MULTI-PERSPECTIVE DATA ANALYSIS OF DRIVERS’ NAVIGATION BEHAVIOUR

Complete Research

Landau, Andreas, Technische Universität Braunschweig, Braunschweig, Germany, a.landau@tu-braunschweig.de
Mattfeld, Dirk Christian, Technische Universität Braunschweig, Braunschweig, Germany, d.mattfeld@tu-braunschweig.de
Ehmke, Jan Fabian, Freie Universität Berlin, Berlin, Germany, JanFabian.Ehmke@fu-berlin.de

Abstract

Due to technological innovation in the automotive sector, more and more vehicle data becomes available. Today, historical trip data can be analysed in order to personalize a vehicle’s navigation device. Thus, it is possible to incorporate drivers’ preferences in routing decisions. To describe drivers’ preferences in a navigation context, it is necessary to model driver behaviour appropriately.

In this paper, we develop three models to depict different perspectives of driver behaviour in order to personalize navigation devices. The core point is to investigate edge utilization along the dimensions of time and space. Edges are the foundation for each navigation device’s digital roadmap. The first, time-oriented model examines the observed speeds on the edges. For the second, space-oriented model, a measure considering the entirety of edges is provided as to characterize the coverage of a driver’s mobility network.

The third model analyses routes consisting of paths of edges. Correlation analysis shows that results obtained from the different models confirm each other. Thus, it is possible to build a well-founded two-dimensional model from well-known attributes, which can be “plugged” into existing navigation devices. Possible support of personalized route computation consists of adapted edge weights and a personalized objective function.

Keywords: Historical trip data, navigation, route computation, personalization.
1 Introduction

Vehicle navigation devices support the driver in following a route if he or she is not familiar with the surrounding road network. A core functionality of navigation is the determination of the optimal route based on a digital roadmap. The digital roadmap is a graph consisting of nodes and edges, which represent crossings and road segments. Assigned to the edges are attributes such as length or legal speed. Route computation is about minimizing an objective function that takes road attributes as well as user preferences into account. In the literature, this problem is well-known as the shortest path problem, which has been one of the most investigated problems since the publication of the first label-setting algorithm by Dijkstra (1959). A more recent, vehicle-oriented description of route computation can be found in Storandt (2012).

Considering drivers’ preferences is an important step for the improvement of route computation. However, it is challenging to model drivers’ behaviour in order to derive individual preferences later on. Research implies three levels concerning the driving task; see Bubb (1993) for a more detailed description. Within the scope of the control level, the driver stabilises the vehicle on a road. The manoeuvre level considers more complex driving tasks such as turning left or right. There is a significant amount of work modelling drivers’ behaviour on these levels. An overview can be found in Cacciaibue (2007). Ploechl and Edelmann (2007) show possibilities to transfer driving trajectories into mathematical formulas. The navigation task belongs to the planning level, which is the most complex one. There are only a few examinations of drivers’ behaviour on this level. One approach, dealing with drivers’ workload caused by characteristics of a chosen route, can be found in Ehrenpfordt and Rataj (2006).

The corresponding knowledge discovery process of extracting and analysing information at this level is not well developed and finding measures describing drivers’ navigation behaviour is still an open challenge. The loosely related issue whether a driver has a risky driving style can be decided in a direct way considering the actual surrounding only, for example the road class or the influence of a car in front. To the contrary, deciding if a driver chooses the optimal route, firstly raises the question of optimality in this context. Furthermore, it is necessary to examine the whole route and to take multiple independent variables into account. Hence a corresponding model is more complex for the planning level. One innovative approach by Pang (2009) uses a neuro-fuzzy approach for modelling the route decision process.

We propose to aggregate historical trip data into information about preferences, which can be used to personalize a navigation device. Due to technical innovation in the automobile sector, it is possible to record a variety of attributes on vehicle operations in order to analyse drivers’ navigation preferences. Besides numerous technical attributes, also data on geographical information as well as driver behaviour can be derived. This often leads to a large set of historical trip data, which may offer sufficient information supporting a more personalized way of navigation. An overview of recent and future developments in the field of navigation can be found in Nagaki (2013).

Standard navigation devices are limited to simple means of adapting speed to drivers’ preferences. A fairly straightforward way is to adapt the speed of an edge by associating observed speeds to the edges of the same speed class, for example. One drawback is that drivers often follow a few routine routes only, i.e., the corresponding edges are traversed very often and have a large influence on the adaption of the speed attributes. However, edges with the same speed attribute can have different characteristics. Consider, for example, an edge located in a small village in contrast to an edge in an urban area. Thus, a narrow focus on speeds only provides an insufficient picture of drivers’ preferences and may lead to insufficient routes; the user-optimal route needs to align with the dimensions time as well as space. Richter, Klippel and Fraser (2004) analyse the different dimensions with respect to the objective function.
In this paper, we extend the well-known time-oriented adaption of edge attributes by explicit consideration of the spatial dimension and extend the obtained result to the objective function. Therefore, we enhance the analysis of single edges to the analysis of paths and road networks, i.e., we first consider the dimensions time, space in a distinct manner, and then relate them in terms of a model which analyses observed routes concerning both dimensions. In particular, time and space are analysed distinctly and related to their one-dimensional counterparts. Results are correlated to each other and to the corresponding results of the one-dimensional models. We will see that the two-dimensional analysis provides a well-founded model of drivers’ navigation behaviour. This model can be used to adapt speed attributes according to the function and location of an edge as well as the objective function, enabling a more sophisticated personalization of route computation.

For model building and calibration, we employ a very large database of historical trip data, which has been recorded in the context of a European driving study. The analysis of historical trip data is conducted for a sample of 98 drivers. Each driver was observed for three months. For two months, the driver was allowed to use a navigation device, and for the third month, the usage of any navigation device was forbidden. We expect that “natural” driving behaviour can be found (1) when a driver uses a navigation system on unfamiliar routes and (2) when the driver chooses a route on his own in familiar areas. Hence, it is possible to compare routes achieved by driver’s intuition and device’s calculation.

The paper is structured as follows. In Chapter 2, the concept of building the particular models is introduced in more detail. We present the dataset of historical trip data used in this paper in Chapter 3. In Chapter 4, required pre-processing steps for aggregation of historical trip data are discussed. The obtained data subsets provide data input for model building in Chapter 5, which forms the base for the two-dimensional model (Chapter 6). In Chapter 7, an application of the model concerning the objective function is shown. We conclude the paper with a summary in Chapter 8.

2 Modelling the Navigation Behaviour of the Driver

Aim of the following analysis is to provide a two-dimensional model for the dimensions of time and space in order to improve the personalization of vehicle navigation devices. We are not aware of a standard approach to do this. Thus, in this chapter, we present a new, data-driven procedure that allows for generating information about driver behaviour. For the analysis, we follow the data-driven concept of knowledge discovery described in detail in Han and Kamber (2006). The resulting aggregates serve as data input for model building. Three different perspectives of historical trip data are considered for model building (see Table 1).

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Perspective</th>
<th>Measure</th>
<th>Edges</th>
<th>Routes (path of used edges)</th>
<th>Network (entirety of used edges)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>Speed</td>
<td>Model 1</td>
<td></td>
<td>Model 2a</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Duration</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Space</td>
<td>Length</td>
<td>Model 2b</td>
<td></td>
<td>Model 3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coverage</td>
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</table>

Table 1. Different perspectives of models providing measures for personalized route computation.
For the “edge perspective”, we analyse observed speeds assigned to edges of a digital roadmap (Model 1). This is similar to the way today’s navigation systems would align speed attributes with observed speeds. The implementation can be done in a straightforward manner as edges are the objective of the analysis as well as of the adaptation. However, this approach ignores the location of an edge in a route or a network. Hence, this model does not consider the space dimension, which is required for personalized route computation, though. Model 1 is extended by a “route perspective”, which focuses on the analysis of paths of used edges. We conduct the analysis of routes in the two following ways. The time dimension is reflected by the measure of “duration” (Model 2a), whereas the space dimensions is reflected by the measure of “length” (Model 2b). Model 3 then follows a network perspective, considering the entirety of used edges. The corresponding measure “coverage” describes the dimension of space. Based on historical trip data, the challenge is to generate information for the route and network perspectives as to making them usable for route computation in standard navigation devices. A process-oriented view on the construction of the particular models is presented in Figure 1.

Figure 1. Process of model building and data aggregation for personalized navigation.
The pre-processing step prepares historical trip data in terms of three target data sets (cf. Chapter 4). The first target data set contains all edges (and their attributes) arising from observed trips. We describe how the corresponding model is calibrated in Chapter 5.1. The second target data set comprises all observed routes, which can be used for benchmarking with a fastest route calculated for the origin and the destination of each observed route by a standard routing reference. This “reference route” and the observed route are compared with respect to the measures length and duration, describing the corresponding dimensions of time and space, cf. Chapter 5.2.

The third target data set is used for analysing the observed network for each driver, i.e., the entirety of all edges for each driver. For this subset, the coverage of the network (rather than the speed) is measured. Each driver is assigned to a “navigation type”, which is built upon the indicators “size” and “structure” of a graph representing the network (cf. Chapter 5.3). To derive a two-dimensional model based on the distinct analysis, we analyse the correlations between the measures of the different models (cf. Chapter 6). The correlations found for measures concerning the same dimension are used to build a spatial and temporal model of the drivers’ behaviour. The model is used for generating a two-dimensional personalized objective function for each driver, combining time and space, and demonstrates possibilities for personalizing the routing component of navigation devices (cf. Chapter 7).

3 Description of the Database

The data used for this analysis has been provided by the project euroFOT. The aim of this field operational test was to analyse the impact of driver assistance systems on drivers’ behaviour, i.e., on how drivers use assistance systems. A detailed description of field operational tests in general can be found in Barnard and Carsten (2010) and, a description of euroFOT in particular, in Kessler (2012). The data includes vast amounts of detailed observations that reflect the impact of personal vehicle navigation devices on drivers’ route choices.

A particular research objective of the field operational test was to analyse drivers’ behaviour with regard to standard navigation devices. To this end, 98 drivers were provided with a well-equipped premium car for a period of three months. The drivers were completely free in using the vehicle and choosing the route for a trip. For two months of the field operational test, drivers were allowed to use a built-in or mobile navigation device. For the third month, the usage of any navigation device was forbidden. We have separated the raw data according to this experimental design, see Figure 2.

![Figure 2. Structure of the historical trip data in the project euroFOT](image-url)
The data contains a very large number of observed trips for each of the 98 drivers. For each time unit (10-20 times per second), a few hundred variables were recorded, including GPS position of the vehicle, speed, and information on whether driver assistance systems were used or not. Additionally, the drivers had to declare if trips are “familiar” to them and if they know the corresponding route. Hence, it is possible to identify whether a driver chose a route based on his or her knowledge or whether the route has been provided by a navigation device. Furthermore, information such as road class or legal speed is also available. As a result, 40000 trips were recorded with an overall trip distance of more than one million kilometres, see Table 2. An illustration of the trips of all drivers is shown in Figure 3. In sum, a large set of historical trip data is available for the analysis of navigation behaviour of drivers.

| Number of participants with complete data set [N] | Overall |
| Number of trips [N] | 98 |
| Driven kilometres [km] | 39 703 |
| Recorded time [h] | 1 013 262 |
| Number of days [N] | 15 129 |
| Overall | 8708 |

Table 2. Characteristic values of the historical trip database.

Figure 3. Visualization of observed trips.
4 Pre-processing of the Data

In order to generate information about the navigation behaviour of drivers, it is necessary to execute different pre-processing steps first. These steps prepare model building and calibration, which are described in detail in the next chapter. For the subsequent analysis, it is necessary to align GPS positions with the road network, i.e., in particular smooth the matching and to clean it from short mismatching to get a continuously valid matching. Hence, it is possible to assign observed speeds to attributes of the corresponding edges. To this end, for each trip, the path of connected edges is analysed. Then, the pre-processing branches according to the three different target data sets required for the analysis in the context of the different models (see Figure 4).

![Figure 4. Structure of the pre-processing steps](image)

For the edge and network perspective, it is necessary to associate the matching for each time unit to an edge and to acquire attributes of the edges. For the edge perspective, a list with all edges is generated, consisting of the number and attributes of the edges. Edges are filtered and classified with respect to the speed (class) provided by the digital map. For the network perspective, the entirety of all edges is needed for each driver. Here, adjacent edges are determined together with the positions of the corresponding nodes and the frequency of usage of the edges. For the route perspective, the analysis of the whole route is of interest. A set of routes is obtained for each driver. First, the observed trips are filtered with respect to the corresponding route and its characteristics. Relatively short routes are discarded, as these routes have may an invalid matching or are matched on restricted roads. Origin and destination of a route are provided along further route characteristics such as duration and length of a route. We use the three subsets of historical data for the analysis described in the next chapter.
5 Generating three Models of Drivers’ Navigation Behaviour

In this chapter, the target datasets described above are analysed to determine the measures introduced in Chapter 2 concerning the dimensions of time and space. The three perspectives are explained in detail in the corresponding sections.

5.1 Adaptation of edge attributes

In this section, the adaptation of edge attributes is described in detail. As mentioned before, our approach is similar to how today’s premium navigation devices would consider driver-specific speeds. In particular, for each driver, the median of all observed speeds in each speed class is determined. Results are depicted in Figure 5. Apart from the lowest speed class, the median is based on thousands of edges for almost all drivers.

Figure 5. Median of observed speeds per driver for each speed class.

For most drivers, the median of the observed speeds of edges belonging to a particular speed class is larger than the corresponding speed of the class provided by the digital roadmap. There are large differences between the drivers, in particular for higher speed classes. This indicates that an adaptation may be meaningful as to aligning expected and actual route durations. The adapted speed attributes can be used for route computation in a straightforward manner.

The corresponding measure “M_Speed” is computed as follows (see Equation 1). We summarize and normalize the percentage of deviation between the median of the observed speed and the speed stored in the corresponding class of the digital roadmap. If the value is larger than zero, the individual style of driving is faster than the stored speeds of the digital roadmap suggest. The value is negative if the driver is actually slower than estimated by the digital roadmap. Note that we do not consider the lowest speed class for speed adaptation, since the average number of edges for each driver is relatively low.

\[
M_{\text{Speed}} = \frac{\sum_{\text{classes}_i} \left( \frac{\text{median}\{\text{speed}_{\text{obs}}\}}{\text{speed}_{\text{class}_i}} - 1 \right)}{\left| \text{classes}_i \right|} \quad \forall \text{classes } i \geq 20 \frac{\text{km}}{\text{h}} \quad (1)
\]
5.2 Benchmarking of routes

To compare the length and the duration of an original route with a reference route, each route is recomputed with a standard routing engine based on pre-processed route characteristics. This allows for the classification of the observed route with respect to length and duration of the route. A detailed description of the recomputation procedure can be found in Landau, Ehmke and Mattfeld (2013).

In particular, we compute the median of the ratios of observed and recomputed route and subtract them by one. This value reflects the deviation of actual and theoretical route length and route duration. Equations 2 and 3 show the metrics for dimensions of time (“M_Duration”) and space (“M_Length”), respectively. A positive value shows that the driver needed less time or chose a shorter route than the fastest route calculation would yield. In this case, the driver would have to drive faster than the speed attributes of the reference routing engine suggest. The results for the routes of each driver are depicted in Figure 6.

\[
M_{Duration} = \text{median}\left\{\frac{\text{Duration}_{\text{recal}}}{\text{Duration}_{\text{obs}}}\right\} - 1 \quad (2)
\]

\[
M_{Length} = \text{median}\left\{\frac{\text{Length}_{\text{recal}}}{\text{Length}_{\text{obs}}}\right\} - 1 \quad (3)
\]

Figure 6. Benchmarked route characteristics per driver.

For a set of 43 drivers, both values are negative, i.e., the actual routes were longer and the drivers needed more time than suggested by the reference routing engine. Furthermore, a set of 23 drivers was able to choose shorter routes, which were faster than the fastest route. 21 drivers chose a route with a shorter distance, but longer duration. For another set of 12 drivers, the opposite could be observed. In sum, most drivers have either two positive or two negative values for both measures. Only for a few drivers, one value is positive and the other negative. Hence, a correlation could be presumed for both measures concerning the different dimensions.


5.3 Determining the navigation type

For the network perspective, we analyse the entirety of all edges used by a driver. The idea to analyse the spatial dimension for single routes can also be found in Jan, Horowitz and Peng (2000). We consider the whole network and model it as a graph as to employ graph-theoretical properties for characterization. In particular, two indicators are determined. The “size” measure describes the reach of the graph. It is determined by the number and the usage frequency of edges and nodes. The “structure” measure characterizes the shape (formed by crossing routes, for example) of the graph building a network of road segments. The analysis considers the number of circles and the character of the interior graph. Based on these indicators, the drivers can be assigned to a navigation type; see Landau, Ehmke and Mattfeld (2012) for a detailed description.

The resulting classification of graph structures is shown in Table 3. The graph of “locally determined” navigation types is small and has a star-like structure. “Explorative” drivers ideally have a large graph with a net-like structure. This is the same for “locally explorative” drivers, but they typically have a smaller graph. The graph of “limited explorative” types is large, but the structure is star-like again. Assignment of drivers to these classes is based on the means of the sample.

<table>
<thead>
<tr>
<th>Structure</th>
<th>Size</th>
<th>Small reach</th>
<th>Large reach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net</td>
<td>Small reach</td>
<td>Locally explorative</td>
<td>Explorative</td>
</tr>
<tr>
<td>Star</td>
<td>Small reach</td>
<td>Locally determined</td>
<td>Limited explorative</td>
</tr>
</tbody>
</table>

Table 3. Classification of the navigation type.

The values of the indicators for each driver range between zero and one, see Figure 7. The grey lines show the means for the two indicators over all drivers. 42 drivers are classified as locally determined and 24 as explorative. Limited explorative or locally explorative drivers can be found in 14 or 18 cases, respectively.

![Figure 7](image-url)

Figure 7. Results of classifying the navigation type per driver

The two indicators are aggregated to obtain a single measure describing the space dimension. This measure “M_Coverage” is supposed to describe the coverage of the complete road network compared
to the network consisting only of the used edges (Equation 4). Note that there is a significant correlation between the two indicators of 0.5328, which can be taken from Figure 7. They are subtracted by the corresponding means, summarized and normalized. Thus, we can provide a single value for characterizing a driver’s network, which is a measure that can be analysed in contrast to the values obtained for the other perspectives.

\[ M_{Coverage} = \frac{\text{Size} - \text{Mean}(\text{Size}) + (\text{Structure} - \text{Mean}(\text{Structure}))}{2} \quad (4) \]

### 6 Developing a two-dimensional Model of Driver Navigation Behaviour

First, we examine the correlations between the measures of Model 1, 2a, 2b and 3. For Model 1, we derive \( M_{Speed} \) reflecting the time dimension. The measures of Model 2a and 2b are \( M_{Duration} \) and \( M_{Length} \), reflecting the dimensions of time and space, respectively. For the network perspective, we consider the measure \( M_{Coverage} \) (space dimension). We expect a correlation of the same dimensions’ measures. A driver who drives faster and comes up with a higher edge attribute should be faster with respect to the reference route than a slower driver. It is also assumed that a driver whose network consists of a variety of different roads is able to find shorter routes with regard to the reference route, especially in urban areas with a high density of roads. Hence, the driver has a deeper knowledge about the road network than the neutral reference, which allows him or her to find a shorter route according to his preferences.

The correlations between the described measures are shown in Table 4 by means of Pearson’s \( r \) coefficient. Measures of statistical significance are depicted in bold face. As expected, there are significant positive correlations between the measures concerning the same dimension. The correlations between \( M_{Speed} \) and \( M_{Duration} \) as well as between \( M_{Coverage} \) and \( M_{Length} \) are positive and significant. There is also a significant positive correlation between \( M_{Duration} \) and \( M_{Length} \). Thus, many drivers have either positive or negative values for both dimensions with respect to the fastest route; see also the results of Figure 7. However, the correlations between the results of different dimensions and perspectives are neither significant nor is there a clear correlation. It is not possible to identify a significant relationship between \( M_{Coverage} \) and \( M_{Speed} \). In this regard, we need a more thorough analysis of drivers’ preferences correlations within future research.

<table>
<thead>
<tr>
<th></th>
<th>( M_{Coverage} )</th>
<th>( M_{Length} )</th>
<th>( M_{Duration} )</th>
<th>( M_{Speed} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( M_{Coverage} )</td>
<td>0.247754</td>
<td>0.126817</td>
<td>0.118426</td>
<td></td>
</tr>
<tr>
<td>( M_{Length} )</td>
<td></td>
<td>0.554719</td>
<td>-0.116234</td>
<td></td>
</tr>
<tr>
<td>( M_{Duration} )</td>
<td></td>
<td></td>
<td>0.266678</td>
<td></td>
</tr>
<tr>
<td>( M_{Speed} )</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

\[ \text{Table 4. Results of the correlation analysis.} \]

Nonetheless, it is possible to build a well-founded model considering the dimensions of time and space. To this end, we use the results of the Models 1, 2a, 2b and 3 to determine the overall measures “\( M_{Time} \)” and “\( M_{Space} \)” (see Equations 5 and 6). These measures provide a value between -1 and 1, which shows the relative preference of the dimension of time and space, respectively.
The two measures can be used for modelling the individual preferences of a driver. Each measure consists of two measures determined independently from different perspectives. The result is depicted in Figure 8, showing assignments for the drivers with respect to the aggregated dimensions of time and space. For 30 drivers, the values for both measures are positive; for 20 drivers, they are negative. A negative value for M_Space and a positive value for M_Time appears 34 times, the reverse case 14 times.

![Figure 8. Overall measures of drivers’ navigation behaviour.](image)

### 7 Applications of the model

To use the above measures in route computation, an objective function is required that combines time and length of a route. For premium navigation systems, this functionality is already available, but parameterization is left to the intuition of a driver. To “plug in” the above measures, it is necessary to normalize M_Time and M_Space and find proportions for a combined objective function. Thus, it becomes possible to consider the speed and distance of an edge for each driver individually. The result of this means of personalization is shown in Figure 9. The proportions vary between the drivers, but in general, time is weighted higher than space.

Another application could be the use of the measure M_Time instead of M_Speed for adapting the edge attributes of speed as base for the routing engine. Both measures belong to the dimension time but M_Time bases on the analysis of two distinct perspectives. In general, the values of M_Time are smaller than the values of M_Speed. Hence, the differences between the driven route and the personalized route, basing on the adapted edges are less pronounced than the differences between the driven route and a standard route. However, it is well-founded as the route perspective is included.
To consider the measure $M_{Space}$ of the space dimension for adapting the edge attributes of speed it is necessary to analyse the correlations between measures of distinct perspectives concerning different dimensions first. After identifying the correlations it will be possible to use the quantified measures for the routing component of existing and future vehicle navigation devices.

![Figure 9. Combined objective function for each driver.](image)

8 Summary

In this paper, we have developed a two-dimensional model of drivers’ navigation behaviour. Based on a very large dataset of a field study, we have determined measures along the dimensions of time and space. We approach these dimensions from three distinct perspectives and find that measures concerning the same dimension or the same perspective are correlated. We thus use them for an aggregated two-dimensional model. The results can be used for adapting the objective function of a standard navigation system’s routing component. Technically, it is possible to determine proportions of time and space for a two-dimensional objective function. Furthermore, the model can be used for a well-founded adaption of the attribute “speed” as the corresponding measures confirm each other, and thus extend existing approaches.

To the best of our knowledge, this is the first approach at developing a two-dimensional model within the planning level of navigation. Hence, it expands the field of driver modelling significantly. As a first step, we have developed measures quantifying drivers’ navigation preferences. A tight relationship between the measures of different dimensions and distinct perspectives could not be identified, though. For further research, more information about the driver has to be taken into account. Furthermore, driver-independent effects such as surrounding route characteristics have to be identified. Future innovations and the availability of more information could be useful for this task.

In this context, it is necessary to explain the strength of the relationship of the measures for different drivers. In addition, more complex models dealing with other aspects of navigation should be considered in the analysis, especially with regard to drivers’ behaviour. One example is fuel consumption of a chosen route depending on drivers’ behaviour. These aspects are directly related with possible economic and environmental benefits of applications based on the described model and are thus interesting topics for further research.
References


