

TITLE: Using Accident Location and interpretable Risk to fine tune Advanced Rider Assistance Systems for Motorcyclists

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ABSTRACT

Motorcycle riding is a popular activity among riders of all ages and the number of motorcyclists is still increasing, despite safety issues being tricky to resolve for this mode of transport. Motorcycle rides constitute a type of vulnerable road user (VRU) since accidents tend to have more severe consequences for them due to the lack of physical protection for riders compared to passengers in passenger cars. Since this is a consequence of the very nature of the vehicle (being less heavy and more dynamic to move) potential safety interventions for motorcyclists need to be based on predictive indicators for unsafe situations and aim to avoid crashes altogether.

This paper presents the results of ongoing work to improve motorcycle safety by finding causally interpretable risk characteristics based on accident data and motorcycle riding dynamics collected from test rides by individual riders. Dynamics data at known accident spots and representative data for individual rider-typical motions is associated to the type of historical accident in order to produce an estimate not only of risky areas and maneuvers, but also to associate types of riding dynamics that put the driver at risk. The relation to potential causes is essential for the inclusion of the resulting risk warnings in the activation of an Advanced Rider-Assistance System (ARAS), in order to produce a tailor-made response to the individual.

INTRODUCTION

Though a popular mode of transport, the share of motorcyclist accidents and in particular fatalities is still remarkably high. In Austria in 2021 for instance, motorcyclists constituted 20.7% of all road user fatalities [1] with the absolute number of motorcyclist fatalities having remained roughly constant over several years, while the absolute numbers of fatalities for several other modes decreased.

Worldwide approaches to improve the safety of motorcyclists are being investigated. Approaches include physical methods of various sorts (see for instance [2]). Studies are also tackling the identification and use of accident hotspots for motorcycling safety research (see [3]). Historical accident data is one of the main guides to understanding motorcyclist safety (see [4]) and will play an important role in the approach presented here.

We present further developments of a method published recently (see [5],[6],[7],[8],[9]) for deriving risk maps based on gathered data during test rides. Vehicle dynamics data on 6 popular motorcycle tracks were collected by 5 experienced riders on a Motorcycle Probe Vehicle (dubbed “MoProVe”, see [10]), which was comprised of a motorcycle with accessible control area network (CAN)-Bus Data and several external sensor systems (additional geo-positioning systems, additional inertial measurement units), as well as a camera to produce video documentation on all rides.

Data was analysed by combining different approaches from machine learning/statistics: Individual riding data was clustered to determine typical motions of each driver, driving dynamics at known accident and finally, separation functions between accident prone dynamics and uncritical dynamics were derived. Going beyond earlier work, the resulting separation functions were now associated with interpretable risk warnings and potential interventions are listed.

Specific risk profiles can be associated to individual riders, by extension allowing to consider specific warnings to the ARAS and interventions during riding. Additionally, the dynamic variables contributing the most to a present warning give further indications on the cause of a risk warning and can be used in a similar manner, to adjust riding dynamics.

The use of an individual rider's profile derived from riding dynamics data and dynamics derived from known accident spots with associated causes paves the way for a much more specific response of ARAS systems, which might save lives without distracting drivers during critical moments.

MATERIALS AND METHODS

Data was collected using a KTM 1290 Super Adventure (provided by KTM [11], to support this research) equipped with several additional data collection systems (see VBOX [12]; Debus & Diebold [13]), to obtain high quality riding dynamics data (in particular angular movements: Yaw-Rates, Pitch-Rates and Roll-Rates) alongside a high-quality GPS localisation.

Measurements

We collected data on 6 different popular motorcycling tracks via 5 different test drivers. Test drivers were instructed to drive in different riding styles (conservative, comfortable, dynamic) to obtain a range of different driving behaviours from each rider. On a given track all riders rode several times (at least 3 times in either direction) so as not to fit our model to any particular ride but rather to more stable tendencies identifiable from several rides in multiple styles. Obtained data was checked for validity, excluding data errors and annotating time spans during which the motorcycle was following other vehicles.

Time based data was projected to a location based (per meter) grid by partners at TU Vienna in earlier work (see [8],[9]),

Accident data was obtained from Statistik Austria for the years 2012 to 2015 on the given tracks. We were interested exclusively in single vehicle motorcyclist accidents and collisions with oncoming traffic (as a proxy for narrow curves with potentially poor visibility).

Model

Our model is based upon per meter values of dynamics data (j yaw-, r roll- and p pitch-rates, as well as a measure of driven curvature, see [6] for details) which are used to fit a separation approach (see [14],[15]), based on known accident locations and k-means clustering (see [14],[16]) of dynamics data. We use a linear separation model (see [14],[17]) to separate cluster centers and dynamics data at known accident locations.

For a set of variables V , consisting of the yaw-rate j , roll-rate r and pitch-rate p (all in degrees per second) and a measure of driven curvature

$$\kappa = \frac{r}{|j|+0.1} \quad (1)$$

we apply a number of transformations to allow for meaningful processing of the obtained data. Firstly, we apply a rollmean over 20 meters for each variable, to smooth the sensor data. Then we split given variables V into positive and negative parts $V_+ = \max(V, 0)$ and $V_- = \max(-V, 0)$ and calculate approximate derivatives of the per meter values i.e., "first differences" of the obtained values $dV(m) = |V(m) - V(m - 1)|$. The idea behind this preprocessing is to allow for separate weights in the statistical model on accelerations and decelerations, as well as left and right movements of the motorcycle.

$$md = (j_+, p_+, r_+, \kappa_+, j_-, p_-, r_-, \kappa_-, dj_+, dp_+, dr_+, d\kappa_+, dj_-, dp_-, dr_-, d\kappa_-) \quad (2)$$

We use k-means clustering on this data to define "standard motions" for each rider and use those as references for "non-risky" dynamics. Conversely, "risky" dynamics are simply defined as dynamics data at known historical accident locations. We use these two references to fit a separation model S based on a linear regression with target values $S = 1$ for risky dynamics and $S = 0$ for non-risky dynamics.

$$S = \sum_V a_V V_+ + \sum_V b_V V_- + \sum_V c_V dV_+ + \sum_V d_V dV_- + \varepsilon \quad (3)$$

In this model equation we have $a_V, b_V, c_V, d_V \in \mathbb{R}$ with ε denoting the error term of the regression. The coefficients in equation (3) can be used to assign values of $S(md)$ for all considered driving dynamics data md

of the form in equation (2). A threshold separation between risky and non-risky dynamics data was defined for each rider and subjected to a joint optimization (see [5] for details).

We used the language R for our implementations [18].

The fit separation function can be used to assign weights dubbed “responsibilities” to all the components of a given data vector md using the contribution each component makes to the positive value of $S(md)$. If u denotes a single element of (a_V, b_V, c_V, d_V) and md_u denotes the corresponding dynamics variable value, then the responsibility U_{md} of md_u for the separation value $S(md)$ is:

$$U_{md} = \frac{u md_u}{\sum_V(a_V V_+)_+ + \sum_V(b_V V_-)_+ + \sum_V(c_V d V_+)_+ + \sum_V(d_V d V_-)_+} \quad (4)$$

In this sense responsibilities denote the share of a positive contribution of the component u to the value $S(md)$ (responsibilities are nonnegative and sum up to 1).

RESULTS

Using the separation approach outlined above, the responsibilities for known accident sites were investigated. To illustrate, we show an example of the responsibilities for all riders combined into a single estimate in Fig. 1, for a right curve and a left curve accident:

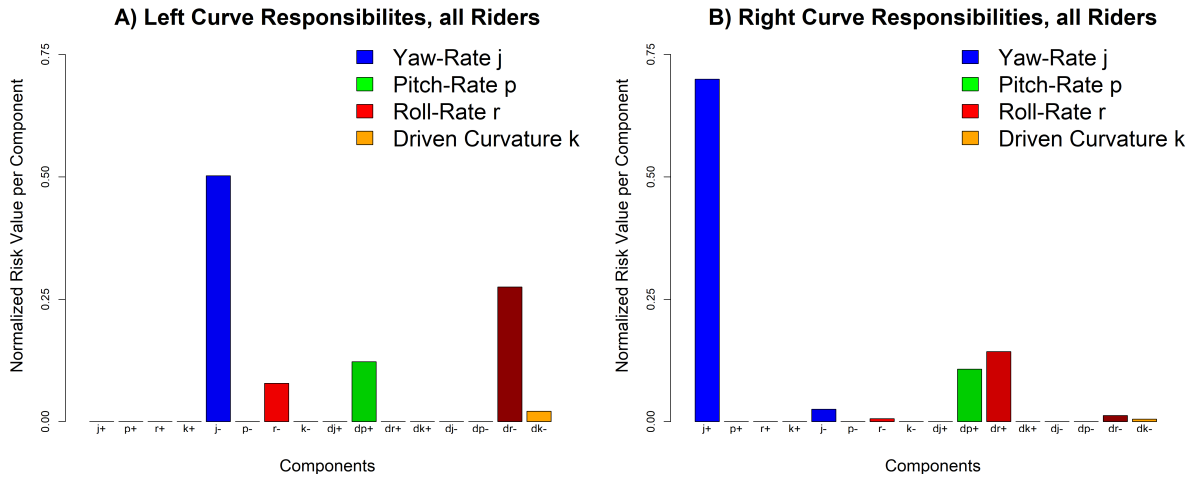


Figure 1: Responsibilities by data component for a) a Left curve with a known left curve accident and b) a Right Curve with a known right curve accident. Data while following other vehicles or having poor satellite connection has been removed.

It can be seen that the primary contribution in Fig. 1 a) stems from the negative yaw-rate j_- and in Fig. 1 b) from the positive yaw-rate j_+ . Investigating the respective yaw-rate values for drivers at accident spots of the same type, we find results depicted in Fig. 2 below.

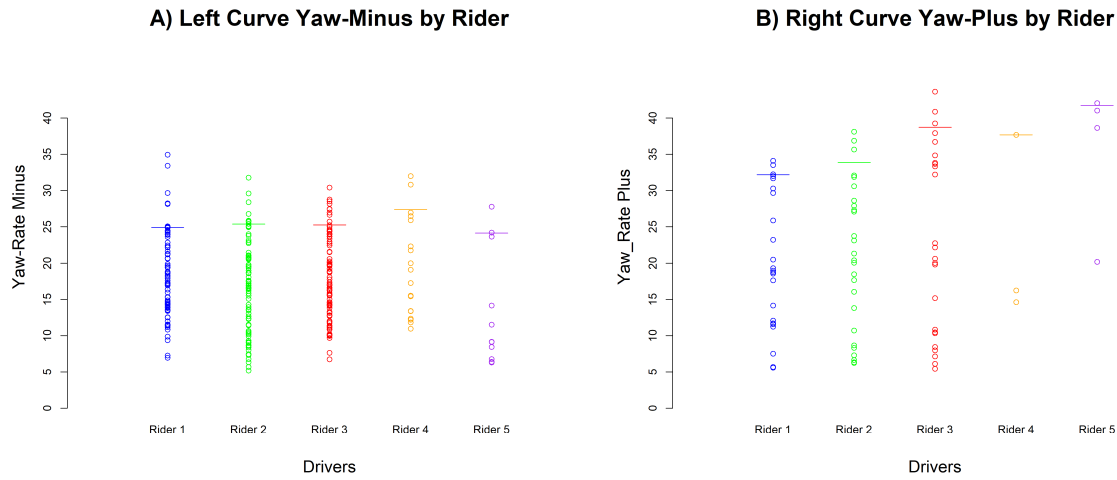


Figure 2: Values of the yaw rate at known accident locations with the 90% quantiles (signified by horizontal bars in the graph) of each rider being represented by a horizontal bar in the data. Panel a) depicts values of the yaw-rate minus at left curve accidents, while Panel b) depicts values of the yaw-rate plus at right curve accidents. Data while following other vehicles or having poor satellite connection has been removed.

This is a first opportunity to determine driver specific thresholds from the dynamics data obtained. We use the distribution shown in Fig. 2 to find a limit in the respective parameter for each rider and consider all values above to be challenging dynamics that might warrant ARAS Systems to prepare to engage. The thresholds can be seen in Fig. 2 as horizontal bars. Since we also note substantial contributions by the change of size in the roll-rate (dr_- and dr_+) and changes in the size of the pitch rate dp_+ to the risk responsibilities of left and right curve, we represent those in a similar manner in Fig. 3 and Fig. 4 below:

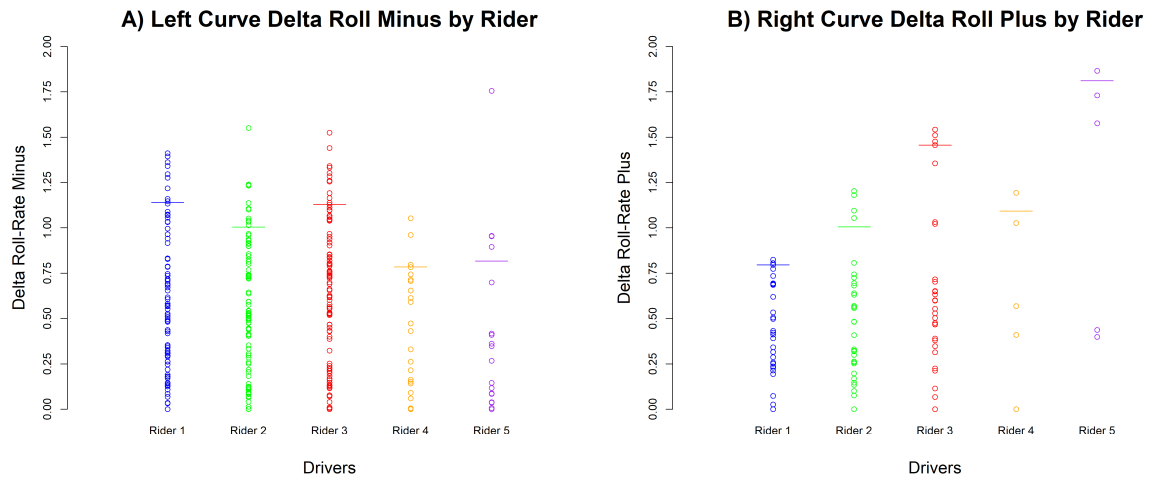


Figure 3: Values of the change in roll rate size at known accident locations with the 90% quantiles (signified by horizontal bars in the graph) of each rider being represented by a horizontal bar in the data. Panel a) depicts values of the delta roll-rate minus at left curve accidents, while Panel b) depicts values of the delta roll-rate plus at right curve accidents. Data while following other vehicles or having poor satellite connection has been removed

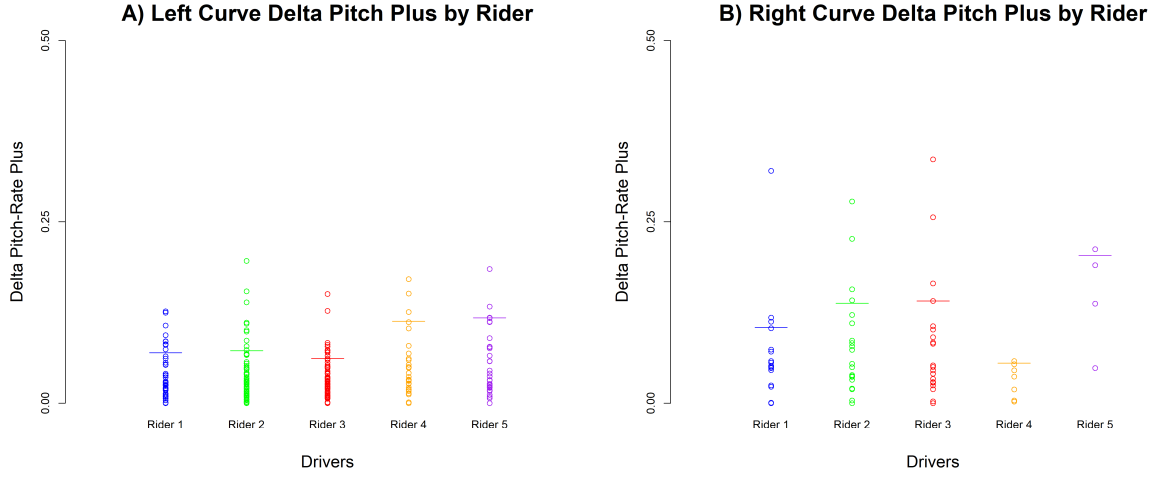


Figure 4: Values of the positive change in pitch rate size at known accident locations with the 90% quantiles (signified by horizontal bars in the graph) of each rider being represented by a horizontal bar in the data. Panel a) depicts values of the delta pitch-rate plus at left curve accidents, while Panel b) depicts values of the delta pitch-rate plus at right curve accidents. Data while following other vehicles or having poor satellite connection has been removed.

We chose thresholds according to quantiles of the respective data. A 90% Quantile is a good starting point to define the thresholds for the challenging domain in terms of driving dynamics. We see that with some variation the 90% quantiles in the yaw-rate are fairly close for our (experienced) test riders for the left curve, suggesting comparable limits to how riders would typically drive in a given curve. Interestingly estimates vary far more widely for the right curve. This may however be due in part to the lower number of accident locations for this type.

This procedure can be applied to obtain thresholds based on different accident locations and types and form specific boundaries on yaw-rate, roll-rate and pitch-rate to inform ARAS Systems such as traction control or ABS.

The thresholds derived in this reference data could then be transferred to drivers having similar driving profiles i.e., using the k-means clusters derived from the general driving data for a rider. The model which has the lowest squared distances in terms of components of the cluster centers md_i^{rc} of the reference data (denoted by rc) and components md_i^c of the not previously classified riders with dynamics data clusters c :

$$Dist = \min_{orders\ of\ c} \sum_c \sum_i (md_i^c - md_i^{rc})^2 \quad (5)$$

This can be used to transfer the threshold determined on the reference data here to riders in general. Thus, the reference high detail data set used in earlier work, can be used to find safety indicators for riders more generally, while the reference data set can continue to be expanded with more reference rider types on more tracks.

CONCLUSIONS

Building on a model of finding accident risk locations from driving dynamics data, we have investigated first approaches in associating particular accident sites with particular risk types. This allows us to derive thresholds for driving dynamics parameters for individual riders for particular accident types. These thresholds can be evaluated quickly even during the operation of a vehicle, thus making this a potential approach to guiding ARAS for motorcyclists. We have furthermore presented first consideration of how to transfer the models fit on precise reference data to more general settings, by using the cluster centers and finding the closest reference types in terms of these clusters.

The kinds of interventions that ARAS might implement based on this information is very much still up for debate. Speed recommendations or regulations could be a way forward, given the drivers experience (as evidenced by their quantile values of driving dynamics during various maneuvers) or, perhaps more challenging, stabilization features to still be developed.

Similar models could be fit to various levels of experience of the respective drivers and particular states (i.e., detecting fatigue from the driving style) and thus instantiate supportive measures in the same manner (reduce available power, recommend speed, stabilize motions).

Using the profiles of certain accident types, it appears feasible that those could also be used to classify accident spots with “unknown” accident causes and develop the methodology further towards accident reconstruction.

The most immediate limitations of these results stem from the size of the data set (5 riders on 6 tracks) and the precision of the available accident data. Quality checking available accident data will be necessary to expand the available data sets. The quality of the transfer of risk models from one rider to another will have to be demonstrated in future data. We note that a system based on these kinds of models might want to have an updating methodology and we have discussed first ideas of such a methodology in [19]. Alternatively, transferability might be sufficient to address this, as there could be clusters/profiles that encode various stages of driver experience.

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