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An Affective Intelligent Driving Agent: Driver’s Trajectory and Activities Prediction

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Abstract—The traditional relationship between the car, driver, and city can be described as waypoint navigation with additional traffic and maintenance information. The car can receive and store waypoint information, find the shortest route to these waypoints, integrate traffic information, find points-of-interest, and alert the driver of a pre-programmed set of maintenance issues related to the car. Here, we propose a new route system that is multi-goal-centric rather than waypoint-centric. Instead of focusing on determining the route to a specified waypoint, as done in commercially available navigation systems, the system will analyze the driver’s behavior in order to extract the potential set(s) of goals that the driver would like to achieve. The system must also understand the city on a number of levels: physical, social, and commercial. This provides the foundation for a social and intelligent driving assistant, that helps the driver achieve his goals and helps the city perform better through interaction between both entities.

I. INTRODUCTION

Current navigation systems are focused on finding waypoints. They are capable of pointing out the shortest route to a destination, integrating traffic information, and identifying points-of-interest. These systems can successfully assist in driving to a fixed desired destination. However, individuals often make trips with the purpose of achieving various goals, such as purchasing gasoline, watching a movie, or participating in a public event, while the physical location of their destination is flexible. Also, driving conditions in the city change in response to different events, influencing the accessibility levels of areas in the city.

We envision a navigation system that mimics the friendly expertise of a driving companion who is familiar with both the driver and the city. Instead of focusing solely on determining routes to a specified waypoint, our system utilizes the analysis of the driver’s behavior in order to identify the set of goals the driver would like to achieve. Furthermore, it involves an understanding of the city beyond what can be seen through the windshield, incorporating information such as business and shopping districts, tourist and residential areas, as well as real-time event information and environmental conditions.

In recent years, a multitude of tags, sensors, locationing devices, telecommunications networks, online social networks, and other pervasive networks are proliferating in cities. They are constantly producing a rich stream of data that can help describe dynamic rhythms in the city. Our navigation system works to recognize underlying patterns in this data pertaining to various aspects of the city including traffic, seasonal information, environmental conditions, commercial offerings, and events. In-car sensors provide information about the driver’s mood, attention span, as well as about interaction with the car, for example navigation decisions, acceleration and braking, climate control, and seat position. Thus, over time, the car can learn about a driver’s habits, routes, and goals, and in the short term, the car can dynamically adjust to the driver’s current state.

II. RELATED WORK

The works related to the research proposed in this paper include: I) Destination and trajectory prediction, II) Semantics analysis of the City and III) Profiling of the City using GPS data.

A. Destination and Trajectory Prediction

The quest for efficient algorithms that predict a full route based on previous driving behavior has motivated a number of relevant research works. We will now give a brief overview of this topic with particular emphasis on data representation and algorithm principles as well as performance and experimental results when available.

In 2006, Tsutomu Terada and his colleagues [1] propose an algorithm for predicting destination given the trajectory so far. They represent historical data in the links of the graph. This data is essentially the count for each destination that was eventually reached passing by that link. This number is then used to determine the probability of reaching destination d from link l . The prediction algorithm then consists of determining these probabilities at each link and producing an ordered list of

predicted destinations. The authors present some results from experiments, but their validity is highly questionable since they focus on only one user (for one year).

From a different trend, Mikolaj Morzy [2] applies Spatial-Temporal Data Mining techniques for the task of trajectory prediction. From the historical set of past traces, the system builds association rules out frequent patterns (e.g. $X_1, X_2 \rightarrow X_3$, i.e. after passing by points X_1 and X_2 , it should pass by X_3). Then, in face of a new trajectory, it tries to find the rule tail that best matches its last links (or the whole trajectory). The experimentation is based on Thomas Birkhoff's Generator of Moving Objects [3].

Froehlich and Krumm [4] present a system for route prediction that clusters past trajectories (trips) into typical *routes*. It then compares the current trajectory with these routes and returns the one that is most similar. Similarity is calculated as average minimal distance of point to curve. I.e. in comparing trajectory A with Route B, for each point of A, it is calculated the minimal distance to a link (a segment between two subsequent points) belonging to B. In both cases, we deal exclusively with GPS points (as opposed to a base map). As argued by many (e.g. [5]), point-to-curve map matching is very much prone to errors with GPS data (especially when such representation is used in both sides, the point to match and the base map itself). In spite of all the filtering they make, better distance measures could be applied (e.g. frechet distance [6]) as well as a more accurate map matching algorithm (e.g. one that uses geometry) would render better results. Using a base map for routes would possibly also improve the outcome.

In [7], the authors propose *WhereNext*, which is a method aimed at predicting with a certain level of accuracy the next location of a moving object. The prediction uses previously extracted movement patterns named *Trajectory Patterns*, which are a concise representation of behaviors of moving objects as sequences of regions frequently visited with a typical travel time. A decision tree, named *T-pattern Tree*, is built and evaluated with a formal training and test process. The tree is learned from the *Trajectory Patterns* that hold a certain area and it may be used as a predictor of the next location of a new trajectory finding the best matching path in the tree. Moreover, they propose a set of measures, tuned on a real life case, to evaluate evaluate a priori the predictive power of a set of *Trajectory Patterns*.

Finally, on a different perspective, Zheng et al [8] focus on understanding peoples behavior in which relates to their travel sequences of stops (as opposed to travel trajectory, as sequences of passed links). The proposed model infers the interested of a location taking into account the following three factors: 1) the interest of a location depends on not only the number of users visiting this location but also these users' travel experiences. 2) User's travel experiences and location interests have a mutual reinforcement relationship. 3) The interest of a location and the travel experience of a user relative values and are region related. The most interesting aspect for our purpose is their graph organization that considers hierarchical clustering of points in space. This allows the

setting up of a different perspective on travel behavior and prediction (e.g. make prediction at different levels, even when the driver is going to a place for the first time). Their work is however motivated towards suggestion of interesting places to visit and travel sequences when in unfamiliar places.

B. Semantics and City

The online extraction of semantic information about the city can reveal at any time information that is not available through other channels[9]. For example, event descriptions or information about places (and their semantic profile) can make the difference in supporting the driver. We use an Information Extraction mechanism, Kusco [10], [11], that extracts the semantic index (set of words associated to an event) using a sequence of well known techniques: Part-of-Speech (POS) tagging[12], Noun Phrase chunking ¹ and Named Entity Recognition (NER)[13]. The goal is to extract relevant entities from online documents and identification of whether they designate people, places, companies, organizations, and the like. We rank the relevancy with TF-IDF (Term Frequency \times Inverse Document Frequency), a common measure in the IR field. Term Frequency measures the frequency of a word within a text while Inverse Document Frequency measures how discriminant is a word in a collection of texts (e.g. a word that appears in every text has little value since it does not differentiate the texts; a word that is unique to a document is considered to be potentially relevant). Other relevant works can be referred in this realm, namely Open Calais [14] and Semantic Hacker [15], which also provide semantic indexes, although their focus is not restricted to information about events and space (which weakens their ability to filter unwanted concepts). A related work, Scarlet [16], which is being integrated with Kusco, works on the extraction of the relations between concepts. Such functionality will allow for a even higher potential for assisting the driver (e.g. knowing that the "performer" of an event is X, the theme is Y, etc.).

C. City Profiling

Over the past decade, our built environment has become thoroughly permeated by digital wireless signals. What is new about this blanket of bits is that, unlike the old unidirectional signals of radio or TV, it is bidirectional. The packets transmitted by cellular phones and WiFi-enabled portable devices are tied to patterns of human behavior and, if properly mined, can potentially reveal a great deal of information. Recent research on the analysis of telecommunication network data has provided a better understanding of dynamics in the city, and in particular on how it is possible to perform a computational and comparative analysis of space through the lens of telecommunications usage [17], [18]. A similar approach can be applied to the analysis of GPS trajectories to understand how the collectivity of drivers sees and perceives the city.

¹<http://www.semanticsoftware.info/>

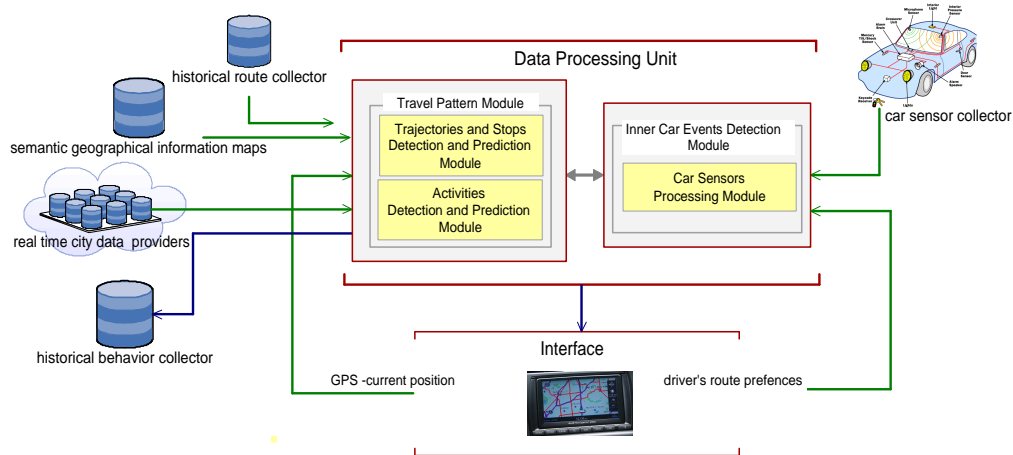


Fig. 1. Activity-based Navigation System Architecture

III. SYSTEM DESCRIPTION

The proposed route system uses the interacting modules to learn and predict the driver's behavior (see Fig. 1). The User Interface is an interface between the system and other outside factors such as the driver, GPS system, and other sensors. The Semantic geographical information map (SGIM) module provides information about geography, map, road, and etceteras. The historical route collector (HRC) records the past driving routes to learn the driver's route behavior. Historical behavior collector (HBC) preserves the past association between the driver's route and city activities to learn and predict the driver's route preferences in terms of association between route and city places. The real time city data providers (RTCP) provide real time information about city events such as traffic, concerts and so on. Car sensor collector (CSC) aggregates car data to monitor the car condition over time. The *trajectory and stop detection prediction* module (TSDP) and *activities detection prediction* module (ADP) are used for learning and predicting the driver's behavior and to calculate the best route to a specified detected location. Finally, the *car sensor processing* module (CSP) senses car sensor data and sends signal to the TSDP and user interface. For instance, the system can warn the driver of low fuel and suggest a new path to the closest gas station.

In this paper we focus mainly on the TSDP and ADP modules. Indeed, they represent our main contribution with respect to commercial navigation systems. TSDP implements a novel data mining method in order to detect the driver's next destination by taking the spatio-temporal driver's history into account. A cluster algorithm is adopted in order to group together similar trips which represent a set of local patterns. Then, this set of clusters indicates a global model of user's driving experience. The prediction is made using the current travel and the global model described above. In the end, TSDP module outputs the next destination of the driver if it has a certain confidence level greater than a given threshold. On the

other side, the ADP infers the interest of a location identifying the correlation between the route and location using the SGIM map and the real time city data.

The SGIM is a map that is augmented with semantic annotation for the points of interest (POI) and classifies places based on the drivers point of view.

For this analysis, we first identify the POI from which typical travel sequences in a given geospatial region. Then, we study places and group together areas where people behave in similar way.

The methodology is composed of the following: The first step is to collect the POI that may be potentially important, such as popular public areas, shopping malls and restaurants, but also rural and office area. POI collection is done by applying web mining techniques to online resources such as the Yellow Pages, Yahoo directories, POI sharing platforms, etc. Then, the second step is to detect the features that allow us to identify the places and then calculate the similarities and differences between them. Finally, we examine how to group similar places and how they are distributed across the city.

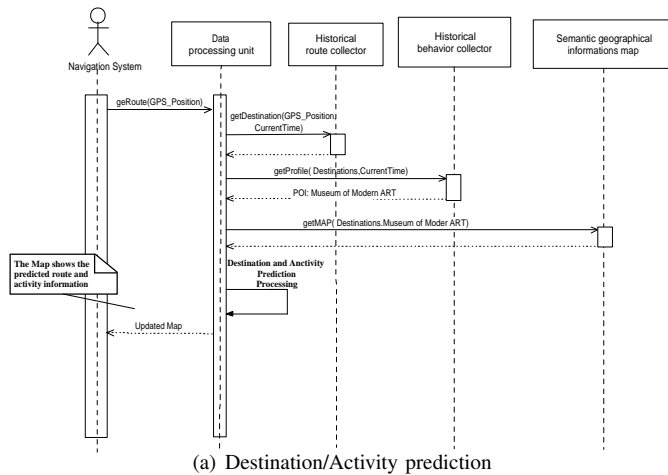
IV. USE CASE

In this section by means of a use case scenario, we show how the system works and how the modules interact with each other.

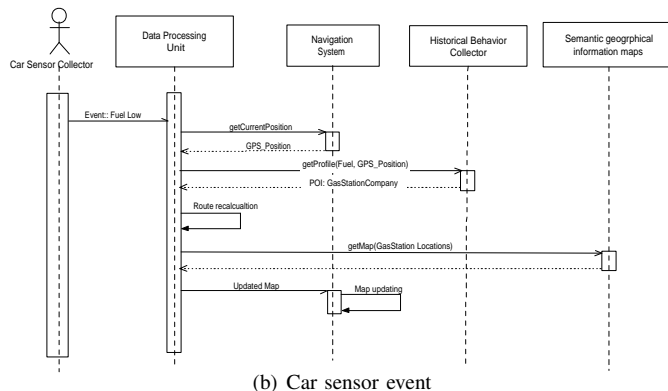
The navigation system suggests the next destination using current time, location and user's profile which is stored on the *historical route collector* (HRC) and on the *historical behavior collector* (HBC). For example, on the last three Wednesdays at 6PM, the user stopped close to the Museum of Modern Art, so when she starts the car somewhere else at 5:30PM, the system recognizes the current time and predicts the Museum as a destination. Moreover, the *Semantic Geographic Information Map* (SGIM) component notices a match with time, location, and a lecture on Architecture, thus it informs the driver about

this event. The whole process for making destination/activity prediction is described in Fig. 2(a).

Furthermore, while driving, the system is notified by the embedded sensor of the car that the fuel is running low. The system knows that the driver always uses a specific gas provider based on the history of her commute (via HBC). The system will select all the nearby locations for that particular gas provider. The choice of the gas stations is made with the interactive map of the touch screen display of the navigation device. Now, the system re-calculates the route including also the gas station stop on the trip for reaching the museum. Fig. 2(b) explains graphically the interaction among car sensors, system and driver.



(a) Destination/Activity prediction



(b) Car sensor event

Fig. 2. Use cases

V. CONCLUSIONS

In this paper we propose a new goal-centric route system rather than waypoint-centric. Instead of focusing on determining the route to a specified waypoint, as done in commercially available navigation systems, the proposed system analyzes the driver's behavior in order to predict the potential set(s) of goals that the driver would like to achieve. Moreover, the system uses city information at different levels: social,

physical and commercial. Thus the system is also able to provide a social and intelligent driving assistant, improving the interaction between driver and the space around him. Further investigation will focus the development of an effective and efficient way to understand the driver's habits in order to improve the quality of suggestions. Moreover, a real case test case will be performed to validate the soundness of our novel approach.

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