Delivery of Travel Information Supported on Surprise and Relevance

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Abstract. One aspect concerning traveler information systems that is particularly important for vehicle drivers is the problem of interruption overload.
In this paper we present an application of concepts from psychology, namely surprise, and user modelling in order to collect, filter and deliver novel and useful information. We finalize with an illustrative example.

1 Introduction

In complex environments such as urban spaces, ubiquitous computational devices are used to collect many kinds of information about the agents - mostly human beings - and their surrounding elements - transportation systems, buildings, weather, etc. This information can be shared among the various agents in order to improve the efficiency of the urban space.

Devices such as cell phones, Personal Digital Assistants (PDAs) and Personal Navigation Assistants (PNAs) can undoubtedly help humans perform better in these scenarios. However, although evolution already provided humans with the selective attention components that indicate which few aspects of the world are significant to the particular problem at hand, at a given time, and place, the amount of information received by those selective attention components may be itself a problem and compromise agent's performance. Moreover, with the increasing number of ubiquitous computing devices this may become even worse.

Humans will receive an overwhelming quantity of information which they cannot handle. This is even more problematic because most of the time this information is provided in a way that needs attention and intervention from the human agent, which means that s/he has to interrupt whatever s/he was doing. This phenomena is sometimes referred as "Interruption overload" [1] and is especially problematic (or dangerous) if the human agent is performing critical tasks like driving a car.

Given this wealth of information coupled with human real-time multi-task processing constraints, devices that incorporate selective attention mechanisms in order to decrease the number of interruptions are fundamental to achieve success in the development of traveller information systems.

With this work, we address the issue of selecting information in complex urban scenarios, with a special focus on traveller information systems in the context of intelligent transport systems (ITS). However, the developed selective information mechanisms should easily be deployed along other contexts.

In the next chapter we present the main motivation for our work. On chapter 3 we present the concept of surprise measuring. We proceed by presenting and discuss some preliminary results on chapter 4 and we finish by present some conclusions and future work on chapter 5.

2 Motivation

Current PNA devices are very effective in providing the quickest or the shortest route to drive from one point to another, some also provide the "most scenic" or the cheapest one, but no matter which is the chosen route, the driver must be concentrated on driving, and so, minimizing the interaction between the system and the driver is essential.

Some work has been done [2] in order to identify the main sources of distraction while driving are: mobile phones; multimedia devices; 'infotainment' systems like internet access; and also PNAs. This study suggest that the extent to which PNAs distract drivers depends highly on how the driver and the system interact, being the process of information input (entry of navigation instructions, changing the systems settings, etc.) the most distracting task, followed by the presentation of guidance information visually and using voice instructions.

Several other studies [9] [10] have focused their attention in determining how distracting can the use of route guidance systems be. Both studies have concluded that in fact using these devices can be very distracting, leading to lane departures and sudden breaking that can lead to accidents.

All the above studies also concluded that using devices with voice instructions is less distracting than those that use only visual information.

One issue that, to our knowledge, no one has addressed is the fact that in specific conditions the driver may know very well the best route (which eventually is also the one that the PNA selects as being the best one), and doesn't need to be constantly exposed to driving instructions for that specific route.

Someone that drives to work everyday may know very well the best route and maybe won't even turn on his PNA. But, what if that route for some reason (traffic, road accident, work on the road, etc.) is not at all the best one? It would be of great value to have the PNA turned on, in order to receive instructions for an alternative route!

We propose a collaborative distributed system that collects information about all the possible routes to drive from one point to another having in mind the current conditions (traffic, weather, etc.) and according to a specific set of variable weights, selects the route that best fits the present scenario.

After the best route is found and before being presented to the driver, the system will compare it against the ones that the driver already has used previously (stored in a personal user model) using a metric of surprise, which will be explained ahead.

If the selected route is quite familiar to the driver (i.e. not surprising), the system won't provide driving directions for that route, since it's assumed that s/he already knows what to do, and the system may switch to a "stand by" mode. But, if the route is considerably unfamiliar (i.e. surprising), then the system will suggest that route and provide the driving instructions.

This way, we are able to provide to the driver only information that s/he don't know already and that is relevant to the specific task that is performing, saving her/him from receiving information already known.

When the driver reaches the destination, anonymized information about the journey will be sent to a central server in order to improve future decisions.

3 A Metric of Surprise

In cognitive science, attentional focus is linked with expectation generation and failure, i.e., with surprise [3]. Therefore, the proposed artificial selective attention component relies on a cognitive model of surprise.

In the last years, several computational approaches to surprise where developed. Some of them, like the ones proposed by Itti et al. [5] and Peters [6] are focused on the role of surprise in computer vision, and because of that they are not easily applicable to our current work.

Lorini et al. [4] presented their conceptual and formal clarification of the notion of surprise. According to them, surprise theory is defined as a formal model, using logic of probabilistically quantified beliefs. They identified three main types of surprise (mismatch-based surprise, astonishment and disorientation) along with the formal definitions. The proposed models are quite formal and well documented but unfortunately they haven't yet been validated with human beings.

Macedo et al. [7][8] also worked on the computational model of surprise. Based on previous psychological experiments they started to work on the basis of the assumption that surprise felt by an agent elicited by an object/event X is proportional to the degree of unexpectedness of X. After several iterations they presented the following expression as the one that best models human surprise:

$$S(X) = log_2(1 + P(Y) - P(X)) \tag{1}$$

In this formula, surprise is defined as the difference between the probability of the event/object with the highest probability, *P(Y)*, and the probability of the event/object that really occurred, *P(X)*. Additionally the formula can capture the apparent nonlinearity of surprise.

This model has been validated with humans in different domains, namely elections and sport game results, and we think it can also be applied in this specific domain.

4 Illustrative Example

With this example we want to show how surprise can be used to identify the information that is considerably unexpected. In this specific scenario, we identify one route to drive from one point to another and we will see if that route is very different from the one that the driver normally uses. For this purpose we measure the surprise that resulted from choosing one specific direction instead of another in intersections (crossroads and roundabouts).

The probabilities of choosing one direction are calculated using the number of times that the driver already selected that direction in the past. In Figure 1 we calculate the surprise choosing to turn to Q and not to R or S, using the number of times that the driver has chosen that direction.

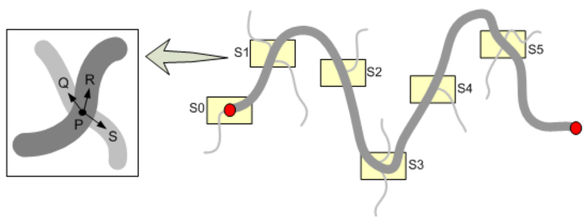

Fig. 1. Example of one intersection

The global surprise of one specific route is given by the sum of the local surprise values calculated in each of the intersections along the route Si divided by the number of intersections where Si is different form zero, j.

$$S = \sum \frac{Si}{j} \tag{2}$$

To illustrate the role of surprise within this domain we've developed a simple test scenario consisting of 2 different points (A and B) in the city of Coimbra, Portugal, and 6 different routes to drive from A to B, as shown in Figure 2.

We proceed by entering each one of the routes in the system to determine the surprise caused by it. When we enter a new route in the system, it will be stored so that in the future that route will be remembered and have into account when the surprise of the next route is calculated.

The routes were entered in the system by the order seen in Figure 2 from a) to f). The local surprise values obtained on each intersection *I-i* as well as the global surprise values can be observed on Figure 3.

In route e) intersection *I-1*, for instance, local surprise *S1* is calculated using the formula presented before. At this intersection, in the past routes, the "driver" has chosen to turn in direction of *I-2* 3 times (routes a), b) and c)) and 1 time in direction of *I-4* (route d)). So, when route e) is presented to the system, at *I-1* we have 75% probability of driving in direction of *I-2* and 25% probability

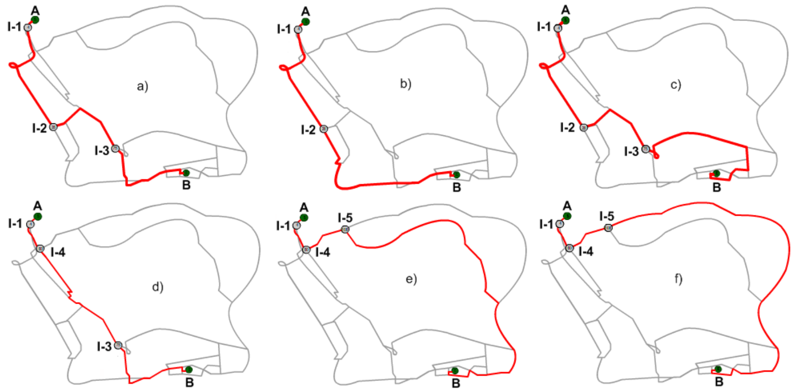

Fig. 2. The six different routes

Route	S1		S2		S3		Stotal
	intersection	value	intersection	value	intersection	value	
a)	I-1	0	I-2	0	I-3	0	0
b)	I-1	0	I-2	1	-	-	1
c)	I-1	0	I-2	0	I-3	1	1
d)	I-1	1	I-4	0	I-3	0	1
e)	I-1	0,585	I-4	1	I-5	0	0,7925
f)	I-1	0,263	I-4	0	I-5	1	0,6315

Fig. 3. Results for running the system with 6 routes

of driving to *I-4*, and, as can be seen, on e) the choice is to drive in direction of *I-4*. This means *P(Y) = 0,75* and *P(X) = 0,25*. Replacing the values in the formula we get:

$$S1(X) = log_2(1 + 0,75 - 0,25) \Leftrightarrow S1(X) = 0,585 \tag{3}$$

The same procedure was followed to calculate *S2* on *I-4* and *S3* on *I-5*.

If the probability of selecting between two destinations is equal, the value of surprise will be 0, which seems to match what happens in real life.

At the end, the local surprise values were summed and divided by the number of surprise values different from 0.

$$S(X) = \frac{S1 + S2 + S3}{j} \Leftrightarrow S(X) = \frac{0,585 + 1 + 0}{2} \Leftrightarrow S(X) = 0,7925 \tag{4}$$

From the results presented above it becomes clear that for the first entered routes the surprise value is equals to 1, since the routes contain decisions that are surprising having in mind the few past decisions, and it starts to be smaller as more routes are entered, since most of them include intersections about which the system already has information on past decisions.

As expected, the system will only return high surprise values when confronted with routes considerably different from the past ones.

5 Conclusions and Future Work

We think that surprise can be used to determine if one specific route is or not familiar for a specific driver. This means that we can reduce the amount of provided information by giving only the one that is unfamiliar to the user. We also understand that much work has yet to be done in this direction.

The surprise model that was chosen has been validated with humans on specific domains, but work must be done to validate the model within this domain.

Something that may deserve our attention, concerns the model of surprise itself, since we cannot exclude the possibility of using an alternative surprise model.

We must also dedicate some effort to the definition of the architecture for the system; decide which metrics for usefulness measurement will be used; and calculate a suitable surprise threshold.

Finally we need to simulate the system and perform field tests.

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