ARTIFICIAL SELECTIVE ATTENTION FOR IN-VEHICLE INFORMATION SYSTEMS

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ABSTRACT: One aspect concerning in-vehicle information systems that is particularly important for vehicle drivers is the problem of information/interruption overload. In this paper we present an application of concepts from psychology, in order to obtain, select and deliver information about the Points of Interest (POIs) that are associated with a driver's travel in order to perform a specific task.

1 INTRODUCTION

In complex environments such as urban spaces, ubiquitous computational devices like cell phones, Personal Digital Assistants (PDAs) and Personal Navigation Assistants (PNAs) are used to provide different kinds of information about the human beings and their surrounding elements to help them perform better in these scenarios.

Although evolution already provided humans with 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 large amount of information received by those selective attention components may be a problem and compromise the person's performance.

Humans will keep receiving overwhelming amounts of information that they cannot handle. Most of the times large amounts of irrelevant information have to be processed in order to find the few items that are really important. This is even more problematic since most of the times this information is provided in a way that needs full attention and intervention from the human being, which means that s/he has to interrupt whatever s/he was doing.

This phenomena is sometimes referred as information overload [1] and interruption overload [2] and is especially problematic (or dangerous) if the human agent is performing attention demanding tasks like driving a car.

Given this wealth of information in conjunction with humans real-time multi-task processing constraints, devices that incorporate artificial selective attention mechanisms with the aim of selecting only the relevant information are fundamental to successfully develop in-vehicle information systems (IVIS), namely PNAs.

Current PNA devices are very effective on providing route guidance for the quickest or shortest route to drive from one point to another, as well as on providing information about the nearest Points of Interest (POI), namely, gas stations, restaurants, hospitals, etc. In this work, we are specially interested on the last type of functions – POI delivery.

The main problem with most existing POI delivery applications, is that they provide information regardless of the user's real context/intention and specially regardless of what s/he already knows. This leads to the presentation of large amounts of irrelevant information that difficult the process of finding the desired information as shown in Figure 2 a).

Several studies [3] [4] have shown that using navigation devices while driving can be dangerous, leading to sudden breaks or lane departures that may end on causing traffic accidents. Taking into account the fact that most of the time the drivers will be using these applications while driving, it becomes even clearer the importance of providing only the relevant information, so that the driver may be focused on the driving process.

To overcome the problem of having large amounts of information to display on top of a map, some mechanisms were already developed in the past. In some cases, the process consists on filtering the POIs according to specific criteria like POI popularity or applying more complex criteria like the relevance of the POI for the current task.

As an alternative/complement to the filtering process, Edwardes et al. [5] identified five different generalization operations in order to make the maps more readable: selection (chose the most representative items according to specific criteria), simplification (use one single icon to represent several POIs based on their spatial proximity), aggregation (similar to simplification, but a different icon representing aggregation is used), typification (merge items of different types using an icon where all the different types are merged) and displacement (move the icons from their original location and use an arrow pointing there.).

To select the most important items, Kime et al. [6] use the concept of relevance of each item for the current context. The relevance of each specific item is calculated by a combination of three different distances: topical (distance between the user's search query) and the item attributes), spatial (geographical distance between the user's location and each item) and temporal (the distance between the period when the item is available and the current time).

Pombinho et al. [7], use a degree of interest function inspired on Furnas work [8] to calculate the relevance of each POI which basically consists on the sum of the differences between the values of target attributes defined by the user and the attributes associated to each POI, which can be numerical (e.g. distance, price) or nominal (e.g. types of food). The POIs with the highest degree of interest are select to be displayed.

Since there are several situations where many POIs may be considered as highly relevant and consequently the list of POIs to display can be very large, three different generalization operations may be used: aggregation, typification and displacement.

Burigat et al. [9] address the same problem using an aggregation of POI icons based on the spatial distance between the POIs which will lead to icon overlapping.

Although, the presented solutions seem to be effective on selecting the most relevant POIs in order to increase map readability, there is an important issue that none addresses, which is the familiarity that the user already has with the selected POIs. In some cases, the user may be considerably familiar with most of the POIs selected as being relevant, so, presenting them will eventually be unnecessary.

Inspired on the concept of natural selective attention [10], we propose the integration of an artificial selective attention (ASA) component, that autonomously select the most relevant and unfamiliar information to provide to the user, preventing delivery of irrelevant or unwanted information.

In cognitive science, attentional focus is linked with expectation generation and failure, i.e., with surprise [11]. Therefore, the proposed ASA component relies on a cognitive model of surprise like the one proposed by Macedo et al. [12]. However, surprise is not enough, since only useful information is relevant. For this reason, the system must also incorporate measures of the relevance of the information for a specific user, based on her/his particular intentions and context.

In the next sections we will present more detailed information about our approach as well as illustrative examples of the system at work. We end by presenting some conclusions and ideas for future improvements.

2 APPROACH

Our approach has the goal of dismissing information about the places that the user knows (e.g. home, work place, parents home, regular restaurant, etc.), because for those places the user knows where they are located and most probably won't even use a navigation device. For these places, the users can always use the Favorite POI feature, that most PNAs provide. Instead, we are interested on providing information that the user is more likely to be unaware (i.e. the most surprising information), and that is useful to the specific task that s/he is performing at the moment.

In order to select the most important POIs we employ information on the users context and intention to filter the POIs in three consecutive steps: relevance, surprise, diversity.

2.1 Determining user's context and intention

One important aspect in such systems concerns determining the user's current context (i.e. where is the user, what is s/he doing, etc.). Although several different attributes can be used to identify the users context like location, identity, activity, time, among others, for now, we use only location and identity.

The user's current location is defined using GPS receivers, which is a widespread and relatively accurate mean of doing it. To determine the users identity, we rely on a simple authentication process using a common pair of username/password which in the future may be replaced by the use of biometric features like fingerprint or facial recognition.

Although we think of using mechanisms to automatically determine the user's current intention/goal, in this early stage of the work, we just assume that the user has input his/her intention/goal as a set of attributes.

2.2 Selecting POIs

With the user's current context and intention defined, we'll obtain the list of POIs that best seem to fit the user's context/intention.

2.3 Relevance

As in some of the above mentioned approaches, we start by determining the relevance of each POI for the current context/intention. The approach used was inspired by the one used Pombinho et al. [7] and consist on the weighted sum of distances between the target attributes input by the user and the ones associated to the POIs.

$$Relevance(POI_i) = \sum_{j=1}^{k} \left(\left(1 - Dist(T_j, P_j)\right) \times w_k \right), w_k \in \,]0,1[\tag{1}$$

Where k is the number of attributes, Tj the value for the target attribute j, Pj the value for the attribute j of a specific POI i, and wk a weight associated to each attribute.

Depending on the type of POIs that we are dealing with (e.g. restaurants, hospitals, gas stations, etc.), different attributes may be used, some numerical and other nominal, so, the distance between the target and the POI attribute values are defined differently. For now, we are assuming that all the items in the list are of the same type.

For nominal attributes (e.g. types of restaurants) the distance is calculated using:

$$Dist(T_j, P_j) = \begin{cases} 0, if\ T_j = P_j \\ x, if\ T_j \approx P_j \\ 1, if\ T_j \neq P_j \end{cases}, x \in \,]0,1[\tag{2}$$

Where x represents the semantic similarity between both attributes, which can be obtained using lexical databases like WordNet [13].

For numerical attributes, several different distance functions can be used depending on the attribute itself as well as on what we are expecting to obtain.

For instance, if we have a target price attribute we may decide that prices below the target should be considered more relevant that the prices above (3).

$$Dist(T_j, P_j) = \frac{P_j - min_j}{max_j - min_j}, Dist(T_j, P_j) \in [0,1] \tag{3}$$

Or, we can consider that regardless if they are above or below, the more distant they are from the target price, the less relevant they are.

$$Dist(T_j, P_j) = \left| \frac{P_j - T_j}{max_j - min_j} \right|, Dist(T_j, P_j) \in [0,1] \tag{4}$$

In the above expressions, maxj and minj correspond to the maximum and minimum values for the attribute j associated to the POIs contained on the list.

Finally, we select the POIs with relevance values greater than a specific threshold α, defined by the user.

Surprise

After determining the most relevant POIs, we proceed by selecting the ones that are most unfamiliar to the user. For this purpose, we use the model of surprise proposed by Macedo and Cardoso [12], which has been successfully validated with human beings. The idea, is to determine the value of surprise felt by the user when confronted with a specific POI within a specific context. Our goal is to select the items with the highest surprise values, which are the ones that the user most probably is unaware of.

To determine the surprise value for each POI, we need to calculate the user's appropriation level, which defines the relation that the user has with each POI. The appropriation level is calculated having into account the contacts that the user had with each POI in the past.

For this purpose, we assume three contact types between user and POI: i) the POI might have been presented to the user; ii) the user might have asked for additional information about the POI (clicked on it); iii) the user might have driven to the POI location using route guidance information provided by the system.

Different weights are attributed to each contact type, so, the user's appropriation level for each POI X is the result of the sum for all weights associated to the past k contacts between the user and that POI (5).

$$AL(X) = \sum_{i=1}^{k} w_i \tag{5}$$

The user's appropriation level for each POI, will be used to determine the probability that it has of being presented to the user (higher appropriation level $\rightarrow$ higher probability). The probability of a specific POI j being choose from a list with k items is given by:

$$P(X_j) = \frac{AL(X_j)}{\sum_{i=1}^{k} AL(X_i)}, P(X_j) \in [0,1] \tag{6}$$

Finally, we will determine how surprising each POI is to the user using:

$$S(X) = log_2(1 + P(Y) - P(X)), S(X) \in [0,1] \tag{7}$$

Where X represents each individual POI and Y represents the POI with the highest probability of being selected.

After determining the surprise value for each POI using (7), the POIs with surprise values higher than the threshold μ are selected to the next phase. These POIs are the ones with which the user had less contacts in the past, or at least the less significant contacts.

One aspect that for now we are not having into account is the fact that the low appropriation level for a given POI may result on the users dislike for that POI (for instance, the user may had a bad experience with a certain place in the past and never wanted to go there again). For this types of situations, an exclusion mechanism should be included.

2.4 Diversity

At the starting point of this step we obtain a list of the most relevant and surprising POIs, but still we may ended up with a significant number of items, so, we still need to determine which POIs are more different from each other, to avoid selecting very similar POIs.

The approach used to determine the most diverse POIs is inspired by Gago et al. [14] and involves determining the difference each POI and all the others based on their attributes.

The system starts by randomly selecting a POIs from the list produced by the surprise filter. Then we calculate the distance from this POI to all the other ones. The one most distant from this one is the second POI entering the group of selected POIs. From this point and for all the remaining POIs we calculate the average distance between them and the ones previously selected. The one with the highest average distance to all the selected ones is the one entering the selected group.

The process stops after n POIs are selected or when there are no more candidate POIs with an average distance to the selected ones above a β threshold.

The diversity between two POIs is calculated using the following expression:

$$D(X,Y) = \sum_{i=1}^{k} Diff(Att_i(X), Att_i(Y)) \tag{8}$$

As mentioned previously, the attributes of the POIs can have different type of values, so also in this case, there must be different ways of calculating the difference between the attributes.

The difference between nominal attributes is calculated using (2) and for numerical attributes we use:

$$Diff(Att_i(X), Att_i(Y)) = |Att_i(X) - Att_i(Y)| \tag{9}$$

Finally, after determining the n most diverse POIs we are able to provide the user with the desired information, which ideally will meet his/her needs without making him/her navigate through huge amounts of unwanted items.

On Figure 1 we show one graphical representation of the described three step process .

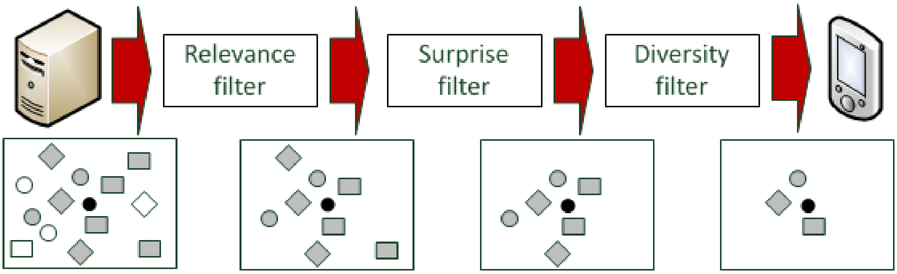


Fig. 1. The three steps of POI filtering

In order to best meet the users preferences, the system has some parameters that can be adjusted: α - relevance threshold; μ - surprise threshold; n – maximum number of POIs that can be presented to the user. Decreasing the α parameter alone will result on the retrieval of POIs that may be considered less useful, for instance, the most distant ones, while decreasing only the μ parameter may result on solutions that are useful, but that are considerably familiar to the user. Changing the value of β or n will influence the number of items displayed. The main difference between them, is that when using β, we are able to obtain a list of items that have a diversity value above a minimum threshold, while when using n, we are requesting the n most diverse items.

3 ILLUSTRATIVE EXAMPLE

To illustrate how the system works, we will use a simple example that consists on using a PDA to obtain information about the restaurants that are near the user's current location. Our goal is to provide the user with the n most relevant, diverse and surprising restaurant options.

As expected, the information provided by the user will highly influence the process of calculating the POIs relevance, for instance "I want a cheap and informal Chinese restaurant" is preferred in opposition to "I want a restaurant".

Given the users intention, we retrieve the nearest m restaurants and proceed by calculating their relevance to the user. Besides its name and location, each POI has additional attributes that will be used to determine the POI relevance. For this specific situation, we use information about the type of food (Portuguese, Italian, Chinese, etc.), the average price; the ambiance (formal or informal); rating (1-10 based on users opinion) and the distance from each POI to the user's current location. The weights associated with the attributes are: type of food – 0,35; average price – 0,15; ambiance – 0,1; rating – 0,15; distance – 0,25.

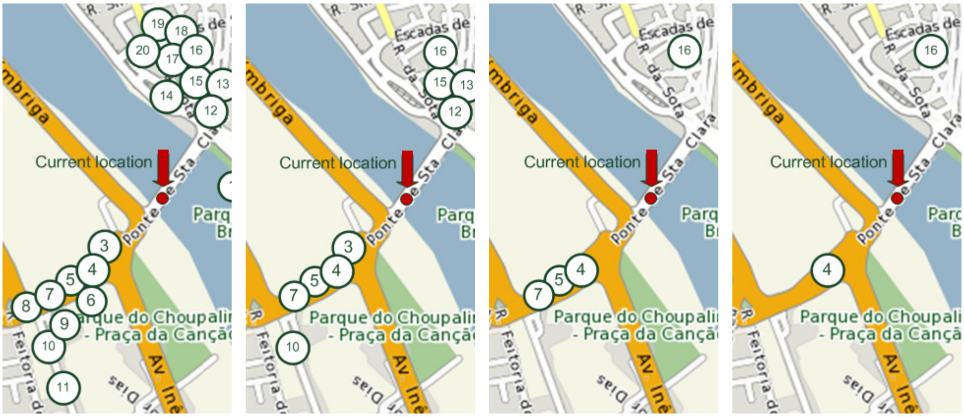
Supposing that we are in Coimbra, Portugal and want to eat something, we may use the system to request information about "Informal Portuguese restaurants with average price of 15€ and average rating of 7". The system retrieves the POIs, listed on Table 1.

Table 1. Example of the 20 POIs initially retrieved

ID	Name	Type	Avg Price (€)	Ambiance	Rating (1-10)	Distance (meters)	Relevance	Past contacts	Surprise
1	Itália	Italian	20	Informal	10	600	0,533	V V	0,64
2	Dom Pedro	Portuguese	25	Informal	6	750	0,683		1
3	Alfredo	Portuguese	20	Informal	4	500	0,775	V V	0,64
4	Pinto D'Ouro	Portuguese	15	Informal	7	600	0,846		1
5	Dom Duarte	Portuguese	25	Informal	4	650	0,675		1
6	Pizzaria Santa Clara	Italian	15	Informal	5	800	0,363	V C T	0
7	O Convento	Portuguese	15	Informal	4	850	0,667		1
8	Tricana	Portuguese	20	Informal	4	920	0,6	V C	0,53
9	Cantinho dos Nobres	Portuguese	15	Informal	5	1000	0,629		1
10	Tasquinha da Ti Irene	Portuguese	10	Informal	6	1050	0,671	V C	0,53
11	Casino da Urca	Portuguese	15	Informal	7	1100	0,638		1
12	Aeminum	Portuguese	20	Informal	5	500	0,8	V C	0,53
13	Cantinho das Escadas	Portuguese	15	Informal	7	550	0,867	V C	0,53
14	Amphitryon	Portuguese	30	Formal	4	600	0,558		1
15	Calado e Calado	Portuguese	20	Informal	4	650	0,713	V C V	0,29
16	Adega A Cozinha	Portuguese	15	Informal	6	720	0,771	V	0,83
17	Giuseppe & Joaquim	Italian	20	Formal	10	740	0,375		1
18	Esplendoroso	Chinese	15	Informal	9	800	0,463	V V	0,64
19	Vitória	Portuguese	20	Informal	5	920	0,625	V	0,83
20	Dom Espeto	Portuguese	25	Informal	4	900	0,571		1

In Table 1 we presented the POIs with their attributes and the relevance and surprise values. The highlighted relevance and surprise cells correspond to values above the specific threshold. Since the surprise value is calculated having into account the past contacts between the user and the POIs, we've created some random contacts, which are represented using V (visualization), C (click) and T (if the user has followed the route guidance to drive to the POI). The system parameters used were $\alpha = 0.65$, $\mu = 0.8$, $n = 3$. As expected, in the first step, the nearest Portuguese food restaurants were selected, since the type and spatial distance are the attributes with highest weights for determining the relevance. Since we've selected an high surprise threshold, only the highly surprising POI (the ones that had no previous contacts) were selected on phase two. Finally, the four more diverse items were selected to present to the user.

On Figure 2 we may observe the evolution of the list of selected POIs through the three steps of the process.



a) initial list

b) after relevance filter

c) after surprise filter

d) after diversity filter

Fig. 2. Results from each step of the process

Using this approach we were able to considerably simplify the map that will be presented to the driver, making it much easier to read it and to focus on the information that is provided. Map in Figure 2 d) is the one that is shown to the user.

It is important to notice that we choose a map as the way to display the POIs, but the same approach could be used if the POIs were displayed as a list of items.

As mentioned before, it's important to emphasize the fact that our main goal is not to provide the user with information about the POIs that s/he already knows, our goal is to do the exact opposite. Anyway, if the user wants to display also those known POIs s/he can do it by decreasing the μ threshold.

4 CONCLUSIONS

There are no doubts that in-vehicle information systems, can help humans perform better in their daily tasks, but it's also true that they are a considerable important source of distraction.

The in-vehicle context is by default a very attention demanding context, so, the development of mechanisms that automatically can select only the relevant information to the driver's context and intention, is crucial.

Although in this particular case, we've focused on POIs, the proposed selective attention mechanism can be also applied on various other aspects concerning delivery of information on the context of IVIS, like for instance, determining if the driver must (or not) receive route guidance information for a specific journey.

In this paper, we've presented an illustrative example of how the system can select information. We make some considerations about the results, which are consistent with what was expected. However, this approach has to be validated in real world scenarios, so, we are currently working on the validation process with a group of users that will use this system to perform specific tasks.

Another aspect that will deserve special attention is the process of determining the driver's context and intention. If we are able to automatically determine the driver's intention, we will be able to proactively select and provide him/her the relevant information for the particular context/intention, reducing even more the interaction between the system and the driver.

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