Lane Accurate Detection of Map Changes based on Low Cost Smartphone Data

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Abstract: Self-driving vehicles rely on High Definition Street Maps (HD Maps) to ensure the safety and comfort of their driving capabilities. However, the road network infrastructure is subject to constant changes (e.g. through constructions works, accidents, ...). Such changes have to be quickly identified to avoid dangerous driving situations, for example through a reduction of driving speed or the safe handover of driving control back to the human. To address this issue we propose a road hazard detection algorithm that identifies and marks the extent of such changes based on crowdsourced GNSS data. To increase the detection speed of our proposed algorithm, we only rely on sensor information in the collection process, that is not only available through vehicles, but as well by cheap and ubiquitous devices carried on by the passengers such as smartphones. To deal with the limited accuracy of the collected data, we enhance existing algorithmic clustering approaches by leveraging additional meta-data such as the quality of the collected GNSS points and the vehicle's current lane position. Our concept is evaluated with real world measurements in a highway construction site scenario showing improved performance in comparison to the Kernel Density Estimation reference algorithm, used versatile in Related Work.

1 INTRODUCTION

Highly automated vehicles are currently a very prominent research topic (Brenner and Herrmann, 2018). To enable the respective functionality, cars rely on a large variety of sensors like cameras, radar, ultra sonic sensors or lidar (Ziegler and et al., 2014). Given the complexity of certain traffic situations and the limitations of individual sensors, current systems further rely on a High Definition Street Map (HD Map)(Madrigal, 2014; Miller, 2014). The HD Map can be seen as an additional virtual sensor. It improves the performance and accuracy of the car's localization and classification capabilities (e.g., of road signs). It further enables the car to anticipate upcoming street curvatures, which are not yet detectable by the on-board sensors. This enhances safety and comfort for the passengers, as the vehicle can compare its own sensor readings with the digital reference presented by the map.

To initially create HD Maps, specialized vehicles with expensive measurement equipment are used. These cars can rely on costly, high-precision sensors like Differential GPS (DGPS) and laser scanners to obtain precise measurement data.

However, the road infrastructure is permanently changing (Plack, 2013). Highly automated vehicles are only able to perform correct driving manoeuvres based on correct, up to date map material. This makes old and outdated information in the HD map a very challenging problem(Rabel, 2017).

Several approaches have already been proposed to leverage the global navigation satellite system (GNSS) data obtained from common production vehicles to create or update standard navigation maps (Brüntrup and et al., 2005; Niehöfer and et al., 2009; Cao and Krumm, 2009; Davies and et al., 2006; Ahmed and et al., 2015). However, these approaches did not address the time critical conditions to precisely identify road hazards, necessary to ensure the safety of self-driving cars requiring an update of their HD map material.

To close this research gap, we argue that any additional sensor device that is carried by the passengers, capable of collecting GNSS data, should be considered in the *detection process* of outdated HD Map

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material. As such devices are ubiquitously carried by humans, they can tremendously increase the detection speed of road hazards to ensure the overall driving safety of self-driving vehicles. Therefore, we rely in our presented work only on low precision GNSS sensor readings obtained by smartphones carried inside of a vehicle, as an example of such ubiquitous devices. We further use readings from additional low cost sensors available in the smartphones as meta-information to enhance the overall precision of the collected GNSS data. Based on this additional meta-information we present a novel weighting algorithm for the clustering procedure of GNSS data. Our algorithm outperforms existing approaches in the creation of lane-accurate clustering results, as evaluated with real-world measurements in a highway construction site scenario.

Based on the proposed weighting algorithm, we present our second contribution, an algorithm that is able to quickly identify lane accurate deviations in the road network infrastructure. The detection is based on the deviation between former obtained clustering results and the latest collected data as well as the overall deviation in the average speed of the vehicles between those two states over time. The performance of the algorithm is evaluated in the aforementioned scenario. The identified areas in the outdated HD map thus can be safely avoided by handing over the driving control back to the human driver. Furthermore the identified HD Map areas can be updated more quickly, by specifically requesting precise sensor readings from the measuring vehicles for them.

After this introduction our paper is structured as follows. In Section 2 we discuss related work for map generation and updating from crowdsourced GNSS traces and the utilization of low cost sensors to improve localization. Based on our survey of related work, we present our concept for map change detection consisting of a clustering algorithm enhancement relying on meta information (Sec. 3) and a deviation detection algorithm (Sec. 4). The real world scenario used to evaluate the performance of our proposed algorithms is described in Section 5. We evaluate our proposed algorithm in Section 6, verifying that the consideration of meta-information achieves improved clustering and detection performance compared to existing approaches. We finally conclude the paper in Section 7.

2 RELATED WORK

In the following, we structure and discuss related work for map creation and map updates according to the achieved accuracy (road- or lane-level) and utilized sensor equipment.

2.1 Road-level Map Generation with Floating Car Data

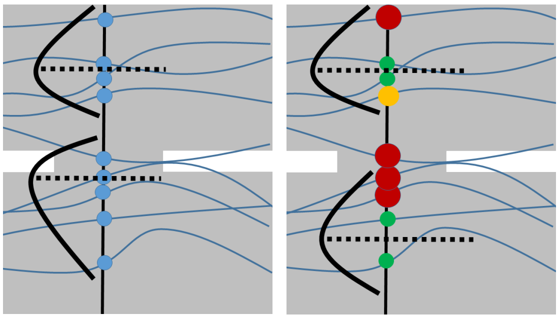
(Brüntrup and et al., 2005) as well as (Niehöfer and et al., 2009) propose a client/server-based architecture that infers the road infrastructure given GNSS traces of an unknown area. Niehofer et al. explicitly utilize GNSS data collected with mobile phones, supporting our own work. The traces are used to either (i) create a completely new road in the network or (ii) gradually update an existing road with further data points. (Cao and Krumm, 2009) rely on a fleet of taxis to acquire their testing data to create road maps. Their approach to infer route data from GNSS traces is innovative by performing so called energy well calculations to assign newly arriving trace data to existing clustering results while altering that data as well. These concepts of gradually updating the already obtained clustering results, to save time, inspired the development of our own deviation detection algorithm. (Davies and et al., 2006) present a framework to create road accurate maps out of collected floating car data. The authors state that modern day GNSS receivers (based on the publications of (K.D. McDonlad and C. Hegarty, 2000) and (R. Prasad and M.Ruggieri, 2005)) have an average standard deviation σ between 3.5 and 4.5 meters. They further state that based on the central limit theorem more than 70 GNSS traces would need to be collected to differentiate between two adjacent roads (not lanes as required for self-driving vehicles). Our work aims to avoid these limits by not only relying on GNSS trace data alone, but on fusing the readings of several low cost sensors together with it.

A comparison of the aforementioned approaches and further works is presented by (Ahmed and et al., 2015). The authors provide OpenStreetMap benchmark material and evaluate the algorithms' runtime, ranging from several minutes to several hours. Their results motivate the necessity for the development of performance optimized map updating algorithms.

All of the aforementioned approaches only achieve road-level accuracy, relying solely on GNSS data. To identify temporary changes in the road infrastructure—e.g., construction sites— to ensure the safety of self-driving vehicles, at least lane-level accuracy is required.

2.2 Lane Accurate Map Generation

One of the first concepts for the automated creation of lane accurate street maps was proposed by (Betaille



(a) Common approach (b) Weighted approach

Figure 1: Illustration of lane center point calculation approaches. In our weighted approach points accuracy are indicated by colour and radius.

and Toledo-Moreo, 2010). In their work they focus on the definition of a lane accurate map and its general creation procedure. To achieve the technically best possible results the authors rely on the coupling of high accurate kinematic GPS (PPK) with dead reckoning estimations of the vehicle itself. The required precise hardware is resembling more the costly equipment used in the aforementioned specialized measuring vehicles to create the HD maps. It is out of the scope of our personal work, as we focus to quickly detect changes in the HD map material using widely available sensor data.

(Chen and Krumm, 2010) propose an algorithm to infer lane accurate road networks from a multitude of GNSS traces through the use of Gaussian Mixture Models. The authors preprocess their GNSS traces by virtually segmenting them through equidistant (e.g. each 50 meters) perpendicular lines across all lanes in the driving direction of the vehicles (see Fig. 1a). Therefore, a random trace is selected as reference and segmented in equidistances. All other traces are then cut accordingly. The resulting intersection points of all traces are then used for the following clustering procedure. This initial concept is also used similarly in several other works(Uduwaragoda and et al., 2013),(Neuhold and et al., 2017),(Sato and et al., 2012). Consequently, we use it as a well established foundation for our own approach described in Section 3.2. Chen et al. cluster the intersection points using Gaussian Mixture Models to identify center points of individual lanes. To test their approach the authors collected data from a fleet of 55 vehicles, each equipped with a standard GPS logger comparable to today's chips built into smartphones. Although the authors do not investigate changes of road networks in their work, they state it as necessary future work, motivating our own contribution.

More recent approaches closely related to our own contribution are presented in (Uduwaragoda and et al., 2013) and (Neuhold and et al., 2017). Uduwaragoda et al. propose the usage of the Kernel Density Estimation Algorithm (KDE) to identify the center lanes of a common 4-5 lane width highway. They test their concept based on trace data that has been collected from a fleet of vehicles carrying GPS enabled phones. The authors state that at least 150 traces collected by their vehicles are necessary to achieve a suitable lane detection accuracy in their scenario. (Neuhold and et al., 2017) achieve similar results using KDE in different scenarios and with different GPS loggers. They still have to rely on a large set of traces $(80-200)$ for accurate lane detection. Furthermore, they utilize information on legally required distances between lanes to increase the performance of their algorithm.

An approach that relies on the fusion of different sensors is presented by Guo et al. (Guo and et al., 2016). They use information from a low-cost GNSS sensor, an inertial measurement system, and orthographic images provided by the on-board camera to create lane specific graphs as foundation for a complete map. Massow et al. (Massow and et al., 2016) also significantly enhance the performance of a pure GNSS-based approach by using additional sensors like a camera and a radar. Both, (Guo and et al., 2016) and (Massow and et al., 2016) support the concept of utilizing additional sensors to improve the accuracy of clustering approaches for lane detection. Radar and camera sensors, however, are rather expensive and also only available in a fraction of currently deployed vehicles. In the following we present works that rely on low cost sensor equipment to achieve accurate localization.

2.3 Lane Accurate Localization with Low Cost Sensors

Two of the most sophisticated works regarding the lane accurate localization of a vehicle using only low cost hardware have been performed independently from each other by Aly et al. (Aly and et al., 2015) and Wu et al. (Wu and et al., 2016). The authors rely on cheap accelerometer and gyroscope sensors, which are present in production vehicles and mobile devices as used in our work. Their proposed solutions do not require knowledge of the initial starting position of the car. Instead, a Markov localization model or a Gaussian probability distribution is used to keep track of all possible initial lane positions. Through the accelerometer and the gyroscope sensors the drivers behavior can be identified (e.g. performing a certain pattern of lane changes as presented in Figure 2). Thereby, the probability of presence for each lane increases or decrease over time with only a single remaining lane in the end. To further improve this concept, Aly et al. suggest to use additional knowledge in the form of so called bootstrap and organic anchors. Boostrap anchors rely on traffic rules, e.g., a right turn is normally performed on the rightmost lane. Organic anchors are conditions on the road surface, e.g. a pothole, that can also be detected by these two sensors. The appearances of such anchors can then be linked to certain lanes. Both approaches achieve a lane identification rate of between 80% and 86%. Comparable work regarding the identification of steering manoeuvres has been proposed by Chen et al. (Chen and et al., 2015). They compare their detection algorithm with a camera-based approach. The comparison shows the robustness of the detection based on low cost sensors, as they are independent from weather effects like sun blinding, rain, fog, and the day and night cycle. In a similar work, Ahmed et al. (Ahmed and et al., 2017) propose to utilize the On-board Diagnostic Interface (OBD) for additional sensor information. However, this approach requires additional dedicated hardware in the vehicle. As discussed, existing approaches for lane-level accuracy either require dedicated—and potentially expensive or unavailable—sensors (Guo and et al., 2016; Massow and et al., 2016) or a large amount of traces used in the clustering process (Davies and et al., 2006; Uduwaragoda and et al., 2013). Both issues prevent a fast detection of temporary situations such as construction sites or accidents. Other approaches rely on assumptions that are not fulfilled under such conditions, such as the correlation between the centers of the different lanes as utilized in (Neuhold and et al., 2017). The utilization of additional, low cost sensor data from mobile phones as proposed in (Liu and et al., 2017; Aly and et al., 2015; Wu and et al., 2016) is a promising direction to achieve the desired accuracy and speed of a map change detection algorithm. Based on their work using a similar lane change algorithm, we detail our concepts for enhanced clustering and deviation detection in the following sections.

3 ENHANCED CLUSTERING WITH META INFORMATION

As motivated in the previous section, we combine GNSS measurements with low cost sensor data (meta information) to achieve precise clustering results on lane-level. We propose to use the following additional information: (i) the number of visible GNSS satellites (Sec. 3.1), (ii) an estimation of the position error provided by the mobile device (Sec. 3.2), and (iii) the accelerometer and the gyroscope of the smartphones to detect lane changes and derive the current lane position based on (Aly and et al., 2015; Wu and et al., 2016) (Sec. 3.3).

3.1 Number of Satellites and Accuracy Parameters

To achieve a proper position estimation a GNSS device requires at least four satellites to be visible. If more satellites are visible the devices are able to further improve the position estimate with information from the additional satellites. Current GNSS devices provide an accuracy estimation with each position returned via their APIs (van Diggelen, 2007). The calculation of this accuracy estimation is at the discretion of the device manufacturer and, therefore, can differ. The API provided by Android smartphones used in our work specifies the position accuracy as a one sigma (68%) reliability estimation of the horizontal accuracy.[1] Consequently, the estimated position lies with a probability of 68% within a circle of the indicated accuracy radius around the estimated position.

In the following, we argue that a higher estimated precision and a higher number of satellites correlates with a position estimate of higher quality, which should be considered more important for the overall lane clustering procedure. We leverage this information to achieve better clustering results in less time as explained in the next section.

3.2 Proposed Weighted Clustering Approach

To reduce the amount of GNSS traces that are required to properly identify changes on the lane-level, we introduce a weighting factor into the common clustering approach (Chen and Krumm, 2010). We automatically annotate the measured GNSS position estimates with the number of satellites and achieved position accuracy for further consideration. In contrast to the common clustering approach(Chen and Krumm, 2010), as explained in Section 2.2 (see Figure 1a as well), we do not select a random trace as reference line. Instead, we select the trace that has the highest number of satellites and accuracy as reported by the mobile device. We assume that this trace will mimic the overall road curvature best and therefore improves the initial segmentation and the creation of segment lines. As not all measured GNSS points are directly located at a segmentation line, we generate

[1]https://developer.android.com/reference/android/location/Location.html

artificial GNSS intersection points. As described by Equation 1 the meta information values of those artificial intersection points are calculated with respect to the euclidean distance (d) of the closest preceding and succeeding measured points and their actual values. To complete the clustering process we then apply the weighted mean as shown in Equation 2 for each of the segments. The weighting function (f_w) is supposed to be adapted accordingly to the available GNSS data. In our evaluation in Section 6.3 we investigate different weighting functions to find the one with the best performance for our data set. This way the latitude and longitude values of the related GNSS estimation are weighted depending on their overall quality. The concept is illustrated in Figure 1b, where the overall quality of the position estimates is indicated by their radius and colour. We assume and verify in our evaluation that even with a smaller number of collected traces more precise results are achieved, as the points with overall better accuracy are taken into higher consideration during clustering.

$$meta\_value_{intersection\_point}(acc, no\_of\_sattelites) = \frac{meta\_value_{pre} * d_{pre} + meta\_value_{succ} * d_{succ}}{d_{pre} + d_{succ}} \quad (1)$$

$$clustercenter(lat, lon) = \frac{\sum(lat, lon) * f_w(accuracy, no\_of\_sattelites)}{\sum allweights} \quad (2)$$

3.3 Annotation of Lane Numbers in the Traces

Even with the additional quality parameters the identification of distinct lanes from noisy GNSS data is still a difficult task. Common clustering approaches overcome this problem through the sheer amount of data points (Uduwaragoda and et al., 2013) that are collected over time. However, this is a serious issue for the detection of temporary deviations as considered in our work. To address this issue, we utilize a lane change detection algorithm as proposed in the related work (see Sec. 2.3) utilizing only low-cost, low-energy accelerometer and gyroscope sensors. Thereby, we can rely on the estimated lane number as additional meta information annotated to the GNSS data.

For our evaluation we implemented a basic lane change detection algorithm, similar to the ones proposed by Aly et al.(Aly and et al., 2015) and Wu et al. (Wu and et al., 2016), from which we derive the vehicles current lane number. The algorithm relies on the combined sensor readings of the accelerometer and gyroscope of the smartphone and detects lane changes based on a static-offset gate of the measured min and max values per time interval. An example accelerometer reading based on our personal data set is shown in Figure 2. The picture has been created without any further noise filtering. Thus it shows very well the capabilities of such sensors to properly detect several consecutive lane changes and accordingly identify the vehicles current lane. Therefore we see the Related Works of Aly and Wu as a prerequisite for our personal work. In this paper we showcase the feasibility of such a lane change detection approach in our context of map change detection. Therefore the comparison to our manually annotated ground truth as investigated in Section 6.2 is its main purpose. The discussed results show, that even our rather simple approach already achieved a good detection rate. Further improvements regarding the lane position detection as suggested by Aly and Wu probably will improve the achievable clustering results even more.

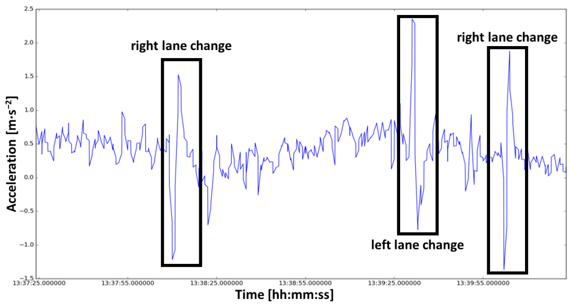


Figure 2: Behaviour of the accelerometer sensor, when performing lane changes.

With the identification of lane changes and the derived annotation of the car's lane position, we enable our algorithm to directly separate our collected GNSS data regarding a specific lane. As evaluated in Section 6.1 this provides our proposed concept with a significant advantage over related clustering concepts, like the Kernel Density Estimation algorithm, which do not rely on lane information. Even over a longer period of collection time we consider this an important advantage for our own approach as it cancels out most of the influence of present Gaussian noise in the collected GNSS data.

4 ROAD INFRASTRUCTURE DEVIATION DETECTION

Based upon the aforementioned enhancements of the clustering procedure, we developed an algorithm to reliably detect lane accurate changes in the road network (e.g. introduced through construction sites or accidents) as the second contribution of this work. The algorithm identifies and highlights those areas, where a certain deviation between historic and newly generated clustering results is detected. The complete procedure is illustrated in Figure 3. First of all the track to be considered for the clustering procedure has to be segmented as described in Section 3.2. For each segment and each lane a distinct lane-segment center point has to be calculated. The entirety of all those center points represents the curvature of the specific lane. Initially, the newly calculated center point is marked as unreliable until a certain amount of traces X is available for the clustering procedure to reduce the influence of faulty sensors and the overall Gaussian noise. The exact number of required traces should be derived individually from the amount of incoming traces over time and the accuracy requirements of the clustering result. We investigate it for our own dataset in Section 6.4. The flowchart of Figure 3 now describes the procedure how further traces are added to the dataset. For each new trace, the trace itself and the last X traces are considered as input for the clustering process. The influence of the last X traces thereby is weighed based on their collection time as described by Formula 3. New traces are considered more valuable and degrade in importance over time. The importance of a trace thereby is also dependent on its quality values (accuracy, no of satellites) combined in a weighting factor w_{meta}. The degradation factor has to be selected individually depending on the amount of incoming traces over time as some streets are roamed less frequently than others.

$$importance\_trace_x = w_{meta} * e^{\left(\frac{(time_{trace\_x} - time_{newest\_trace})^2}{degradation\_factor}\right)} \quad (3)$$

If the newly obtained clustering result deviates by a threshold value T from the currently assumed lane center point, a deviation is assumed to be present. In our example evaluation described in Section 6.7 we considered a value of $2/3 * lanewidth$ for T, as the width of a lane accepted by the road authorities can be significantly lower. We consider this value therefore as a first proposal that is to be further optimized in future work. The old center point is then added to a vector of historic center points. If this history storage already contains other old center points the new clustering result is further compared with each of them by calculating their deviation T. If for one of them the achieved value is smaller than T it is assumed to be the new lane center point. This way our algorithm is able to handle situations in which a construction site has been finished and the old road course is present again, without starting the initial collection process once again. If no fitting historic lane centers are present, the newly calculated clustering result is assumed to be the new lane center point for its related segment on the highway.

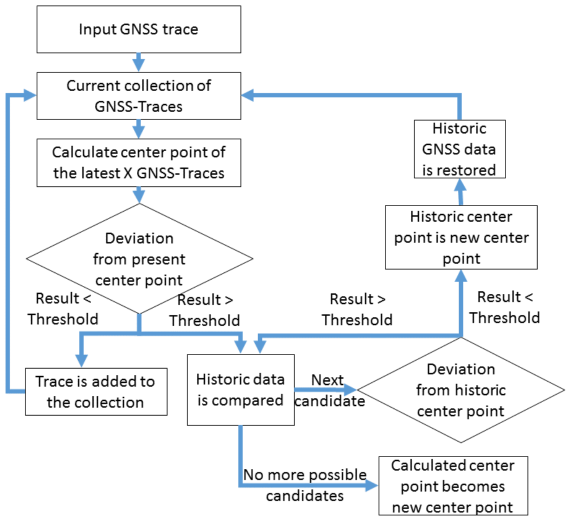


Figure 3: Deviation detection algorithm.

Besides the longitudinal deviation along a track our algorithm also has to provide the latitudinal extend of the detected road hazard. Only through an early warning ahead of the road hazard a safe handover from the self-driving vehicles back to a human driver can be ensured. Our proposed algorithm therefore additionally considers the average achieved speed for each lane segment along the track to identify the actual extent of the detected construction side or similar road hazard. As the speed is normally gradually reduced before a construction side (e.g. from 120 km/h down to 80 or 60 km/h) and then increased again to its former value it provides a good indicator for begin and end of the construction site. The achieved results for our evaluation are presented in Figure 11. Our algorithm only indicates the presence of a constructions side if both detection conditions are met. Therefore the average speed at the considered track segment has to be suitably reduced (80 km/h or below) and a certain deviation in the road course has to be present. Otherwise a false detection could be possible. A reduction of speed for example could also be induced by a common traffic jam in the morning rush hour.

5 SCENARIO DESCRIPTION

To investigate the performance of our proposed deviation detection algorithm in a real-world scenario, we performed several test drives, to collect data from construction sites. The dataset, which we used for this publication, contains over 1.934.000 GNSS points. It will be published on github[2] to provide benchmark material for future algorithms in this field of research. Each data point is annotated with our considered meta-information (the vehicles current lane, the GNSS position's accuracy value and the number of available satellites). Furthermore we manually tagged the start and the end of each experienced construction site to later rely on as ground truth. The measurement points have been collected from April 2016 to January 2017. Within this time over a dozen constructions sites have been added into the dataset, located in urban, suburban and rural areas. To illustrate the capabilities of our approach and the developed algorithm we show the results accordingly for a construction site on the German highway A67 between the cities of Rüsselsheim and Darmstadt as illustrated by Figure 11. GNSS traces have been collected in both directions, with 369 traces in the direction to Darmstadt and 292 in the direction to Rüsslesheim. For the following graphs we present the achieved results of the driving direction from Rüsselsheim to Darmstadt. We ensured to have a sufficiently large amount of traces for each of the lanes of this two lane highway to be able to evaluate the benefits of our lane accurate filtering of the GNSS data.

To resemble an actual large scale deployment of our approach several different smartphones (Nexus 4, Nexus 5, Blackberry Classic and Samsung Galaxy S7) with different quality levels of GNSS sensors have been used to collect the location data. These phones therefore were placed on the dashboards of the probe vehicles to resemble a possible usage scenario of the end-customers.

6 EVALUATION

We selected the Kernel Density Estimation Algorithm (KDE) as reference algorithm, as it is the most frequently used and best performing algorithm throughout the Related Work presented in Section 2. To compare the results of the KDE clustering algorithm with our approach, we manually annotated a reference line located on the center dashed line of the highway using satellite images (see Figure 4). To be able to safely perform its driving task an automated vehicle has to stay in the boundaries of its current lane. Therefore we chose the deviation of the calculated lane center lines provided by the investigated algorithms and this

Figure 4: Reference line created from satellite images of the center dashed line.

reference line in the middle of the two lane highway, as our performance metric. This initial performance evaluation, described in the following paragraphs was executed on a section of the highway A67, where no construction side was present. That way we could rely in our evaluation on the rules of federal regulation in Germany. They require each lane of our investigated two lane highway to be exactly 3.75 meters wide.[3] An ideal clustering algorithm therefore would achieve a calculated deviation from all its predicted lane center points to the reference line of 1.85 meters. These optimums are indicated by dashed lines in the following plots. Figure 5 shows the achieved results for both lanes of the highway and all our investigated algorithm combinations. It is explained in detail in the following.

6.1 Effect of the Lane Annotation

In a first step we evaluated the influence of the lane index parameter for each collected GNSS point on the final clustering results. This index number enables the filtering of GNSS traces initially regarding their specific lanes before the data is handed over to the clustering algorithm. Therefore the lane changes during the test drives had been automatically annotated through our described algorithm (see Section 3.3), as well as manually by the push of an according button for a ground truth comparison. The results presented in the plots of Figure 5 are based on all 369 traces that have been collected for the driving direction from Rüsselsheim to Darmstadt on the A67. To avoid the malicious influence of GNSS points that might have been collected exactly during a lane change our data filtering algorithm neglected those points. The three points, which are measured directly previous to, during the lane change and directly afterwards are removed from the lane specific data set. To compare the achievable clustering performance we executed a common mean center point calculation algorithm for each segment line using our lane specific filtered data. As comparison the Kernel Density Estimation Algorithm was executed on the same data, but without the

[2] https://github.com/florianjomrich/construction_side_traces_fjom

[3] https://www.forschungsinformationssystem.de/servlet/is/275112/

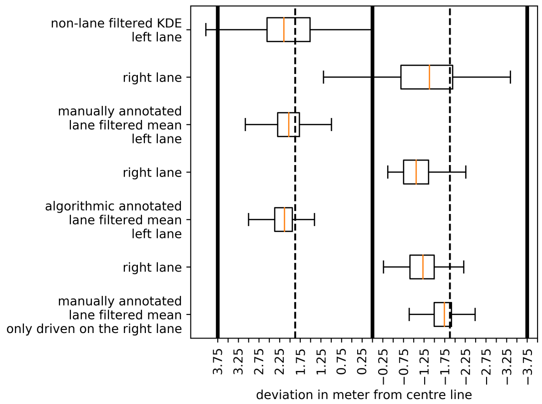


Figure 5: Comparison of different algorithm clustering results for both lanes and all available traces.

lane filtering.

For both lanes it is clearly visible that prior filtering based on lane annotations (as described in Section 3.3) has a significant impact on the obtained clustering accuracy. The variance of the obtained KDE center points is much higher, than the simple mean calculation approach executed on the pre-filtered data. For some instances, the center point calculated by the KDE algorithm lies outside of the actual lane boundaries. This is most likely due to bad reception accuracy of GNSS receivers in current smartphones, which can reach several meters. The simple mean center point calculation, which could rely on our lane specific pre filtered data, achieved much better variance values and stayed within the lane boundaries for all 225 individual segments along our selected track. Unexpectedly, the results obtained for the right lane had a visible static offset to the middle of the road towards the center line. The average of all estimated center points on the left lane in contrast was (as expected) close to the actual center of the lane.

We investigated this phenomenon by executing several drive tests (37 in total) for which the drivers had been told to stay on the right lane for the whole time of the track. The obtained results therefore are shown in the lowermost plot of Figure 5. It is clearly visible that this plot does not have the aforementioned static offset. As a conclusion we suppose that the difference in the obtained results is probably due to the driving behavior of the test drivers and the collection procedure of sensor data readings within our Android smartphones. As the investigated scenario is a two lane highway the right lane was mostly occupied by slowly driving trucks. The test drives have been conducted with common sedans from our fleet, therefore most of the time these vehicles overtook the slower driving trucks. In conclusion the vehicle either stayed consistently on the left lane or drove on the right lane with more interruptions due to lane changes to overtake a truck. Within the Android smartphone a Kalman filter is already smoothing the obtained GNSS traces. In our opinion, the Kalman filter is unable to capture two immediately consecutive lane changes correctly, leading to the displacement of the reported GNSS locations. This is an aspect that has to be considered in future work, as one might want to filter the incoming GNSS trace data accordingly. The speed of the vehicles (trucks are slower than normal cars in average) and the previous driving behavior (identifiable through other sensors like the accelerometer and the gyroscope) are probably good indicators therefore. Consequently, we present results based on data gathered on the left lane of the highway for the remainder of this evaluation.

6.2 Algorithmic vs. Manual Annotation

As a second step in our investigation we wanted to compare the achievable accuracy results of our algorithm induced lane annotation compared to the manual annotated ground truth. This test was performed to ensure that our proposed concept is also capable to be deployed in future devices without the requirement of any mandatory input from the user. We implemented the algorithm to automatically detect the lane changes of the vehicle while driving based on the status changes of the accelerometer and the gyroscope built into the smartphone, as described in Section 3.3. The achieved results of the algorithmic annotation in comparison to the manually annotation of lane changes for both lanes are shown in Figure 5. It is clearly visible that both approaches perform comparably well. There is no clearly better performing approach as for the left lane the results obtained from the manually annotation seem to be slightly better, whereas on the right lane the algorithmic annotated results tend to be a bit better. The obtained results are very promising, as they showcase that an actual deployment of such a system is certainly possible. We assume the achievable results could be further enhanced by optimisations in the lane change detection. Our implementation for example, which was purely based on static thresholds, performed considerably good and might be further enhanced with dynamic speed dependent changes of the used thresholds for the lane change indicators.

6.3 Impact of Weighting Functions

As the next step to improve the performance of our lane clustering process even further we introduced the aforementioned weighting concept for each col-

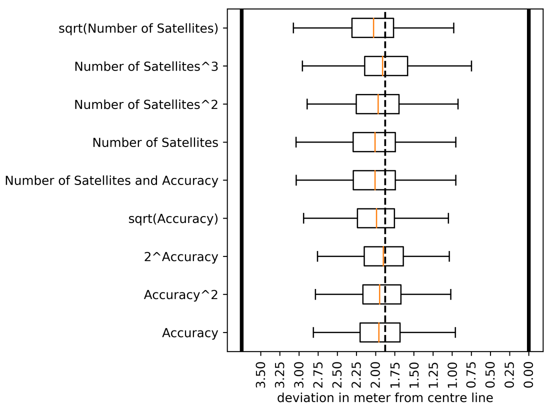


Figure 6: Comparison of different weighting functions (left lane data).

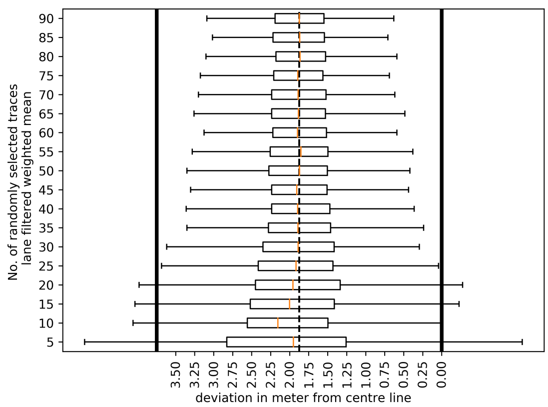


Figure 7: Influence of different amounts of available input traces on clustering performance (left lane data).

lected GNSS point. The weighting algorithm takes the included meta data into account to calculate the importance of each data point before the actual clustering procedure is executed. It considers the number of satellites, that were visible to the GNSS receiver of the smartphone, as well as the accuracy value that is provided by the Android API for each measured GNSS point. As more available satellites tend to provide a better localisation we took their number directly into account for the weighting. The accuracy value was considered inversely important as a smaller accuracy means a more precise localisation.

To investigate the importance of both meta data values, we evaluated different weighting functions (see Formula 2), with the results being shown in Figure 6. The obtained results showcase that both, the number of satellites and the accuracy, improve the achievable precision, when considered with high importance. For the comparison we again took all GNSS points into consideration for the driving direction between Rüsselsheim and Darmstadt. We achieved the best clustering performance with the parameters set to weigh the $NumberofSatellites^3$ or $2^{Accuracy}$. As the configuration of $2^{Accuracy}$ achieved less variance we considered it as our reference weighting function for the following evaluation steps. However, we see these results still as a first investigative look and consider further optimization potential in the weighting procedure itself for future work.

6.4 Clustering Performance for Different Numbers of Traces

As the required time to achieve a reasonable clustering result is crucial for our use cases, we also investigated the behaviour of our proposed weighted mean clustering algorithm when considering different amounts of traces as input. The obtained results for the left lane of the highway A67 are presented in Figure 7. From the different boxplots it is visible that our weighted mean clustering approach reaches an accuracy within the suggested lane boundaries reasonable fast between 35 to 45 randomly selected traces. By increasing the amount of random traces up to 90 we achieve only slight performance improvements in comparison. Although the clustering approach clearly benefits from a much higher number of traces as shown by Figure 5, we can state that a difference detection with an accuracy in the regions of the lane width can be achieved much quicker. The overall achievable performance can also be improved by selecting only high quality traces as described in Section 6.6. Future devices with a higher measuring accuracy should obviously further reduce this required number of traces.

6.5 Influence of Weighting on Lane Filtered Data

Another question that we addressed in our work is the impact of our additional meta information. We specifically wanted to clarify if the information required for the weighting procedure (number of satellites and the accuracy) is worthy to consider for an initially lane-filtered data set or if the lane filtering itself is the only important factor required to achieve better clustering results. Therefore we let our three algorithms (mean, weighed mean and KDE) run on our full lane-filtered data set. The achieved results are presented in Figure 8.

As expected the results of the KDE clustering algorithm also benefited from the lane filtering process. However its achieved clustering performance is comparable to the standard mean calculation, which achieves a much better execution time performance compared to the KDE. The weighed mean achieved

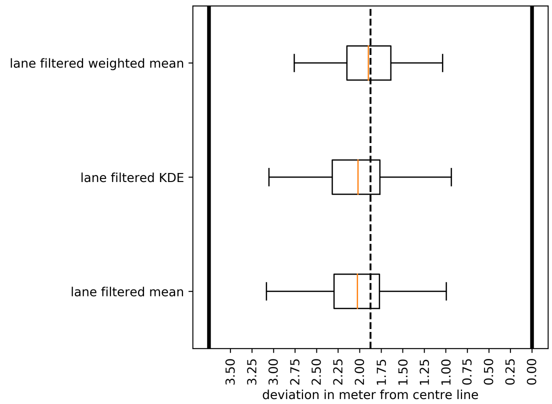


Figure 8: Comparison between weighting and non-weighting algorithms using all available pre-lane filtered traces (left lane data).

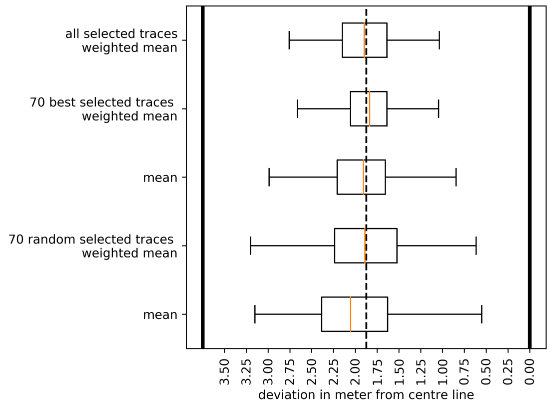


Figure 9: Performance comparison between randomly selected traces and the most accurate available traces (left lane data).

the best clustering results based on our collected GNSS traces. We are well aware that other works might have achieved better overall performance results as they are highly dependent on the used hardware. However, based on our results we could verify the performance improvements achievable with the consideration of meta-data, even when relying on a largely varying set of measurement devices as described in Section 5. Furthermore, we did not take any dependencies between the two calculated lane center points into account, as done by other Related Work (Neuhold and et al., 2017). We did not rely on them to achieve our results, as these conditions might not hold true in our considered scenarios of construction works and accidents.

6.6 Influence of Trace Selection

Motivated from our previous results, we investigated the influence of the overall quality of the collected traces. Therefore we conducted a test where we compared the 70 most accurate (best) traces of our full data set with another set of 70 randomly chosen traces (see Figure 9). The amount of 70 best traces was selected, as our investigation indicated that at around this amount of traces the achievable accuracy saturated in our clustering approach. Thus, we assumed that a lot more traces would be required to further improve the clustering results. As time is a critical factor in the updating procedure of a map regarding a construction side or an accident this aspect was critical for us to be investigated. The best traces were selected based on the average accuracy of all their interception points with the created segment lines. The trace with the lowest average in those 225 points is the best trace of our data set. Figure 9 clearly shows that the selection of traces has a significant impact on the quality of the clustering result. As expected the selection of best traces achieved a significantly better clustering result than the other group based on a random selection. Interestingly, the 70 selected traces achieved comparably good performance results as using all traces that we could collect (indicated by two upmosts plot in Figure 9). This strengthens our initial assumption. As a conclusion it might be well worthy to consider only a high qualitative subset of all collected traces in a continuous updating procedure over a long period of time, with many cars driving by, to successfully and efficiently maintain an accurate update of the current status of the road network. If new traces do not show any significant sign of deviation from the current clustering results or they are not much better in the average of their overall achieved accuracy values, they might possibly be neglected as well. However, further investigation in future work with a larger set of traces is required to verify this observation.

6.7 Construction Site and Deviation Detection

Based on the positive results obtained from the previously described evaluation steps we than further continued the evaluation of our deviation detection algorithm. We evaluated the first performance results of our algorithm in an example scenario on a different part of the highway A67, where a construction site was present in May 2016, as illustrated by the Google Earth satellite images in Figure 10 and 11. The investigated scenario shows the feasibility of our deviation detection algorithm to react on updates of the road structure very quickly as the provided data set for this section of the highway with its specific construction side status contained only a rather small data set of 15-25 GNSS traces per lane. Even with this small

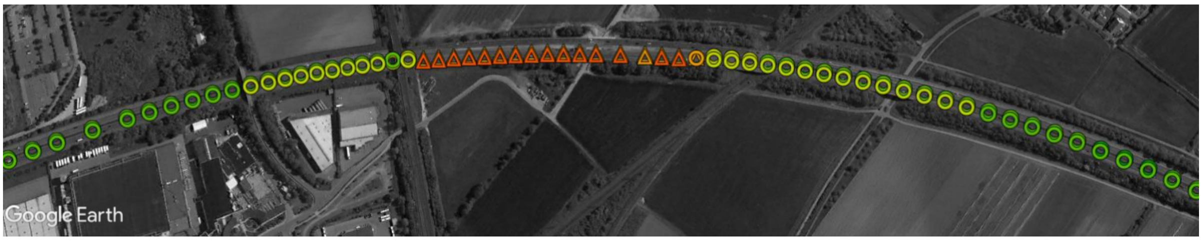
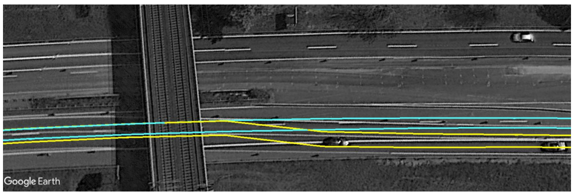
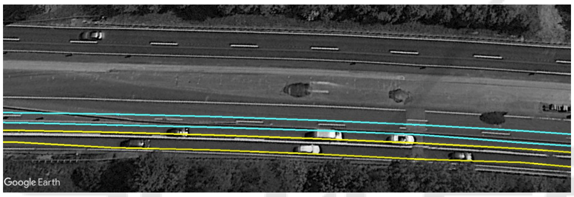


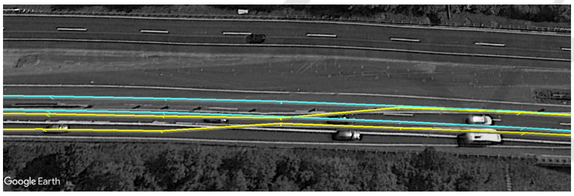
Figure 11: Correlation between the average vehicles speed (indicated by colour) and the location of the construction side (indicated by triangles). Speeds right before and in the construction side range from 90 km/h down to 57 km/h (yellow - red). Before and after the construction side normal driving speeds of around 125 km/h are reached in average (green).



(a) Start



(b) Middle



(c) End

Figure 10: Sections of the investigated construction site (yellow) in correlation with the situation after the completion (cyan).

amount of data our algorithm was able to resemble the entrance and the course of the construction side well and stays in the given lane boundaries in each considered segment. Only at the exit of the construction side is an unrealistic assumed distance between the two lane center points visible. We propose to avoid such situations by relying only on a larger subset of traces, as investigated for our dataset in Section 6.4. The introduction of a minimum distance condition between the two adjacent lanes in the post processing of the GNSS data is considered as part of our future work. A further reduction of the distance between two adjacent clustering segments in a detected deviation environment could probably also improve the achievable performance.

7 CONCLUSION AND FUTURE WORK

Within this work we presented our deviation detection algorithm to detect and visualize the extend of construction sites and other road hazards on a lane accurate level. This algorithm has been designed with the usage scenario of frequent HD-Map updates in mind. Such lane accurate maps are required to improve the safety and comfort while driving highly automated. To ensure the accuracy of such maps time critical map updates are required.

Our deviation detection algorithm mainly benefits from improvements in the general clustering process required for identifying the current lane curvature. These are namely the usage of available meta-information such as the number of available satellites, the accuracy of the obtained GNSS location and the current lane in which the vehicle was driving at that point in time. This meta-information is used to improve the commonly known clustering process of the collected GNSS traces as described in the Related Work (Chen and Krumm, 2010). We evaluated the benefits of this additional meta-data in a comparison of our own processing pipeline with the state of the art Kernel Density Estimation clustering algorithm, showing significant performance improvements. The evaluation procedure was based on a large self-collected GNSS data set, which was obtained from common smartphones in a highway driving scenario. We discuss and evaluate in this work that such cheap mobile devices can provide lane-accurate location information required for the HD-map update through our proposed intelligent sensor fusion.

The proposed weighting algorithm of the initially obtained GNSS data performs well but can be further enhanced in future work. Possible improvements affect the importance consideration of the incoming traffic data and the weighting of the quality of the traces. This includes the consideration of influence factors such as the quality of the used GNSS chipsets, which is likely to increase in the following years[4], as well as the adaptation of the clustering process resolution based on the average driving speed of the vehicles.

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