Nationaal Lucht- en Ruimtevaartlaboratorium
National Aerospace Laboratory NLR

Executive summary

A surprise model for use in agents in simulated environments

Problem area
Realistic, human-like decision making is critical in the construction of humanlike Computer Generated Forces (CGFs) in tactical fighter simulations. Currently, CGFs are lacking in this respect, providing unrealistic, often scripted behaviour. New approaches in decision making modelling need to be sought.

Description of work
A computational model has been developed with which surprise intensity and its effect on behaviour can be generated, based on findings in psychological literature. In this revised version the introduction and case study has been extended, as well as the simulation section, in order to adapt the paper to the target group of the Mission and Simulation Group conference.

Results and conclusions
The model has been tested against a simulation of a historical event in air combat, Operation Bolo. Three behavioural properties have been evaluated. Conclusion is that the model does generate surprised behaviour in line with expectations.

Applicability
This model can be used in CGFs in order to make their behaviour more realistic in situations where humans would react surprised.

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Author(s)
R.J. Merk

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Nationaal Lucht- en Ruimtevaartlaboratorium, National Aerospace Laboratory NLR

Anthony Fokkerweg 2, 1059 CM Amsterdam,
P.O. Box 90502, 1006 BM Amsterdam, The Netherlands
Telephone +31 20 511 31 13, Fax +31 20 511 32 10, Web site: www.nlr.nl

Nationaal Lucht- en Ruimtevaartlaboratorium

National Aerospace Laboratory NLR

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Summary

Humans and animals react in recognizable ways to surprising events. However, there is a lack of models that generate surprise intensity and its effects on behaviour in a realistic way, leading to impoverished and non-humanlike behaviour of agents in situations where humans would react surprised. To fill in this gap in agent-based modelling, a computational model is developed based on psychological empirical findings and theories from literature with which agents can display surprised behaviour. We tested this model in a simulated historical case from the domain of air combat and evaluated three behavioural properties against these simulated runs. The conclusion is that the model captures aspects of surprised behaviour and thus can help make agents behave more realistically in surprising situations.

Contents

Introduction

In training simulations, there is an increasing demand for realistic computer-controlled actors for a number of reasons, such as cost effectiveness and the ability of having larger amounts of actors. One promising approach to construct computer-controlled actors is the agent-based approach [8]. Agents are commonly seen as software entities that exhibit flexible, intelligent behaviour and in many cases their behaviour is supposed to be humanlike. Agents have been successfully used in military training simulations [5] [15].

One way to make agents more realistic is to augment then with computational cognitive models that enable agents to mimic cognitive processes as they occur in humans. One example of an integral human mental process is surprise.

Surprise is considered an adaptive, evolutionary-based reaction to unexpected events with emotional and cognitive aspects [2] [14] [15]. Experiencing surprise has some effects on human behaviour, for example, expression through facial expressions [2] and the interruption of ongoing action [6]. However, there is little attention to the phenomenon of surprise in agent research and few agents have human-like mechanisms for generating surprise intensity and surprised behaviour (one of the few exceptions for example is [9]). This leads to impoverished and unrealistic behaviour of agents in situations where humans would react surprised.

The phenomenon of surprise has a more specific relevance in the military domain, besides its general importance as a basic human emotion. The element of surprise is considered an important factor in military operations by many military experts. Strategists such as Sun Tzu, F.C. Fuller and John Boyd have stressed the advantages of surprising the enemy (see e.g. [13]).

From the previous paragraphs we can conclude that having realistic surprise models that are useable in simulation agents is useful. Because of this we propose in this paper a computational model that can be used in agents operating in training simulation that makes their behaviour more humanlike in surprising situations. The model is based on psychological empirical studies and is verified in a simulated scenario from the domain of military aviation against a number of properties.

1 Theory

One of the more influential models that explain the mechanisms behind how surprise intensity is generated in humans is the *expectancy-disconfirmation* model [16]. According to the expectancy-disconfirmation theory, the main contributing factor to surprise is expectancy disconfirmation. In this view, people create expectations on how events in the world unfold. If they subsequently encounter an event that does not fall within their expectations, they will be surprised. This leads to an attribution process, a form of causal reasoning which leads to an attribution of the situation to certain causes in order to make sense of the situation. The duration of this causal attribution process depends on not only the surprise intensity but also other factors such as importance and valence of the surprising event. A number of experiments in [16] show that expectancy disconfirmation is indeed an important factor for surprise.

Several criticisms have been raised on the expectancy-disconfirmation model. They mainly contest the claim that expectancy-disconfirmation is the only factor that determines surprise intensity.

The experimental results from [4] show in a number of experiments that unexpected events that are seen as more important by a subject are experienced as more surprising. Also, failures are seen as more surprising than successes, establishing a correlation between the valence of an event and the intensity of surprise the event evokes. Further research confirms these findings.

Other research [9] shows that an unexpected event is seen as less surprising if the surprised person is offered a reasonable explanation that more or less justifies the occurrence of the surprising event. This is explained by the authors as several experiments [18] show that amongst other factors, events that are familiar are less surprising. In the experiments, participants are more surprised if result contrast with earlier experiences. In other words, the event was more novel to the surprised person.

In conclusion, we have the following factors that influence the intensity of surprise:

1) expectation disconfirmation,
2) importance of observed event,
3) whether the observed event is seen as positive or negative (valence),
4) difficulty of explaining / fitting it in schema
5) novelty (contrast with earlier experiences).

Besides the intensity of surprise, the effects of surprise on behaviour are explored in psychological research. Resulting from this research is the conclusion that one of the main effects of surprise that is interesting for agents in training simulations is that it interrupt current activity and slows down the response to the surprising events because of the causal attribution process [6] [18]. A consequent of this is that less time remains for actual decision making. As some studies have shown, decision making quality suffers under time pressure [11]. Especially in military tactical situations, decisions are made under considerable time pressure. It is reasonable to assume that a surprise indirectly leads to less quality in responding behaviour in time-critical situations such as military tactical situations.

So we have two possible effects of surprise on behaviour that could be incorporated in agents:
1) slower response to surprising events compared to unsurprising events,
2) quality of response to surprising events is lower compared to unsurprising events.

2 Model

The model has been defined as a set of temporal relations between properties of states. A state property is a conjunction of atoms or negations of atoms that hold or do not hold at a certain time. The exact choice for what atoms to use depends on the actual model and domain and is defined by an ontology for that model. To model dynamics, transitions between states are defined.

In order to obtain an executable formal model, the states and temporal relations between them have been specified in LEADSTO [1], a temporal language in which the dynamic relations can be defined in the form of temporal rules that can be executed. Let α and β be state properties. In LEADSTO specifications the notation $\alpha \twoheadrightarrow_{e, f, g, h} \beta$ means:

if state property α holds for a certain time interval with duration g, then after some delay (between e and f) state property β will hold for a certain time interval h.

As all of the temporal relations used in the model are of the form $\alpha \twoheadrightarrow_{0,0,1,1} \beta$, the notation $\alpha \twoheadrightarrow \beta$ will be used instead. Intuitively, the symbol $\twoheadrightarrow$ can be read as an if-then rule, where the consequent holds at the next moment in time.

2.1 Model overview

The surprise model can be divided into four parts: event evaluation, surprise generation, the sensemaking process and the effects of sensemaking on behaviour. In figure 1 an overview of the causal relations between the various states of the model is shown.

In the model, events in the environment are continually monitored and evaluated. This evaluation consists of determining the degree of expectation disconfirmation, how important the event is to the subject and how novel the event is. This evaluation is then used to generate the surprise intensity. As the evaluation happens continually, this means that there is a surprise intensity value at any moment.

Based on the surprise intensity, the sensemaking process can be initiated, continued or halted. The sensemaking process is roughly analogous to the causal attribution process in the expectation-disconfirmation theory [18]. Its purpose is to revise the agent's beliefs on the current situation that have been invalidated by the surprising event. The sensemaking process has a feedback influence on surprise intensity, lowering it over time. This feedback represents the idea that the functional role of surprise is to regulate the sensemaking process. As sensemaking proceeds, the need for sensemaking decreases and likewise surprise intensity is lowered.

The last part of the model deals with the effects of sensemaking on behaviour, represented by plans. The type and quality of the behaviour is determined by the beliefs the agent has and the time pressure, which rises with a longer sensemaking duration.

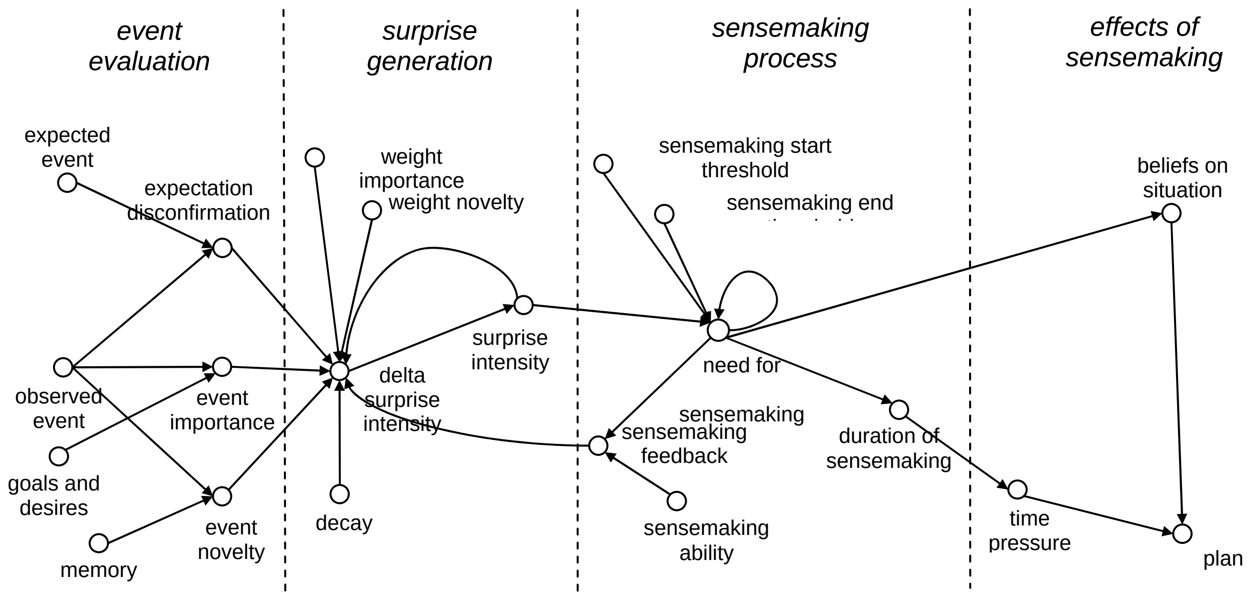

Figure 1: Overview of the surprise model

2.2 Event evaluation

The three outcomes of the evaluation in our model are expectation disconfirmation, event importance and event novelty. These outcomes are represented by a real value between 0 and 1. We have not formalised the process that generate the evaluation outcomes as the focus of this paper is on generating surprise intensity and resulting behaviour. In this section we give some guidelines and ideas on how to interpret and generate these values.

The function of expectation disconfirmation in the model is to measure 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 perceived impact the event has on the agent. A higher importance indicates that the event has relative far reaching consequences for the agent. Calculating the event importance can be done on basis of the goals, plans and desires the agent has, as well as other subjective aspects.

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 could be used for generating the value for event novelty.

2.3 Surprise generation

Surprise intensity is represented as a real value between 0 and 1. In the model, the surprise intensity is not directly calculated. Instead, the rate of change or derivative is calculated and this rate of change is then added to the current surprise intensity value. This rate of change is called the delta surprise intensity in the model.

The calculation of surprise intensity can then be informally described as follows:

If currently the surprise intensity has value si and the delta surprise intensity has value dsi, in the next moment the surprise intensity will have the value si + dsi

More formally,
surprise_intensity(si) &
delta_si(dsi) $\twoheadrightarrow$
surprise_intensity(si + dsi)

The influences that determine surprise intensity that we 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. Two factors decrease surprise intensity, sensemaking feedback and decay. The idea behind the sensemaking process reducing surprise intensity is that the process in the model represents a cognitive effort to reduce surprise by explaining the event and fitting it in an revised view of the situation. The sensemaking feedback value represents the degree of success of explaining the surprising event. In contrast to this, the decay factor represents the non-cognitive factors that reduce the intensity of emotions like surprise over time. Informally, the calculation of the delta surprise intensity occurs as follows:

If currently the surprise intensity has value *si*, there is an expectation disconfirmation with value *ed*, the importance and novelty of the currently observed events have respectively the values *i* and *n*, the weights for importance and novelty have values *wi* and *wn* and th e decay parameter has value *d* and the sensemaking feedback has value *sf*, the delta surprise intensity for the next time step is determined by the formula

$$dsi = (1 - si) \cdot ed \cdot (wi \cdot i + wn \cdot n) - (si \cdot (d + sf)) \qquad (1)$$

More formally, in LEADSTO format:

surprise_intensity(si) &
expectation_disconfirmation(ed) &
weight_importance(w_i) &
importance(i) &
weight_novelty(w_n) &
novelty(n) &
sensemaking_feedback(sf) &
decay(d)
$\twoheadrightarrow$
delta_si($(1 - si) \cdot ed \cdot (w_i \cdot i + w_n \cdot n) - (si \cdot (d + sf))$)

As formula (1) is an important part of the model, we will examine it in more detail. Formula (1) consists of the addition of two expressions, (2) and (3).

$$(1 - si) \cdot ed \cdot (wi \cdot i + wn \cdot n) \qquad (2)$$

$$- (si \cdot (de + sf)) \qquad (3)$$

Expression (2) is about the factors that increase surprise intensity while expression (3) represents the decreasing factors. Expression (3) is negated so that sensemaking and decay can be represented by positive values.

In expression (2) 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. These two assumptions are captured with expression (2). The weights *wi* and *wn* add up to 1, so that the outcome of $ed \cdot (wi \cdot i + wn \cdot n)$ alway lies between 0 and 1. With these weights, the relative influence between the two factors can be tuned.

We multiply $ed \cdot (wi \cdot i + wn \cdot n)$ with $(1\text{-}si)$ in order to keep the value of surprise intensity below 1. As this value increases, the value of $(1\text{-}si)$ decreases, reducing expression (2) and thus reducing the increase of formula (1). Including $(1\text{-}si)$ ensures that the surprise intensity value changes smoothly over time.

In expression (3), the value obtained from the sensemaking process feedback and the decrease parameter are simply added. We multiply this addition with *si* for a similar reason as with the inclusion of the term $(1\text{-}si)$ in expression (2): to keep the value of surprise intensity above zero.

2.4 The sensemaking process

The process of sensemaking is abstracted in our model. It is represented by two dynamic properties, the need for sensemaking and the sensemaking feedback.

The first property, the need for sensemaking, is represented by a Boolean variable that is used to control the sensemaking process. If its value is true, the process is active and if false the process is inactive. The sensemaking process has two direct effects: it lowers surprise intensity by means of the sensemaking feedback and it causes beliefs the agent has on the situation to be revised.

Two parameters, the sensemaking start threshold and end threshold, determine when the need for sensemaking becomes true. The sensemaking process start as the surprise intensity rises above the start threshold, which causes the surprise intensity to drop. The sensemaking process continues until the surprise intensity falls below the end threshold. This mechanism represents the idea that the computationally costly process of sensemaking only takes place if a considerable surprise takes place and that this process endures until the feedback from sensemaking has reduced the surprise sufficiently.
Formally, the rules for determining the need for sensemaking are as follows:

```
surprise_intensity(si) &
sensemaking_start_threshold(start_thr) &
start_thr <= si
↠
need_for_sensemaking(true)
```

surprise_intensity(si) &
sensemaking_end_threshold(end_thr) &
si <= end_thr
↠
need_for_sensemaking(false)

need_for_sensemaking(currentValue) &
surprise_intensity(si) &
sensemaking_start_threshold(start_thr) &
sensemaking_end_threshold(end_thr) &
end_thr < si &
si < start_thr
↠
need_for_sensemaking(currentValue)

The second property, the sensemaking feedback, can only have two values: zero if the need for sensemaking is false and a value equal to the sensemaking ability parameter if the need for sensemaking is true. As we have no empirical support on the precise dynamics of surprise intensity, we have kept the mechanism for sensemaking feedback as simple as possible. In this mechanism, the sensemaking ability is a parameter than indicates how well sensemaking progresses. With this parameter it is possible to differentiate between skilled, experienced pilots and less experienced pilots.

2.5 The effects of the sensemaking process

As explained in section 2, the occurrence of sensemaking has two effects on behaviour: delay in response and decline in response quality. The delay in response is implicitly modelled in the model because the sensemaking process takes a number of time steps to complete. Only after the sensemaking process finishes can a response to the event be made. Time pressure is calculated by dividing the duration of sensemaking by the maximal possible duration, resulting in a value between 0 and 1. A higher time pressure results in a lower quality plan.

3 Case Study

In order to test the model, we constructed a case study loosely based on a historical event in air combat, Operation Bolo [7] [12]. Operation Bolo was a US Air Force (USAF) offensive operation during the Vietnam War against the North Vietnamese Air Force (NVAF). It is considered to be one of the most successful surprise attacks in air combat history.

The NVAF continually attacked the USAF the F-105 Thunderchiefs during their bomber missions in hit-and-run strikes, disengaging before the Americans could mount a counterattack. In response to this, colonel Robert Olds, and experienced fighter pilot in the USAAF, planned a deception. A number of F-4 Phantoms, which were superior air combat fighters compared to the much more sluggish F-105 would fly along the standard bombing route. These F-4s would fly in a bomber-like formation, have bomber equipment with them that could be detected by the NVAF and otherwise try to look like F-105s on a bombing mission but would carry anti-air missiles instead of bombs with them.

Using these ruses, the Americans hoped that they could lure the NVAF fighters into open combat. The plan did indeed work. At January 2, 1967, 28 American fighters engaged 16 NVAF fighters, destroying 7 Vietnamese airplanes with no losses on the American side [7].

Although detailed information on the mission is hard to find, there is evidence that confirms that the Vietnamese pilots behaved surprised and that this had effects on the situation. One of the American pilots has stated that the NVAF pilots appeared to be confused[1]. Also, a military report on the operation states that “...however, the NVN air Force apparently did not expect a strike and their reaction to Operation Bolo was much slower than anticipated [3]. This is in line with the psychological research indicating that surprise leads to a slower response.

Based on this event, we constructed a case against which we can test our model. In this case, the agent plays the role of a Vietnamese fighter pilot. It expects to intercept an enemy bomber formation with no air-to-air missiles. In one situation, the agent will indeed encounter a bomber and subsequently should not be surprise. In the other situation, the agent will encounter fighters well equipped for air combat which should surprise the agent. What our model should show is that an agent using the model will react in a worse and slower way to this unexpected situation compared to the expected situation.

4 Simulation

The model described in the previous sections has been used to run a number of simulations, using the LEADSTO software environment as described in [1]. Within this software environment simulation traces (i.e., sequences of states) can be visualised. An example of such a simulation trace can be seen in Figure 2 and 3. Here, time is on the horizontal axis, the state

[1] In the History Channel documentary “Dogfights”, season 1, episode 2 (“Air Ambush”, 11/10/06), Robin Olds says that “They [the NVAF pilots] realized that we were not Thuds [nickname for F-105]...Mass confusion”.

properties are on the vertical axis. A dark box on top of the line indicates that the property is true during that time period, and a lighter box below the line indicates that the property is false.

An environment and scenario for the agent has been implemented based on the case described earlier. We programmed a simple mechanism for expectation generation in the agent. It is given a list of events that should occur after each other, representing a script or prototypical chain of events. As we based the case on Operation Bolo, this script mimics the historical events. The script is take_off, reach_interception_point, detect_aircraft and aircraft_recognition_bomber. The agent generates an expectation based on the first element in this list and generates an expectation based on the next element every time it observes an event.
The behaviour of the agent is represented by a plan. There are three possible plans in this scenario: offensive_tactics_high_quality, offensive_tactics_medium_quality and offensive_tactics_low_quality.
These represent the same
offensive tactics that the Vietnamese displayed in the historical case, with different levels of quality so that the effect of surprise can be shown.

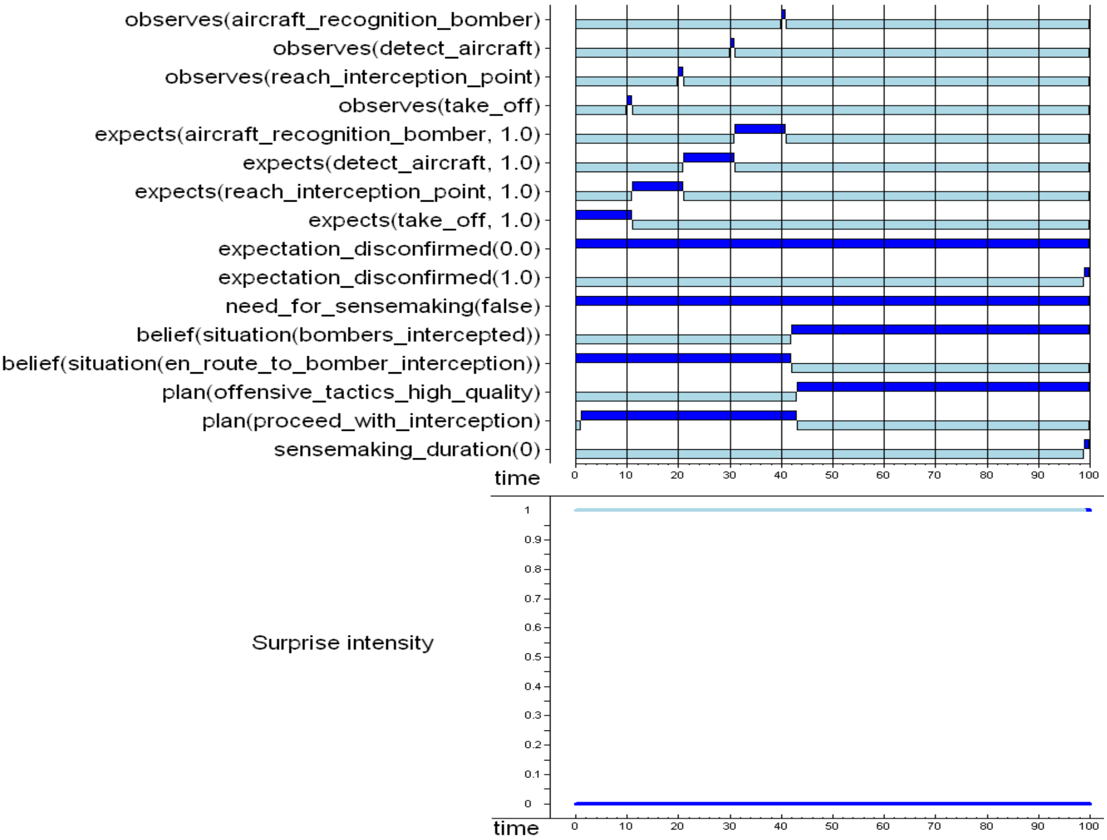

Figure 2: Partial trace of the model reacting to an unsurprising event (from LEADSTO software)

Quality of response in this context is a measure of the lethality, survivability and resource control of the behaviour. These three measurements are a standard way of evaluation military effectiveness of tactics. In this simulation, the importance and novelty of events are parameters, as is sensemaking ability. An agent representing an experienced pilot has a low value for novelty (he has seen it all before) and a high value for sensemaking ability (experience improves situational evaluation).

To give an impression of how the model behaves, figures 2 and 3 shows the traces of two simulation runs executed in the LEADSTO software environment. In both traces the agent is configured to represent an inexperienced pilot, with a high novelty value for events and a low value for sensemaking ability. In the run visualized in figure two, the agent is given a scenario that corresponds with his expectation, resulting in a non-surprising situation. There is no delay, no sensemaking process and therefore the resulting tactic is of high quality.

In contrast, figure 3 shows a run in which an inexperienced agent encounters a surprising event: fighters instead of bombers. At the moment the agent sees that the enemy aircraft is a fighter, the expectation disconfirmation becomes 1 and coupled with a high importance and novelty values of 1.0, the surprise intensity rises. Coupled with a low sensemaking ability, the duration of the sensemaking is quite high (21 time steps out of a maximum of 30), so time pressure is quite high, lowering the quality of the response plan.

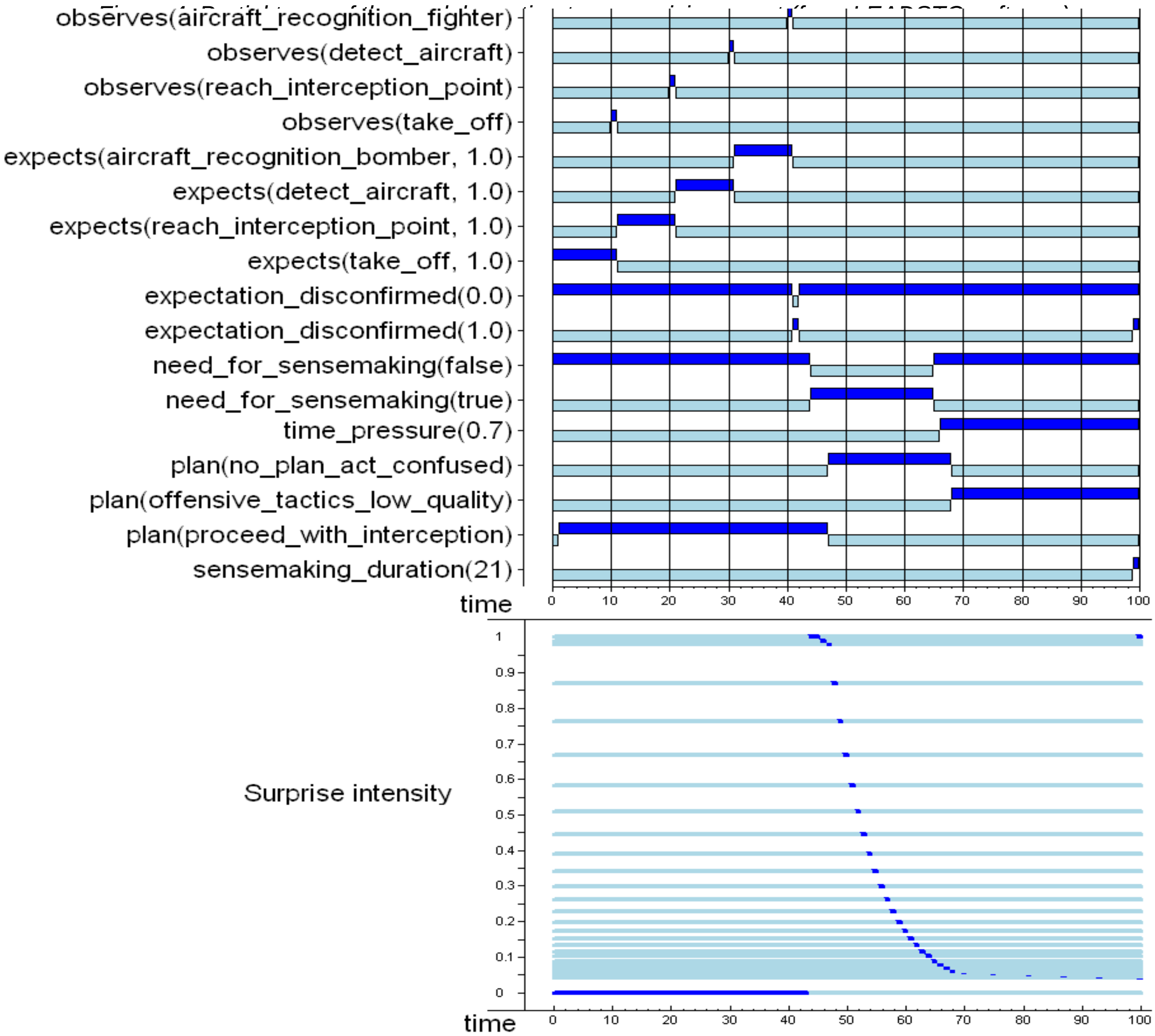

Figure 3: Partial trace of the model reacting to a surprising event.(from LEADSTO software)

5 Evaluation

Three behavioural properties have been identified to evaluate the behaviour of the proposed model. In order to test whether the model satisfies these properties, 8 differently configured simulations of the model have been run, the results of which can be seen in table 1. The first property is that if an agent observes an event which it did not expect, it will react slower and with a response of lower or equal quality than if the event was expected. As table 1 shows, trace 1 and 3 have identically configured agents. With surprise, there is a considerable delay and lower quality in response. Likewise with traces 2 and 5, a delay occurs with surprise.

The second property is that an agent representing a more experienced pilot will react faster and with a higher quality response to the same unexpected event than an agent representing a less experienced pilot. Traces 3, 4 and 5 illustrate this. Duration and quality level decrease with higher sensemaking ability and lower novelty.

The third property is that unimportant unexpected events do not result in a sensemaking process (and thus are effectively ignored by the agent). This holds for the medium experienced (trace 7) and very experienced configurations (trace 8), but not for the inexperienced configuration (trace 6). Further testing showed that no sensemaking takes place if the event novelty in trace 6 was lower than 0.9, which is still a reasonable parameter choice for representing an inexperienced pilot.

Table 1: Simulation results. Expectation disconfirmation, event importance and event novelty refer to the aircraft_recognition events.

trace	configuration description	sensemaking ability	expectation disconfirmation	event importance	event novelty	duration of sense-making	quality of response[2]
1	no surprise, inexperienced agent	0.1	0.0	1.0	1.0	0	high
2	no surprise, very experienced agent	0.3	0.0	1.0	0.1	0	high
3	important surprise, inexperienced agent	0.1	1.0	1.0	1.0	21	low
4	important surprise, medium exp. agent	0.2	1.0	1.0	0.5	10	medium
5	important surprise, very experienced agent	0.3	1.0	1.0	0.1	6	high
6	unimportant surprise, inexperienced agent	0.1	1.0	0.1	1.0	16	medium
7	unimportant surprise, medium exp. agent	0.2	1.0	0.1	0.5	0	high
8	unimportant surprise, very experienced agent	0.3	1.0	0.1	0.1	0	high

[2] The quality of response is the quality of the agent's plan at the end of the trace.

6 Discussion

This paper introduces a computational model for surprise generation and its effect on behaviour. A number of psychological theories and empirical studies found in the literature have been integrated into a single model. Verification shows that the model does indeed generate different behaviour in surprising events and with different representations of experience and importance evaluations.

There has been some research on computational models of surprise for use in agents. A notable example is S-EUNE [9], an agent architecture which uses surprise intensity to enable agents to explore unknown environments. S-EUNE differs from the model in this paper in many ways, most notably in the mechanism of surprise generation (in S-EUNE only expectation disconfirmation is used for calculating surprise intensity) and the lack of a sensemaking process. The model presented in this paper can be used as part of an agent in simulated environments so that its behaviour is enriched with differentiated behaviour in case of surprising events. Additionally, the model incorporates the effects of experience and differences in personal capabilities in sensemaking, so that the generated surprised behaviour is further differentiated. While the model is relatively simple and there is room for improvement in for example the representation of the sensemaking process, it addresses the current lack of realistic models of surprise and its effect on behaviour in agent research.

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