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Identification of patterns in motorcycle riding dynamics at known accident sites

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Abstract

The positive trend of declining accident numbers in Austria's traffic sector in general, is not seen for powered two-wheelers (PTWs). Furthermore, fatality numbers of motorcycle-riders on Austria's road network is increasing and show for 2017 the highest number since 11 years. This negative trend was the reason for a research project, funded by the Austrian Road Safety fund. The scope of the project was a feasibility study on proactive, semi-automated risk assessment of roads especially designed for PTWs. For this study riding dynamics data have been gained by a motorcycle test vehicle. By analyzing measurement data collected by this highly instrumented PTW, road sections where identified, with a high probability that an accident may occur at some time in the future. The analysis results were obtained by an algorithmic methodology, based on clustering and statistical methods, for determining critical sections via similarities to known accident sites in riding dynamics data.

Keywords: motorcycle test vehicle; traffic accident research; accident investigation and analysis; traffic safety, machine learning; riding dynamics.

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Nomenclature

CAN-bus	A Controller Area Network is a vehicle bus standard devised to connect independent electronic control units with each other, facilitating communication and other functions.
CEP	Circular Error Probable refers to the radius of a circle, centered at the true position, containing 50% of the estimated positions.
GPS	Global Positioning System
IMU	Inertial Measurement Unit
PTW	Powered Two-Wheeler (Motorcycle)

1. Introduction

For people of all ages, riding a motorcycle as a spare time activity or on a daily basis has become very popular. Therefore, the risk of getting involved in an accident should be reduced to a minimum. Of the overall number of road accidents in Europe, about one sixth concern riders or their passengers of Powered Two-Wheelers (PTW). This is remarkable since the number of registered motorcycles is much smaller compared to e.g. cars, and, moreover, PTWs are less frequently used over the course of a year. A detailed look at the situation in Austria reveals numbers well above average: about 1850 motorcycle fatalities were reported for the last 20 years with an additional 66.500 injuries having occurred within this time period. The percentage of fatal accidents of motorcycle riders and their passengers among the totality of all traffic accident victims has been increasing in Austria: From a percentage of 5.7% (1992) there has been a steady increase, with a new peak in 2017 as high as 20.0% (Statistik Austria, 2019). As shown in Fig. 1 the positive trend of decreasing accident numbers over years for car drivers who have been injured is not true for motorcyclists.

Two factors contribute significantly to this negative situation. Firstly, the design of motorcycles is inherently unsafe since it is impossible to include many of the safety features known from passenger cars. Secondly, in Austria PTWs have seen a substantial increase in registration numbers in recent times.
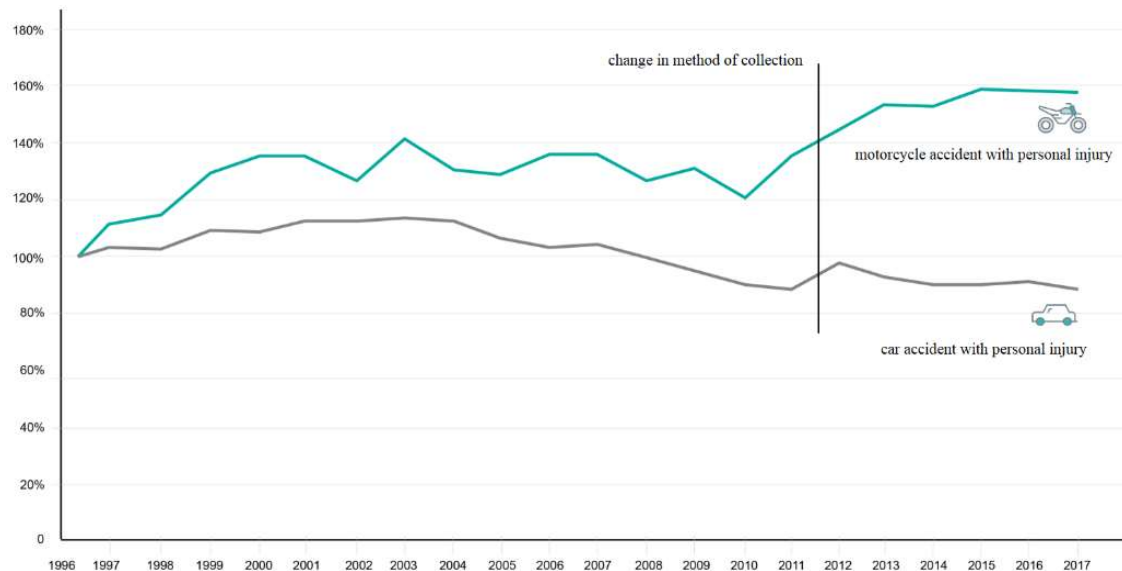

Fig. 1: Comparison of car and motorcycle accidents between 1996 and 2017 in Austria (relative numbers).

Statistical data as presented above need to be carefully analyzed and interpreted. But there is no doubt among experts, that many of the improvements that have contributed to decreasing accident and/or fatality numbers in other vehicle categories, cannot be applied or do not work for PTWs, at least in Austria (Praschl,2006).

This indicates a need for specific studies on motorcycle accidents, as the possible causes of motorcycle accidents are different from those of other vehicle categories. Only by understanding the specific conditions of motorcycles in a traffic environment a reduction in motorcycle accident numbers may be achieved.

In most countries, it is common for the transport infrastructure, and in particular the road network, to undergo regular safety audits. In carrying out these road safety checks, of course known accidents and in particular accident accumulations are taken into account and are observed. This allows the road management a posteriori to identify critical road sections and to react appropriately. The drawback of this approach is evident. Accidents have to happen first and afterwards the causes may be identified.

To overcome the principle weakness of this reactive approach, a different and proactive strategy is applied and investigated here. In this feasibility study, the attempt is made to predict possible accidents at identified critical road sections. The identification and evaluation of such critical sections is based on vehicle dynamics data, collected with a highly-instrumented test motorcycle (Ecker, Saleh, 2016). In this paper, the methods and some results of the traffic safety study ("viaMotorrad") specifically aiming at contributing to a deeper understanding of motorcycle accident risk, are presented.

2. Method and Equipment

As mentioned in the introduction, the basic idea of this study is to collect dynamic data from a motorcycle passing road sections with and without accident occurrences. By training a machine learning system on these data, it is expected that the trained system would identify sections with high accident risk potential by analyzing dynamic data from measurements on new and untrained roads (Schwieger, Saleh, Hula, Ecker, Neumann, 2018). For the purposes of the project, the measurement vehicle had to fulfill a number of criteria: It had to be equipped with modern on-board measurement systems and had to provide an extension of the data collection of the externally added systems. Furthermore, it had to be user-friendly and provide access to internal hardware and software features.

A motorcycle KTM 1290 Super Adventure fulfilled these requirements and was kindly provided by the manufacturer. This PTW is powered by a 1300cc V-twin engine, delivering 160 HP (horse power) and a maximum torque of 108 Nm (Newton Meter). Its dry weight is 222 kg. This powerful motorcycle provides a multitude of onboard systems such as Motorcycle Traction Control (MTC), Motorcycle Stability Control (MSC), Combined-ABS (C-ABS), Motor Slip Regulation (MSR), a semi-active suspension system (SCU). These rider assistance systems rely on numerous sensors, such as several brake pressure gauges, wheel speed sensors, a throttle position sensor and many more. It was essential for this project to sample and record as many on-board signals as possible to have a full set of data for the subsequent analysis to choose from. The system data were obtained via the vehicle CAN-bus, for which access was given by the manufacturer to the project team.

For measurement of vehicle dynamic data and position data the test motorcycle was instrumented with two additional and independent measurement systems. Both systems consisted of a data logger, one or more IMUs for measuring 3-axis accelerations and 3-axis angular velocities, and one or two GPS-antenna for position and speed measurements. Also the recording of the on-board sensor signals via the CAN-bus was possible with both systems. Multiple redundant measurement of signals was intended for several reasons, not only but also for reliability. Especially with GPS-signals it turned out to be very advantageous to have more than one antenna, since the quality of the signal depends on the antenna position and on the manufacturer and how the GPS-signals are sampled and processed.

Since measurement rides took place on regular roads and within normal traffic, it was also important to make time-synchronous annotations via markers in the data stream for easier interpretation of the recorded signals. During the development phase of the test motorcycle, it turned out, that using the marker feature is only useful for single and occasional events. More complex traffic or driving situations needed a different means of event recording and therefore two on-board cameras were installed.

Figure 2 shows a sketch of the instrumented motorcycle, referred to as "MoProVe" in the following, and the additional features added for the measurement tasks. "2D-system" refers to one of the two autonomous and vehicle-independent measurement systems (2d-datarecording, 2019), consisting of a high-speed data logger and associated

sensors. "GPS-antenna" stands for the, altogether, 4 GPS-antennas. "video box" is the name for device to record the video signals from the two on-board cameras. "V-box" is the product name of one of the powerful data logger by the company Racelogic (VBOX automotive, 2019). CAN-bus denotes the on-board data bus of the motorcycle. "steering angle sensor" indicates an additionally applied sensor to measure the steering angle on the handlebar. Finally, IMU refers to the altogether 3 inertia measurement units (IMUs) installed at different locations on MoProVe.

Another useful feature of MoProVe is the option to activate or deactivate assistance systems i.e to disable the Combined-ABS by a switch. This provides the means to imitate a simple motorcycle, without additional and fancy features.
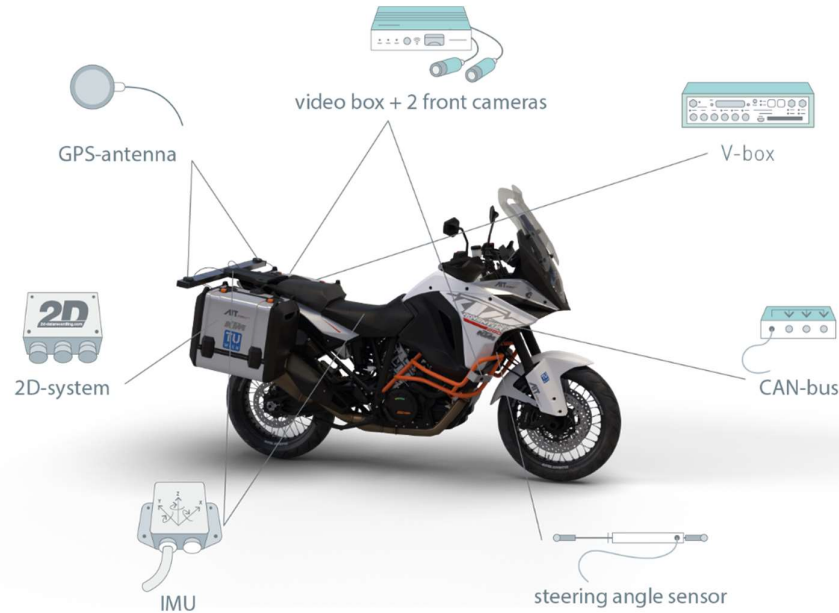

Fig. 2: MoProVe (motorcyle test vehicle) and instrumentation

The recorded signals can be classified in 4 different categories:
  (1) Motion Signals (displacement, angles, velocities, accelerations, wheel speeds, etc.)
  (2) Vehicle signals (engine speed, throttle position, brake pressure, etc.)
  (3) Position signals (GPS-data)
  (4) Video signals (Two on-board cameras)

Each signal category needed specific treatment when the signals were processed.

Ad (1) Acceleration signals from the 4 IMU sensors were different to some degree, mainly because of different mounting position of the IMUs. This was not a problem in general and averaging worked very well. The roll angle rates measured by the IMUs were used to calculate the roll angle by numerical integration. Wheel speed signals were very reliable without signal dropout. However, wheel slip and other influences made it difficult to calculate travel distances from wheel speed signals. Speed signals obtained from integrated acceleration signals suffer from the fact that the measurement axes move as the motorcycle rolls, yaws and pitches. For precise and double-checked data a smart evaluation and conversion software has been developed.

Ad (2) Signals from the motorcycle sensors are e.g. engine speed, gear position, throttle position and various brake pressure signals. Time needed for the preparation of such systems was fortunately minimal and therefore only little effort was needed to make use of these signals.

Ad (3) Besides of the speed and acceleration signals, relative and absolute position with errors as low as possible were among the most needed output signals. When the satellite signals were strong and received from a sufficient number of sources, the relative position accuracy was excellent and the absolute position accuracy was very good

and did fall frequently below the 95% CEP (Circular Error Probable) of 3 meters for standard position measurements. However, the test tracks were all located in a mountainous landscape, which led to signal dropouts and consequently to a loss of position accuracy. This made it impossible in a few cases, to compute a position from GPS-signals only. However, in such cases, position data reconstruction was carried out, based on the IMU-signals. Starting from a known position, the path of the vehicle could be determined by double-integration of the acceleration signals in all three axes, combined with the integration of the angular speed signals, also provided by the IMUs. This is a well established procedure, but needs to be correctly implemented, since the axes of the 6 sensors move freely and all signals need to be transformed into the inertia reference frame.

Ad (4) As outlined above, a dual on-board camera system was implemented, to record visual information also. This video information is evaluated in two ways. First, it helps to interpret dynamic data correctly. Sudden braking maneuvers or steering actions that are caused by a specific traffic situation and which are not related to the road itself or the infrastructure, can be identified and excluded from a further analysis. Second, the video information was also a crude substitute for a lateral distance sensor. As mentioned above, position accuracy from the GPS-signals is not sufficient to determine exactly the lateral distance of the vehicle position within its left and right limits. Therefore, the on-board videos were evaluated manually with the help of a software tool with regard to the lateral distance to the right border and the centerline of the road.

3. Test design and procedure

The entire study was completed in a two step procedure, task 1 was the data collection and preparation, task 2 was devoted to the data analysis. Part of the first task was the road selection. Six road sections in lower Austria and Styria were included in our study. Three of them are famous motorcycle tracks where accidents with one-lane vehicles have occurred in past above average. Additionally, three other tracks with similar road characteristics were included, which do not show a significant accident accumulation.
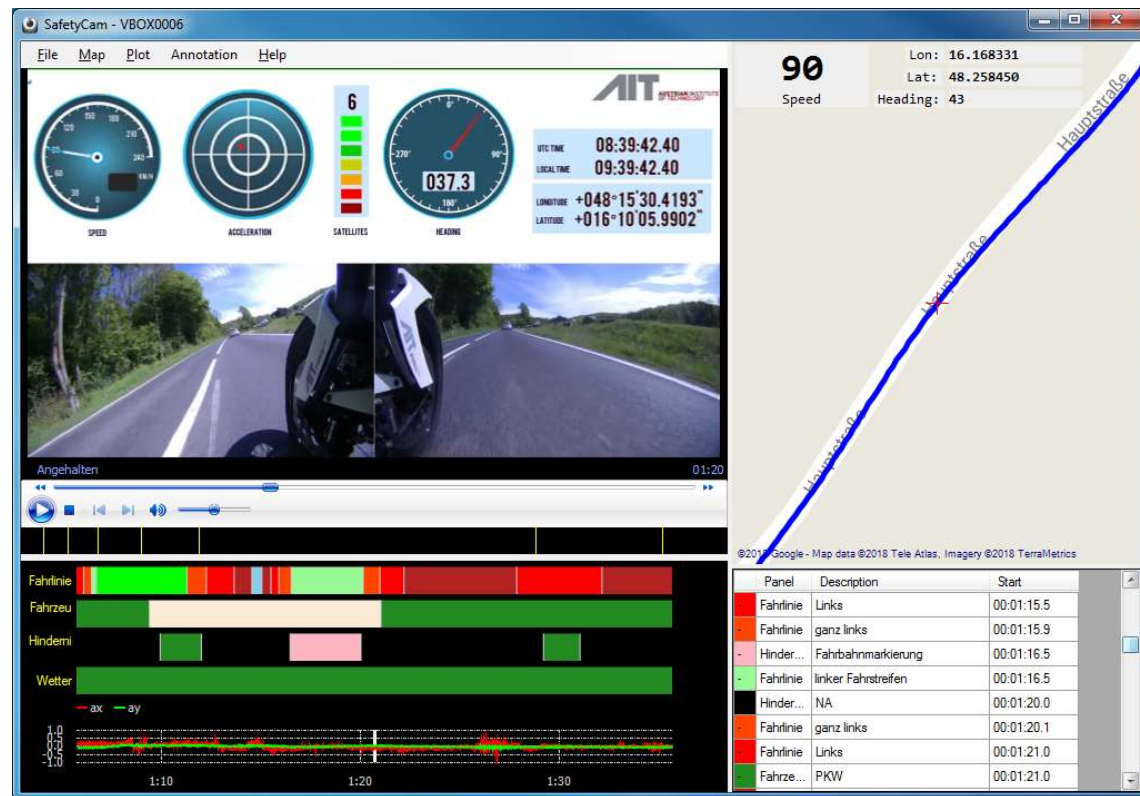

Fig. 3: Screen shot of the software tool to evaluate and annotate footage from test rides.

The measurement rides were performed by 6 experienced but not professional or trained test riders. Young and unexperienced riders could not be included in this study as the very expensive test motorcycle could not be put at risk. The authors acknowledge that the quality of the results may be improved by a larger number of riders and by more diversity in the observed riding style and dynamics. However, for this project, the stated aim was to investigate the feasibility and the possible quality of revealing motorcycle accident risk from riding dynamics. Thus, it would be essential that the method would yield instructive results without needing a huge amount of measurement data from many riders and that it could be applied even on a small statistical base of the sampled data.

Data has been collected on all selected road sections by each rider several times, typically 5-6 times. This turned out to be a crucial feature towards stable results, in that an "average ride" for each rider could be calculated and single events could be removed from the classification of the elements of the road section. Test rides took place during normal traffic hours and in a considerable number of rides it was necessary to eliminate events such as an overtaking maneuver or a hold-up behind an agricultural vehicle. Weather and road conditions were good and dry. Test rides took place during daylight and were distributed throughout the day to compensate for unfavorable light conditions.

The second task comprised the data preparation. Part of these relatively complex preparations was the examination of the on-board camera footage. The entire video material was screened and encounters with other road users were marked, provided that the situation had an influence on the own driving style. Thereby, occasional disturbances due to other traffic could be eliminated from the data material and did not have an influence on the analysis. Also, the lateral position of the test motorcycle relative to the right and the left road boundary was visually determined, classified and manually entered. This procedure turned out to be very time-consuming and has not been yet completed for all test runs. Figure 3 shows a screen shot of the interactive software tool used in this preparation step.

Another very important task in the course of data preparation was the conversion from time-based data series to travel-based data. Due to the operating principle of data loggers, data sampling is done at a certain sampling frequency, leading to data stored as time-series. This representation is very inconvenient, when it comes to comparing and combining data series, since different riding speeds between two points along the road lead to different time intervals. Therefore, it was of utmost importance to calculate for every time stamp in those data series the exact geographical position. "Exact" means in this context an accuracy of less than +/- 0,5m since the resolution of the travel-based data series had to be 1 Meter. Although the absolute position error was frequently better than the 95% CEP (Circular Error Probable) of 3 meters, it was still necessary to carry out a rather time-consuming numerical correction and improvement of the position data.

Figure 4 (left) explains the need for data-conversion from time-based to travel-based data series. The sketch to the left visualizes the effect of different speeds on the distance travelled within a certain time period, e.g. the sampling interval. The plot to the right shows different riding paths in a sharp right turn. Note that the difference in driven distance by the three different riders is almost 3m after negotiating just one turn.
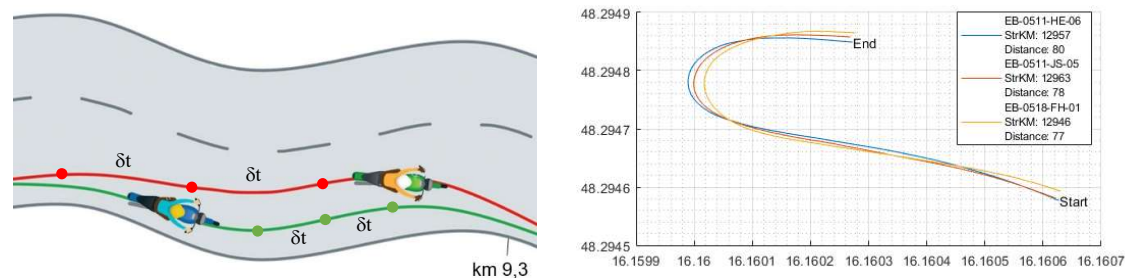

Fig. 4: Time series over 60 sec. of two different measurement rides (top, bottom), adjusted for same location at left vertical line. Higher speed used in ride 2, covering more distance when reaching right vertical line. Green signal-roll rate, blue signal - roll angle.

After completing the position data correction, it was relatively simple to convert the time-series of all measured signals to a travel-based representation and project them on a grid with 1m spacing. This means that from here on, all data (measured and static) are prepared and set up for every Meter along the road section under investigation.

Figure 5 shows the x-accelerations (longitudinal direction) over a distance of 3km, as an example of a data series, converted from a time-based to a distance-based representation. In this figure, signals from nine different runs are superimposed and adjusted such that measurement points sampled at the same line of the 1m-grid are plotted accordingly on the x-axis. Major acceleration peaks (positive and negative) can be identified in all data series, since the route layout may e.g. require a braking action of the riders to reduce the speed before a turn. Therefore, the shape of signals is related to the road section and characterizes it. Also, one can see that the acceleration data vary within the runs in certain sections more and in certain sections less. Such a higher variability in a signal may have various reasons. One can be that this section is more difficult to navigate and therefore the riders can handle it once better and once less well. The point is that such signals are a kind of fingerprints of a route and contain a lot of hidden information. To get access to this valuable information, two difficulties have to be mastered. First, not all measured signals contain the information sought for and so the right signals have to be selected. Second, the information is hidden and has to be retrieved. A simple explanation of the next steps is to analyze and look for signals that show characteristic patterns at known accident sites. The next section will provide more and in-depth details on the methods used further in the course of this study.
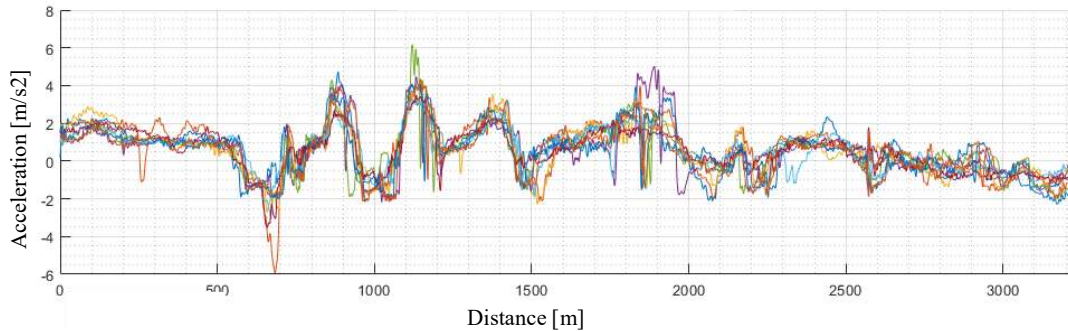

Fig. 5: Signals of the longitudinal acceleration of nine different measurement runs, represented over distance.

4. Data mining

Since it was not clear at the beginning, which signals are best suited for this new approach, a trial and error method was used to select the most significant signals. The presently implemented statistical model uses the smoothed (via a rolling average with a window of 60m) data of nine dynamic variables, including X-, Y- and Z- accelerations, the Yaw-, Roll- and Pitch-Rates, as well as the driven curve radius (curvature) and the changes in altitude (slope gradient).

The model itself is established in three steps: Firstly, determining "default" dynamics (common and/or averaged values) and extracting dynamics at known accident sites. The location-based dynamics data are smoothed by computing a rolling average of neighboring values, rather than the raw dynamics data. Secondly, calculating a separation between the normal dynamics and the dynamics at accident sites (Duda, Hart, Stork, 2001), then using this difference to assign a value to each meter and using values at the accident sites to determine a limit value for each driver (Draper, Smith, 1998), (Seber, Wild, 1989). Thirdly, creating an overlay (via summation and normalization) across all test drives, of transgressions of the limit values and determining the local maxima of a smoothed version of the resulting "warning surface" along the track.

Then the obtained local maxima are considered as warning points along the studied tracks and to each of them is a range of 40m in either direction assigned (based on an assumed speed of about 70 km/h). This range is based on the assumption that a "pre-" and "post-trigger" area of an accident may account for several seconds of influencing the dynamics at the recorded accident site. Moreover, it has to be taken also into account that the registered actual accident sites may not be exactly the crash locations, in which we consider riding dynamics to being potentially related to the observed maximum (dubbed the "Warning Area" or "Influence Area" around a maximum).

A color scheme is used to represent and differentiate between 4 classes of local riding dynamics, defined by the relative frequency of limit transgressions that occurred on each meter i.e. the relative "height" of the overlayed surface (the "danger function" or "danger surface"). Furthermore, another rolling mean of this danger surface is computed. A meter on the track is coded as "yellow" if a local maximum of the danger function occurred within 100m and upto 15% of test drives demonstrated a limit value transgression at this spot. It is coded "orange" if a local maximum of the danger function occurred within 100m and at least 15% of test drives demonstrated a limit value transgression at this spot, but no more than 50% of all test drives did. A meter on the track is coded as "red" if a local maximum of the danger function occurred within 100m and more than 50% of all test drives showed exceeding values. Code color "green" is used if no local maximum of the danger function occurred within 100 m. An accident site is then considered to be "hit", if it is within the 100m area of a "yellow", "orange" or "red" spot. The cutoff values were chosen as a first approach here and were not derived from separate statistical criteria.

5. Results

The statistical model was fitted according to the accident site data and riding dynamics of all 6 measured tracks. Then the statistical model was applied to each data set and risk prediction levels were calculated. Table 1 shows the statistic parameters for all tracks investigated. Geographical maps of tracks with superimposed colored risk level predictions and accident locations are shown and discussed below. See Fig. 6 and Fig. 7 for "Kalte Kuchl".

Table 1. Percentage of covered accidents and risk level areas.

	Exelberg	Höllental	Kalte Kuchl	Adamstal	Mauerbach	Preiner Gscheid	Weighted share
Percentage of "yellow" area	18,4%	15,7%	13,6%	21,2%	24,4%	3,9%	15,5%
Percentage of "orange" area	8,1%	13,7%	12,0%	8,3%	17,7%	12,8%	11,4%
Percentage of "red" area	6,0%	5,4%	19,4%	5,7%	0,0%	3,0%	7,8%
Number of recorded Accidents	22	21	31	8	3	5	-
Percentage of accidents included in the area	59,1%	52,3%	74,2%	50,0%	33,0%	40,0%	60,0%

Overall, a majority of the known accident sites were included in the indicated risk areas, while 35% of all tracks lengths were classified other than "green" (little or no risk level). The Kalte Kuchl track specifically shows a high percentage of accident sites found, but also a larger proportion of covered areas. This is largely due to the high amount of serpentine shaped parts along the Kalte Kuchl track.
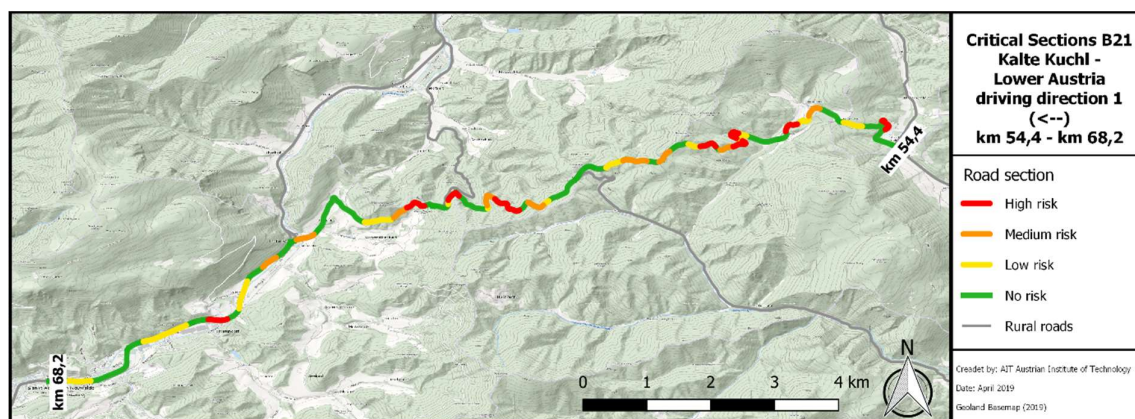

Fig. 6: Critical sections for Kalte Kuchl, driving direction 1

The statistical model identifies locations of locally heightened accident risk, by comparing test driver dynamics data to riding dynamics of the same drivers at given accident sites and by overlaying the results of multiple drivers along the given track. In this study only single person accidents and frontal collisions are evaluated. It is assumed that these types of accidents are especially reflected in the riding dynamic data. Riding dynamics and accident sites data of popular motorcycle tracks were used to fit the statistical model. The result of 60% accident hits with 35% of the tracks classified by an elevated risk level suggests that there are objectifiable similarities in the riding dynamics occurring in at least a sizeable subset of observed accident sites. Thus, the results show, that the riding dynamics of multiple drivers provide a feasible means of objective identification of points of motorcycle accident risk, since a considerable proportion of accident sites across 6 different tracks is identified by the applied method.
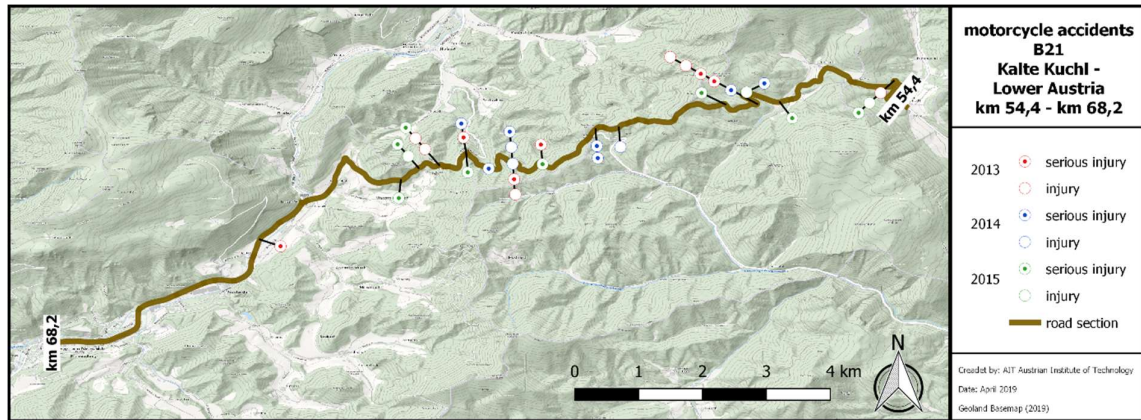

Fig. 7: Location of motorcycle accidents 2013-2015, Kalte Kuchl, all directions. Compare with Fig.6.

Given the primary locations of the local maxima (serpentine shapes and sharp curves), it is concluded that the found locations are not random and the model manages to generalize hidden properties of at least a substantial portion of these accident sites. This comes at the price of using a somewhat "broad" area around the danger function maxima, which are then considered as "influence areas" of the maximum. Ultimately, 35% of the driven road kilometers become classified by this way. While this is a substantial reduction from having to consider the whole tracks as dangerous or not dangerous, this is still a larger area than desirable for the purposes of, for instance, road safety inspections by regulatory authorities. One may suspect, that among the obtained maxima, there may be quite a few "false positives" i.e. maxima of the danger function at spots that are not necessarily dangerous as such. A possible cause for this may be the inclusion of accident sites that are in fact not well characterizable through riding dynamics.

Unfortunately, accident reports may not necessarily pinpoint always the exact location, riding direction or cause of accident occurrence, thus introducing a baseline uncertainty into the model considerations. It therefore appears unlikely that all accidents under consideration would show recognizable features in the dimensions of riding dynamics, which is why the model is allowed to be somewhat lenient about the separation of accident site dynamics and on average riding dynamics i.e. by using an average separation, rather than a strict criterion. Given a larger number of accidents however, it might be possible to restrict the considerations to more sharply defined groups of accidents, based on expert opinion. In turn this might allow a stricter separation of normal dynamics and accident risk dynamics.

The classification of maxima within our risk estimation into 4 risk groups, based on the percentage of test rides that showed an individual limit transgression near the maximum, provides additional and well needed details to prioritize some predicted dangerous spots over others. For instance, we note that there is a road stretch with a high number of maxima (20) in the left area of Figure 8, although just one accident has occurred there within the observation period, see Fig.7. Those maxima all fall into the "yellow" class of local maxima and thus can be seen as "least concern", on a track that predominantly shows "orange" and "red" maxima. This underlines the importance of differentiating between different types of maxima to correctly asses the relevance of the obtained predictions on each track. Indeed, this may be track specific, in the sense that on tracks with few extrema overall

or a general lack of "red" predictions, it may be prudent to consider "yellow" maxima as well, while for more "dangerous" tracks it makes sense to prioritize the "orange" and "red" maxima.
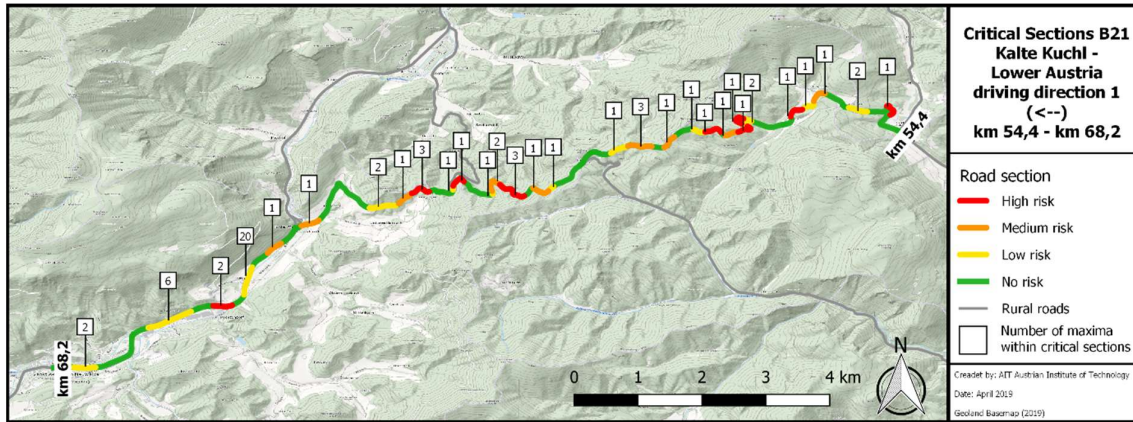

Fig. 8: Number of maxima within critical sections for Kalte Kuchl, driving direction 1. Compare with Figs. 6 & 7

On several occasions, one finds maxima in similar locations in both driving directions, which can be seen as a measure of consistency in that these bidirectional spots are usually seen near specific road geometries (sharp curves), which plausibly should affect riding dynamics in both directions.

Furthermore, sometimes maxima of the risk function are found near accident sites without information on the driving direction of the occurred accident. If there is a nearby maximum in only one driving direction next to the recorded accident site, we may take this as an indication for further investigation of whether the accident may in fact have happened in the same direction. Together with information on which parameters most commonly contributed to the risk classification near this site, this may be a hint for an accident cause, though this will require further improvements on the interpretability of the danger function.

An ongoing challenge is the identification of causes of a given occurrence of a maximum of the risk function. The difficulty primarily stems from the nature of the risk function, as an overlay respectively sum, of individual limit transgressions. While this provides much needed stability and generalizability beyond the differences between individual rides and riding styles, it does complicate the direct attributability of individual parameter effects to the overall risk estimate. Possible remedies could consist of keeping track of the causes of individual limit transgressions and counting the number of occurrences in each variable, possibly with weighted counts, if we were to reflect differing importance of the contributions of some variables over others. Alternatively, computing a gradient of the overall danger function with respect to the dynamics parameters would be possible via the chain rule of differentiation, via the intermediary step of computing derivatives with respect to the individual test rides. Both approaches will be investigated in future works, alongside with further data fit improvements.

Limitations include the need to extend the available data and validate the findings more generally on tracks not currently used in fitting the model. There is a need to provide a diverse and representative sample of motorcycle tracks, different motorcycle hardware, and possibly driver types, in order to extract more robust and generalizable results. By no means it is claimed, that all motorcycle accidents, or even just single person motorcycle accidents, would be related exclusively to riding dynamics. Rather, it is hoped to contribute a certain level of predictability and generalizability to the difficult problem of identifying risky or dynamically demanding motorcycle tracks.

The current method is based on a relatively small sample of test drivers. Their individual riding styles and the aforementioned small number impose limits on generalizability. Both issues should however be addressed by increasing the number of drivers and recalibrating the model accordingly. Nevertheless, within this feasibility study it was shown that generalizable patterns in the riding dynamics around the locations of previous accidents could be identified and can be processed by a statistical model. This is an improvement towards objective assessment of motorcycle accident risk locations through riding dynamics of a sample of test drivers.

6. Outlook

The output of this method provides a classification of "risk spots" into "low", "medium" and "high" priority zones. This can be seen as an early kind of "hazard map" on a given track. With this visualization, risk road sections may be investigated, and accident prevention measures can be taken. Ideally, this method would be applied and calibrated to a as extensive and representative network of motor cycling relevant tracks as possible. A possible use might be a priority ranking of road sections based on motorcycle safety/risk and the identification of necessary measures to be taken to increase road safety for bikers.

Possible future applications include the identification of road infrastructure needs for motorcycle safety, based on the locations revealed by the algorithm developed and possibly the analysis of riding styles through a comparison of reference types. Methodological improvements will include the exploration of more approaches to clustering and subsequent classification and to smoothing the time series data. An important step forward will be the exploration of the interpretability of the maxima of the risk function, which might allow to train the method yet more rigorously, based on expert feedback and accident in-depth studies.

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