An approach for predicting vehicle velocity in combination with driver turns

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Abstract Statistical information such as average traffic flow on a road network link are not precise enough to enable detailed in-vehicle optimization strategies. Energy efficiency measures are further restricted if the vehicle is not aware of the destination of the trip. A modular and dynamic approach for predicting the vehicle speed in combination with driver turns is introduced. The objective is to adapt the vehicle components to the upcoming speed and state. The cloud-based approach foregoes the user-based selection of a route, trip destination or individual points of interest but is mainly based on historic speed profiles of different drivers. The concept provides a two-stage approach. The first stage is the prediction of upcoming turns and trip segments based on the historical features and the currently driven road segments. The second stage uses this information to predict the vehicle's speed.

Keywords Intelligent transportation systems · Speed profile · Trip prediction

Abbreviations

DTW	Dynamic time warping
FOT	Field operational test
FPD	Floating phone data
FCD	Floating car data
ITS	Intelligent transportation systems
OSM	OpenStreetMap
OD	Origin-destination

POI	Points of interest
TMC	Traffic message channel
VEM	Virtual electromobility focused on taxi and commercial traffic in Munich

1 Introduction

The objective is to enable forecasting of the future vehicle's state. Optimization measures to increase safety and efficiency can be derived at, on that information. In Intelligent Transportation Systems (ITS), this prediction is achieved by an intelligent network of driver, vehicles, and infrastructure. State of the art driver assistant systems limit the prevision of vehicles to the range of built-in radar or vision-based sensors. Traffic Message Channel (TMC) information, Floating Phone Data (FPD) or Floating Car Data (FCD) generate an image of the current traffic situation with the data from multiple users. Historical information can be used to predict the traffic situation or to recommend an alternative route for the driver. This is already a part of a predictive electronic horizon that combines a preselected destination with information on the upcoming road sections. With actual traffic flow and elevation information, an on-board driver assistance system function can calculate the most energy efficient vehicle speed or vehicle state. Existing optimization measures mainly have two limits:

- Most aggregated information available in automotive navigation systems are general and limited to statistical features like average traffic flow on a road network link and do not represent a full speed profile.
- The navigation system is fully aware of the trip destination and the next road links. If the destination

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is unknown, the preview is limited to the end of the road section.

Ericsson [6] shows that driving patterns are multidimensional and identifies 16 independent factors out of 62 driving pattern parameters. However, several factors are responsible for emissions and fuel consumption. They are mainly related to the travel speed profile and acceleration behavior of the driver. In particular, optimization measures for vehicles benefit from a wide, highly detailed prediction horizon. The objective of most optimization concepts is to overrule driver behavior or display suggestions to drive more efficiently.

This paper presents a modular and dynamic approach for predicting the vehicle speed in combination with driver turns. The objective is to adapt the vehicle components to the upcoming speed and state. Our cloud-based approach foregoes the user-based selection of a route, trip destination or individual Points Of Interest (POI) but is mainly based on historic traveling speed profiles of different drivers and a map-based approach. The following requirements are:

- The system should be based on anonymous FCD and TMC information.
- The method needs to be valid for cities, highways, and rural areas.
- The method must focus on a mid- to long-range prediction of vehicle speed. A cooperation with internal vehicle vision-based sensors, Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) Communication is conceivable, but not considered in this paper.

Our concept provides a two-stage approach. In the first stage, the prediction of upcoming turns and trip segments is based on the historical features and the currently driven road segments. In the second stage, this information is used to predict the speed of the vehicle.

Multiple traveling speed profiles per road segment were clustered according to a similarity measure. A representative speed profile distinguishes scenarios and driver types which can be assessed appropriately to the situation. In contrast, conventional vehicle driver models are often based on mathematical equations. These equations do not represent human behavior because of multiple influence factors. To identify the most probable speed cluster, we use live traffic flow information and the overall behavior of the driver. The behavior is calculated from statistical features of the previously driven road segments of the current trip. We present the overall approach and preliminary results of our two-staged prediction approach.

The following section examines the related work. Section 3 gives an overview of our proposed approach and the relevant sub-steps. Section 4 shows preliminary results of

the applied methods. Section 5 concludes with a discussion and points out further steps.

2 Related work

FCD and FPD are increasingly used in ITS. Quiroga [22] describes a technique based on GPS data for travel time studies. Ye [25] utilizes GPS data at irregular intervals to forecast traffic flow on road links. Traffic flow prediction has extensively been investigated in the past. For example, using historical traffic flow information Dauwels et al. [2] developed a method which predicts traffic flow in urban sub-networks for multiple horizons.

2.1 Trip prediction

Besides the use of floating data for traffic velocity forecasting, Lin [17] discusses various applications for GPS data to investigate mobility patterns. He mentions that individual mobility behavior is highly regular. Mobility patterns can also support intelligent traffic management applications. Djukic [3] describes in detail the use of Origin-Destination (OD) Matrices for traffic management. The elements of the OD-matrix describe the flow of vehicles or passengers from the origin O to the corresponding destination D. The matrix represents an image of frequently visited POI if scaled to a higher road network level or monitors flows at intersection level. Most OD-matrices are time-dependent and can be calculated for a single user or in general. Therefore, OD-matrices can predict trips or destinations. Krumm [14–16] has been working on driver turn prediction for the next road segment using simple Markov Models as well as end-to-end routes. Eldaw [4] developed a method for location prediction based on the data of multiple users instead of most methods utilizing the data of individuals. Guangtao [8] introduces a short-time route prediction that considers actual traffic conditions. Hendawi [9] outlines future challenges in spatio-temporal queries. For long-term predictions most algorithms focus on the destination itself, but not necessarily on the road segments traveled to reach the destination.

2.2 Speed profile prediction

ITS focuses on predicting an average traffic flow information at road segment level instead of generating a highly accurate speed profile. As a counter example, a detailed information about speed on the following road segments can be used for hybrid electric vehicles HEV to improve the operational strategy of the components. Engstle [5] com-

bines OpenStreetMap (OSM) [20] navigation information, TMC, elevation data and vehicle state attributes to predict a speed profile using a mathematical model. Wollaeger [24] calculates fuel-reduced speed profiles by means of Dynamic Programming. These kinds of models are often limited to non-urban road types or cannot represent different scenarios on urban roads. Kerper [12, 13] uses Dynamic Time Warping (DTW) as a distance measure for the speed profile samples of a fixed segment length. Hierarchical clustering of the distance measure creates different speed profile classes as a result. A Markov Model determines the most probable future speed profile for the upcoming segments. This profile is independent of time or traffic state and works as a reference to a calculated fuel-reduced speed profile.

3 Methods

3.1 Overview

An overview of the system architecture is displayed in Fig. 1. The vehicle is defined as a mobile sensor collecting FCD including GPS information. Many vehicles already feature a mobile router connecting the vehicle via mobile network to the internet. This interface is mainly used for information and entertainment. We use the interface to connect the vehicle to a server. The FCD contains inter alia the actual position and speed information and is transmitted periodically. The data of completed trips from Origin to Destination are stored in a database. Individual information about the driver or vehicle is not mandatory for our approach, instead, the data are crowdsourced from different drivers and vehicles. Section 3.2 describes the data source and necessary preprocessing steps. We use a map-based approach and live TMC information for online application. As described, we follow a two-staged approach. Section 3.3 introduces the trip prediction method. The output of this first stage directly enters into the speed prediction model. Section 3.4 summarizes the selected methods of this stage to generate a representative speed profile over several road segments, defined in the trip prediction. This information is transferred back to the vehicle.

3.2 Data source and preprocessing

For the proposed approach, the main data source is the conducted Field Operational Test (FOT) Virtual electromobility focused on taxi and commercial traffic in Munich (VEM) [23]. Smart phones track approximately 90 taxis and 20 commercial vehicles equipped with an internal combustion engine in the area of Munich and Upper Bavaria. Besides the mobility data acquisition, an electric vehicle is simulated in a smartphone application [11]. The original GPS, speed information, and the simulated data are transferred to the server infrastructure according to [1]. The sample time of the GPS data as main information is one second. The FOT started in 2013 and is still in progress. As additional data source, we use live traffic information from [10]. We access traffic flow information at regular intervals of approximately 15 min for the corresponding regions. The data are stored in a PostgreSQL database.

For our map-based approach, we use OSM which provides open source map data with road and location-specific attributes. These attributes contain geometrical information, maximum allowed speed, position of traffic signals, stop signs, and road class amongst others. Since original OSM data are not routable, the map data are converted using OSM2PO [21]. As a result, road segments are split at intersections, which enables the map-based approach. The map data are added to the FOT data using a map-matching algorithm [7, 19]. Furthermore, the traffic flow information is assigned to the corresponding road segments.

3.3 Trip prediction

To identify the following road segments, we use scalable, time dependent OD-matrices. The road network is therefore separated by the original OSM road class information. Figure 2 illustrates the segmentation of the network into primary and secondary areas. The road classes Motorway and Primary define the primary areas. These road classes define the primary area 0. Primary areas are furthermore detailed in multiple secondary areas, defined by Secondary road classes. These secondary areas contain the remaining road classes for Tertiary and Residential roads. For the road

Fig. 1 Overview of the system architecture

Fig. 2 Road and area segmentation

network of Munich and Upper Bavaria, we define approximately 100 primary areas and 900 secondary areas. By means of the FOT data, we generate OD-matrices for the primary and secondary areas, which determine the time-dependent probability for a vehicle to relocate to a bordering area of the same class. Besides areas, we generate OD-matrices including FOT data for time-dependent turn probability for each intersection.

We improve the OD-matrices at intersection level with a stationary Markov Model of higher order. Equation 1 defines the Markov Model of 3rd order. The states X are defined as the ids of the segments of the road network split at intersections. We create a model for each id as $X_n = i_n$. The transition probability to the next road segment X_{n+1} is calculated in consideration of the two previous road segments X_{n-1} and X_{n-2} . In addition, the model can be refined by limiting the transitions to a specific time slot, such as weekdays and weekends or a specific time of day.

$$P(X_{n+1} = j | X_n = i_n, X_{n-1} = i_{n-1}, X_{n-2} = i_{n-2}) \quad (1)$$

With respect to the last-driven road segments, the probability for the next road segment can be determined using statistical information of trips from other users. We can also apply this method to various road segments ahead. The processing time for calculating all possibilities increases disproportionately with distance. Therefore, we combine the approach for the OD-matrices of primary and secondary areas with the intersection level. We can prebuild probable paths at intersection level inside a secondary area. If a transition to a bordering secondary or primary area occurs, the prebuilt probable paths of the area can be

assembled. As a result, we receive probable road segments' overlapping areas, which are used as input variables for the speed prediction model. The length of the most probable path is freely definable.

3.4 Speed prediction

The routable OSM-based segmentation of road segments is the basis for building representative speed profiles. Lohrer et al. [18] describes the process in detail, which is summarized as follows. The speed data of the FOT trips represent different scenarios at various times and traffic states. However, patterns are recognizable inside the multiple speed profiles. We extract the repeating behavior and define a finite set of profiles as representative. Therefore, for each trajectory of the FOT, we determine speed/distance relationships. On this basis, we apply a clustering technique with a FastDTW distance measure. As the speed/distance profiles can be interpreted as time-series, FastDTW returns a distance measure to each profile. This measure permits a distortion in the position axis. Speed profiles containing a stop at slightly different positions are considered to be comparable.

To accelerate the FastDTW method, it is only applied to profiles with the same previous and subsequent road segments. Furthermore, this set of profiles is divided, subject to containing a stop. The pairwise distance for each combination of profiles generates a distance matrix. Spectral Clustering is used to identify clusters of the speed profiles. The profile in the center of each cluster's subset is defined as representative. The representative speed profiles are defined as states. We use a Markov Model of higher order to identify the most probable representatives of subsequent road segment. For each road segment, we define a Markov Model to determine the probability of transition to a representative of the subsequent segment with respect to the previous three segments driven.

In addition, multiple factors influence the choice of vehicle speed. For inner-city mobility, traffic flow is a major factor. We consider this by adding TMC information. The Markov Models are refined by being limited to profiles which occurred during similar traffic flow.

4 Results

4.1 Trip prediction

The preliminary result for our proposed trip prediction model is the probability distribution of upcoming road segments. Figure 3 illustrates this for an isodistance map. The border represents the driving distance from the center heading north towards each direction within an equal

Fig. 3 Probability weighted isodistance for a vehicle heading north

distance of 3 km. The color intensity outlines the actual probability of the upcoming road segments. Based on that information, we can construct the most probable path and further considerable paths for the vehicle.

4.2 Speed prediction

As an example for the representative speeds, Fig. 4 illustrates an access road to the inner circle road in Munich. On the left side, all FOT data for this road segment are illustrated. The algorithm introduced in Sect. 3.4 is applied on the data set. The representative profiles generated with the method is shown on the right side of Fig. 4. In addition, this example exposes that conventional information of the road

network is insufficient, because the maximum allowed speed on this road segment is set to 50 km/h.

Figure 5 illustrates the relation between traffic flow and an appropriate representative speed profile. The upper part of the figure indicates the traffic speed on the access road to the inner circle road presented in Fig. 4. The data used is collected from HERE [10]. The plot shows the distribution of traffic flow on this road segment on workdays during the duration of two weeks. These data are independent from our FOT data. The lower part of Fig. 5 indicates the distribution of related representatives of the FOT, illustrated in Fig. 4. For example during night time, there is a high probability of Cluster 1-1, Cluster 1-2 and Cluster 1-3. This represent no congestion as well as high mean traffic speed. During noon, there is a high probability of Cluster 2-1, Cluster 2-2 as well as Cluster 1-3. During that time congestions occur more frequently at the end of the segment. The mean traffic speed in the upper part of Fig. 5 drops noticeably, too. As the data are recorded during the duration of two weeks, there exists a large variation. A low traffic speed corresponds to higher congestions represented in Cluster 2-2. Traffic jams occur more frequently during rush hour, where Cluster 3-1 and Cluster 3-2 are prevalent. The results demonstrate a strong correlation between the mean traffic speed and the representative profiles. We therefore use TMC information, to adapt the Markov Model and improve the result of the prediction algorithm.

5 Discussion

Our proposed approach combines a trip prediction algorithm with a speed profile prediction. We presented the system architecture of the approach, necessary Data Mining and Interpretation methods. Furthermore, we

Fig. 4 Representative speed profiles of a secondary link road segment

Fig. 5 Probability distribution of representative speed profiles compared to traffic speed of a secondary link road segment during workdays

introduced the used data source, preprocessing, transformation steps, and preliminary results.

The system is able to provide further information to vehicles for the upcoming road segments and vehicle state. This information can be used to reduce the energy consumption of the vehicle. As main data source, we use crowd-sourced historical information of individual users. Live traffic information can enhance the method. The map-based approach and data storage enable the system to build additional statistics for each road segment. In addition to the speed profile, we can aggregate information about travel time, energy consumption or for example CO₂ emissions. Our prediction method uses the speed on previous road segments to predict further details of the trip. Even if the vehicle has no knowledge of the trip destination, our method for prediction of the upcoming road segments based on historical information of multiple road users can qualify the vehicle to adjust to the current trip.

Future research should prove the quality of the prediction methods with respect to the size of the prediction horizon. In addition, driver-specific models could be established to identify individual behavior in the historical data. Individual route-specific attributes, for example POIs, can be added to improve the trip prediction. In our next step, we will demonstrate that our approach can be used for multiple purposes in vehicle applications and simulation models.

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