room for questions. In particular, she highlights that a person will first develop situation awareness, only then decision making will follow, and that finally the selected actions will be performed:

Environment → Situation Awareness < *Perception* → *Interpretation* → *Projection* > → Decision Making → Performance

Nevertheless, this particular linear transformation is not supported by the current viewpoints in neuroscience; instead, situation awareness, decision making, and performance of selected actions are viewed as one compound process in which all subprocesses dynamically interact, striving for actions with an optimal result. Endsley has explicitly separated situation awareness from the process itself, which she calls situation assessment [12] (in her terms, SA is a product and situation assessment is the process to make decisions which follow up on the developed SA). Having this fundamental concern, there is a necessity of better explaining SA in terms of current evidence from a cognitive science perspective, in such a way that the explanations can be used in relevant application domains (such as the aviation domain), for instance by simulating complex situations in a more realistic and detailed manner (cf. [13]).

2 Neurological Background

Cognitive processes of action formation are complicated and on the exact mechanisms involved have not been fully unraveled yet. Nevertheless, due to the developments in brain imaging and recording techniques, researchers are gaining more and more insight in human cognition. According to those insights, human action selection is for a main part determined by automatic unconscious processes such as habitual tasks (a task will become a habitual task through a learning process, depending on its frequency and recency (cf. [6])). Nevertheless, stimuli received from the environment contain far more information than a person can process in a given time. To cope with this, it seems that two main processes play a role, namely bottom-up and top-down control. Processes related to bottom-up effects are more automatic and are mainly data driven, triggered by factors external to the agent (humans are also agents (see [14])) such as salient features of a stimulus [15]. Top-down effects are internally guided based on prior knowledge, intentions, and long-term desires and they are internal to the observer and unrelated to the salient features of a stimulus [5], [15], [16], [17].

When investigating the brain circuits related to human cognition, it seems that these consist of complex loops, rather than linear chains [4]; therefore, higher order coupling among processes has been observed, rather than those processes being categorically independent. Similarly, the bottom-up and top-down processes are also not isolated; instead, there is overlap among these two, even at the neural level and many pieces of evidence have been found that demonstrate the interplay among these two in the context of attention and perception, together with other supportive cognitive states [5], [15], [17]–[19]. The bottom-up processes have many relations to perception and emotions, and more details of the cognitive basis of these have been separately presented in previous work (see [20]). The amygdala was noted as a key element in bottom-up processes, which include monitoring the salient features in stimuli and projecting them onto higher levels of cognitive processing (the amygdala has connectivity with eight of the cortical areas [21]). Furthermore it has been observed that the amygdala directly shapes perception when perceiving an emotionally salient stimulus [22]. Attention is another important cognitive state that is related to the interplay among bottom-up and top-down processes: in particular through bottom-up attention and top-down attention. In [15] it has been pointed out that the posterior parietal cortex (PPC) and prefrontal cortex (PFC) could be segregated for distinct roles in bottom-up and top-down attentional systems, and the close interaction of these regions with each other is highlighted to explain the constant influence of these two processes to orient the attention necessary for more sophisticated cognitive control processes (cf. [17], [23], [24]). In addition, the prefrontal cortex has long been assumed to play an important role in top-down driven cognitive control, as a temporal integrator. The higher order interconnectivity of the PFC with other cortical and subcortical areas has been interpreted as indicating a process that generates and maintains information when sensory inputs are weak, ambiguous, rapidly changing, novel and/or multiple options exist [18], [25]. Furthermore, neurocognitive evidence for some of the main factors of top-down processes (i.e., intention, attention, subjective desires and awareness) has been presented separately in previous work [26].

In the current paper, a specific interest is given to understand reasons for poor or incorrect perception. One suitable analogy for this is the literature on distraction, which explains why and how people get distracted from their current task (under a poor 'Level 1 SA', agents are unable to switch to proper perception due to the focus developed on selected items or data in the stimulus). Once a person is focusing on something, there are many reasons why he/she may sometimes be distracted and sometimes not. This is interesting to study the question what are the causes that prevent a person from processing other important cues in the environment (as an example from [27]: people attending to a ball game have failed to notice a woman walking across the pitch and holding up an umbrella). To explain this phenomenon, the load theory of attention and cognitive control [28] provides detailed information about early versus late selection schemes. Early selection is a perceptual selection mechanism associated with automatic (or passive) behavior [29]. The main reason behind this mechanism is the limited processing capacity of our perception under a high level of perceptual load. Because of this, an agent under high perceptual load is unable to shift his or her selection to other salient features in the environment. Instead, when the perceptual load is lower, the agent is capable of perceiving information in parallel (cf. [29]–[31]). Nilli Lavie's summary on this provides a complete overview for this (see [27, pp. 143–144]). Indeed, there is empirical evidence that shows a competition effect under low perceptual load, but not with high perceptual load [31]. Therefore, when receiving new stimuli with no perceptual load, all features may be processed completely, which will lead to the development of perception on the salient features, while at the same time the perceptual load will increase. Once the perceptual load is high, the agent seems to be unable to pay attention to additional features. Moreover, perception is related to early selection, whereas cognitive controlling through attention is related to late selection (late selection is not considered in this paper).

3 Description of the Computational Model

The model in this paper is an extension of the previous work presented in [13], but extended by incorporating the idea of perceptual load, to explain the cognitive reason for poor Level 1 SA. Fig. 1 presents the cognitive model and Table 1 summarizes the abbreviations used. The model takes inputs from two world states WS(s_k) and WS(b_i), where s is a stimulus (that can be either external or internal to the agent) that may lead to an action execution, and b_i represents the effects of the execution of an action a_i. The model accepts multiple inputs in parallel. Therefore, in this model, external input is a vector s_k, where k inputs are taken in parallel. The input WS(s_k) leads to a SS(s_k), and subsequently to a SR(s_k). Moreover, the model includes both conscious and unconscious aspects. The states: SR(b_i), PD(b_i), PA(a_i), F(b_i), Per(b_i, s_k), and PO(a_i, b_i) are considered to be unconscious and contributing to bottom-up processes. In contrast, the states: SD(b_i), Att(b_i, s_k), CInt(b_i, s_k), and PAwr(a_i, b_i, s_k) represent more conscious influences, contributing to top-down processes. The dotted box represents the boundary between external and internal states: the states inside the dotted box represent internal cognitive states (those have a relatively higher firing rate).

The unconscious bottom-up process of action selection is modelled by combining Damasio's as if body loop (cf. [32]) (through PA(a_i) → SR(b_i) → F(b_i)) and James's body loop (cf. [33]) (through PA(a_i) → EA(a_i) → WS(b_i) → SS(b_i) → SR(b_i) → F(b_i)). According to 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 preparation state PA(a_i) for action option a_i suppresses preparation of all its complementary options PA(a_j) with j≠i (see Fig. 1), and therefore by a kind of winner-takes-all principle, naturally the option that has the highest valuated effect felt by the agent will execute through the body loop. Furthermore, according to the literature, the predictive effect and sensed actual effect of the action are added to each other through an integration process (cf. [2]); this is expected to be reflected in this model through the SR(b_i). Through this, it is also possible to demonstrate the difference between when predictive and actual effects are the same and not. This process is further strengthened by embedding PD(b_i) and Per(b_i, s_k). The PD(b_i) facilitates short-term desire effects on action execution that has the ability to strengthen the current action selection based on its desires (as a bias injected to the process). In parallel to the action preparation

Table 1. Nomenclature for Fig. 1

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

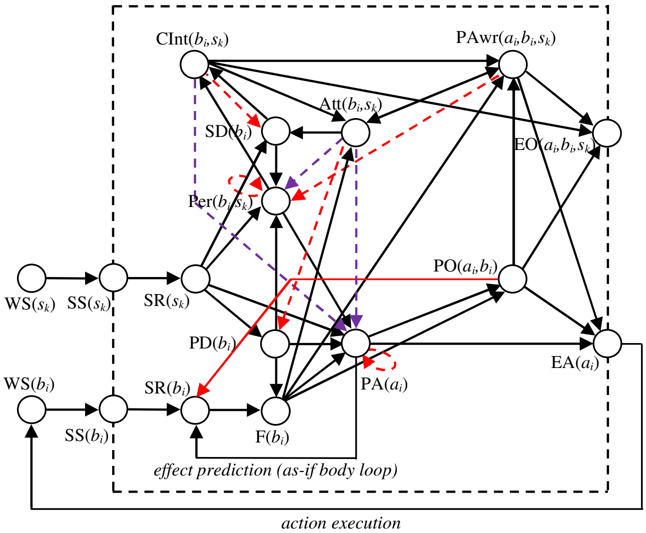

Fig. 1. Overview of the computational cognitive agent model. The arrow → represents a direct activation of state B by state A, arrow → represents a direct suppression of state B by state A, arrow ⇢ represents a suppression of all the complements of the 'ith' state of B_i by state A_i (where 'i' represents an instance of a particular state), and ⇢ represents a direct activation of state B_i by state A_i while suppressing all the complements of the 'ith' state of B_i.

process, the Per(b_i, s_k) also develops based on the salient features of the stimulus s; this will strengthen the bottom-up process which leads to even further strengthening of the action preparation process (due to the activation that spreads from Per(b_i, s_k) to PA(a_i)). Furthermore; by having a suppressive link from the Per(b_i, s_k) state to itself, the competition among perceptual entities as mentioned in Section 2 is represented (cf. [31]). Each suppressive link's negative effect (strength) is relatively proportional to the strength of that particular perceptual state and therefore the perception state for element i that has the highest activation suppresses its complements most strongly. As a result, the strongest candidate will dominate the competition and naturally will contribute for a stronger perceptual load. Due to this developed perceptual load, the agent will not automatically attend to other salient features (unless a particular attention is put on some salient feature intentionally). Furthermore, this selected perception will be strengthened by the agent's attention and subjective desires (see Fig. 1). While the agent is passively (unconsciously) performing action selection as explained in Section 2 (for more details see [26]), the agent starts to activate bottom-up attention (this is represented by the link from F(b_i) to Att(b_i, s_k)). The main functionality of the bottom-up attention is to pass current information into higher order cognitive states. Due to this bottom-up attention, the agent will activate its SD(b_i), which in turn leads to a CInt(b_i, s_k), and subsequently back to the attention state again. This cyclic process represents the transformation from bottom-up to top-down. Furthermore, this is in line with the idea of transforming Level 1 SA to Level 2 SA in Endsley's model (i.e., from perception to comprehension) in terms of a dynamic process [9], [11], [12]. Intention is considered to trigger goal directed preparation (see [26]) and therefore this model includes that effects via the Att(b_i, s_k). Once the attention (and its subjective aspects) has been developed, it injects conscious biases (through the top-down attention) into the action preparation and perception states. This is represented through the links from Att(b_i, s_k) to PA(a_i) and Per(b_i, s_k), and these links (purple dotted arrows) play a special role: while activating the matching option (i.e. ith option) they suppress all complements of the ith option. This emphasizes the conscious influence on action formation, and therefore attention will quickly enable the agent's concentration, which may shorten the time required for action selection. More importantly this will strengthen the current perception even further, and due to strong subjective feelings the agent may not be able to shift its attention easily (nevertheless, over longer time spans, attention will naturally get diluted; however, those effects are yet not included in this model).

Together with these processes, the agent will develop a state of ownership, which mainly determines to what extent an agent attributes an action to himself or to another agent. This particular aspect is important when it comes to situations where collaborative situation awareness plays a role, e.g. through collective decision making (although this is not in the scope of this paper). Also, as explained in previous works (see [13], [26]), the agent will develop an awareness state of action a_i that is related to effect b_i and stimulus s_k. According to Haggard [2], [4], there may be an influence from awareness states to action selection; therefore, this model includes a link from the PAwr(a_i, b_i, s_k) to the EA(a_i) (however, note that there are also claims that awareness of motor intentions does not have any influence on action execution, but emerges after action preparation and just before action execution [1], [34], [35]). Due to the empirical evidence that supports that awareness appears just before action execution, the current model includes that aspect by having awareness be affected mainly by higher order cognitive states; also, it does not affect many other states directly. The agent will execute the selected action a_i and then this action will have an effect in the environment (through WS(b_i)), and be sensed again, as explained earlier through the body loop. Finally, the agent has the ability to communicate the process (e.g., verbally) through state EO(a_i, b_i, s_k). In addition to the suppressive links mentioned here, a few more are included in the model; more details on those can be found in [13], [26].

Each connection between states has been given a weight value (where ω_{ji} represents the weight of the connection from state j to i) that varies between 1 and -1. To model the dynamics following the connections between the states as temporal–causal relations, a dynamical systems perspective is used, as explained in [36]. Furthermore, each state includes an additional parameter called speed factor γ_i, indicating the speed by which the activation level of the state 'i' is updated upon receiving input from other states. Two different speed factor values are used, namely fast and slow values: fast values are used for internal states and slow values for external states. The level of activation of a state depends 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 current activation level according to differential equation (1). As the combination function for each state, a continuous logistic threshold function is used: see equation (2), where σ is the steepness, and τ the threshold value. When the aggregated input is negative, equation f(x) = 0 is used. To achieve the desired temporal behavior of each state as a dynamical system, the difference equation represented by equation (3) is used (where Δt is the time step size).

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

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

$$y_i(t + \Delta t) = y_i(t) + \gamma_i \left[th\left(\sigma, \tau, \sum\nolimits_{j \in s(i)} \omega_{ji} y_j \right) - y_i(t) \right] \Delta t \tag{3}$$

4 Analysis of Level 1 SA by Simulation

According to the statistics provided by Endsley for the aviation domain (see [10], [11]), 76% of the errors related to poor SA were Level 1 errors, which are due to a failure to correctly perceive information (mainly due to poor design or limitations in user interfaces). The focus of this paper is to model the cognitive behavior as a process for Level 1 SA. The same generic example is used as was used to understand Level 1 SA in [13], which is taken from the Airbus Company. The example is summarized as "Focusing on recapturing the LOC and not monitoring the G/S". More specifically, it refers to a situation where a pilot is supposed to consider information from both devices (i.e., the LOC (Localiser) and the G/S (Glide Slope)), but due to biased perception (s)he only develops perception on LOC and not both on LOC and G/S. To simulate this example, two input stimuli (s_1 and s_2) have been used. One input triggers action selection based on reading the LOC data only, and the other one triggers action selection based on reading the data from both LOC and G/S combined. Details on all the input information and parameter values (Δt, γ, σ, τ, and weight values) for each state can be found in an external appendix[1]. In this simulation, the main cognitive state of interest is the perception state, and the process used to influence this is the perceptual load. Therefore, for all weight values in the model and for all options (two options have the potential to trigger: a_1 and b_1 & a_2 and b_2), identical values are used, except for the connection weights between {(SR(s_k), PD(b_i)), (PD(b_i), Per(b_i, s_k)), (SR(sk), Per(b_i, s_k)), (SD(b_i), Per(b_i, s_k)), (Att(b_i, s_k), Per(b_i, s_k))}. Also, in this particular simulation, the 'complements-suppressive' link from Per(b_i, s_k) to Per(b_j, s_k) (where j≠i) has the same weight value (therefore no bias is introduced through this link, but the suppression is only proportional to the strength of the particular state). Upon receiving the two input stimuli, the agent will prepare for two action options PA(a_1) and PA(a_2), where action a_1 is based on information from the LOC device and action a_2 is based on information from both devices. From the simulation results in Fig. 2, it can be seen that the provided input stimuli have relatively large effects on SR(s_k) for both options, with the maximum of 0.53 per each. Nevertheless, the agent only generates a strong action preparation state for action option a_1: the level of PA(a_1) becomes very high (with a max of 0.85), just like that of perception state Per(b_1,s_1) (with a max of 0.85). Instead, for action option a_2 it has a very weak Per(b_2,s_2) (max of 0.03) that contributes to the development of a poor PA(a_2) (max

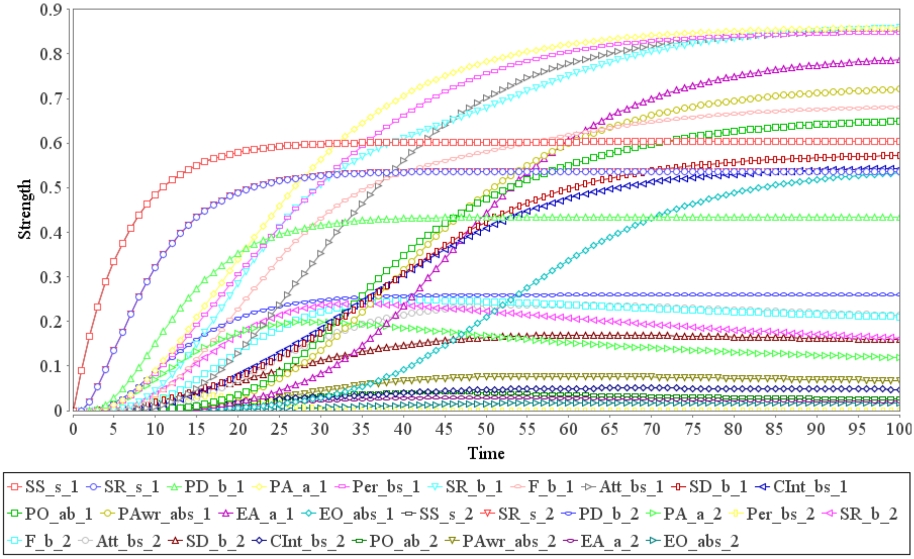

Fig. 2. Simulation details for Level 1 SA example

[1] http://www.few.vu.nl/~dte220/IEAAIE15Appendix.pdf

of 0.12). Hence, merely through this effect of incomplete perception (as Endsley highlighted), the agent has not developed the right situation awareness (in this case the 'correct' awareness would have been PAwr(a_2,b_2,s_2)). Instead, the 'incorrect' awareness state PAwr(a_1,b_1,s_1) (max of 0.74) is generated, based on wrong perception.

More importantly, this simulation has illustrated that the model can reproduce the effect of perceptual load under early selection while having identical weights for each option, except the five modifications mentioned earlier. Therefore, a bias has been injected through the process from perception to action selection process, and mainly with the support of unconscious processes, the agent has moved towards action selection (note that Level 2 and 3 SA are assumed to be more conscious than Level 1 SA). Subsequently, the agent generates sufficient activation levels for all the other states related to option a_1, and finally executes the action EA(a_1) (max of 0.78) with a PAwr(a_1,b_1,s_1) of max 0.74.The maximum activation levels of the other states related to option 1 are: F(b_1) is 0.68, Att(b_1,s_1) is 0.84, SD(b_1) is 0.57, CInt(b_1,s_1) is 0.54, PO(a_1,b_1) is 0.65, and EO(a_1,b_1,s_1) is 0.53. This pattern is as expected based on previous works (see [26]). In addition, the agent has properly integrated its sensory representations and its feeling on predictive effects and sensed actual effects. This can be explained by the two-step sigmoid curve (for SR(b_1) there is a slight saturation at time point 40, and then with the execution of EA(a_1) this is increased again with a slightly higher steepness) [2]. If the agent's predicted effect and its sensed actual effect would not be the same, then there would not be such two-step sigmoid behavior.

5 Discussion

This paper has presented a neurologically inspired cognitive model which is adapted from [13] and extended with process behind perceptual load. This model has some differences compared to what Endsley suggests; mainly, it moves away from the idea that there is a causal chain from SA to Decision Making to Performance Evaluation. In the proposed model, these 3 aspects are still exist but are more aligned with the findings from a neuroscience perspective. The simulation example used to illustrate the behavior of this model (for Level 1 SA) is the same as was used in [13]. Nevertheless, the simulation in the previous work did not use the same weight values, and the following links had different values: {(PA(a_i), SR(b_i)), (SR(s_k), PD(b_i)), (Att*(b_i,s_k), PD(b_i)), (Att*(b_i,s_k), PA(a_i)), (PA*(a_i), PA(a_i)), (CInt*(b_i,s_k), PA(a_i)), (SR(b_i), F(b_i)), (PD(b_i), F(b_i)), (CInt(b_i,s_k), SD(b_i)), (F(b_i), Att(b_i,s_k)), (Per(b_i,s_k), CInt(b_i,s_k)), (SR(s_k), Per(b_i,s_k)), (SD(b_i), Per(b_i,s_k)), (PAwr(a_i,b_i,s_k), Per(b_i,s_k))}, where '*' represents 'complement' options. Therefore, in that approach (i.e. [13]) a perceptual bias was realized through a primary unconscious action prediction process together with the support of conscious states. Also, for the 'complement-suppressive' links, different weight values were used. Therefore, the biased behavior was represented through the combination of all these weight values. Instead, in this new version, the approach was further improved, since it models perception through the process of perceptual load. For each action option, exactly the same values were used, except for {(SR(s_k), PD(b_i)), (PD(b_i), Per(b_i,s_k)), (SR(s_k), Per(b_i,s_k)), (SD(b_i), Per(b_i,s_k)), (Att(b_i,s_k), Per(b_i,s_k))} which are related to perception and performative desires. Hence, based on these simulation results, this model demonstrates the basic features of perceptual load and further explains the construct of poor Level 1 SA as a cognitive process in more realistic manner. A model like this will be useful mainly in complex simulations where cognitive details are essential (e.g. air traffic controlling situation under an emergency conditions). In multi-agent based simulations a main limitation is lacking of nature inspired realistic models to mimic the natural behavior and cognition behind it. Having a model like this will contribute to fill this gap and even be useful in training simulations to improve the human cognition though these processes.

Acknowledgment. I wish to thank Prof. Jan Treur and Dr. Tibor Bosse at VU University Amsterdam, for their great support and supervision in all the phases of this work. This work is part of the SESAR WP-E programme on long-term and innovative research in ATM. It is co-financed by Eurocontrol on behalf of the SESAR Joint Undertaking (SJU).

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