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Detection of One-Handed Riding during Activation of Automated Braking

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ABSTRACT

Concerning automated emergency braking of motorcycles the maneuver controllability is assumed to be dependent on rider awareness and seat position. Within this paper it is studied if the disadvantageous position of one-handed riding can be classified during activation of automated braking based on motorcycle dynamics sensors only. Based on measurements of a rider study different classifiers are derived, which can detect one-handed riding during straight ride at the beginning of automated braking. At this time, the deceleration is still small and uncritical, so that a weakened parameterization of automated braking is possible.

Keywords: automated braking, rider position, classification

1 INTRODUCTION

Research activities investigating automatic emergency braking for motorcycles are increasing [1, 2]. These activities focus on the controllability of automatic braking interventions assuming a proper rider position with both hands on handlebar. In [3] it is examined by user tests all ridden with both hands on handlebar if partial braking maneuvers can get the rider in a prepared-for-braking state. As indicator the riders handlebar forces are evaluated. Also in [3] a simulator study to analyze the influence on manual-visual distraction during automated braking on riders ability to control the motorcycle is described. As one of the manual distractions the rider has to perform one-handed riding on the simulator.

Concerning automatic braking it is obvious that one-handed riding will be a critical situation, which should be detected. This is possible by direct sensing with extra sensors at the handlebar grips, which produce extra sensor costs. In contrast, all bikes equipped with an active safety system like Motorcycle Stability Control [4, 5], are equipped with an inertial sensor platform. This sensor platform measures the bike turn rates and accelerations, so that the signals are already available for the given task of detection of one-handed riding.

2 RIDING STUDY

To obtain a measurement database a riding study with 14 test riders of different age and different riding experience is carried out. The test bike is equipped with a 6D inertial sensor unit at the sprung mass called as bike sensor set. Additionally a steering angle sensor and a yaw rate sensor at the fork to measure the steering rate are mounted. All sensors together are called extended sensor set. Furthermore an inertial sensor unit is attached on the riders back.

Automated braking is realized in the way as illustrated in Figure 1. At time t = 0 s automated braking is triggered. The engine torque is quickly reduced close to zero (1st plot) before the wheel pressures ramp up with a defined distribution between front and rear wheel (2nd + 3rd plot). The pressure at the front wheel starts to rise clearly at approximately 200ms. The last plot shows the resulting bike deceleration.

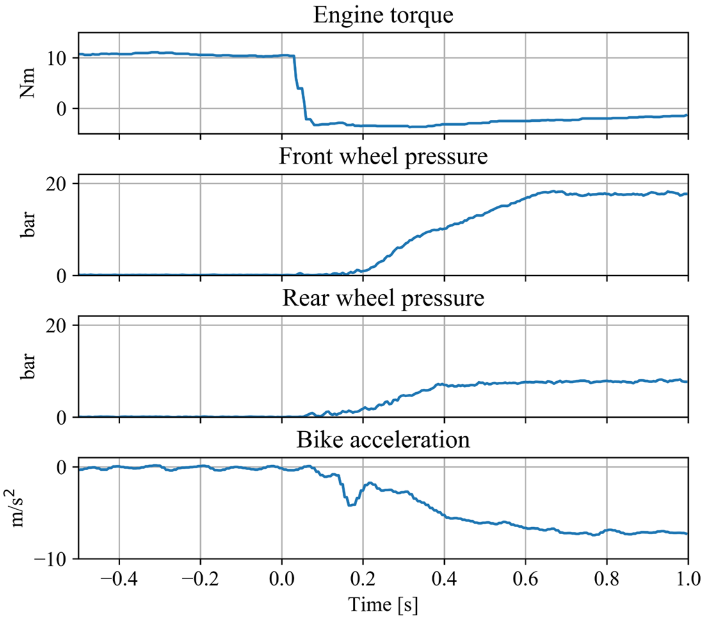

Figure 1. Control variables of automated braking with resulting deceleration

The small deceleration jerk shortly before 200ms results from the abrupt reduction of engine torque. For the riding tests two different deceleration profiles are realized. One as illustrated in Figure 2 with fast ramp up in 600ms to a constant deceleration of about -7m/s^2, the other with a slower deceleration ramp twice as long.

Figure 2 shows the test track. In the first marked section the bike has to be accelerated up to approximately 70 km/h. Subsequently when riding straight at constant speed automated braking is triggered randomly in the second marked section. The test riders are informed that automated braking will take place in this section, but the riders do not know the exact intervention point. During the riding study the test riders are instructed to adopt different riding positions like riding in the correct position with both hands on handlebar, with only one hand on handle bar of only one foot on foot rest. The riding positions are taken up for several rides in permuted orders. 60 measurements of one-handed riding and 55 measurements of riding with both hands on handlebar are available and valid for the described study. These data are separated in training-, validation- and test data with 60%-20%-20% partitioning. The classifiers are developed on the training data and evaluated with the validation data. The test data are used only after classifier development to evaluate the results.

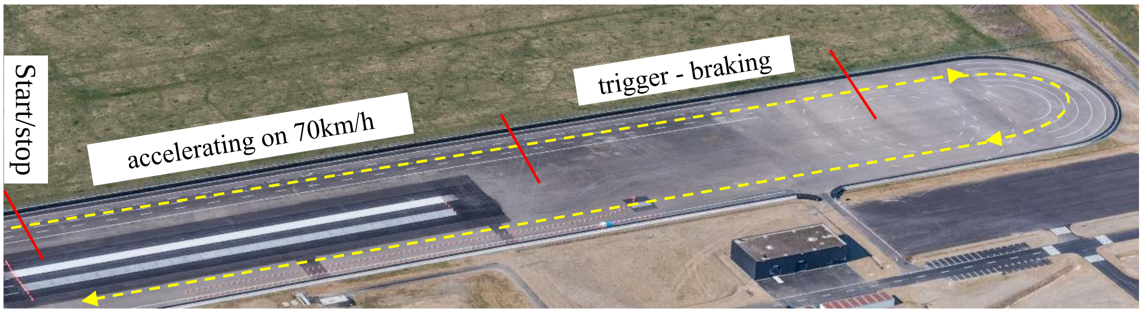

Figure 2. Test track and experimental setup

3 CLASSIFICATION METHOD

To find signals suitable for rule-based classification for each measured signal a mean value over time is calculated with measurements of one-handed or two-handed maneuvers respectively. With these mean value progressions a normalized signal amplification of one-handed riding with respect to two-handed riding is determined. Signals with high maximal normalized signal amplification at an early time of braking are chosen for classifier development. For the bike sensor set, these are the roll and yaw rate of the bike, its roll angle and the lateral acceleration. These signals describing the lateral motion are in some way obvious from consideration of ride dynamics. Starting to brake while riding one-handed causes a one-sided handlebar force. This force produces a steering torque affecting the lateral motion of the motorcycle. Surprisingly, the normalized signal amplification of rider's pitch rate, measured with the inertial sensor unit at its back, is not prominent.

Figure 3 shows in the 2nd and 3rd plot the mean values over time for the signals identified as suitable for classification. The solid lines are the signal mean values for two-handed riding, the dashed lines for one-handed riding both for maneuvers with fast ramp up of brake pressure. In the first plot the mean signal values of the front wheel pressure and the deceleration are depicted. It is clearly visible that the automated braking maneuvers are identical independent if ridden two- or one-handed.

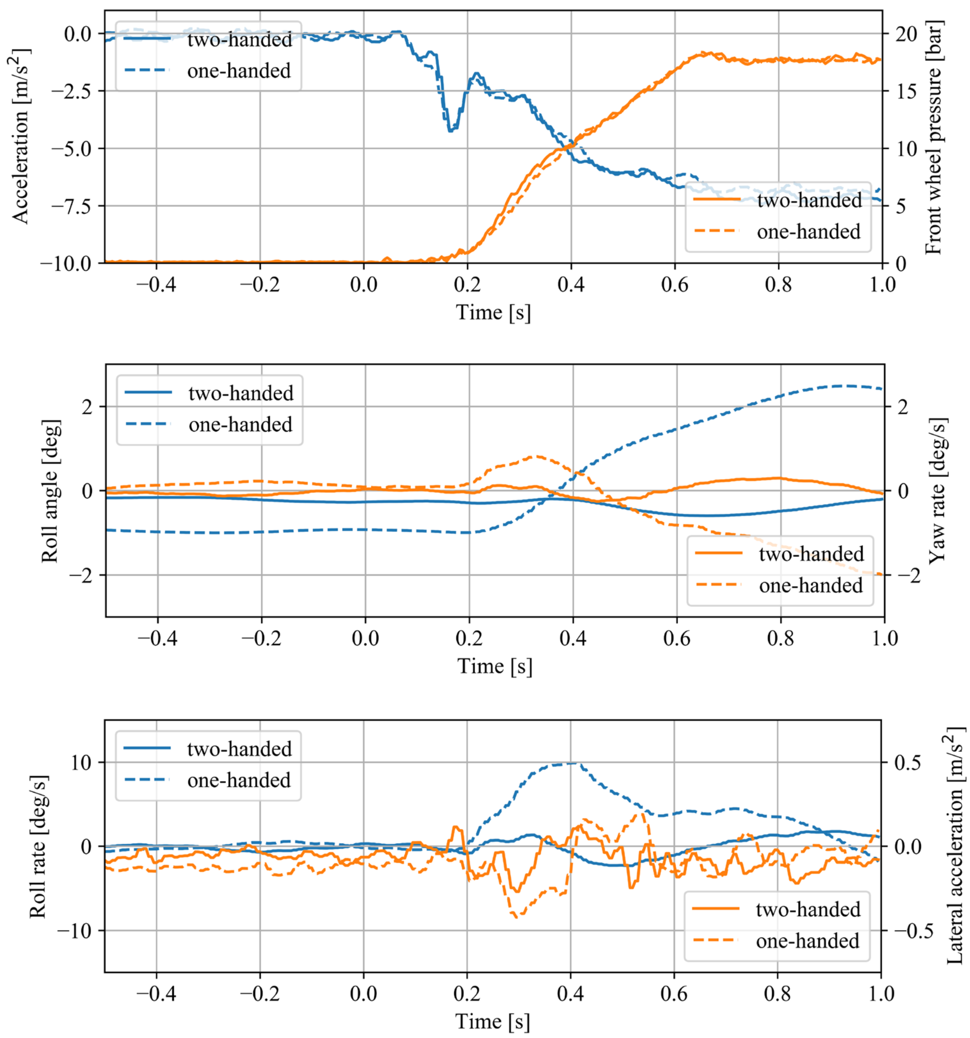

Figure 3. Mean value over time for training data set of signals describing lateral dynamics of bike. Solid: two-handed, dashed one-handed.

The deviations between two-handed and one-handed riding can be seen clearly for all signals, but the maximum deviations and the time where they occur differ. The roll angle (2^{nd} plot, blue lines) and the yaw rate (2^{nd} plot, orange lines) show large maximum deviations at later time. The maximum deviations of the roll rate (3^{rd} plot, blue lines) and of the lateral acceleration (3^{rd} plot, orange lines) already occurs at beginning of automated braking with a significant value for the roll rate.

3.1 Single value based classification

First, a threshold-based classifier using only current signal values is derived. In a 4-stage rule, this means a rule for each signal, it is checked every time step whether the signal exceeds a multiple from its threshold th_{sig}. Multiples of 3, 2 and 1 are checked. If this is the case a common counter for all stages called Certainty Grade is incremented dependent on the multiple of th_{sig}. One-handed riding is classified if after the last rule the Certainty Grade exceeds a fixed threshold. This fuzzy rule base classification is based on a method described in [6].

As initial signal thresholds, the maxima of the mean signal distances with respect to idealized straight ride are chosen. These are calculated with the measurements of two-handed riding of the training data set. Based on these initial values the thresholds are optimized with the goal of high classification rate and small mean time for classification. On the one hand the threshold of lateral acceleration, in some kind an instable signal for classification with risk of wrong classifications, is increased. This means that its influence on classification is reduced. On the other hand the influence of the roll rate is increased with a decreased threshold.

A detailed consideration which rule releases the classification leads to the roll rate as dominant signal involved in every classification. With the described classifier using only signals of the bike sensor set 97% of the training data are classified correctly. For slow ramp up the mean detection time of one-handed riding is 0.42s and 0.31s for fast ramp up.

Using additionally the steering angle and the fork yaw rate of the extended sensor set for single value based classification does not provide better results.

3.2 Time series based classification

In contrast to single value based classification in time series based classification also the signal history is taken into account. By evaluating multiple sampling points automated braking can be separated in different maneuver states. These are listed in Table 1 and illustrated in Figure 4.

Table 1. Different maneuver states at automated braking

Yellow	Straight ride before automatic braking.
Green	Trigger of automated braking, period of reduction of engine torque.
Blue	Period of load change.
Red	Period where brake pressure at the front wheel starts to rise significantly.
Grey	Stable maneuver dynamics, settled steering system.

Looking at the lower plot of Figure 4 the small values of the roll rate (blue) and the steering angle (orange) in the yellow region show the straight ride. The acceleration in the upper plot (blue line) clearly depicts the load change in the blue region. In the red region the start of pressure built up (upper plot, orange line) can be seen. To detect the current maneuver state, the state machine uses beside the signals of the bike sensor also the engine torque and the wheel brake pressure.

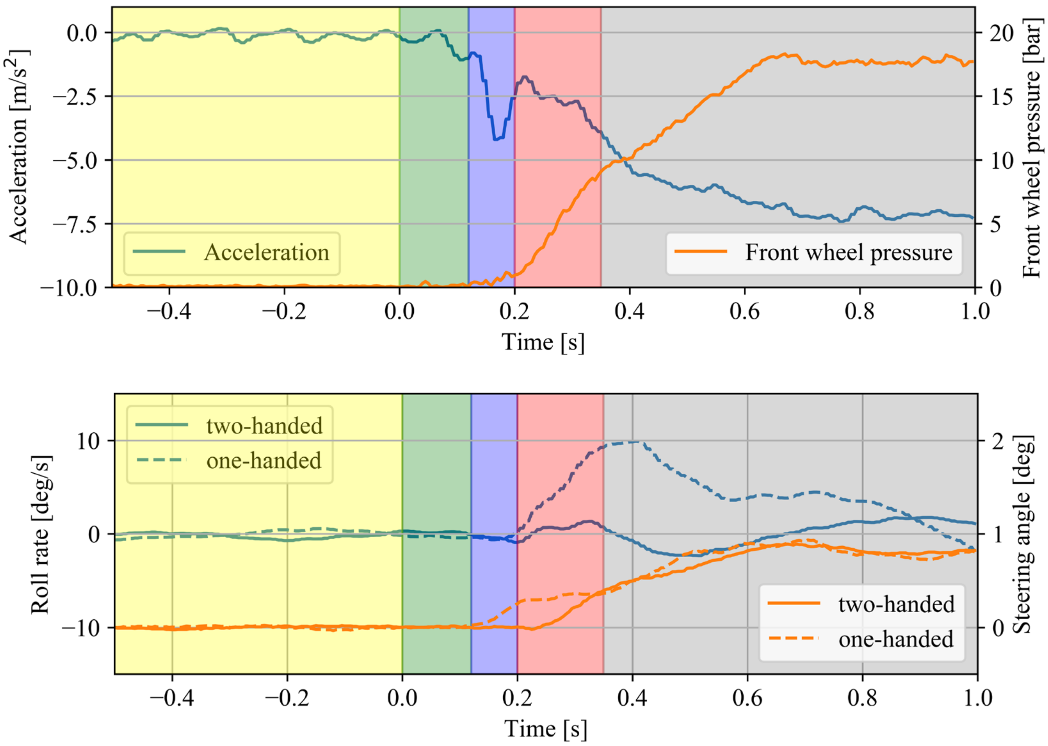

Figure 4. Maneuver states: straight ride before intervention (yellow), trigger of automated braking (green), load change (blue), pressure ramp up (red), maneuver settling (grey)

With the knowledge of the current maneuver state it is possible to define state dependent classification rules. For this purpose, it is checked in each maneuver state if defined signals change their values over given thresholds. If yes one-handed riding is detected.

Using only signals from bike sensor set similar results as for single value based classification are obtained. Again the roll rate is the dominant signal with its strong change during the maneuver state of pressure build up (Figure 4, lower plot, blue dashed signal (red region)). In contrast with the steering angle as signal of the extended sensor set the needed time for classification can be reduced significantly. In case of one-handed riding the deceleration of the load change already leads to a certain steering angle (Figure 4, lower plot, orange dashed signal (blue region)) caused by the one-sided handlebar force. The classifier exploits this maneuver state dependent information.

On the test bike automated braking is realized in the way that front wheel pressure is only applied at one brake disk. This is the reason for the non-zero steering angle in the grey region for two- and one-handed riding.

4 RESULTS

All classifiers developed on the training data are validated with the validation data and finally tested with the test data. A mean detection accuracy of all four classifier of 97% is achieved for the test data. Also for all data (115 measurements) the mean detection accuracy is 97%. Concerning the detection time the results of all classifiers are summarized in Figure 5. On the left side the results for fast pressure ramp up and on the right side for slow pressure ramp up are depicted. The upper plots show the mean values of the applied front wheel pressures (orange) and the resulting decelerations (blue). The different maneuver states are coloured as described in chapter 3. In the lower graphics box plots of detection times of one-handed riding are depicted differentiated by training (blue), validiation (green) and test (red) data. Results of each classifier named in Table 2 are given in one row.

Table 2. Type of developed classifiers

ts_ext	Time series based with extended sensor set
ts_veh	Time series based with bike sensor set
sv_ext	Single value based with extended sensor set
sv_veh	Single value based with bike sensor set

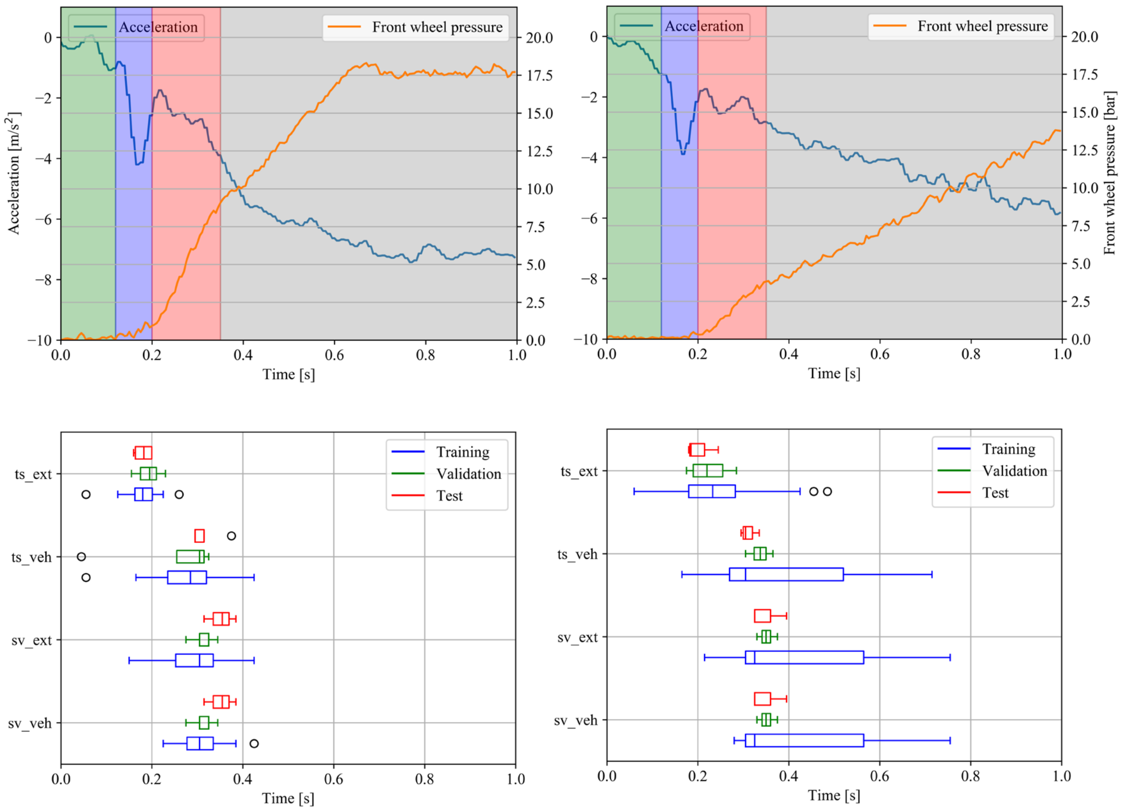

Figure 5. Box blots for detection time of different classifiers (sv: single value based, ts: time series based) using different sensor sets (veh: bike sensor set, ext: extended sensor set). Left fast ramp up, right slow ramp up.

The box plots illustrate the following quantities. The median as a perpendicular line within the box, the upper and lower quartile marked by the upper and lower limitation of the box, the largest and smallest value marked by the antenna, which lie within a distance of the 1.5 multiple of the interquartile range from the quartiles and the outliers as circles. The narrow distribution for validation and test data is due to the lower number of measurements.

The results show that all classifiers detect one-handed riding in most cases before 50% of the final wheel pressure is achieved. For classifiers sv_veh, sv_ext, ts_veh the detection times are similar. The results for classifier ts_ext using additionally the steering angle show the reduced detection time. In case of fast pressure ramp up one-handed riding can even be detected earlier. For each classifier the medians of detection time for training, validation and test data are close to each other. This means that the classifiers can be generalised presumed that the condition of straight ride is given.

5 CONCLUSIONS/OUTLOOK

All presented classifiers which use available motorcycle dynamics sensors are able to detect one-handed riding at straight ride already at the beginning of automated braking, where the wheel pressure and the deceleration lie below 50% percent of its final value. This allows to adapt the braking strategy dependent on the classified rider position. Using the steering angle signal, which is not available on motorcycles currently, one-handed riding can be classified significantly earlier. A small deceleration jerk is sufficient for classification, which could be exploited by an activation cascade for automated emergency braking.

All classifiers are developed under the condition of straight ride. In a next step, it has to be checked if the classifiers can be adapted to curve ride.

REFERENCES

[1] N. Merkel, R. Pless, K. Scheid and H. Winner, "Limits of Autonomous Emergency Brake Systems for Powered Two-Wheelers – an Expert Study", *Proceedings of the 12th International Motorcycle Conference 2018,* Köln, Germany, 1-2 October 2018, p. 122-144

[2] G. Savino, M. Pierini, J. Thompson, M. Fitzharris and M.G. Lenné, "Exploratory Field Trial Of Motorcycle Autonomous Emergency Braking (MAEB): Considerations On The Acceptability Of Unexpected Automatic Decelerations", *Traffic Injury Prevention*, 2016, DOI: 10.1080/15389588.2016.115521

[3] N. Merkel, R. Pleß, H. Winner and Th. Hammer, N. Schneider, S. Will, "Tolerability of unexpected autonomous emergency braking maneuvers on motorcycles – a methodology for experimental investigation", *Proceedings of the 26th International Technical Conference on the Enhanced Safety of Vehicles ESV2019,* Eindhoven, Netherlands, 10-13 June 2019

[4] G. Matschl, M. Mörbe and C. Gröger, „Motorcycle Stability Control – MSC The next step into safety solutions for motorcycles", *Proceeding of the 10th International Motorcycle Conference 2014,* Köln, Germany, 2014, p. 128-154

[5] M. Lemejda and R. Willig, " A New Interial Sensor Unit for Dynamic Stabilizing Systems of Powered Two Wheelers", *Proceedings of the 9th International Motorcycle Conference 2012,* Köln, Germany, 2012, p. 66-84

[6] Hisao Ishibuchi und Tomoharu Nakashima. „Effect of rule weights in fuzzy rulebased classification systems". *IEEE Transactions on Fuzzy Systems Vol. 9. No. 4,* August 2001, p. 506–515.