Situation Awareness for Proactive In-Car Recommendations of Points-Of-Interest (POI)

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Abstract. Recommender systems have become widely used for providing personalized product, media and travel information. Our goal is to apply them in automotive scenarios by recommending Points-Of-Interest (POI) such as fuel stations, restaurants or parking places. Furthermore, driver distraction caused by user interaction is a problem in automotive scenarios. We aim to reduce interaction by providing recommendations in a proactive manner. To give an example, proactive recommendations of fuel stations are of interest for the driver if he is expected to run out of fuel or reachable fuel stations. To enable proactive in time recommendations, context plays a fundamental role. It describes user situations which determine the relevance of recommendations. Our contribution is a new model for situation awareness tailored to proactive recommendations in automotive scenarios. Unlike other approaches, our model allows for incorporating past and future situations for assessing the relevance of a recommendation in the present. The presented model is based on fuzzy logic to cope with different sources of uncertainty. The implemented scenario is a proactive POI recommender for fuel stations using situation descriptions for fuel level states and number of reachable fuel stations. The evaluation shows that the model allows to determine significant situation changes. This information can then be used to derive decisions on when to recommend a fuel station.

1 Introduction

In the last couple of years more and more information has become digitally accessible, but only a fraction might be of interest to a user in a specific situation. Recommender systems aim to reduce this information overload by selecting a subset based on user preferences [9]. Although they are mainly applied to desktop systems in product and media recommendations, there are many efforts to bring them to mobile devices. This is driven by affordable sensors and increasing computational power of mobile devices. Researchers try to incorporate physical context, like location, to improve recommendation [2]. Our approach uses context to enable proactive decision making for recommendations of Points-of-Interest (POIs) like restaurants, hotels or fuel stations.
An obvious scenario for recommending POIs in automotive environments is a fuel station recommender. A proactive recommender could check the fuel level, the type of fuel the car needs and the reachability of fuel stations. Knowledge-based or content-based recommendation approaches are suitable for calculating recommendations of fuel stations by taking user preferences for brand, fuel price and detour into consideration. Another interesting scenario comes with recommending opportunities for rest stops, e.g. parking places, fuel stations, restaurants or hotels. To determine the right time for recommending, the driver state, like fatigue or stress, could be used.

In contrast to interactive systems the user in proactive systems is not in the loop but above it [11]. Instead of the system answering user queries interactively it works off tasks and is supervised by the user. Our goal is to enable proactivity in automotive recommender systems, an area that has not gained much attention so far. As mentioned in [10], this is because the risk to bother the user is very high. New and improved sensors in modern cars and richer content can overcome this problem by judging relevance of information more accurately. In cars, sensors to measure driver context can be mounted unobtrusively, but driver distraction and information overload are a problem.

In the work of [8] the main requirements to a proactive recommender system are described as: (1) Relevance of information: The right information at the right time to the right user, (2) Unobtrusiveness: Avoid disturbing and annoying the user, (3) Long-Term memory: Remembering what the user has done and using it. Our focus in this paper concerns the first aspect.

We present ongoing research on a model for situation awareness. Calculation of personalized and context aware recommendations are also part of our research project but not addressed in this paper. Our contribution in this paper is the interpretation of Endsley’s situation awareness model for proactive recommender systems. It is based on fuzzy logic to handle uncertainty in situation recognition and prediction. The basic idea behind our model is to incorporate past and future situations for in time decision making in present. We implemented the model using user routes for future prediction. The scenario for evaluating our approach is a fuel station recommendation system.

The remainder of the paper is organized as follows. In Sec. 2 we describe fundamentals of context and situation awareness and discuss related approaches. In Sec. 3 we explain our approach for situation awareness and present in 4 an implementation and its evaluation based on user routes. We close with conclusions and future directions in 5.

2 Fundamentals and Related Work

We start with some fundamental descriptions of context and situation. Then other approaches for situation awareness are analyzed.

In [4] context is defined as “any information that can be used to characterize the situation of an entity”, which is a common definition in the field of context-aware computing. Hence, a situation takes different states and is determined by a
Every situation has a current state, which is valid for a finite amount of time. For instance, situation ‘meeting’ has the states ‘in a meeting’ or ‘before a meeting’ and the first state begins with the end of the second. Furthermore, situation awareness is generally defined by Endsley in [5] as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future.” Endsley separates situation awareness in three levels. On level 1 context is sensed to recognize situations. Level 2 is the comprehension of the recognized situation and on level 3 a projection of the situation into the future is done. Our model of situation awareness in proactive recommender systems is based on this separation.

The work in [7] also focuses on situation awareness in proactive and mobile information systems based on Endsley. Their model consists of four layers from raw sensor and information data to situations consisting of actions and relations to other situations. Uncertainty of context and situation recognition are not handled in the model. Although the model is based on Endsley, level 3 is not addressed explicitly. [1] handles uncertainty of situation recognition for mobile recommender systems by so called ‘interval stabilization’, which makes sure that situation changes only occur when the context changes significantly. Every situation change leads to inference with rules, but past and future situations do not affect a recommendation. The authors in [3] handle uncertainty by using fuzzy logic for automatic recommendation of services. Situations are on the consequent side and temporal and spatial aspects are in the antecedent condition of rules. E.g., the situation ‘pre-meeting’ is given if the user is close to the meeting room in time and space. The main shortcoming of situation awareness models so far is, that they are designed for actions when a specific situation occurs, which is in our understanding a reactive behavior. To enable proactive recommendations, we need a model which is able to react before a situations occurs. This allows delivering of in time information to support the user in the upcoming situation.

3 A Model for Situation Awareness in Proactive Recommender Systems

In this section we describe our model for situation awareness based on fuzzy logic. First, we explain the motivation for fuzzy logic and how our model can be classified in mobile recommender systems. Afterwards, we present the different levels of the model following Endsley’s definition.

3.1 Overview

We decided to use fuzzy logic [12] as an inference and modeling technique to incorporate uncertainty and avoid ramp up problems of learning methods. Smooth transitions between values in a fuzzy set allow modeling a system without abrupt behavior, which should be avoided in proactive recommendation systems. Fuzzy logic also allows transparent behavior of a system by using linguistic
variables, which accounts for the acceptance of a proactive recommendation system. Weighted rules are able to handle heterogeneous situations with different importance.

A mobile user has to make several decisions on the way [6] which leads to diverse techniques to assess alternatives depending on the cognitive load of the decision. To assist a mobile user some decisions can be made by an autonomous system, delivered proactively and assessed by the user. The decisions our proactive recommender system tries to make are:

1. In which situation is a recommendation for a task relevant?
2. Which POIs conform to quality and context preferences of a user?

The first decision considers the relevance of a recommendation for a task. We define a task as a common activity a user wants to perform, e.g. eating, resting or refueling. Our system supports the user with these tasks by recommending POIs. To determine if a recommendation is relevant, the situation of the user has to be sensed and assessed. The second decision is about which POI fits best to both context and user preferences. The result is a so called consideration set of POIs, a list which consists of the POIs to recommend. Finally, the consideration set and user situations have to be merged to a final decision by weighting alternatives.

We focus here on the first aspect and describe in the following our 3 level situation awareness model for recommender systems based on Endsley’s theoretical model. The idea behind our work is to assess current as well as upcoming and past situations for present decision making. This corresponds to user behavior in decision making: A user estimates future situations (e.g. time, location, fuel level) and weights alternatives (a cheaper fuel station vs. reachability considering current fuel level).

3.2 Situation Awareness Level 1 and 2

Figure 1 depicts the first two levels of our situation awareness model. On the first level raw data sensed about user, environment and device is used to recognize a situation. Several techniques to fuse sensor data can be used on this level, e.g. fuzzy logic, Bayesian networks or simply taking the raw sensor value. On level 2 situations have to be interpreted to be used in a proactive recommender. This is done by mapping a crisp situation description to fuzzy variables. Every situation is represented by exactly one situation fuzzy variable and can take on different states represented by the values of the fuzzy variable. For example, the situation ‘fuel level’ maps a numeric value for the amount of fuel in the fuel tank to a fuzzy interpretation like ‘full’, ‘nearly empty’ or ‘empty’ on level 2. On level 1 the numeric value is sensed by sensors inside the tank. Independence of situations on level 2 is assumed to make sure that new situations can easily be integrated without changing old ones.

We use so called level 2 rules to infer from situations on recommendation goals. Recommendation goals comprise the relevance for a task and constraints on the consideration set like number of POIs. Level 2 rules consist of one or
Fig. 1. Recognizing situations on level 1, comprehending situations on level 2 with fuzzy variables and infer fuzzy recommendation goals by level 2 rules.

more states of a situation in the antecedent condition and a recommendation goal in the consequent condition. The antecedent part includes only states from one situation variable. Otherwise the aggregation of situations would already be done in the rule, which makes situations dependent. If this is the case, a new fuzzy variable on level 2 is introduced as aggregation of the two old ones. An example of a level 2 rule is ‘IF fuellevel IS empty THEN relevance, refueling IS high’.

So far, a recommender based on level 1 and 2 is only able to behave reactively because only current situations are taken into regard. To enable proactive behavior, past situations as well as future situations need to be integrated.

3.3 Situation Awareness Level 3

Level 3 allows for awareness of future and past situations at the present point in time $t_0$. Awareness of the past includes remembering context parameter values at $t_{-1}$ and further behind. Looking into the future means to predict context parameter values at $t_1$ and following. The model does not depend on which method is used to predict future context values as the prediction is done on level 1. A discussion of methods to predict context values is out of the scope of this paper. Knowing about future or past situations is not enough to handle them in present. Situations occurring ‘soon’ have a different impact on a decision than ones occurring ‘much later’. Therefore we ‘connect’ situations influencing present decisions.

Figure 2 shows how situations from the past and the future are connected to the present. Connection fuzzy variables describe the ‘distance’ between a situa-
tion state and the current point of making a decision. The distance is determined by the beginning of the next occurrence of a state in the future and ending in the past respectively. It can be either in time or in space. By modeling the connection as fuzzy variable uncertainty of prediction is handled.

Inference is done with so called level 3 rules. These rules extend level 2 rules by combining the situation in the antecedent condition with a connection fuzzy variable, like ‘IF fuellevel IS empty AND distance IS close THEN relevance_refueling IS high’. The rule complements the example of rule 2 by adding a length distance to the situation state ‘empty’. The relevance is determined as ‘high’, because the car is running out of fuel in ‘near’ distance. This allows for in time decision making before a critical situation state like an empty fuel tank occurs.

### 3.4 Importance and Contribution of Situations

The inference with fuzzy logic involves firing of several rules depending on situation states. Yet not all situations are equally important for assessing the relevance of a recommendation. For example, a situation state like ‘number of reachable fuel stations’ is ‘critical’ should not be weakened by a less important situation state like ‘fuel level’ is ‘medium full’. Rules involving more important situation states should dominate the inference. Therefore, the degree of importance of situation states is determined by weighting the rules they are involved in. To obtain weights, they are either statically assigned to the rules or dynamically established by methods like pair-wise comparison of occurred situation states.
4 Evaluation

We implemented the model in Java using jFuzzyLogic for creating fuzzy variables and rules. It is embedded in an OSGi-based framework for navigation prototyping with a route planner, map matcher, digital map and a map renderer. This allows for evaluating the model using real road data.

To evaluate our approach, we simulate a scenario with two situation fuzzy variables (fuel level and number of reachable fuel stations), one connection fuzzy variable (length distance) and one goal (relevance). The scenario features a car entering a rural area with low coverage of fuel stations (situation variable: reachability of fuel stations). The fuel level of the car is assumed to be half of the capacity (situation variable: fuel level). Hence a fuel recommendation is not needed because the driver is not used to refueling given a semi-filled tank. However, fuel stations are of relevance (goal variable: relevance) that early (connection variable: distance), because the driver will leave the area with many reachable fuel stations. For simplicity reasons, the number of reachable fuel stations with current fuel level is simulated decoupled from the fuel level. We run the simulation for a route with approximately 800 km with a start fuel level of 40L and number of reachable fuel stations of 20.

As soon as the driver selects his route, the system performs a context prediction of fuel level and the number of reachable fuel stations on level 1 and interprets the result by a situation fuzzy variable on level 2. For instance, ‘fuel level = 40L’ is represented by state ‘medium full’ of situation ‘fuel level’. Inference is made by level 3 rules using the connection fuzzy variable ‘distance’. The nearest distance to the beginning of a state is determined by a state membership of at least \( \alpha \) (\( \alpha = 0.8 \) in our case). The state membership represents the membership to the value of a fuzzy variable which ranges from 0.0 to 1.0. The result of the whole process is a set of relevancies for every situation state occurring in the future. Finally, the maximum relevance is taken as the relevance at the current position. This process is repeated for fixed steps along the route assuming the driver is in future.

Figure 3 shows the resulting set for the simulated scenario in two parts. In the first part of the route (a), less and less reachable fuel stations are available. This situation dominates over a medium full fuel tank in the inference. Assuming the driver has refueled his tank leading to more reachable fuel stations, the second part (b) is dominated by situation states of the fuel level. In (a) the relevance based on reachable fuel stations does not increase until after 17 km, long before the reachability is starting to decline at 100 km. The relevance drops gradually until no fuel stations are reachable any more. On the second part of the route in (b), relevance increases long before the state of the fuel level becomes critical with ‘empty’ or ‘reserve’. The relevance declines gradually until the situation is reached (e.g. at 300 km and 450 km). When only reserve fuel is available the relevance is zero because recommendations at this point are too late. Note that not a fuel station is irrelevant with reserve fuel but rather recommending fuel stations.
Fig. 3. Prediction of situation and relevance along a route separately for fuel level and reachable fuel stations and fused. (a) shows the first part of the route where reachable fuel stations dominate and (b) where fuel level dominates.

To reflect the different contributions of both situations, we used static weights from table 1. Situation states indicating higher relevance are given more weight, independent from the situation itself. The idea is that at least one situation state indicating high relevance is needed to know that a recommendation is relevant. Weighting situation states means weighting rules they are involved in. The fused relevance of the situations is also shown in Fig. 3. In (a) the influence of fuel level situation states is low and does not contribute to the fused relevance. In (b) the opposite contribution is shown. Many reachable fuel stations make a lower contribution then upcoming fuel level situation states, like ‘empty’ or ‘nearlyempty’.

<table>
<thead>
<tr>
<th>goal variable ‘relevance’</th>
<th>zero</th>
<th>low</th>
<th>mid</th>
<th>high</th>
<th>highest</th>
</tr>
</thead>
<tbody>
<tr>
<td>rule weights</td>
<td>0.1</td>
<td>0.3</td>
<td>0.5</td>
<td>0.8</td>
<td>1.0</td>
</tr>
</tbody>
</table>
An example of which rules are fired for a specific position on the route is depicted in table 2. These are all situation states measured in a horizon of 100 km from the position 77 km on the route. Relevance is high because of upcoming reachability declining (see Fig. 3 (a)). The maximum of all measured situations is taken, which is 73 (high relevance) in this case.

**Table 2. Fired rules**

<table>
<thead>
<tr>
<th>relevance</th>
<th>rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 (zero)</td>
<td>if (fuellevel IS full) AND (distance IS at) then relevance IS zero [weight: 0.1]</td>
</tr>
<tr>
<td></td>
<td>if (numberReachableGasStations IS many) AND (distance IS at) then relevance IS zero [weight: 0.1]</td>
</tr>
<tr>
<td>63 (high)</td>
<td>if (fuellevel IS mid) AND (distance IS near) then relevance IS mid [weight: 0.5]</td>
</tr>
<tr>
<td></td>
<td>if (numberReachableGasStations IS enough) AND (distance IS near) then relevance IS high [weight: 0.8]</td>
</tr>
<tr>
<td>12 (zero)</td>
<td>if (fuellevel IS full) AND (distance IS at) then relevance IS zero [weight: 0.1]</td>
</tr>
<tr>
<td></td>
<td>if (numberReachableGasStations IS many) AND (distance IS at) then relevance IS zero [weight: 0.1]</td>
</tr>
<tr>
<td>73 (high)</td>
<td>if (fuellevel IS mid) AND (distance IS near) then relevance IS mid [weight: 0.5]</td>
</tr>
<tr>
<td></td>
<td>if (numberReachableGasStations IS critical) AND (distance IS near) then relevance IS highest [weight: 1.0]</td>
</tr>
</tbody>
</table>

Our goal was to enable decision making for in time recommendations based on situation awareness. As Fig. 3 shows, situation state changes occur significantly, i.e. the relevance fuzzy variable changes its value. Recommendations become relevant when the relevance jumps from ‘zero’ to a higher value caused by an upcoming situation state. The closer the situation state causing the relevance increase the lower the relevance. A local maximum plateau (e.g. from 70 to 130 km in 3 (a)) determines the area where a recommendation is most useful and its relevance.

5 Conclusions and Future Work

In this paper we presented a model for situation awareness in proactive recommender systems. It allows connecting future and past situations to the relevance of a recommendation at present to make in time recommendations. Uncertainty of situation recognition and prediction is supported by using fuzzy variables. Varying importance of situations is handled by weighting rules.

We have shown that our model is applicable in a simulated scenario. Significant situation changes can be derived to make proactive decisions about a recommendation before the user gets in critical situations. Further evaluation should be made with past situations like the user’s driving behavior.
Although the model shows good results with two simple situation variables, we want to apply it to more complex scenarios in the future. A user study shall show if the modeling corresponds to user’s way to incorporate situations in decision making. Therefore a comparison between our model and similar ones based on simpler structures or statistical approaches is planned. One of our next steps is to connect the situation awareness model with a context-aware recommender which uses context and user preferences to select fuel stations. This is the second decision in our proactive recommender system.

References