A Surprise-based Selective Attention Agent for Travel Information

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ABSTRACT

This paper describes an agent that can be integrated in travel information systems so that these provide only the relevant/interesting travel information for travelers, preventing these from a superabundance of information and unnecessary interruptions. To do that the agent includes a surprise-based artificial selective attention mechanism grounded on psychological and neuroscience theories of selective attention and surprise which defend that surprise plays an undeniable role on attention focus. Our claim is that only travel information that diverges from the norm or is unfamiliar to the traveler should be considered relevant and therefore delivered to the traveler. We describe the architecture of the surprise-based selective attention agent and illustrate its critical role in an en-route travel information system.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Experimentation

Keywords

Filtering travel information, Selective attention, Surprise, ATIS, BDI agents

1. INTRODUCTION

Typically, travel information breaks down into two categories: static information, which is known in advance and changes infrequently, and real-time, dynamic information, which changes frequently. Static information includes planned construction and maintenance, special events, tolls and payment options, transit schedules and fares, intermodal connections, commercial vehicle regulations, listings of roadside services and attractions, maps and navigational instructions, and historical travel times by location and time of day, day of the week and season. Real-time information includes roadway conditions, including congestion and incident information which change minute-by-minute, alternate routes which can vary depending on the degree of congestion, whether transit vehicles are on schedule, the availability of spaces on parking lots, the identification of the next stop on a train or bus, the location or arrival time of the next train or bus, and travel time to a destination which can also vary depending on the time of day.

Advanced Travel Information Systems (ATIS) are designed to assist travelers in making pre-trip and en-route travel decisions by providing them pre-trip and en-route information. Pre-trip information is to inform travelers of traffic and transit conditions before they select a route, mode, departure time, or decide whether to make a trip. En-route information provides drivers information pertaining to traffic conditions, incidents, construction, transit schedules, weather conditions, hazardous road conditions, and recommended safe speeds while en-route. This information allows the drivers for instance to select the route which is best for them. Information can be provided while en-route by variable message signs, commercial radio, highway advisory radio, personal communication devices (e.g., cellular telephones, Personal Digital Assistants — PDAs, Smartphones) or in-vehicle navigational systems.

With wireless ATIS, the historic distinction between pre-trip and en-route information is starting to blur. Travelers are increasingly able to receive information, often in real or nearly real time, both before and during their trips because of the existence of all those mobile devices. The new wireless and web technologies are used both to gather traffic information (e.g., cell-phone probes, incident reports by cell phone users, GPS (Global Positioning System) / GIS (Geographic Information Systems) tracking for incident management) and disseminate it (e.g., Internet postings of up-to-date transit schedules, advice issued through on-board navigation systems, advisory services delivered through mobile phones, PDAs or Smartphones).

However, while these information systems can undoubtedly help humans perform better in these complex traveling scenarios, if the amount of information achieves a level that is unhandled, instead of being beneficial, it is a problem. Moreover, with the expected increase in the number of these travel information systems, in the number of the information technologies used to disseminate information and the countless kinds of information provided, this may become even worse. Humans will be continuously receiving a superabundance of information which they cannot handle by themselves. Although, evolution already provided humans with the selective attention components that indicate which few aspects of the world are significant to the particular problems at hand, the amount of information received by those selective attention components may be itself a problem and compromise agents' performance. This is even more problematic because most of the time this information is provided in a way that affects especially the high level natural selective attention, which is involved in strategic cognitive choices such as the preference or shift of a task or activity over another. This means that humans might have to interrupt whatever they are doing to deal with the information provided by those information systems. This phenomena is sometimes referred as "Interruption overload" [?] and is especially problematic (or dangerous) if the human agent is performing critical tasks like driving a car. Actually, there is evidence indicating that those devices are the cause of many vehicle accidents [?, ?].

Given this wealth of information coupled with human real-time multi-task processing constraints, incorporating selective attention mechanisms in devices is a fundamental strategy to any chance of success, since this would decrease the number of interruptions. Moreover, it is contended that while many traveler information systems are innovative and make use of cutting edge technologies, they lack real machine intelligence and therefore may be limited in their ability to service the traveling public over the long-run. On the one hand, a wave of technological developments, in particular the increasing deployment of GIS and, on the other hand, the introduction and rapid market penetration of mobile devices such as cell phones boosted the development of ATIS towards what has been termed Intelligent Traveler Information Systems (ITIS) [?], in which artificial intelligence techniques are drawn upon to create systems capable of providing travelers with more personalized planning assistance.

Selective attention, the capability exhibited by humans for selecting the relevant portions of information from the environment, has been thoroughly researched over the last 100 years in psychology and more recently in neuroscience (e.g., [?, ?]). It is thought to be necessary because there are too many things in the environment to perceive and respond to at once. However, at present there is no general theory of selective attention. Instead there are specific theories for specific tasks, tasks such as orienting, visual search, filtering, multiple action monitoring (dual task), and multiple object tracking.

It is generally agreed that surprise and curiosity/interest play an essential role in selective attention [?, ?, ?, ?, ?, ?, ?, ?, ?, ?]. In fact situations that include novelty, incongruity, unpredictability, surprise, uncertainty, change, challenging and complexity certainly demands greater attention than a stimulus distinguished by none of these properties. Moreover, these properties are also those assigned to situations that cause curiosity [?, ?, ?, ?, ?, ?]. .

The computational models of surprise proposed by Itti and Baldi [?, ?, ?] quantify low-level surprise visual stimuli, and at this point does not account for high-level or cognitive beliefs of human observers. Both approaches focus on the role of surprise in visual attention (the perception of objects, movements, or scenes), and both are mainly concerned with the detection of unexpected events and the computation of surprise intensity. For example, central to Itti and Baldi's surprise model is the proposal to compute surprise intensity as the distance (measured by the Kullback-Leibler divergence) between the prior probability distribution over a set of hypotheses and the posterior distribution resulting from the Bayesian updating of the prior distribution on the basis of new information.

A similar approach has already been proposed by Schmidhuber in the context of reinforcement learning and neural nets. Schmidhuber [?, ?] used artificial curiosity as a reward that enables an artificial agent to acquire quickly learning examples from the environment during its exploratory activity. Oudeyer [?] used artificial curiosity as an intrinsic motivation for improving the learning progress of a developmental robot. Both computational models of curiosity subsume, to some extent, models of surprise in that curiosity intensity relies on error prediction. However, much like Itti and Baldi, and Peters' computational models of surprise, Schmidhuber and Oudeyer's computational models of curiosity are applied only to low level or raw sensorial data. Although some surprise theorists (e.g., [?]) have claimed that surprise can also be elicited at "lower" levels of representation than the propositional level, specifically by perceptual mismatch, it is doubtful whether perceptual mismatch per se causes the experience of surprise in humans [?]. As argued by Losee [?], there are more complex kinds of information such as beliefs. According to cognitive theories, these mental states are actually the most important information inputs for those cognitive processes such as surprise and curiosity. Therefore, good models of surprise and curiosity should take this higher level kind of information into account.

Opposed to these approaches relying on low-level, raw information, Macedo, Reisenzein and Cardoso [?, ?] and Lorini and Castelfranchi [?, ?, ?] proposed, independently, computational models of surprise that are based on the mechanism that compares newly acquired beliefs to preexisting beliefs. Both models of artificial surprise were influenced by psychological theories of surprise (e.g., [?]), and both seek to capture essential aspects of human surprise (see [?] for a comparison of both models). In agreement with most theories of human surprise, both models of artificial surprise conceptualize surprise as a fundamentally expectation- or belief-based cognitive phenomenon, that is, as a reaction to the disconfirmation of expectations or, more generally, beliefs. Furthermore, in both models, beliefs are understood as propositional attitudes (e.g., [?]), and a quantitative belief concept (subjective probability) is used. Both artificial surprise models draw a distinction between two main kinds of expectations or beliefs whose disconfirmation causes surprise (see also [?]): Active versus passive expectations. Although Macedo and Cardoso initially used the same surprise intensity function, according to which the intensity of surprise about an event is proportional to its unexpectedness, Macedo, Reisenzein and Cardoso subsequently opted for a "contrast model" of surprise intensity. This model assumes that the intensity of surprise about an event reflects its probability difference to the contextually most expected event (see also, [?]).

The model of surprise developed by Macedo, Reisenzein and Cardoso is combined with another for curiosity to drive the exploratory behaviour of a Belief-Desire-Intention (BDI) artificial agent. Macedo [?] stated a clear distinction between surprise and curiosity, although according to Meyer et al surprise elicits curiosity. However, the actual Macedo's computational model of curiosity is based solely on the idea that novelty and uncertainty (measured by entropy) elicit curiosity/interest (e.g., [?, ?]). According to psychological theories of curiosity [?, ?, ?, ?], this model as well as those of Shmidhuber or Oudeyer are incomplete in that they don't take into account other variables such as complexity.

In spite of the importance of selective attention in travel information systems such as in driving [?, ?], to our knowledge, only [?] applied a surprise-based mechanism for filtering information. However, the computational model of surprise has no apparent relation to human surprise, which we think it is very important in that we are trying to substitute human attention.

In this paper we describe the integration into the ATIS of such artificial attention mechanism focusing on its surprise-based component, at least at the level of personal devices so that only relevant travel information for the task their human masters are carrying out is selected and communicated to them. Our approach relies on the psychological and neuroscience studies about selective attention, whose main aspects were already considered in the computational models of surprise and curiosity proposed by Macedo [?]. In fact, those models already capture the variables of unexpectedness, unpredictability, novelty, and uncertainty. Specifically, we adopt, adapt and improve those computational models of surprise and curiosity developed by Macedo and Cardoso [?, ?, ?, ?, ?, ?, ?, ?] and, in addition, include also an utility metric, so that only the information that is both curious and useful is selected and transmitted to the human travelers. In order to assess the effectiveness of the surprise-based selective mechanism, we compare the selections made by the devices and by humans under similar circumstances.

The next section describes the computational model of surprise-based selective attention and outlines the architecture of the agent in which it is integrated. This will be followed by presenting the application of this kind of agents in travel systems. We then describe an exploratory study about the contribute of the surprise-based selective attention agent to solve the travel information overload of its master. Finally, after a short discussion, some conclusions are presented and suggestions for further work are made.

2. A COGNITIVE COMPUTATIONAL MODEL OF SURPRISE-BASED SELECTIVE ATTENTION

Selective attention may be defined as the cognitive process of selective allocation of processing resources (focus of the senses, etc.) on relevant, important or interesting information of the (external or internal) environment while ignoring other less relevant information. The issue is how to measure the relevance of information. What makes something interesting? In cognitive science, attentional focus is linked with expectation generation and failure, i.e., with surprise [?]. Therefore, it is reasonable to consider that any model of selective attention should rely on a cognitive model of surprise. However, surprise is not enough. Happiness/pleasantness may also play also a fundamental role on attention [?, ?, ?]. According to cognitive theories of emotion and specifically to belief-desire theories of emotion [?], happiness is directly related to congruence and relatedness between new information and the intentions or the motives/desires of a human agent. For this reason, the system must also incorporate a measure of the expected reward or utility of the information for a specific human agent, based on her/him particular intentions and desires at hand. Other variables such as novelty (different, unfamiliar), complexity (hard to process, challenging, mysterious), uncertainty, coping potential [?, ?, ?, ?, ?, ?, ?, ?] (according to previous studies, there is evidence indicating that these variables elicit curiosity/interest [?, ?, ?, ?, ?, ?, ?, ?, ?]), might also been taken into account.

In order to accomplish all those requirements, we developed an architecture for a personalized, selective attention mechanism (see Figure ??). We assume this mechanism is incorporated in an agent which interacts with the external world receiving from it information through the senses and outputs actions through their effectors. We also assume the agent is a BDI agent [?, ?, ?], exhibiting a knowledge or belief container, a module of feelings, as well as intentions and desires. In addition, we also assume the agent contains other resources for the purpose of reasoning, decision-making and communication. The first of the steps is concerned with getting percepts (module 1 in Figure ??). The second is the computation of the current world state (module 2 in Figure ??). This is performed by generating expectations or assumptions for the gaps of the environment information provided by the sensors based on the knowledge stored in memory. We assume that each input information resulting from this process goes through several sub-selective attention devices, each one evaluating information according to a certain dimension such as surprise (module 4 in Figure ??), novelty (module 5 in Figure ??), uncertainty (module 6 in Figure ??), complexity (module 7 in Figure ??), coping potential (module 8 in Figure ??), and pleasantness (i.e., utility or congruence to agent's goals and desires — happiness; relatedness to agent's goals and desires) (module 9 in Figure ??) taking into account some knowledge container (memory — preexisting information, that should reflect the human information) (module 10 in Figure ??), and the intentions and desires (motives — module 12 in Figure ??). The values of surprise, curiosity (includes novelty and uncertainty), happiness, etc. are computed by the feeling module (module 11 in Figure ??). There is a decision-making module (module 13 in Figure ??) that takes the values computed by those sub-selective attention modules into account and computes an overall relevance/interesting value for each input information. Then, this module of decision-making selects the higher relevant information and allocates appropriately resources (reasoning, processing, displaying, communication resources, etc.) (module 14 in Figure ??) to deal with it. In this sense, the selective attention mechanism is on the basis of other cognitive abilities of the agent in that it decides in which information those other cognitive abilities should focus.

In this paper we will focus on the surprise-based selective attention mechanism. We claim that any computational model of selective attention should capture a cognitive model of surprise. We will describe in more detail the surprise-based selective attention module as well as all those secondary modules that surrounds (serves) it.

The process of making the right decision depends heavily on a good model of the environment that surrounds agents. This is also true for deciding in which information should the agent focus. Unfortunately, the real world is not crystal clear to agents. Agents almost never have access to the whole environment, mainly because of the incompleteness and incorrectness of their perceptual and understanding components. In fact, it is too much work to obtain all the information from a complex and dynamic world, and it is quite likely that the accessible information suffers distortions. Nevertheless, since the success of agents depends heavily on the completeness of the information of the state of the world, they have to pursue alternatives to construct good models of the world even (and especially) when this is uncertain.

According to psychologists, cognitive scientists, and ethologists [?, ?], humans and, in general, animals attempt to overcome this limitation through the generation of assumptions or expectations to fill in gaps in the present observational information. Note, however, that not all those expectations are made explicit. However, the reasoning of the agent may be improved if its model of the world also contains a good model of the future worlds. In this case, the process cannot be confined to filling in gaps in the information provided by perception because there is no information at all of those worlds. In order to overcome this limitation, agents also exhibit the ability to make predictions about future states of the world, taking the present world and inference processes into account (module 2 in Figure ??). When the missing information, either of the present state of the world or of the future states of the world, becomes known to the agent, there may be an inconsistency or conflict between it and the assumptions or expectations that the agent has. As defended by Reisenzein [?], Gärdenfors [?], Ortony and Partridge [?], etc., the result of this inconsistency gives rise to surprise which in our model of selective attention and according to previous studies plays a central role in selective attention. It also gives rise to the process of updating beliefs, called belief revision (e.g., [?]).

Following the pluralist view of motivation (e.g.: [?]) , the module of basic desires (basic motivations/motives) (module 12 in Figure ??) contains a set of basic desires that drive the behaviour of the agent by guiding the agent to reduce or to maximize a particular feeling [?]. In this paper we focus on agents that exhibit the basic desire of surprise that directs the agent to feel surprise, i.e., to satisfy that basic desire the agent selects focusing attention on aspects of the world that make it feel surprise.

The module of feelings (module 11 in Figure ??) receives information about a state of the environment and outputs the intensities of feelings. Following Clore [?], we include in this module affective, cognitive, and bodily feelings. The latter two categories are merged to form the category of non affective feelings. This means that this module is much broader than a module of emotion that could be considered. Feelings are of primary relevance to influence the behavior of an agent, because computing their intensity the agent measures the degree to which the basic desires are fulfilled. In this paper, we highlight the feeling of surprise. We adopted Macedo, Cardoso and Reisenzein computational model of surprise [?, ?]. In contrary to other computational models such as Itti and Baldi's which are appropriate solely to the lower level of selective attention required in raw sensorial attention, this computational model was empirically tested against human surprise ratings and fits well human surprise and therefore it is appropriate for reasoning about non-raw data such as high level, cognitive beliefs and knowledge. It will ensure that given some information and the agent's belief store, only that information that is unexpected or unpredictable will be object of alert. Note, however, that Lorini and Castelfranchi's surprise model is also appropriate to be incorporated in this agent's architecture. Macedo, Cardoso and Reisenzein computational model of surprise suggests that the intensity of surprise about an event E_g, from a set of mutually exclusive events $E_1, E_2, \ldots, E_m$, is a nonlinear function of the difference, or contrast, between its probability and the probability of the highest expected event E_h in the set of mutually exclusive events $E_1, E_2, \ldots, E_m$.

Definition 1. Let $E = E_1, E_2, \ldots, E_m$ be a set of mutually exclusive events. Let E_h be the highest expected event from E. The intensity of surprise about an event E_g from E is given by:

$$Surprise(E_g) = \log(1 + P(E_h) - P(E_g)) \qquad (1)$$

The probability difference between $P(E_h)$ and $P(E_g)$ can be interpreted as the amount by which the probability of E_g would have to be increased for E_g to become unsurprising. The formula implies that, in each set of mutually exclusive events, there is always at least one event whose occurrence is unsurprising, namely, E_h.

The memory of the agent (module 10 in Figure ??) stores information (beliefs) about the world. This information includes the configuration of the surrounding world such as the position of the entities (objects and other animated agents) that inhabit it, the description of these entities themselves, and the descriptions of plans executed by those entities. The information is stored in several memory components. There is a metric (grid-based) map to spatially model the surrounding physical environment of the agent. Descriptions of entities (physical structure and function) and plans are stored both in the episodic memory and in the semantic memory (see [?] for more details).

3. SELECTIVE ATTENTION TO TRAVEL INFORMATION

An ATIS database provides information of various types to the travelers. On the other hand, data is continuously collected from sources such as travelers, traffic sensors, and weather service. Selective attention agents may be integrated at two levels (see Figure ??): in personal devices to act as personal assistant selective attention agents, and in the ATIS database itself. In personal devices the goal of the selective attention agents is to avoid unnecessary interruptions to their users by enabling that only interesting information is provided to them. In the ATIS database the goal is to ensure that irrelevant information is not stored in the ATIS database.

Let us illustrate these two roles of selective attention agents, in this case based solely on surprise. Suppose that a traveler has the following expectations for the traffic conditions of a certain road, for a certain time: 1% of probability of "good traffic conditions" (event E_1), 9% of probability of "moderate traffic congestion" (event E_2), and 90% of probability of "excessive traffic congestion" (event E_3). Should the traveler be alerted if the real time traffic conditions are bad? Suppose also his/her surprise-based, selective attention, personal assistant agent is setup with the same set of expectations. This surprise-based selective attention agent customized to produce an alert only when the surprise value of information is above the 90% level wouldn't provide that information to the traveler. Actually, according to Equation ??, the surprise value of E_3="excessive traffic" is:

$$\begin{aligned} Surprise(E_3) &= \log(1 + P(E_3) - P(E_3)) \\ &= \log(1 + 0.9 - 0.9) = 0 \end{aligned}$$

Notice that in this case the event E_3="excessive traffic congestion" is the one with the highest probability in the set

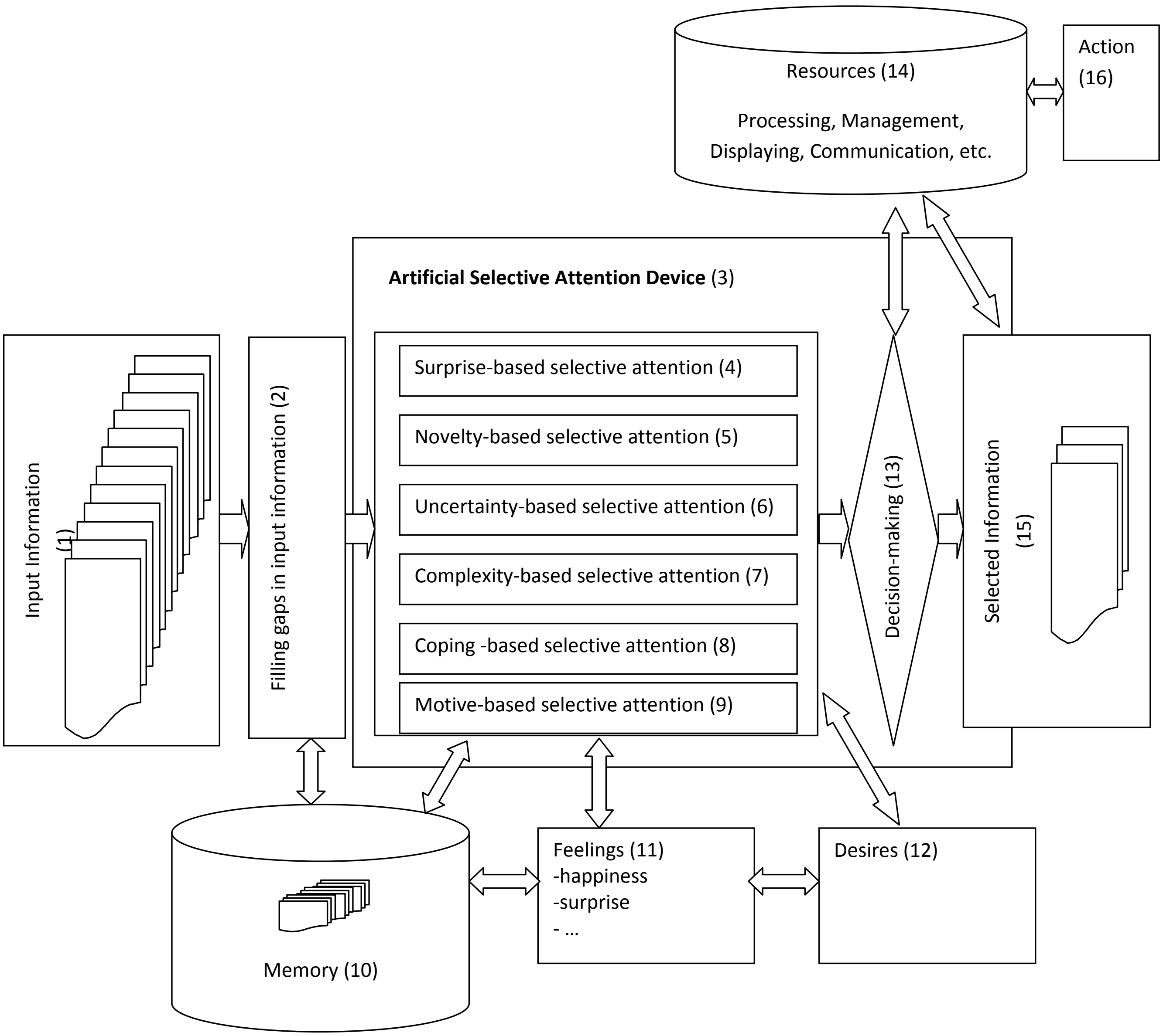

Figure 1: Architecture of an artificial selective attention agent.

of mutually exclusive events. If the traveler beliefs strongly in that why should he/she be notified?! If the real time traffic condition is E_2="moderate traffic congestion", the surprise value now is:

$$\begin{aligned} Surprise(E_2) &= \log(1 + P(E_3) - P(E_2)) \\ &= \log(1 + 0.9 - 0.09) = 0.855 \end{aligned}$$

which is still below the level of triggering an alert (90%) and therefore no alert is produced. However, if the real time traffic condition is E_1="good traffic condition", the surprise value now is:

$$\begin{aligned} Surprise(E_1) &= \log(1 + P(E_3) - P(E_1)) \\ &= \log(1 + 0.9 - 0.01) = 0.918 \end{aligned}$$

which is enough to trigger an alert. Notice that the level of triggering an alert is customized and therefore the accuracy of the selective attention agent depends on it. For instance, if the level was 85% the agent would produce an alert in the second situation which for some people might be a reasonable choice. This example is about traffic conditions information, but it is worth of notice that it might be applied also to any other kind of travel information such as GPS traces, points of interest, weather conditions and road conditions.

Using a surprise-based selective agent in the ATIS, only the collected information that is above a specified level of surprise for the surprise-based selective attention agent in the ATIS would be considered relevant to be added to the ATIS database. Consider that this database contains the information that the traffic conditions of a certain road at a certain time are 1% of the times good, 9% moderate and 90% bad. Suppose also that only information with a surprise value above 90% is allowed to be added to the database. If someone submits the information that the traffic conditions are moderate or bad, this information would not be added to the database. However, if someone submits the information that the traffic condition is good, this would be worth of addition to the database, because it is a less familiar situation.

4. EXPERIMENT

We did an exploratory study in order to compare the relevance value computed by the selective attention agent and the relevance value computed by humans. While the relevance value rated by humans is of subjective nature, the relevance value computed by the artificial selective attention agents is based rigorously on expectations computed from statistical data collected from previous traffic situations in the past 30 days for a certain place, all at the same time of the day. The artificial agent used Equation **??** to compute the relevance value which in this case is confined to surprise. We select a street from a city (Bissaya Barreto Avenue, in Coimbra, Portugal) and configured a selective attention agent to provide real time information about the traffic conditions in that street to 5 volunteer travelers whose path include that street. We collect the relevance the travelers assign to the information the agent delivered during 10 days at the same time (9h:00m) and always concerning the same street. The real time traffic conditions of the 10 days of the experiment are presented in Table **??**. In addition,

Table 1: Traffic conditions of the 10 days of the experiment.

Day	Traffic condition
1	Good
2	Excessive
3	Excessive
4	Good
5	Excessive
6	Moderate
7	Good
8	Excessive
9	Moderate
10	Excessive

after the trip, the information the agent didn't delivered because its surprise value was below the triggering level of alert was shown to the travelers and these were asked to rate the relevance they would assign that information if it was delivered.

Figure **??** shows the comparison of the relevance value rated by humans with those computed by the agent based solely on surprise. As it can be seen, the correlation is very high (0.99), but still there are some discrepancies. For instance, we noticed that humans assign total relevance for information with a surprise value above about 80%. Moreover, we noticed that some situations in which the agent didn't delivered information, the humans rated a low (but different from 0) relevance value for that information. However, they didn't consider that it would be worth of delivery. Although not shown in the chart, the experiment shows that using the 90% level of triggering an alert the agent failed twice (day 6 and day 9) according to the traveler opinions. In those two cases, they say that the agent should have provided information. However, when we decrease the triggering level to 80% the performance of the agent was very good with no incorrect decisions.

5. DISCUSSION AND CONCLUSIONS

We presented an approach to deal with travel information overload relying on a surprise-based artificial selective attention mechanism that may be integrated in travel information technologies. The exploratory experimental results indicate that the mechanism performs well, contributing to the decrease of interruptions when driving. However, the performance of the selective attention mechanism depends on several factors such as the reference class [**?**] considered to computed the expectations and the triggering level of alert. With respect to the reference class, it is worth of notice that the artificial selective attention agent computes the degree of belief based on a frequentist approach to probability, contrasting with the humans's subjective expectations. For instance, to compute the probability of bad traffic conditions for a certain place, the agent might take several options such as taking all the traffic history of that place into account for the computation of the probability, or restricting these data to those situations that happened at that place at a certain season, day of the week or even specifically time of the day.

As demonstrated in the previous two sections, the triggering level of alert has direct influence on the performance

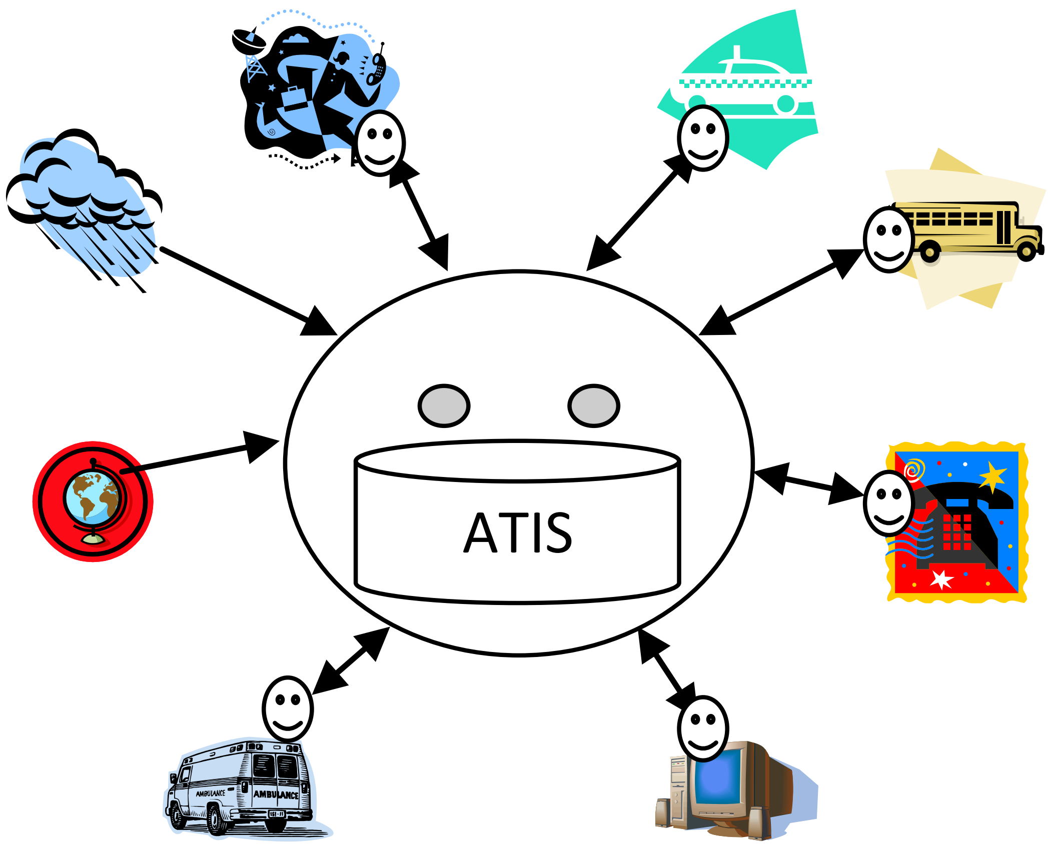

Figure 2: Selective attention agents, information sources and information dissemination of an ATIS; the smiley faces represent the selective attention agents. The ATIS itself is embedded into a selective attention agent.

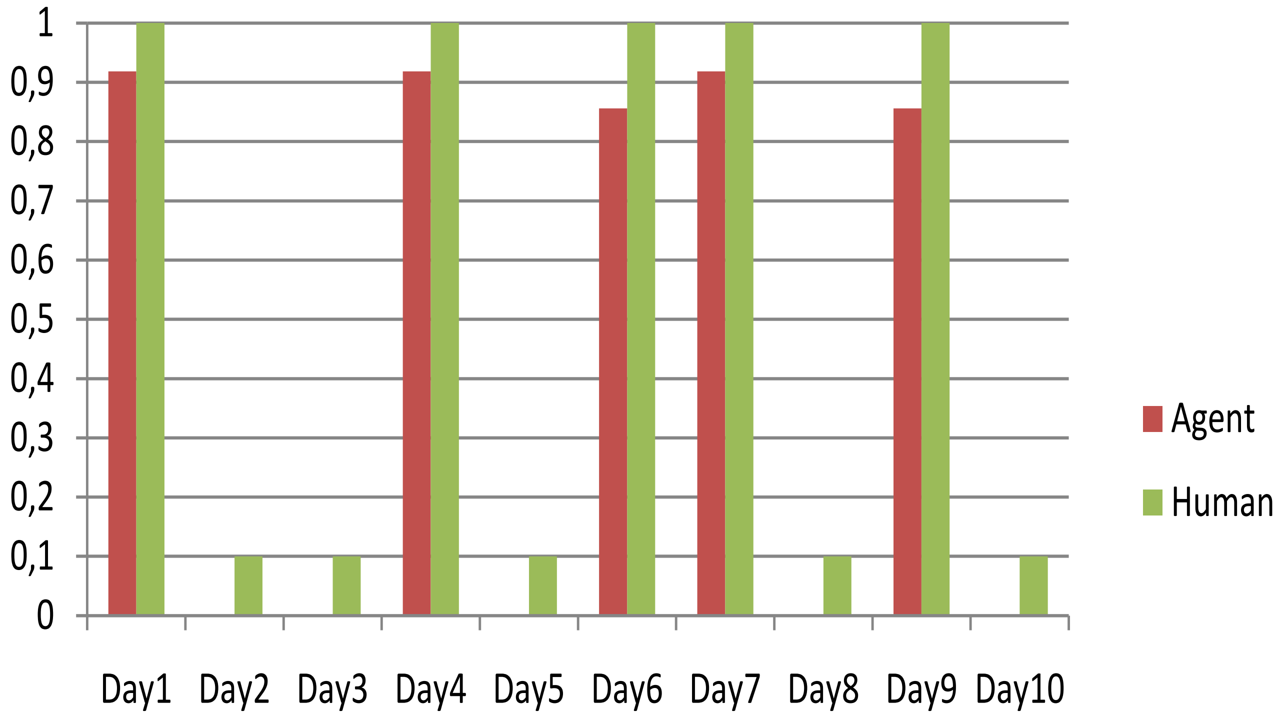

Figure 3: Comparison between the relevance rated by humans and the surprise-based relevance computed by the selective attention agent.

of the agent. However, if the agent is to act as a personal agent the triggering level may change from human to human. Therefore, a pilot experiment should be carried out to determine the the most correct triggering level on average for the travelers.

The experiment that we carried out needs further improvements. In order to assess the significance of the results, the number of travelers and the number of locations (streets, roundabouts, etc) involved in the experiment should be increased. Furthermore, in order to generalize the evidence for the role of the surprise-based selective attention mechanism on travel information, several kinds of travel information should be considered in the experiments such as information about roadside services and attractions, maps and navigational instructions, roadway conditions (including congestion, incidents, construction and other hazardous road conditions), weather conditions, alternate routes which can vary depending on the degree of roadway conditions, whether transit vehicles are on schedule, the availability of spaces on parking lots, the identification of the next stop on a train or bus, the location or arrival time of the next train or bus, and travel time to a destination.

As mentioned above the surprise-based selective attention mechanism allows the agent to alert for travel information that is unexpected. Although the variables of novelty, unexpectedness, complexity and uncertainty are quite related, and sometimes used as synonyms in the literature, we defend that they are different and therefore having different and indispensable roles in the selective attention mechanism, and to some extent complementing each other. While novelty means new information, uncertainty means that new information will probably be acquired. Information is a decrease in uncertainty which, according to information theory, is measured by entropy. New information is surprising, but there might exist information that, although it is not novel, it is surprising. It is also worth of notice that the definition of surprise adopted in this paper is different from the notion of *surprisal* from information theory [**?**, **?**]. To illustrate the difference between the surprise-based and these related selective attention mechanisms consider the following example. Suppose that an agent has the following expectations for the traffic conditions of a certain road, for a certain time: 1% of probability of "good traffic conditions" (event E_1), 9% of probability of "moderate traffic congestion" (event E_2), and 90% of probability of "excessive traffic congestion" (event E_3). In this case, if the agent receives the information that the traffic conditions of that road, at that time, are good, this information is not new since it already happened in the past according to the agent's memory. However, this information is surprising (actually very surprising: 91.8% of surprise), but different from its surprisal value (6.64).

As mentioned above a selective attention agent may be located either at the personal devices or at the ATIS itself. It is worth of notice that when it is located at the personal devices, even though the agent may not communicate to their master pieces of information below the triggering level of alert, this information is stored in their memory so that it can be taken into account to update the probability distributions in memory. This way, this information influences the computation of expectations in the future and therefore the future selections. On the contrary, the selective attention agent located at the ATIS filters the information below a specified level of relevance, preventing its storage.

Another important issue that influences the performance of the agent is whether to consider expectations of the humans or those computed from statistical data. The experiment was done with the latter method. However, for the purpose of assessing the performance of the selective attention agent it might be more appropriate to give the artificial agents the same expectations of humans so that they act under the same conditions. Nevertheless, in terms of practical application it makes more sense to make the agent compute its own expectations.

The experiment described in this paper makes the simplification that the events are all equally related to one's intentions in that all the travelers include in their trajectories the street that was chosen for the study. However, in reality things doesn't happen this way. The following example illustrates this point. Suppose someone is driving and intend to go to a certain place. Suppose that he/she is informed by his/her traffic information system that there is a traffic congestion in a street which is part of the path that he/she is going to follow. Suppose also that he/she receives a similar information but with respect to another street which is not included in his/her trajectory. He/she would be more attracted by the former information than the latter. Assume this two pieces of information are not new, not surprising (those streets are usually congested) or equally surprising. The major difference between these pieces of information is that the former is related to his/her intentions/goals and the latter is not. Therefore, in addition to those very related sub-selective attention mechanisms based on surprise, novelty, complexity and entropy, the pleasantness-based selective attention mechanism plays a central role in selective attention.

In spite of these illustrative examples explaining the difference between the roles of all those sub-selective attention mechanisms, further experiments should be carried out to assess the contribute of all of them to the the overall selective attention mechanism. A factorial experiment in which the several sub-selective attention mechanisms are the factors (the independent variables) should be done.