2018 IEEE Intelligent Vehicles Symposium (IV)
Changshu, Suzhou, China, June 26-30, 2018

Traffic Mapping for Autonomous Cars

Nicolai Steinke[1], Fritz Ulbrich[1], Daniel Goehring[1] and Raúl Rojas[1]

***Abstract*— Today's car traffic is dominated by human drivers. Autonomous cars must comprehend the behavior of human drivers in order to fit in current daily traffic scenarios. To achieve this goal, analysis of the behavior of other traffic participants is necessary. In this paper we present a system to record, store, and analyze the movements of other traffic participants with an autonomous car and evaluate traffic maps, which are obtained from real world experiments. The evaluation shows that the maps cover more than 80% of the driveable area with a precision of 80 to 90%. Additionally, we present the results of a traffic behavior change detection heuristic, which can detect anomalous traffic conditions.**

I. INTRODUCTION

Human drivers tend to follow the traffic rules less strict than a computer, which could lead to conflicts in future driving environments, consisting of a mixture of autonomous and non-autonomous cars. In some situations humans choose to ignore lane markings or traffic rules, especially on large junctions or roundabouts the lane markings are considered more as a guidance than a rule. Some driving maneuvers of autonomous cars could be surprising to human drivers, if autonomous cars follow the traffic rules and lane markings strictly without exceptions. The resulting conflicts could be avoided, if autonomous cars are capable of a cooperative driving behavior, so that they adapt themselves to human traffic behavior to minimize misunderstandings. In order to realize this human inspired driving behavior, data of human driving behavior must be analyzed and evaluated.

In this paper we present an efficient approach to record, store, and evaluate trajectories of other traffic participants. We generate maps from these trajectories, evaluate their accuracy and examine the coverage of the road surface from real world experiments. Additionally, we demonstrate how a detection for anomalous traffic behavior could be implemented. Finally, we present and discuss the results of a proof of concept implementation of the proposed methodology. This approach lays a foundation for the implementation of human inspired driving behaviors in autonomous cars. It could be used to adapt path planners and improve the intention prediction in autonomous cars. Also could the maps be used to analyze the traffic behavior to improve the layout of junctions and roundabouts. This paper is structured as follows: Section II briefly presents the state of art in traffic evaluation and traffic aware path planning for autonomous vehicles, Section III describes the platform that was used for the traffic recording and the architecture of the mapping framework. In Section IV we provide details about the performed experiments, evaluate the accuracy and evolution of the created traffic maps, and present a simple detection for anomalous traffic behavior. The last section draws conclusions, and gives recommendations for further research work on the topic.

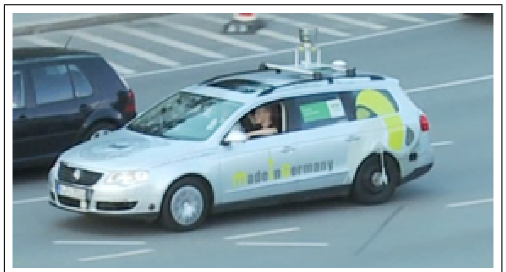


Fig. 1. The autonomous car "MadeInGermany" at the Großer Stern roundabout in Berlin. Image source: [9].

[1]DCMLR, Germany, Computer Science Institute, Freie Universität Berlin, {nicolai.steinke | fritz.ulbrich | daniel.goehring | raul.rojas}@fu-berlin.de

II. RELATED WORK

The interpretation of the modern street traffic as swarm and the usage of bulk traffic data is a common approach in scientific publications dealing with traffic phenomena [7] [8] [9]. Several research works are dealing with the inference further information from vehicle probe data [2] [10]. The vehicle probe data is generally obtained via GPS-devices with low accuracy which renders it unusable for navigation purposes of self-driving cars. The GPS-receiver of the autonomous car "MadeInGermany" (see Fig. 1) is equipped with a highly accurate differential-GPS sensor which is capable of localization with centimeter-level-precision. With the precise self-localization and the measurements of the lidar sensors, other observed cars can be tracked with a high accuracy. With this traffic movement data path planning for autonomous vehicles is possible. This was demonstrated by Ulbrich et. al. [9], who developed a local path planner for autonomous cars based on the trajectories of other tracked cars. The path planner could navigate the car in a dynamic traffic environment without having to rely on prerecorded maps. This could benefit self-driving cars in situations where prerecorded maps are not sufficient, because the traffic behavior changes rapidly throughout the day. Especially in situations where no lane-markings are available the driving behavior varies depending on the amount of traffic. In junctions without lane markings and a certain degree of traffic this often results in human drivers following imaginary lanes as if lane markings where available. Extracting these imaginary lanes from the trajectory data of other drivers could benefit autonomous cars to adjust to the human behavior in these situations. The

978-1-5386-4451-5/18/$31.00 ©2018 IEEE

clustering and analysis of vehicle trajectories got increased attention in recent research [1] [2] [4] [6]. But this research is mostly performed on camera images of static scenes because it is expected to deliver promising results for surveillance systems which will be capable of classifying trajectories and detect anomalies [1] [4] [6]. With our approach we collect the trajectory data from a moving vehicle and build the traffic maps in real time.

III. RECORDING AND MAPPING ARCHITECTURE

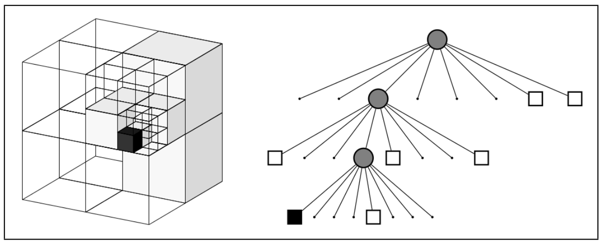


Fig. 2. Schematic representation of an octree. Free nodes are white, partly occupied grey, and occupied black. Leafs in the unknown state are depicted as dots. The left side shows the spacial representation, the right side shows the tree structure. Image source: [3].

In this section we briefly present the recording test carrier "MadeInGermany", the mapping architecture, and the used third-party-libraries.

A. *"MadeInGermany"*

The "MadeInGermany" (Fig. 1) is a research autonomous car platform of the Freie Universität Berlin. It is capable of fully autonomous driving using its perception systems including: several radar systems, lidar scanners, cameras, and a highly accurate differential-GPS receiver. The sensors responsible for the recognition of other vehicles are the six Ibeo "Lux" lidar scanners (Ibeo Automotive Systems GmbH), which are mounted in the front and back of the car and provide a 360° recognition, classification, and tracking of other traffic participants. More information on the "MadeInGermany" and the AutoNOMOS research project can be found in [5].

B. *OctoMap framework*

For mapping purposes the OctoMap-Framework is used, which is an efficient and extensible three-dimensional mapping framework based on octrees [3]. Octrees divide three-dimensional space into cubic volumes, which are recursively divided into eight smaller cubic volumes until a predefined minimum volume size is reached. This size defines the resolution of an octree [3]. Octrees can be queried in coarser resolutions, which means that the tree is not traversed until a leaf node is found but a intermediate node is returned instead. Every leaf-node of an octree can have one of three states: "Free'", "Occupied'" or "Unknown'". Non-leaf nodes can also assume a partly occupied state if some but not all child nodes are marked as occupied. In Figure 2 an exemplary octree is displayed with its spacial extends and its tree structure.

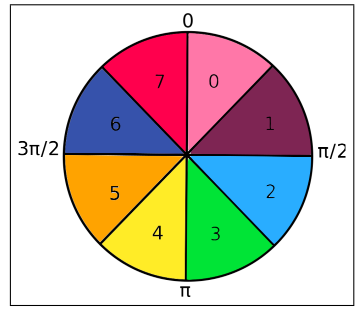


Fig. 3. The eight different direction classes on the unit circle with colors used for the visualization in OctoVis.

C. *Mapping System*

In order to store the detected obstacles in an octree-friendly representation they have to be rasterized. The Ibeo sensors are capable of measuring the extends of a detected vehicle. However, the length is often undetectable, especially when driving right behind another car. For that reason, the rasterization process uses a fixed length of 3 meters for all detected vehicles and only for the rasterization width, the detected width, rounded to a multiple of the octree resolution, is used. The Ibeo sensors also record the driving direction and speed of any perceived vehicle. The driving direction is discretized into one of eight possible driving directions. Since every node of the octree has eight neighbors in the plane, we decided to use eight directional classes. These direction classes are evenly distributed on the unit circle, so every direction class spans an angular range of $\frac{\pi}{4}$ (see Fig. 3). The discretized traffic observations of other participants are stored in an OctoMap structure. Consecutive observations of the same vehicle that fall into the same node of the OctoMap are discarded to avoid having very slowly moving vehicles overrepresented in the map.
Every node of the octree holds the count of vehicle observations for all direction classes and the averaged traveling speed. The three-dimensional nature of the octree framework makes it possible to record traffic maps in multi-level road scenarios, e. g. bridges, parking lots and highways. The speed value of intermediate nodes is calculated as the weighted average of the speed values of the child nodes and the observations are the summed observations of the child nodes for every direction class. The equations 1 and 2 describe the calculations for the speed ($s \in \mathbb{R}$) and the observation count for the direction classes ($d \in \mathbb{N}$) for non-leaf nodes:

$$s = \frac{\sum_{i=1}^{n}(\sum_{j=0}^{7}(d_i(j)) \cdot s_i)}{\sum_{i=1}^{n}(\sum_{j=0}^{7}(d_i(j))} \tag{1}$$

$$d(j) = \sum_{i=1}^{n}(d_i(j)) \tag{2}$$

where n is the number of child nodes, $d_i(j) \in \mathbb{N}$ returns the count of observed cars for the direction class j of the child node i and $s_i \in \mathbb{R}$ is the average speed value of i.

D. *Visualization*

For visualization purposes the tool OctoVis is used which is part of the OctoMap framework. A 3D-renderer for the traffic maps was implemented for OctoVis which visualizes the average direction of every node with its color and its observation count through the transparency. Fig. 3 shows the colors used by the OctoVis renderer for the possible direction classes.

IV. Experiment and Analysis

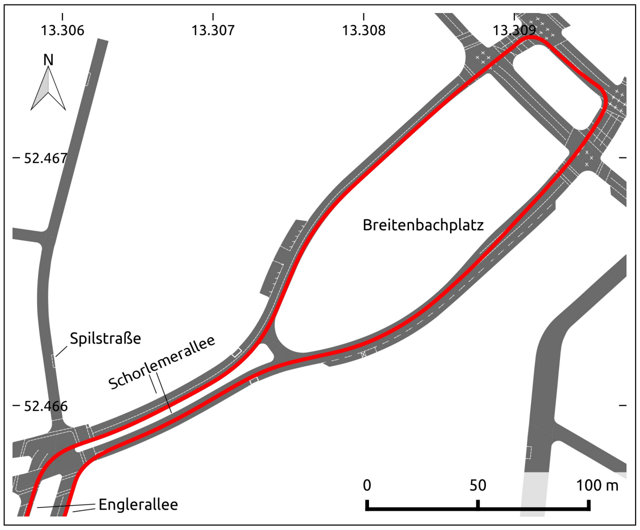
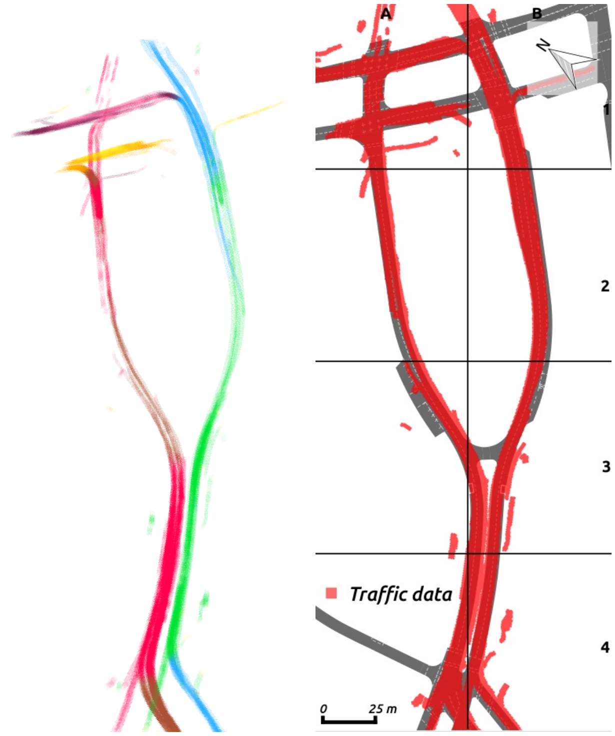


Fig. 4. Driving path (red) of the "MadeInGermany" for the first experiment on the Englerallee street (bottom left), Schorlemerallee street (left to center) and Breitenbachplatz (center to top right). CRS used: WGS84 (EPSG:4326).



(a) Rendering of the traffic map (b) Traffic map (red) as street map overlay

Fig. 5. Comparison of a rendering of the traffic map and the traffic map as overlay over a street map.

Two experiments were performed to evaluate the accuracy of the traffic maps and to detect traffic anomalies. The first experiment was carried out on Breitenbachplatz and Englerallee street in Berlin (see Fig. 4) and represents a common urban scenario with a medium sized junction. The second took place on the big roundabout "Großer Stern" in Berlin to evaluate the approach in a more complicated road setting and to find possible traffic anomalies. The "MadeInGermany" performed four laps on the Breitenbachplatz and passed the Englerallee and Schorlemerallee streets four times in each direction for the first experiment. The data collection for the Großer Stern experiment consists of drives through the roundabout from every connecting street (see Fig. 8).

A. First Experiment: Breitenbachplatz

The experiment was performed at noon time with light to average traffic conditions and took 16 minutes. The driving path is shown in Fig. 4. The car performed a U-turn just slightly south from the south-western end of the map (Fig. 4). The observations made during this 180 degree turn are omitted because the main purpose of the traffic mapping is to focus on junctions and roundabouts. The resulting map is displayed in Fig. 5. In the rendering the color shows the average direction of the observed cars and the intensity of the color correlates to the number of observations. Neglecting some map errors, due to erroneous observations of other cars far off the street, the map is correctly attributed. The accuracy evaluation in the next subsection confirms these impressions. The following observations can be made from the resulting traffic map (Fig. 5): No car was observed driving into the Spilstraße which is located in the quadrant *A4*. The map has only a low observation count in the quadrants A2/B2 and A3/B3 because there are no traffic lights and the average driving speed is relatively high, which results in shorter recording times for this parts of the map. A big chunk of street is missing in the quadrant B1. This is caused by the fact that the car drove around the Breitenbachplatz only in counter-clockwise direction, thus never driving on this part of the Breitenbachplatz. Also the timing of the traffic light phases prevented the "MadeInGermany" to detect the passing cars from the other direction in this part of the map. In the bottom part of the quadrant A1 is a major misclassification which starts at the border of the street and goes on the pedestrian way to the entrance of a subway station. This was probably caused by a baby carriage or a wheelchair that was misclassified as car by the Ibeo sensors. Only one of the two lane streets in the quadrant A2 is used. This seems to be related to the parking area on the side of the road (see Section IV-D).

B. Accuracy

For the accuracy evaluation precise maps of the driveable streets were needed. We created the required precise maps based on high resolution aerial photographs manually. Bicycle ways and parking spaces were excluded. First the general accuracy was measured. This was done by checking for every observation whether it is located on driveable area or not. The results of the general accuracy evaluation are depicted in

Table. I. An observation, which is a measurement of a vehicle by the Ibeo scanner, is counted as positive if it is located on legally driveable area (i.e., on the street). The results of the

TABLE I

RESULTS OF THE GENERAL ACCURACY EVALUATION

resolution	positives count	positives %	total count
1.0 m	50,972	95.2	53,513
0.5 m	395,267	94.0	420,527
0.33 m	1,096,381	94.3	1,162,914
0.25 m	1,901,917	94.1	2,021,902

general accuracy evaluation (Table I) show a high accuracy of at least 94 percent regardless of the chosen resolution of the OctoMap. The small differences in the accuracy are caused by the rounding during the rasterization process.

The second accuracy evaluation was executed on a per node basis, i.e., only OctoMap nodes with a configurable amount of observations where considered occupied. This enabled us to calculate the *recall* of the recorded OctoMap, which equals the percentage of occupied nodes in the driveable area. A recall of 100% means that all nodes of the drivable area are occupied; hence every part of the street is used by at least one vehicle. Additionally, the F_1 score was calculated as follows:

$$F_1 = 2 \cdot \frac{precision + recall}{precision \cdot recall}.$$

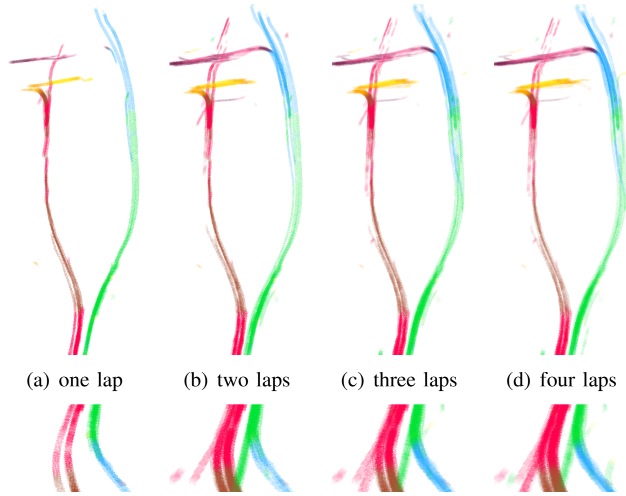
In order to mitigate misclassifications, we introduced a

TABLE II

NODE BASED ACCURACY EVALUATION

thres.	precision % 1	precision % 2	precision % 4	recall % 1	recall % 2	recall % 4	F_1 % 1	F_1 % 2	F_1 % 4
res.:									
1.0m	87.4	89.8	95.2	75.4	69.3	52.4	81.0	78.2	67.6
0.5m	84.4	86.3	89.6	81.8	79.6	70.5	83.1	82.8	78.9
0.33m	85.2	86.5	89.0	80.2	78.2	70.6	82.6	82.1	78.7
0.25m	84.4	85.8	88.4	81.5	78.7	70.3	82.9	82.1	78.3

threshold value, which defines how many observations a node must contain to be considered occupied. Table II shows an accuracy comparison of different resolutions and thresholds. The precision rises with higher thresholds, but the recall subsides. The F_1 score is consistently the highest for the 0.5m resolution. While having the highest precision values, the 1.0 m resolution has the lowest recall, which results in a poor F_1 score. The other resolutions are close in their F_1 score with 0.5 m scoring highest. The 0.5 m also has lower memory requirements than its higher resolution counterparts, which makes it the best choice for this experiment. The 0.33 m resolution behaves slightly different than the others because it has a shorter static obstacle length: it is 2.97 m instead of 3.0 m because it is divisible without remainder by 0.33 m.



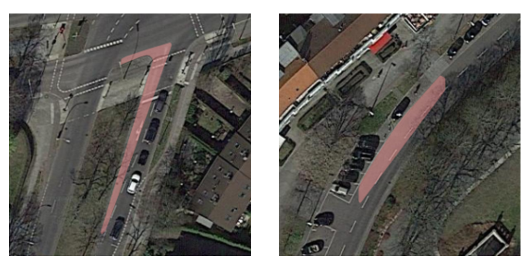
(a) one lap (b) two laps (c) three laps (d) four laps

(e) two passes (f) four passes (g) six passes (h) eight passes

Fig. 6. Comparison of the evolution of the Breitenbachplatz and the junction Englerallee-Schorlemerallee during the laps.

C. Evolution

Fig. 6 shows the evolution of selected parts of the generated traffic map during the experiment. The top row shows the Breitenbachplatz, while the lower row shows the evolution of the traffic map of the junction Englerallee-Schorlemerallee. The side-by-side comparison of the top row shows the state of the traffic map after each lap in counter-clockwise direction. The bottom row compares the change after every two passes of the test carrier (one in every direction). The resulting maps of the first lap of the Breitenbachplatz and the first two passes of the junction Englerallee-Schorlemerallee are incomplete. The Breitenbachplatz map is not closed and the map of the junction is lacking several streets. After the second lap (Breitenbachplatz) or the fourth pass (junction), the maps are rather complete and do not improve significantly in the following laps or passes. The accuracy values for the eight different passes (one per direction) and the four laps are shown in Table III.



(a) Unused lane of the junction Englerallee-Schorlemerallee. (b) Unused lane in front of parking spaces.

Fig. 7. Results of the anomaly detection. Aerial imagery: ©2017, Google, DigitalGlobe, GeoBasis-DE/BKG, GeoContent.

D. Detection of anomalies

The resulting traffic maps can be used to detect anomalies in the traffic flow. For that purpose the generated maps were compared with complete maps. In a complete map

TABLE III

NODE BASED ACCURACY EVALUATION OF THE MAPS OF THE JUNCTION SCHORLEMERALLEE-ENGLERALLEE AND THE BREITENBACHPLATZ.

	Precision %		Recall %		F1 %	
Pass	Br.-pl.	Junction	Br.-pl.	Junction	Br.-pl.	Junction
1	91,2	64,8	46,4	16,0	61,5	25,6
2	88,6	83,8	70,6	51,9	78,6	64,1
3	89,2	83,9	78,7	77,7	83,6	80,0
4	88,6	83,9	80,2	78,2	84,1	81,0
5		81,5		78,6		80,0
6		81,1		84,2		82,6
7		80,2		84,6		82,3
8		78,8		84,6		81,6

every node on the street is marked as occupied; therefore, a complete map defines the expectation of a completely used street without any anomalies. The maps are compared using a difference operation, and the resulting clusters of differences are filtered by area. Small clusters (smaller than the size of a typical car) are to be found at the borders of the streets because the vehicles are usually driven in the middle of the road. Big clusters (spanning over the whole road) are most likely streets that are rarely driven and where no observations were made. Cluster that only span on a lane of a street with high traffic volumes indicate anomalous traffic behavior and should be investigated.

Fig. 7 shows the results of the detection of anomalies after the area-based filtering. The filtering was based on the area of the clusters: clusters smaller than 60 m^2 and clusters larger than 150 m^2 were filtered. The first of the two remaining results is shown in Fig. 6 (a). It is the lane of the junction Englerallee-Schorlemerallee which leads straight to the Spilstraße or left onto the Schorlemerallee street. Since the Spilstraße is a rather small one-way road, it is not surprising that no car went that way. More interesting is the fact that no car went left onto the Schorlemerallee, but it is not necessarily an anomaly in the daily traffic. The second result is caused by more interesting human driving behavior. The parking spaces on the right site of the road lead to regular distractions of the traffic of the right lane. Berlin's drivers know that and thus avoid this lane even if no car is leaving a parking space. This is the kind of anomalous traffic behavior that are hardly predictable for autonomous cars which was detected by the traffic anomaly detection.

E. Second Experiment: Großer Stern

The second experiment was performed on the Großer Stern in Berlin, Germany. The "MadeInGermany" was driven for about 35 minutes on a normal weekday with light to average traffic conditions on the Großer Stern. To generate a realistic traffic map, the roundabout was entered or exited through each connecting street at least once (see Fig. 8). The resulting traffic map covers 88% of the driveable area of the roundabout with 288,092 nodes at 0.5 m resolution and a precision of 90%. Figure 9 shows the OctoVis visualization with color coded direction classes. Despite some misclassifications (e. g. in the bottom left part) the map has a high quality and even most of the lanes are clearly visible. The anomaly

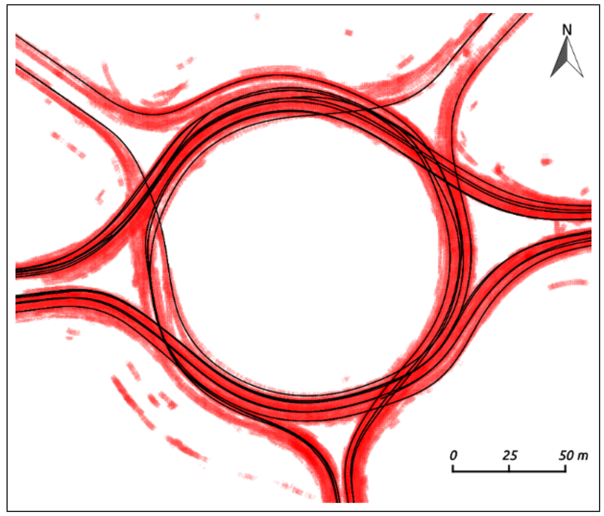


Fig. 8. Großer Stern map data (red) with test carrier driving trajectory (black).

Fig. 9. OctoVis visualization of the Großer Stern map.

detection shows much more results on this map than on the traffic map of the Englerallee street and Breitenbachplatz. The results are displayed in Fig 10 with anomalies smaller than 60 m^2 filtered. The roundabout Großer Stern has a spiral design this means new lanes start from the center and lead to the exits. This results in unused portions of the most central lanes because drivers tend to avoid the innermost lanes on this roundabout. Most of the other anomalies are drivers who drive far on the left side of the outermost roads. This seems to be caused by the parking spots where drivers want to leave room for possibly open car doors. The long anomaly in the south-western part of the map is a result of a temporary construction work performed at that place. The biggest anomaly on the map and the small one in the middle of the second innermost lane on the western part of the anomaly map (Fig. 10) are also quite remarkable. They stem from the fact that if a single lane splits up into two lanes in the same direction, the driver will follow the right one. Both, the big anomaly and the smaller one are located right after such a lane split.

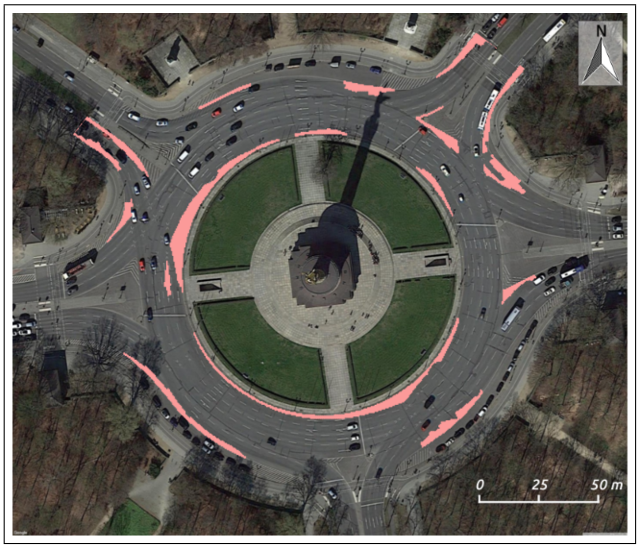


Fig. 10. Results of the anomaly detection of the Großer Stern map. The recognized anomalies are displayed in pastel pink. Aerial imagery: ©2017, Google, DigitalGlobe, GeoBasis-DE/BKG, GeoContent.

V. CONCLUSIONS

In this paper, we presented an approach for live traffic mapping for autonomous cars. The trajectories are stored discretely and efficiently in an OctoMap data structure. We evaluated the accuracy of the generated maps, analyzed the evolution in a daily traffic scenario, and presented and evaluated a use case of a traffic anomaly detection. The analysis of the accuracy showed that the maps are reasonably accurate and cover most of the driveable space. The comparison of the different octree resolutions showed that a resolution of 0.5 m offers the best balance between accuracy and memory consumption. The analysis of the evolution of the traffic maps implied that at least two passes of the area of interest are needed to get a complete map. We suggest a map sharing approach via Vehicle2Vehicle communication to overcome this limitation.

The detection of traffic anomalies were presented as practical use case. Despite being only a simple implementation, the results of the application of this heuristic to the experimental data is promising and could improve the path planning of autonomous vehicles in modern street traffic.

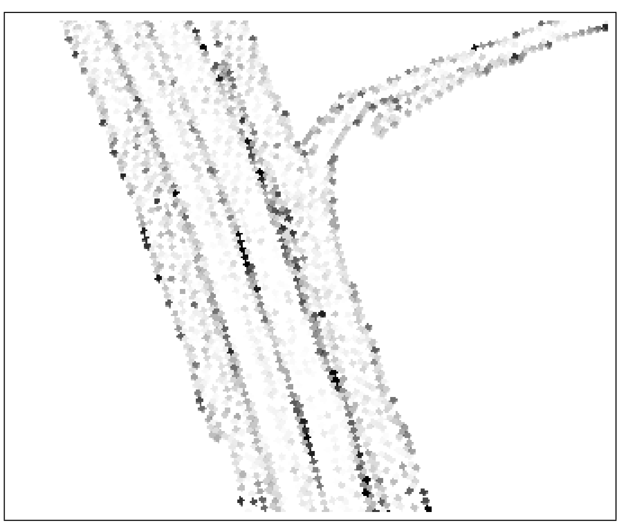


Fig. 11. Gradient based rendering mode of the traffic map.

The work presented in this article lays a foundation for further research. The simple traffic anomaly analysis could be refined and applied to bigger and more complex road scenarios. Also the velocity of the cars was tracked but not evaluated for the anomaly detection. The traffic map architecture could be extended with additional features such as time of day or vehicle type. With the inclusion of cyclist and pedestrians the traffic maps could be used in the research of the interactions of motorized and non-motorized traffic participants. Building upon this work the real world usage of the traffic environment especially the space management on street level could be analyzed which could help autonomous and semi-autonomous cars to structure drive-able space which is not structured by lane markings, e.g., parking spaces in residential areas, or big roundabouts without, or only with few lane markings. A visualization proof of concept that the lane information is derivable from the traffic maps is displayed in Fig. 11. This proof of concept visualization utilizes the gradient of the observation count visualize the implicit lane information in the traffic maps.

VI. ACKNOWLEDGMENTS

This work was supported by the Deutsche Forschungsgemeinschaft (DFG), SPP 1835 - Kooperativ interagierende Automobile and by the Bundesministerium für Verkehr und digitale Infrastruktur (BMVI) - Automatisiertes und Vernetztes Fahren auf digitalen Testfeldern in Deutschland.

REFERENCES

[1] Fu, Z. and Hu, W. and Tan, T., Similarity based vehicle trajectory clustering and anomaly detection, IEEE International Conference on Image Processing, ICIP 2005.

[2] Guo, D. and Liu, S. and Jin, H., A graph-based approach to vehicle trajectory analysis, Journal of Location Based Services. 2010 Taylor & Francis, p. 183–199.

[3] Hornung, A. and Wurm, Kai. M. and Bennewitz, M. and Stachniss, C. and Burgard, W., OctoMap: An efficient probabilistic 3D mapping framework based on octrees, Autonomous Robots. Springer 2013, p. 189–206.

[4] Johnson, N. and Hogg, D., 1996. Learning the distribution of object trajectories for event recognition. Image and Vision computing, 14(8), pp.609-615.

[5] AutoNOMOS Labs. AutoNOMOS Project. AutoNOMOS, 2016. http://www.autonomos-labs.de/.

[6] Li, X. and Hu, Weiming and Hu, Wei, A Coarse-to-Fine Strategy for Vehicle Motion Trajectory Clustering, 18th International Conference on Pattern Recognition, ICPR 2006, vol. 1, pp. 591-594. IEEE, 2006.

[7] Penner, J. and Hoar, R. and Jacob, C., Swarm-Based Traffic Simulation with Evolutionary Traffic Light Adaption, Proceedings of the IASTED International Conference on Applied Simulation and Modelling (ASM). Crete, Greece: ACTA Press, 2002.

[8] Senge, S., Ein Bienen-inspiriertes Schwarmintelligenz-Verfahren zum Routing im Straßenverkehr. Universität Oldenburg, 2014.

[9] Ulbrich, F. and Rotter, S. and Goehring, D. and Rojas, R., Extracting path graphs from vehicle trajectories. Intelligent Vehicles Symposium (IV). 2016 IEEE, Gothenburg, Sweden, p. 1260–1264.

[10] Yuan, J. and Zheng, Y. and Xie, X., Sun, G. and Huang, Y., T-Drive: Driving Directions Based on Taxi Trajectories, IEEE Transactions on Knowledge and Data Engineering, 2013 IEEE, p. 220–232.