Integrating Situation Awareness and Surprise: a Computational Agent Model

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Abstract—**To increase realism of virtual agents in serious gaming applications, computational models of human cognitive processes can play an important role. This paper presents a computational agent model that integrates models for situation awareness and surprise. The crucial element in the integration of both models is a mechanism that matches beliefs about the situation from the situation awareness model with expectations about the world from the surprise model. To evaluate the integrated model, it has been implemented within an existing simulator for F16 pilots, and four variants of the model were tested within a domain-specific scenario. The results indicate that the model has promising capabilities to enhance realism of virtual agents.**

Keywords - cognitive modelling, serious gaming, situation awareness, surprise.

I. INTRODUCTION

An important requirement for applications of serious gaming for simulation-based training is to provide realistic virtual characters displaying human-like behaviour; e.g., [16]. To achieve this, a useful source is found in cognitive and neurological areas addressing human possibilities and limitations. Often knowledge of a specific human phenomenon is taken as a point of departure to design a biologically plausible agent model for this phenomenon. In this way agent models can and actually have been developed displaying, for example, human-like forms of attention, decision making, emotion, fatigue, mindreading (or Theory of Mind), situation awareness (SA), surprise (e.g., [6, 7, 12]). In some application areas such 'single-phenomenon' agent models may be useful. However, in other application areas multiple phenomena play a role. For such applications different models have to be integrated.

This paper addresses agent models for the domain of simulation-based training for combat flight, and in particular the role of both situation awareness and surprise. Agent models to act in such a training environment need to display both phenomena. By maintaining an adequate model of the environment a form of situation awareness is achieved as a basis for comprehension and prediction of what is to be expected. However, still unexpected events may occur to the agent and may lead to a state of surprise. The focus of this paper is on how the combination of situation awareness and surprise can be achieved in an agent model by integrating computational models for each of these separate phenomena as described, respectively, in [7] and [12].

Situation awareness is defined in [5] as: perception of cues, comprehension and integration of information, and projection onto future events. The extent to which an agent has situation awareness depends on the available cognitive resources. In demanding circumstances such as in air traffic control or military combat a reduction in situation awareness will often negatively affect performance. Surprise is considered a response to unexpected events with emotional and cognitive aspects (for example [4, 15, 13]). Experiencing surprise affects human behaviour, for example, expression through facial expressions [4] and the interruption of ongoing action [8].

The agent model integrating situation awareness and surprise presented here has been developed for simulation-based training in combat flight simulation, which is a common method used to train fighter pilots; e.g., [9, 14]. This integrated model reuses elements of the computational model for situation awareness described in [7] and the model for surprise presented in [12].

In the paper, Section II describes the modelling approach used, and Section III the integrated computational model for situation awareness. In Section IV it is described how the model has been tested in a case study, using an existing simulator for F16 pilots. Finally, Section V is a discussion.

II. MODELLING APPROACH

To model the different aspects related to the creation of situation awareness and surprise from an agent perspective, an expressive modelling language is needed. On the one hand, qualitative aspects have to be addressed, such as observations and beliefs of agents about the world. On the other hand, quantitative aspects have to be addressed. For example, the extent to which a certain belief is active within the agent's working memory can best be described by a real number, and the update of such activation values can best be described by a mathematical formula.

The hybrid executable language LEADSTO [3] fulfils these desiderata. This language, which is a sublanguage of the Temporal Trace Language (TTL) [2], integrates qualitative, logical aspects and quantitative, numerical aspects. This integration allows the modeller to exploit both logical and numerical methods for analysis and simulation.

The languages LEADSTO and TTL are based on the assumption that dynamics can be described as an evolution of states over time. The notion of state as used here is characterised on the basis of an ontology defining a set of physical and/or mental (state) properties that do or do not hold at a certain point in time. These properties are often called *state properties* to distinguish them from dynamic properties that relate different states over time. A specific state is characterised by dividing the set of state properties into those that hold, and those that do not hold in the state. Examples of state properties are 'agent A observes world fact W', or 'agent A has belief B with an activation level of 0.6'. Real value assignments to variables are also considered as possible state property descriptions.

In LEADSTO, direct temporal dependencies between two state properties in successive states are modelled by *executable dynamic properties.* LEADSTO subsumes specifications in difference equation format. For more details, see [3].

III. The Integrated Agent Model

In this section the integrated agent model for situation awareness and surprise is described in more detail.

A. *The Situation Awareness Model*

In the model situation awareness is represented by dynamically generated and updated sets of observations and beliefs (cf. [Hoogendoorn et al., 2011]). The observations represent the input the agent receives from its environment. Observations are represented in the form

observation(AGENT, WORLD_INFO, REAL)

where the first argument is the owner of the observation, the second argument the world info the observation is about and the third argument the certainty of the owner that the world info really holds. Beliefs are represented in the form

belief(AGENT, WORLD_INFO, REAL, TIME)

where the first argument is the owner of the belief, the second argument the world info the belief is about, the third argument the activation level of that belief and the fourth argument for what time the agent holds that belief.

Generation of beliefs makes use of an underlying mental model. This is a network of observations and beliefs where connections have strengths indicated by a real number in the interval [*0, 1*]; along these connections activation is spread throughout the network. A connection has a source observation or belief and a destination belief. Activation is spread from the source via the connection to the destination belief.

Updating the beliefs consists of three phases (cf. [5]): *perception*, *comprehension* and *projection*. In *perception*, the certainties of observations are determined and used to derive the activation values of those beliefs directly connected with the observations. In *comprehension*, the activation values of beliefs on the present and the past are updated. In *projection*, the activation values of beliefs for the future are updated. Each of the three phases has a time limit which determines how much time the update process for that phase may take. These three time limits model the phenomenon that humans under time pressure take shortcuts in their reasoning and have degraded situation awareness.

Perception

In the perception stage, the certainty values of the observations are used to calculate the activation values of a subset of beliefs on the current situation, those connected directly with observations. Currently, it is assumed that an observation is only connected to one belief. The belief activation update formula for perception is as follows.

$$V_B(t+\Delta t) = V_B(t) + [\alpha_B\, (th(\sigma,\ \tau,\ V_O(t)) - V_B(t)) - \gamma_B\, V_B(t)]\ \Delta t$$

Here the symbols mean:

B The belief for which the activation value is calculated.
O The parent observation of B.
α_B The update speed parameter (how fast recent updates influence the activation value) for B.
γ_B The decay parameter for B
$V_B(t)$ The previous activation value of B.
$V_O(t)$ The certainty value of observation O.
$th(\sigma,\ \tau,\ V_O(t))$ The threshold function, with parameters σ (steepness), and τ (threshold value).

The continuous logistic threshold function used is as follows:

$$th(\sigma,\tau,V) = \left(\frac{1}{1+e^{-\sigma(V-\tau)}} - \frac{1}{1+e^{\sigma\tau)}}\right)(1+e^{-\sigma\tau)})$$

Here the symbols mean:

σ Steepness parameter
τ Threshold parameter
V Input value

Comprehension

In the comprehension phase, the activation values of all the beliefs on the present situation are updated. A belief is updated exactly once during a cycle. To ensure that the update of a belief is based on the most recent information, a belief is only updated if all its parent beliefs are updated; the belief graph is assumed to have no cycles. In each iteration, a belief is selected to be updated. For this belief, all the incoming connections that come from an active belief are used to update the activation value of the selected belief. The selected belief is marked as considered and the next iteration starts. This continues until either the time limit of the comprehension phase is reached or all beliefs on the present and past are updated. The calculation of the activation value of a belief B is done by using only those connections whose source belief has an activation value higher than the minimal activation value. This models the phenomenon that activation only spreads from beliefs that have some degree of activation.

The update function for belief activation is as follows.

$$V_B(t+\Delta t) = V_B(t) + [\alpha_B\, (th(\sigma,\ \tau,\ \Sigma_{C\in g(B)}\ \omega_{C,B}\ V_C(t)) - V_B(t)) - \gamma_B\, V_B(t)]\ \Delta t$$

B The belief for which the activation value is calculated.
α_B The update speed parameter (how fast recent

updates influence the activation value) for B.

γ_B The decay parameter for B

$V_B(t)$ The previous activation value of B.

$V_O(t)$ The certainty value of observation O.

$th(\sigma, \tau, V_O(t))$ The threshold function, with parameters σ (steepness), τ (threshold value for B).

$g(B)$ The set of beliefs C connected to belief B as destination

C A belief from the set $g(B)$.

$\omega_{C,B}$ The strength of connection from C to B.

Projection

If the time limit has not been reached, the projection stage is started. In projection, beliefs on the future are updated. The process is the same as with beliefs on current situation, only with a different start set of beliefs.

B. The Surprise Model

In the surprise model, adopted from (Merk, 2010) events in the environment are continually monitored and evaluated. This evaluation consists of determining the degree of expectation disconfirmation [18], how important the event is to the subject and how novel the event is. This evaluation is used to generate the surprise intensity. As the evaluation happens continually, there is a surprise intensity value at any moment. The outcome of the evaluation aggregates expectation disconfirmation, event importance and event novelty, which are each represented by a real value between *0* and *1*. *Expectation disconfirmation* measures the degree of discrepancy between the expectations of the agent and the actual observed events. The higher this value, the more unexpected the event is to the agent. Event *importance* measures the impact the event has on the goals and desires the agent has. A higher importance indicates that the event has relative far-reaching consequences for the agent. Event *novelty* gives an indication of how familiar an event is, how often the agent has experienced this situation before. A mechanism that links the agent's episodic memory on similar previous experiences with the observed event is needed for generating the value for event novelty.

Surprise intensity is calculated in a dynamic manner: the rate of change or derivative is calculated and this rate of change is then used to update the current surprise intensity value. This rate of change is called the delta surprise intensity in the model. The influences that determine surprise intensity identified in the previous section are used in the calculation of delta surprise intensity. The expectation disconfirmation, event importance and event novelty are the factors that increase surprise intensity. Decrease of surprise intensity is based on a decay parameter ζ. The calculation of surprise intensity can then be informally described as follows:

if the surprise intensity at time t has value *si*
and the delta surprise intensity has value *dsi*,
then at $t+\Delta t$ the surprise intensity will have the value $si + dsi\ \Delta t$

More formally,

$$si(t+\Delta t) = si(t) + dsi(t)\ \Delta t$$

The value for the delta surprise intensity is determined as follows:

If at time t the surprise intensity has value *si*,
and there is an expectation disconfirmation with value *ed*, the importance and novelty of the currently observed events have respectively the values *i* and *n*,
and the weights for importance and novelty have values w_i and w_n
and the decay parameter has value ζ
then at time *t* the delta surprise intensity has value $(1 - si) \cdot ed \cdot (w_i \cdot i + w_n \cdot n) - \zeta si$

More formally:

$$dsi(t) = (1 - si(t))\ ed(t) \cdot (w_i\ i(t) + w_n\ n(t)) - \zeta si(t) \qquad (1)$$

As formula (1) is an important part of the model, we will examine it in more detail. The expectation disconfirmation is multiplied with the sum of the importance and novelty factors that are themselves multiplied with their weight values. The reason for this construction consists of two assumptions: first the assumption that without expectation disconfirmation, there is no surprise. Second, the assumption that importance and novelty have a different effect in that they alone do not lead to surprise. For example, observing an important event that has been expected should not lead to surprise. The weights w_i and w_n add up to *1*, so that the outcome of $ed \cdot (w_i \cdot i + w_n \cdot n)$ always lies between *0* and *1*. With these weights, the relative influence between the two factors can be tuned. The expression $ed \cdot (wi \cdot i + wn \cdot n)$ is multiplied by $(1\text{-}si)$ so that the value of surprise intensity stays below *1*. Including this factor $(1\text{-}si)$ also ensures that the surprise intensity value changes smoothly over time.

C. Integrating the Situation Awareness and Surprise Model

Integration of the situation awareness model and the surprise model (see Figure 1) uses an interaction between the models involving determination of the expectation disconfirmation value *ed*. This is done in the first place by specification of which situations (co-occurrences of beliefs) are considered as expectation disconfirmation.

In the general surprise model as described in [12], certain aspects were left unspecified, as meant to be added for specific applications of the model. In the model described in the current paper, these aspects have been expanded upon to obtain a more specialised model. In particular, the determination of expectation disconfirmation, novelty and the sensemaking process have been specified in the current model.

Expectations, observations, earlier experiences (novelty) and sensemaking can be seen as playing a role in forming situation awareness, as these aspects all relate to information on the agent's environment. Expectations are essentially based on beliefs on future events, earlier experiences can be represented by beliefs on the past and sensemaking can be viewed as belief derivation.

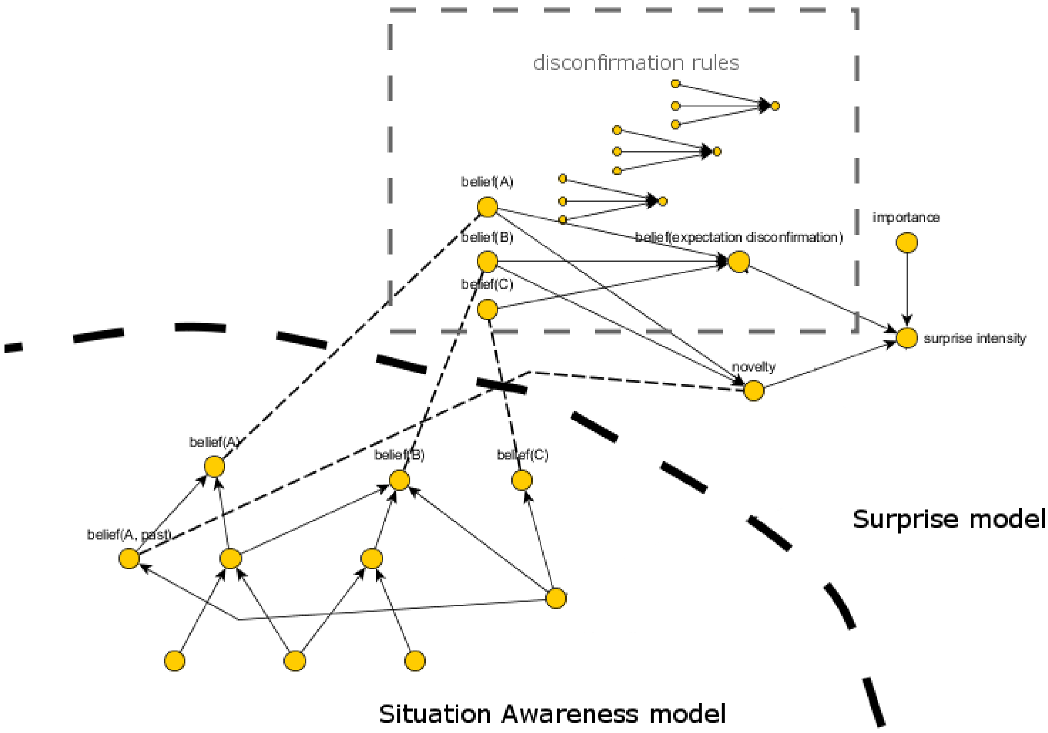

Fig. 1: Overview of the integrated model

These aspects being seen as taking part in situation awareness, the surprise model can be seen as describing a meta-reasoning process that monitors the situation awareness for expectation disconfirmation. Expectation disconfirmation is modelled as a form of belief inconsistency: the agent believes on the one hand that some X has been true, is true or will be true and then on the other hand forms the opposite belief.

To determine *expectation disconfirmation*, two elements are needed. First, beliefs on the world are needed. It is assumed that these beliefs are available in the form

belief(AGENT, WORLD_INFO, REAL, TIME)

where the first argument is the owner of the belief, the second argument the world info the belief is about, the third argument the activation level of the belief, and the fourth argument for what time the agent holds that belief. While the Situation Awareness model described in [7] is used to supply these beliefs in this paper, any model that generates beliefs with an activation value and a temporal aspect can be used for supplying the beliefs.

Second, to determine expectation disconfirmation a set of disconfirmation specifications is needed. These specifications determine which combinations of beliefs are inconsistent and to which extent: what expectation disconfirmation value the inconsistency creates. For example, an agent cannot believe that an object is at two different places at the same time. This can be represented, for example, by the following disconfirmation specification:

$belief(Agent, position(X, L_1), A_1, present) \wedge$
$belief(Agent, position(X, L_2), A_2, present) \wedge L_1 \neq L_2$
$\rightarrow expectation\_disconfirmation(Agent, f(A_1, A_2)).$

Here the combination function $f(A_1, \ldots, A_n)$ determines the disconfirmation value with n activation values A_i as input. The function f should be a monotonically increasing aggregate function of the input activation values mapping to values between 0 and 1, for example the average, or based on a logistic function such as

$$f(X_1, \ldots, X_k) = th(X_1 + \ldots + X_k)$$

with

$$th(\sigma, \tau, W) = 1/(1+e^{-\sigma(W-\tau)})$$

for some theshold and steepness parameter values τ and σ.

Another example of a disconfirmation specification, this time involving temporal relations is:

$belief(Agent, X, A_1, future),$
$belief(Agent, Y, A_2, present),$
$belief(Agent, before(X, Y), A_3, always)$
$\rightarrow expectation\_disconfirmation(f(A_1, A_2, A_3)).$

With the set of beliefs supplied by the situation awareness model and a set of disconfirmation specifications given, the surprise model can generate expectation disconfirmation values. However, novelty and importance are also needed to determine surprise.

For the current model it is assumed that *importance* is determined in a separate process, as importance is linked to goals and motivations, which are not covered by situation awareness. In contrast, novelty can be directly related to situation awareness.

Novelty is a measurement of how familiar the events that lead to surprise are. This can be determined by taking into account the beliefs on past occurrences of the events or facts referred to in the beliefs about the present that occur in a disconfirmation specification. If a belief is active on the past of the same world information X as a belief on X in the present in an applicable disconfirmation specification at the time the specification is considered, its activation value will be taken into account for determining the novelty of the accompanying surprise. For example, if

belief(Agent, X, A_1, present)

occurs in the disconfirmation specification considered, and

belief(Agent, X, A_2, past)

is an available belief, then the novelty of *X* is taken as $(1\text{-}A_2)\,A_1$. In the binary case with both A_1 and A_2 are *1*, the novelty is *0*, whereas for $A_1 = 1$ and $A_2 = 0$, the novelty is *1*.

Any beliefs in an applicable disconfirmation specification with a *past* or *always* time label are ignored for determining the novelty, as those beliefs are already about the past.[1] For multiple beliefs about the present, the novelty is determined using a monotonically increasing aggregate function f of the individual values. If $n_1, \ldots, n_k$ are the values of novelty for the different beliefs on the present in a given disconfirmation specification, then $f(n_1, \ldots, n_k)$ is the aggegate novelty value for this disconfirmation specification at that point in time.

Given the ingredients as discussed, the surprise level is determined as follows:

(1) **Determining expectation disconfirmation ed_{ds}**
Evaluate the disconfirmation specifications: if a specific disconfirmation specification *ds* applies, as an outcome a certain level of expectation disconfirmation ed_{ds} for this specific *ds* is determined from the activation values involved in *ds*.

(2) **Determining novelty n_{ds}**
The novelty n_{ds} of the current situation is determined taking into account the beliefs on the present in the disconfirmation specification *ds* and which of them are also past beliefs

$$n_{ds} = f(n_1, .. , n_k)$$

where the n_i are the novelty values for the different beliefs on the present occurring in *ds*:

$$n_i = (1\text{-}A_{i,2})\,A_{i,1}$$

with $A_{i,1}$ and $A_{i,2}$ the activation values of the given present and past belief, respectively.

(3) **Determining delta surprise intensity dsi_{ds}**
The disconfirmation value ed_{ds}, importance value i_{ds} and novelty value n_{ds} are aggregated into one value for the delta surprise intensity dsi_{ds} for the given disconfirmation specification *ds* using the model for *dsi* in Section IIIB, i.e.:

$$dsi_{ds} = (1 - si)\, ed_{ds} \cdot (w_i\ i_{ds} + w_n\, n_{ds}) - \zeta\, si$$

(4) **Determining overall delta surprise intensity *dsi***
The delta surprise intensity values dsi_{ds} for the different applicable disconformation specifications *ds* are aggregated into one delta surprise intensity value *dsi*, using the combination function *f*, i.e.:

$$dsi = f(dsi_{ds1}, .. , dsi_{dsn})$$

(5) **Determining surprise intensity *si***
The delta surprise intensity *dsi* is used to update the value of surprise intensity *si* as described in Section IIIB:

$$si(t+\Delta t) = si(t) + dsi(t)\,\Delta t$$

D. Effects of Surprise in Behaviour

Surprises have effects on behaviour in two different ways: (1) by triggering specific behavioural responses, and (2) by slowing down the normal cognitive functions to maintain situation awareness. The first effect is realized in by having specified behavioural specifications that only can be triggered when the surprise level is high enough. The behavior specification for being surprised deviates from a normal behaviour in the sense that 1) its execution is more delayed and 2) it is less optimal in regards of achieving the goals, thus representing confused and shocked behavior.

IV. CASE STUDY

As this paper is part of a larger research effort to generate more human-like agents to improve the quality of tactical training simulators for the Royal Netherlands Air Force, the model is tested against a case study in the domain of air-to-air combat.

A. Scenario

To test the integrated model, a scenario from the domain of air combat has been implemented in STAGE. STAGE is a software tool that lets one build a tactical database and then simulate dynamic, interactive, complex, and realtime tactical and operational environments. These environments, called scenarios, contain individual platforms (such as planes, ships, trucks, radar sites) that interact through detection, communication, engagement and/or destruction. Platforms may be equipped with weapons, such as guns, artillery, and missiles, and other defining characteristics.

In the scenario there are two fighter aircraft, one controlled by an agent equipped with the integrated model as described in the current paper, the other by a non-expert human. The agent, controlling the Red aircraft, has the goal to reach an objective, while the human, flying the Blue

[1] With a more finely grained time representation in which beliefs on the past can be about different episodes (for example one about yesterday and another about last year), past beliefs could be taken into account if they are further back into the past.

aircraft, must defend the objective against enemy attack. Besides the two aircraft, a couple of SAM (Surface to Air Missile) sites defend the objective. These are ground-based weapon platforms that can attack and destroy enemy aircraft, for example the MIM-104 Patriot. If Red comes within the weapon range of a SAM site, the SAM site will fire a missile at Red, which will destroy Red if the agent takes no further action.

According to fighter pilots, the best way for a pilot in such a situation to avoid getting hit by the SAM missile is to throw out chaff (a countermeasure that disrupts the radar of the SAM site and lowers the change of impact of the missile), followed by a 'beam' maneuver: this means that the aircraft is flown at a right angle to the direction of the SAM site. For simplicity's sake, we assume that when a pilot throws out chaff and then beams, the SAM missile is defeated and will not hit his aircraft.

The twist in this scenario is that the SAM sites have their radar switched off and their existence unknown to the agent. Only when Red gets within their weapons range will they switch on their radar and fire a missile at the agent's aircraft. Such SAM sites are known as 'SAM traps' or pop-up SAMs; this tactic has been used in real life. As the agent does not know about the SAM sites nor has any means of detecting them before they launch their missiles, an attack from such a SAM site will be unexpected, thus surprising.

The situation awareness belief graph for the agent is shown in Fig. 2. At the bottom there are the observations, derived from the Red aircraft's radar, radar warning receiver (a sensor that detects the emissions of other radars) and knowledge on SAM site locations. Above that, past, present and future beliefs are derived from the observations through connections. Three beliefs are especially important:

belief(incoming_air_to_air_missile,X, future)
belief(incoming_sam_missile,X, future)
belief(before(in_sam_range, incoming_sam_missile), X, always)

If the first of these beliefs becomes active, the agent will intent to avoid the human-controlled Blue aircraft and fly away from Blue. If the second belief becomes active, the agent will intent to defeat the SAM missile. This intention can be executed in two ways, depending on whether the agent was surprised by the missile launch or not. If not surprised, the agent will throw out chaff, beam for a while and then turn away from the SAM site. If the agent was surprised, it will act confused for a while (represented by a zigzag maneuver) and then will turn away from the SAM site. The belief

belief(before(in_sam_range, incoming_sam_missile), X, always)

is used to represent the fact that the agent expects to be within SAM weapon range before a SAM missile is launched. For the use case, only one disconfirmation rule has been used:

belief(Agent, X, A_1, future),
belief(Agent, Y, A_2, present),
belief(Agent, before(X, Y) , A_3, always)
$\rightarrow$ *expectation_disconfirmation(f(A_1, A_2, A_3))*

This rule represents the fact that, if the agent believes that some event *X* happens before event *Y* and *Y* happens right now while it believes that *X* is to happen in the future, there is a belief inconsistency and thus an expectation disconfirmation.

To evaluate whether the situation awareness model and the surprise model contribute to make the agent's behaviour more realistic, the agent was tested against four trials. In these trials, the parameters of the model have been varied. In the Surprise+ setting, the surprise model works as described in Section III above. In the Surprise- setting, the surprise model is turned off and the surprise intensity will always be zero. In the SA+ setting, the situation awareness model is fully updated, while in the SA- setting the time limits for the perception phase, comprehension phase and the projection phase are set low enough that not all beliefs in each phase can be updated (about 75% of all beliefs in each phase are updated).

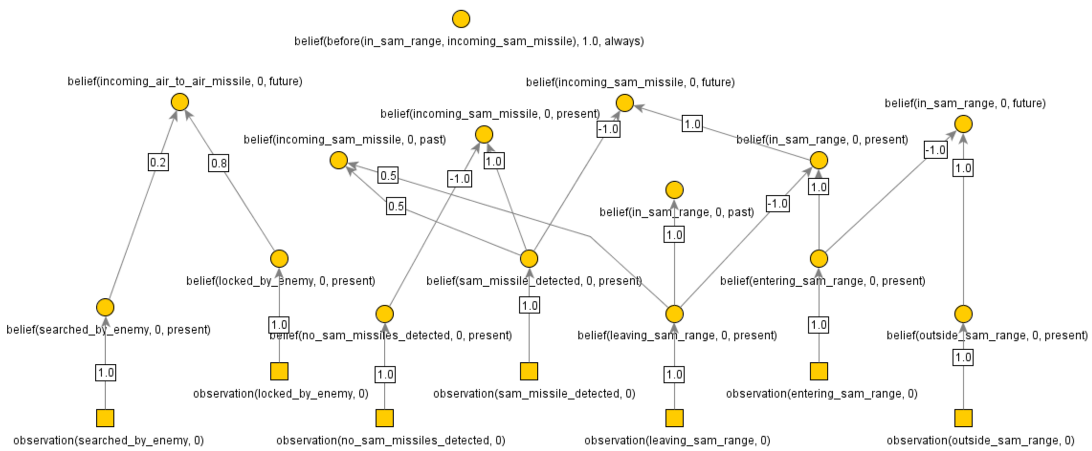

Fig. 2: Situation awareness belief graph

B. Results

To show the results of the agent's behavior, Figs. 3 through 6 are screenshots of the STAGE simulator running the scenario as described. The red aircraft, controlled by the agent starts in the west and tries to reach the objective (red circle) in the east, while Blue, controlled by a human, tries to flank Red and lure him into the range of the Patriot SAM site to the southwest, indicated by the large circle. The red and blue lines are the flight paths of the respective aircraft.

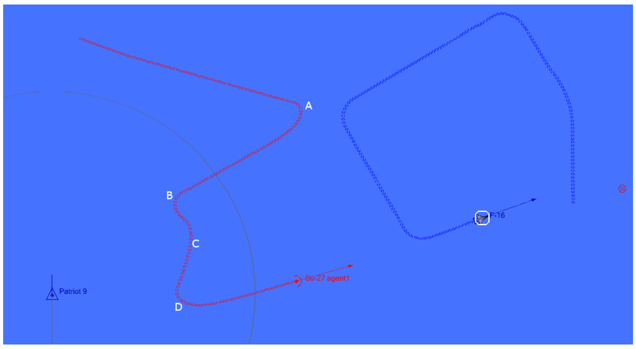

Fig. 3: Flight paths (SA+, Sur-)

In Fig. 3, the agent fully updates its beliefs but its surprise model is inactive. At point A, the agent detects Blue and flies away from the enemy. At point B, the Sam site shoot a missile at the agent, which throws out chaff. At point C, the agent starts to beam and at point D, the agent starts moving away from the SAM site.

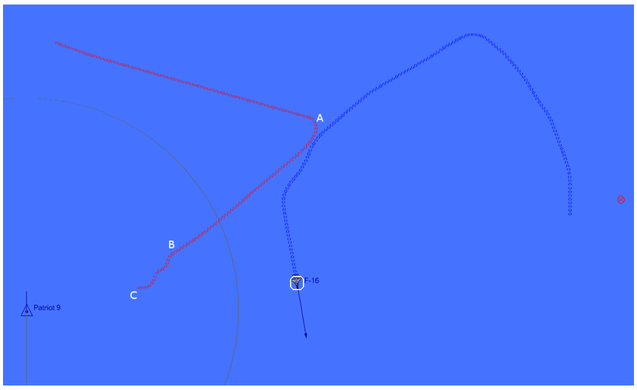

Fig. 4: Flight paths (SA+, Sur+)

In Fig. 4, the difference in the agent's behaviour when it is surprised is visible. Again at point A it detects the enemy and flies away. However, at point B, when the SAM site launches its missile, the agent neglects to throw out chaff and instead acts confused (seen here as a zigzag move) as a result of its surprise at being fired upon by an unexpected SAM site. At point C the SAM missile intercepts the agent and it is killed.

In Fig. 5, the agent has reduced situation awareness and can only update a limited amount of beliefs, while its surprise model is deactivated. While not clearly visible in the figure, the agent reacts much slower to the detection of Blue. At point B, when the SAM site launches its missile, the agent does not react at all, because its future belief regarding the impact of the SAM missile is never updated due to the low time limit. At point C the agent is killed by the SAM missile.

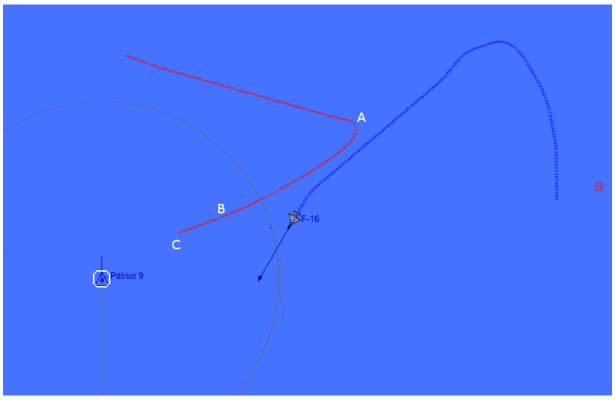

Fig. 5: Flight paths (SA-, Sur-)

Fig. 6 shows the results of the trial where the agent has reduced situation awareness and with the surprise model activated. However, the agent's expectation disconfirmation and thus its surprise intensity never rises as the future belief for missile impact, which never becomes active due to reduced SA, is necessary to activate the disconfirmation rule. Because of this, the agent behaves the same with surprise on and off when having reduced SA.

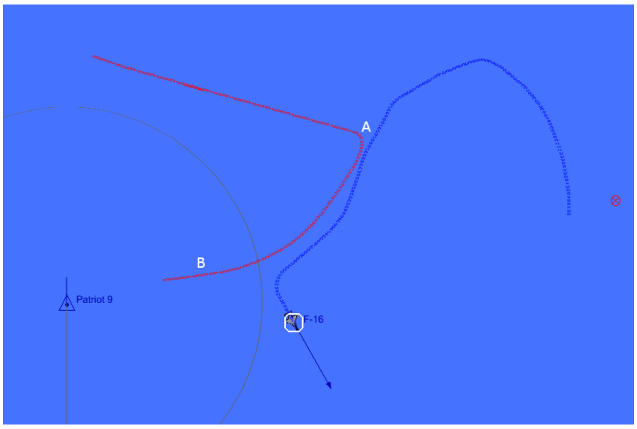

Fig. 6: Flight paths (SA-, Sur+)

V. Discussion

In order to enhance realism of virtual agents in serious gaming applications, computational models of human (cognitive) processes can play an important role. Although many computational models have recently been developed for separate human processes (e.g., [6, 7, 12]), less research has been done that addresses the combination of such models. As a first step in that direction, this paper presents a computational agent model that integrates situation awareness and surprise. The model combines the situation awareness model described in [7] with the surprise model described in [12]. The former was based on Endsley's three-phase theory on situation awareness [5], whereas the latter was inspired, among others, by the expectation disconfirmation theory from [18]. The integration of both models was achieved by matching beliefs about the situation that are generated by the situation awareness model with expectations about the world that are present within the surprise model. As a result of this matching process, a certain degree of expectation disconfirmation is calculated, which (combined with values for novelty and importance) leads to a certain degree of surprise. Subsequently, surprise has an effect on behaviour by triggering specific direct responses, and by slowing down the normal cognitive functions to maintain situation awareness.

A preliminary evaluation of the integrated model has been performed, by implementing it within an existing simulator for F16 pilots, and by running a domain-specific scenario with four variants of the model (i.e., SA+/surprise+, SA-/surprise+, SA+/surprise-, SA-/surprise-). The results indicate that the possibility to manipulate levels of situation awareness and surprise enables the modeller to create a richer variety of behaviours, which correspond to different characteristics of humans. For example, an experienced pilot, who was asked to evaluate the behaviour of the agent under different settings, stated that an agent with partial SA was perceived as more realistic but less experienced than an agent with full SA.

Compared to other models in the literature, the presented model is innovative because it integrates the processes of situation awareness and surprise within one computational model. Although both of these processes have been modelled separately (e.g., [6, 10, 20]), mechanisms to combine the two have not been fully explored. Furthermore, earlier models for the design of intelligent agents with SA (e.g. [10, 20]) do not represent all necessary aspects and stages of SA as have been distinguished in this paper. A more detailed model of SA can be found in [Juarez-Espinoza and Gonzalez, 2004], but it does not make use of a general method to integrate observations into higher level beliefs and is therefore difficult to apply in new situations. Finally, a computational model proposed for situation awareness that takes Endsley's model [5] as a point of departure is described in [17]. The first two phases are covered, but the temporal projection phase of Endsley's model is not modelled in [17].

Future work will address further testing of the model, using different and more complex scenarios. In addition, a more elaborated experiment is currently being set up, in which multiple domain experts (F16 pilots) will play realistic missions against different variants of the integrated model, and will be asked to evaluate various aspects of the agent's perceived behaviour by means of a questionnaire.

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