Extracting Traffic Lanes from Floating Car Data

Masterthesis

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Summary

The objective of this master thesis is to utilize real-world Floating Car Data to extract road lane centrelines and lane-level intersections. We utilize existing map creation algorithms to extract our lanes and propose an approach to extract lane centrelines in intersection areas.

The data set is provided by HERE and covers a 2.6 km long motorway segment and four intersections with inner-city highways in the city of Augsburg. The data was recorded from 6. to 12. November 2017. After preprocessing the data, we create a road network graph to assist the lane extraction process using the implementations of Ahmed et al. (2015a). To extract geometries from the FCD traces we use a method utilizing the Kernel Density Estimation (KDE). The resulting lane geometries possess inconsistent coverage and accuracy. On motorways, we have a higher correctness, than on the inner-city highway segments. Overall, we are able to extract the correct centre lane points with a 60%-80% probability. Reasons for the low extraction rate is the high positional error and the uneven distribution of the data. The resulting intersection geometries depict an accurate representation of the lane relations, if the amount of input traces is sufficient and the lane geometries are accurate.

1 Utilizing Floating Car Data to generate high-definition Road Geometries

Navigable maps have become a daily presence in our everyday life. With the evolution of smartphones and automotive equipment navigation systems accompany us wherever we travel. These digital maps are presented as road network graphs. The graphs are a generalized representations of the road geometry, in which nodes represent intersections, road splits and merges, and edges represent roads (Schrödl et al. 2004). Creating and updating these maps is expensive and labour intensive. The data is collected by survey vehicles equipped with expensive devices and processed in labour intensive processes (Ahmed et al. 2015a). Due to the high survey cost the maps are updated infrequently and lag behind in road construction substance (Liu et al. 2012b). Map suppliers, such as HERE or TomTom, have since scaled back on the expensive field surveys and switched to other, cheaper alternatives, such as crowd sourcing or image processing.

With the political and economic focus on Intelligent Transportation Systems (ITS) and autonomous driving new requirements for digital maps arise. To support ITS and autonomous driving, vehicles need
to be able to locate their precise position on the road down to the centimetre.¹ To address these challenges ultra-precise digital driving instructions are needed. Standard road network graphs are no longer sufficient for these new maps.

The commoditization of GPS technology and the low costs of fleet management has enabled the generation of large amounts of vehicle tracking data (Ahmed et al. 2015a). This data is called Floating car data (FCD), or Probe Vehicle Data or Vehicle Tracking Data (Pfoser 2008). FCD is positional data acquired from individual vehicles through GPS devices, mobile phones or Bluetooth devices. This data is often a byproduct of existing processes and already available in vast quantities (Liu et al. 2012b). The benefits of FCD compared to other map creation solutions are: low cost, quantity, high coverage, actuality, and no dependence on the collector.

FCD indirectly represents the underlying road network, as the vehicles should drive on existing roads (Chen & Krumm 2010). If we assume that people generally drive in the middle of the lane, we can expect FCD to also cluster in the middle of the lane. This enables us to extract road centrelines and, even more desirable, lane centrelines from FCD.

The objective of this thesis is to use real, available FCD to extract road lane centrelines. Our focus lies on motorway roads as well as roads surrounding intersection areas. Further, we plan to model the intersections themselves on a lane-level. The geometries are extracted using only the provided FCD and are not supplemented with further data. For this thesis, we use FCD provided by HERE and sampled in the week from 6.11.2017 to 12.11.2017. This data therefore represents current and real circumstances.

2 Extraction of Road Lane Centrelines

In recent years lane extraction algorithms have emerged in literature, which propose methods to extract lane-level geometries. The GPS data produced by these experiments is typically of high quality, with a low standard deviation and a sample frequency of 1 Hz. Since real FCD consist of data created by different vehicles and drivers, using different GPS devices and different sampling intervals, emulated traces do not correspond to reality. Most of the surveyed lane extraction literature conducted the evaluation of their algorithms for motorways or high-level streets without turns. For this thesis in addition to a motorway segment, four intersections in the city of Augsburg are selected.

To extract traces from FCD we first need a common road network graph. As extracting the lane structure with the help of a validated high-precision road network graph is impracticable for unmapped regions, a basic road network graph is first derived from the traces. For this purpose four selected algorithms from the implementations of Ahmed et al. (2015a), which are provided on their website, are used on the

data. We compare the resulting road centreline geometries and use the basegraph closest to reality as our input for the lane extraction process.

We chose the Kernel Density Estimation (KDE) to extract lanes for this thesis, as literature using this method (Uduwaragoda et al. 2013; Neuhold et al. 2017) seems to produce good results, without assuming lane parallelism, and models lane splits and merges. We create perpendiculars to the basegraph geometries centrelines in a regular interval. We then intersect the traces with the perpendiculars and use the coordinates of the resulting intersection points as input for a KDE. The local maxima of the KDE distribution represent the detected lane centres.

As we did not find much literature on the modelling of lane-level intersections, we propose and implement our own approach for our selected intersections. We apply the assumptions that vehicles drive in the middle of the lane and that lanes can be derived from a certain quantity of traces, to intersections. After map matching our traces to the geometries created in the lane extraction process, we apply the methods used for lane extraction to the intersection traces.

2.1 Processing the Data

Following preprocessing approaches in literature, we clean the data using the point’s position and additional attributes. We check the attributes for validity, as the HERE-dataset is not consolidated. To filter incorrect speed information we introduce a minimum and a maximum threshold. We also remove points with incorrect headings. To further reduce erroneous data, we cluster the FCD points using the DBSCAN-algorithm (Density-based spatial clustering of applications with noise) (Ester et al. 1996). The algorithm uses the distance between points in a dataset to partition the data into clusters and noise, enabling the detection of outliers. We use the DBSCAN in this thesis, since the algorithm is very versatile, detects any number of clusters, adapts to each dataset and is not limited by the form or size of the dataset. After cleaning the FCD points, we transform the points into traces. We connect chronologically successive points of the same vehicle with straight lines to polylines. We then split the traces according to the data’s sampling interval. The split traces are then filtered by their length. This ensures that the remaining traces are compiled from constant measurements.

2.2 Extracting a Basegraph

To extract the road centreline we use a selection of map creation algorithms. We compare the selected algorithms and apply them to our data. From the map creation repository of Ahmed et al. (2015a) the methods of Ahmed & Wenk (2012), Davies et al. (2006), Cao & Krumm (2009), and Edelkamp & Schrödl (2003) are selected. From the tested algorithms, only Ahmed & Wenk (2012) produced an acceptable road network graph for our data.
2.3 Extracting Traffic Lanes

To extract the road lane centres, we use the basegraph created from our data and remove intersection areas to concentrate on straight road segments. We then create perpendicular lines to the road segments in 10m intervals along the centrelines. The perpendiculars are intersected with our traces. For each direction, we handle the intersection points as a separate input dataset. We chose the input values (X- or Y-coordinates) of the KDE dynamically, depending on the orientation of the perpendicular. The value covering the widest range of values is used as input data. The coordinates are further filtered by setting a 5% cut off interval to catch outlier traces that deviate from the original distribution.

A KDE estimates the probability density function (PDF) of a random variable. It depends on the two parameters kernel and bandwidth. The Kernel Density Estimator places a Kernel above each data point, which reaches its highest value at the respective point. The kernels of all data points are then summed up and result in the probability density function curve.

The kernel function specifies the shape of the kernel placed on each point. For this thesis we use the Gaussian kernel, as it is commonly used in literature (Neuhold et al. 2017; Uduwaragoda et al. 2013) and the form of the kernel has hardly any influence on the result (Zucchini et al. 2003). The bandwidth controls the width of the kernel and has a large impact on the accuracy of the KDE. A large bandwidth oversmoothes the function, hiding important peaks, while a low bandwidth creates a sensitive curve with many maxima. Some popular methods to select an appropriate bandwidth are rule of thumb, cross validation and direct plug-in (Botev et al. 2010). We choose Silverman’s Rule of thumb (Silverman 1986), as other methods are too computationally intensive. Since the Silverman’s Rule tends to oversmooth our data, we divide the bandwidth by a certain factor.

The KDE produces a density function from which we derive the local maxima. The output centre points of each KDE are checked for outliers. The local maxima represent the detected centres of the lane and are connected to lane centrelines.

2.4 Modelling Intersection Lanes

To model intersection areas, we utilise the methods used in the lane extraction process and apply them to traces in the intersection area. As input, we use the created basegraph, traces and lanes. We assign lanes to each intersection and map match the traces to these lanes, while considering the lanes and traces heading. After every lane is allocated its traces, we search for matches between different lanes. If two lanes have at least 10 traces in common, a relation is noted. For every relation we apply the methods used in section 2.3 to create the lane geometry.
3 Results and Discussion

The resulting lanes on the motorway segments show interruptions in their geometry and inconsistencies in the coverage of neighbouring lanes. The reason lies with the data, as the traces do not accumulate to density peaks at these locations. By inspecting the resulting lane centrelines, we observe, that the geometries are not always in the middle of the lane. The distribution of the data, measurement errors and the smoothing factor of the KDE lead to shifts of the lane centreline. Another factor is the vehicle operators driving behaviour. Apart from obvious errors in the created lane geometries, the algorithm detects many lanes correctly and constantly. The inner-city highways are located near intersection areas, and therefore produce noisy data. On these road segments the algorithm is able to detect single correct lanes but tends to over or underestimate the actual number. The statements regarding the lane creation process given for the motorway segment also apply to the inner-city highways.

The intersection lanes represent all relations found for this intersection. The connecting lanes conform to the underlying trace data and produce good results considering the extracted road lanes. Our algorithm matches traces only to existing lane geometries, regardless of whether the lanes represent the actual road structure. Another disruption is the lack of data for roads of lower road levels. Especially the surveyed intersection areas have turns that are not well represented by the data, for instance ramps. The road level of the surveyed geometries determines the amount of available data. Motorways have a higher driving count, than secondary or tertiary streets. While lanes based on lower numbers of traces can be impacted by outliers, most of the lanes resulting from a high number of traces correctly represent the intersection geometry and are outlier resistant.

The FCD used in this thesis originates from a heterogeneous data source. The data has points that deviate from their original position, because of GPS and measurement errors, and is produced by various sampling intervals of up to 6s. This leads to traces overlapping to nearby roads and outside the actual road structure. Inaccurate density clusters either need to be removed in the preprocessing process or after their creation in a lane centre evaluation process. According to Neuhold et al. (2017) the assumption that the highest density of traces corresponds to the lanes centre does not apply to input datasets with a significant accumulation of positional errors. The combination of trace quantity and positional errors “fills” the valleys between the density maxima of the KDE curve. Differences in density are evened out and lead to the detection of inaccurate lane centre points and the omission of accurate lane centre points.

As we do not create our own FCD and create a road network graph with one edge for both road directions, we do not distinguish between traces of opposite roads until after intersecting the perpendicular lines with traces. This also affects the basegraph, since the centreline of the road network graph should be between traces with opposite heading but is shifted to the highest density of traces instead.
To quantify the quality of our results, we choose the motorway segments as representatives for all surveyed areas. We estimate the correctness of the depicted lane centre points by calculating the ratio of correct extracted lane centres to expected lane centres. The results show that our lane centre points have a correctness between 60% and 80%. The appropriate number of traces required to depict correct lane geometries is difficult to estimate. The correct lane geometries, in terms of correct lane number and accuracy, in this thesis use 200 to 1000 traces for creation of one lane. We therefore estimate the minimum number of traces required for a lane centreline extraction from our data with our methods at 200. For our intersection modelling process, we estimate a minimum number of approximately 20 traces to assure a lane geometry is reflecting reality. As the lane intersection algorithm preselects the traces and confirms their affiliation to the connected lanes, the number of traces required to form an intersection link is small compared to the amount of traces needed for the lane extraction process.

4 Future research

As technology advances, the accuracy of GPS devices will also improve. This will lead to an overall quality increase of crowd sourcing data. The utilization of this data will continue to become increasingly important in the future. Future research should therefore focus on cleaning raw FCD and improving the quality of traces.

One way to enhance the quality of the input data is to expand the preprocessing process and continue to sort out inaccurate data. Further approaches to remove noisy traces could be the detection of sudden changes in heading and velocity, the location of traces with a high offset, or the comparison of traces to their neighbouring geometries. We could also reduce the data’s sampling interval threshold. All additional preprocessing steps will further decrease the amount of input data and thus the number of traces. To get steady results, we require a higher amount of raw data. Another idea is to identify accurate traces and weight them higher than inaccurate traces. This would utilize the high precision traces present in the dataset.

Another important issue is the specification of algorithm parameters. Through this master thesis, we had to set several parameters for each algorithm. The parameters were tested against our data and chosen according to the produced results. Different sets of data will require an adjustment of the algorithms parameters. We find, that current literature does not emphasize how dependent the parameters of introduced methods are on the data. Especially when thinking about the automation of the lane extraction process and utilization of these methods for ITS, it is important to discuss the adaption of the algorithms to the data. Research should concentrate on automating the preprocessing methods and introducing a learning, dynamic system.

To improve the exclusion of incorrect lane centres, the evaluation process could be extended. Neuhold et al. (2017) use a distance matrix to assess the plausibility of lane centres. A critical analysis of the
derived lane centres will improve the accuracy of the lane geometries. We could further facilitate the lane centre extraction process, by estimating or depriving the actual number of lanes from the data. By comparing the created lane centres of both directions, we could identify and revise overlapping lane centres.

When using vehicle traces for geometry creation, it is important to note that the traces do not represent the centreline of the lane, but the actual driving behaviour of the vehicles owner. The driver’s behaviour can cause a deviation of one meter from the centreline (Dolancic (2016)). If a lane geometry tailored towards the driving behaviour of humans is inconvenient or beneficial depends on the use case of the lane network graph.

We hope that this thesis emphasizes the limits and challenges of extracting lane geometries in road and intersection areas from real-world FCD. The introduced methods and algorithms can be used as a basis to understand and enhance the lane creation process and create road network maps from scratch. This thesis also proposes a density based approach to model intersection lanes, which provides material for new discussions.

Publication bibliography


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