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An Approach for Automatic Riding Skill Identification

Overview about the Methodology and first Results

Overview

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Structure:

- Motivation
- State of the Art
- Rider Skill Assessment Concept
- Probabilistic Segmentation
- Rider Skill Indicator
- Results
- Conclusion & Outlook

Introduction

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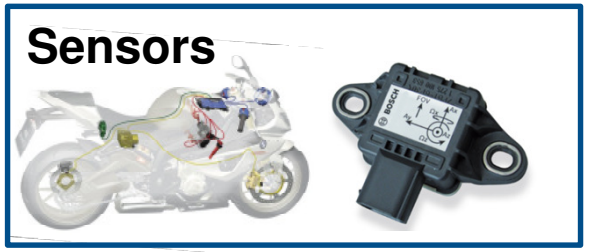
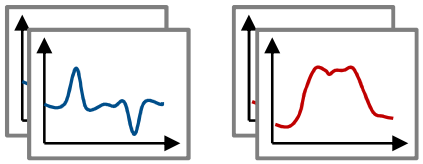
Vehicle

Sensors



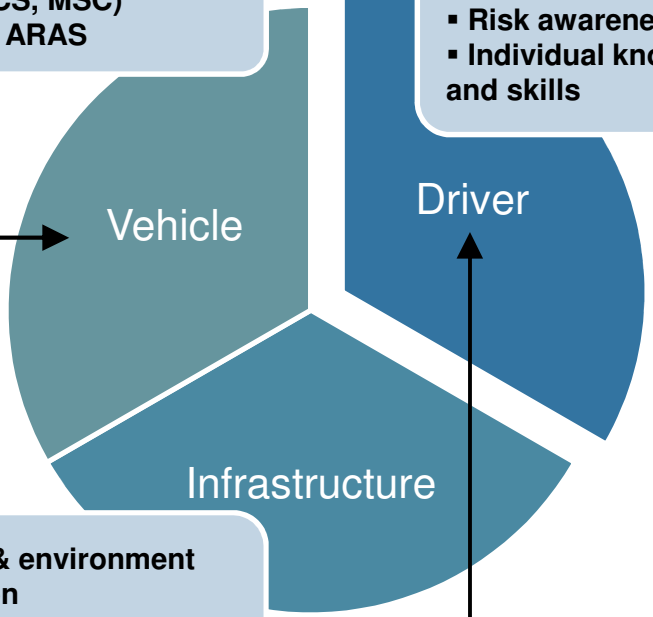
Motion data



Safety Structure

- Safety systems (ABS, TCS, MSC)
- Future ARAS

- Mental workload
- Risk awareness
- Individual knowledge and skills



- Road & environment condition
- Emergency infrastructure (E-Call)

Rider Model

- Use Cases?

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Introduction

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Use case for knowing the riders' behavior and proficiency?

- **Adaptive feedback**
  - **Improve knowledge and skills through feedback about scenarios / riding quality**
- **Advanced Rider Assistance Systems (ARAS)**
  - **Rider (skill) adaptive warnings (e.g. max. curve speed warning)**

Problem Statement

- **How can we evaluate cornering scenarios with respect to identify rider skill? Can riding errors be detected?**
- **Can we find correlations between the performance of cornering maneuvers and their context?**

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State of the Art

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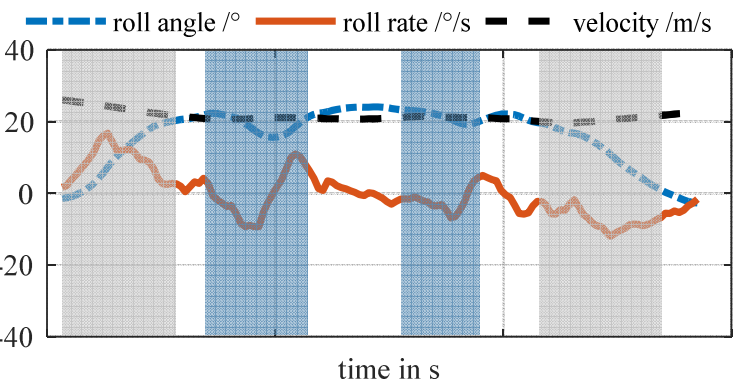
State of the Art and their limitations.

- **Distribution models of roll-angle or x-y-acceleration**
  - **Highly depend of speed limit, environment, traffic conditions and rider mood.**
  - **reflect risk rather than vehicle control skills**
    - **reaching physical limits results in no safety margins**
  - **no information about stabilization or guidance skills**

- **Explicit scoring Methods**
  - **designed for very specific scenarios**
    - **e.g frequency based approach of Yoneta et al. (2012)**

Problem: Overlapping frequency range from corrective action and turn-in / turn-out



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Segmentation based concept for Rider Skill Identification

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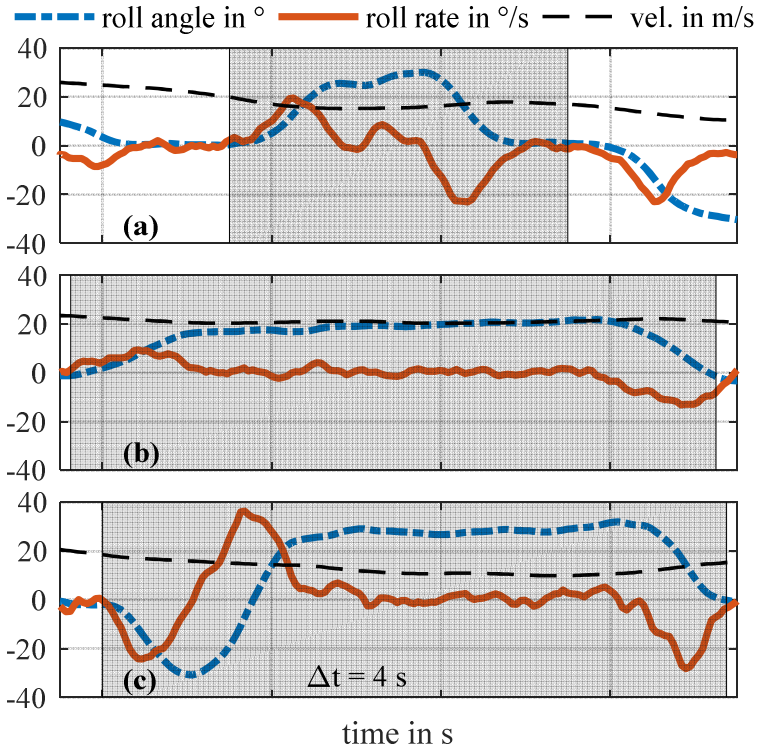
Why Segmentation?

- Various extremely different cornering scenarios!
  - Segmentation into reoccurring segments enables normalization for scoring.
- Human switch between different simple control strategies during complex driving maneuver.
  - roll-in & roll out
  - stabilization of roll angle
- Evaluation of segments (Control-Level) and their sequence (Guidance-Level)



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Probabilistic Segmentation

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Definition of Maneuver Primitives (MP)

ID	Name	No.	Previous
S	Straight driving	1	6,9
SR	Stationary right	2	4,5,8
SL	Stationary left	3	5,7,8
RI	Roll-in right	4	1
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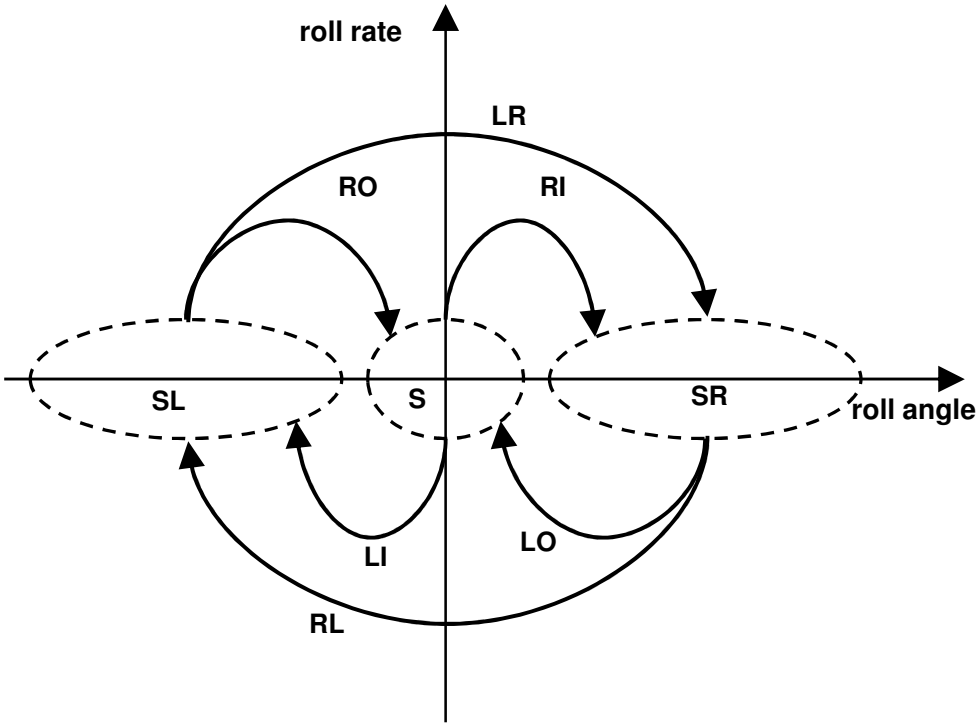

- **Sequential Order of Maneuver Primitives!**

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Probabilistic Segmentation

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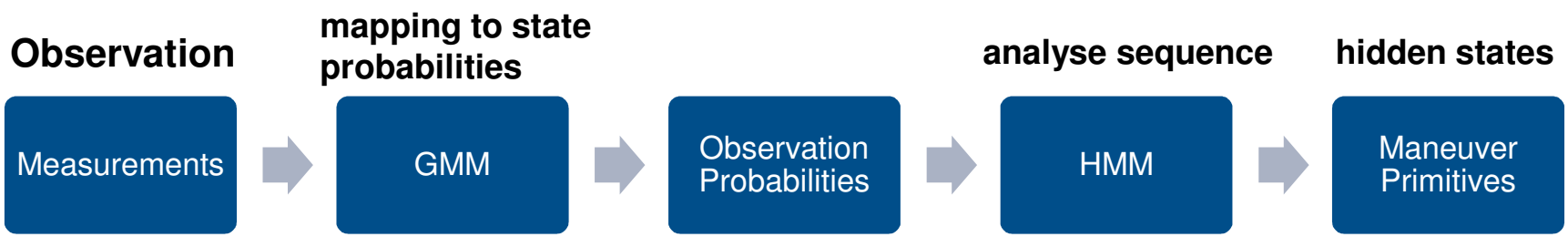
Gaussian mixture Hidden Markov models (GMM-HMM)

- **HMM models unobserved hidden states by a sequential probabilistic approach**
  - **allows to use the sequential order of measurements**
- **GMM is used to model the probability that an observation is emitted from an hidden state**
  - **captures the magnitude / values of the measurements**
- **Supervised training possible**



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Probabilistic Segmentation

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Results:

- **Algorithm vs. human reference**

	Tot.	Maneuver primitive specific				
	m	m_1	m_2	m_3	m_{4-6}	m_{7-9}
Absolute match rate in %	88,7	94,2	88,4	90,9	89,5	88,8
	Δt in s					
	0.1	0.2	0.3	0.4	0.5	1
Difference Ref. – Pred. < Δt, in %	47.8	75,2	77,7	85,1	88,7	95

- **Human vs. human (visual) match rate**

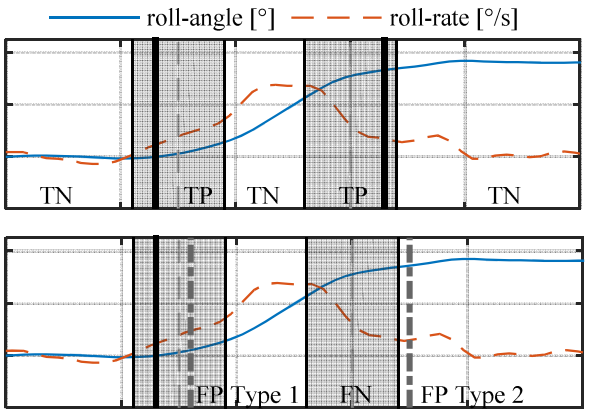
	Sub.1	Sub.2	Sub.3	Sub.4	Sub.5	HMM
Sub.1	1	0.84	0.86	0.82	0.84	0.83
Sub.2		1	0.85	0.83	0.81	0.80
Sub.3			1	0.83	0.83	0.86
Sub.4				1	0.80	0.81
Sub.5					1	0.81

Evaluation Criteria:

- **Absolute match rate:**

$$m_i = \begin{cases} 0 \; if \; l_{human,i} \neq l_{algorithm,i} \\ 1 \; if \; l_{human,i} = l_{algorithm,i} \end{cases} \quad m = \frac{1}{n}\sum_{i=1}^{n} m_i$$

- **State transition points**



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Rider Skill Indicator

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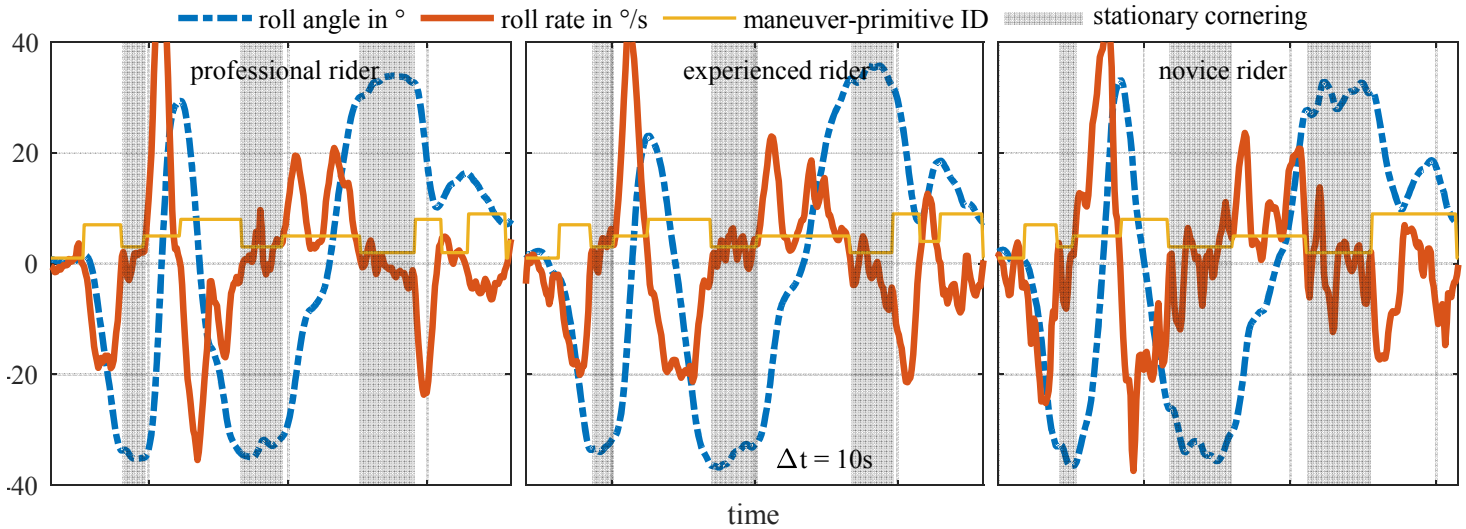
Comparing Riders of different proficiency, riding experience:



- **visual and numerical analysis shows that roll rate oscillation increase from professional test rider to novice rider**
- **Hypothesis: Oscillation in stationary cornering segments are mainly caused by**
  - **… low stabilization skills** 
  - **… wrong path planning / motion design (e.g. steering impuls to build up roll angle)** 

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Rider Skill Indicator

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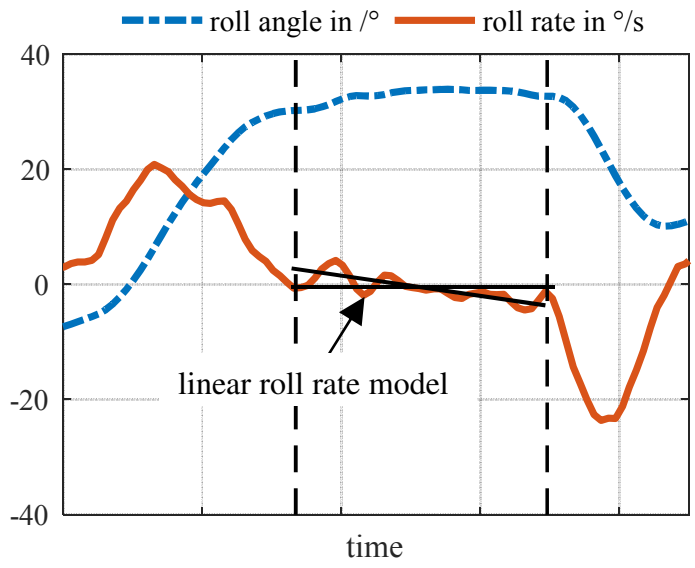
Assumption for an ideal stationary segments:

- rider meets the desired roll angle for a given road curvature and the current vehicle speed. No over- or undershoot of the roll angle.
  - roll rate ≈ constant ≈ 0 ⟶ $B_{1\,SR,SL} = \sigma(\dot{\varphi}) \approx 0$
- Problem: Short and very smooth driven curves produce $\sigma(\dot{\varphi})$ >> 0
  - roll rate can follow a linear model
  - $B_{2\,SR,SL} = \mathrm{RMSE}(\dot{\varphi} - \dot{\varphi}_{lin}) \approx 0$



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Rider Skill Indicator

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Experiments

- **Test rides on open public roads in Odenwald, Germany**
  - **2 Sections covering sharp (R=25m) to wide (R=200m) curves on different road surfaces**
  - **Route has been driven 3 times in both directions.**
  - **Only stationary cornering segments with a minimum duration of 1s and minimum roll angle of 15° are considered to be evaluated.**
- **5 Test riders**

Rider	F1	F2	F3	F4	F5
category	professional	experienced	experienced	experienced	novice
Riding experience in km	Test rider of Honda R/D Germany	> 40.000	> 100.000	> 20.000	< 3.000
Riding experience in years		> 10	> 20	> 5	< 1

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Results stationary segments

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Cumulative Distribution of B_2 in stationary segments SL and SR

- **CDF Plot x-Axis: score B_2 , y-Axis: probability that score is ≤ B_2 .**
  - **slope ~ Variance, $p_{0,5}$ = Median ⟶ desired: high slope & most left.**

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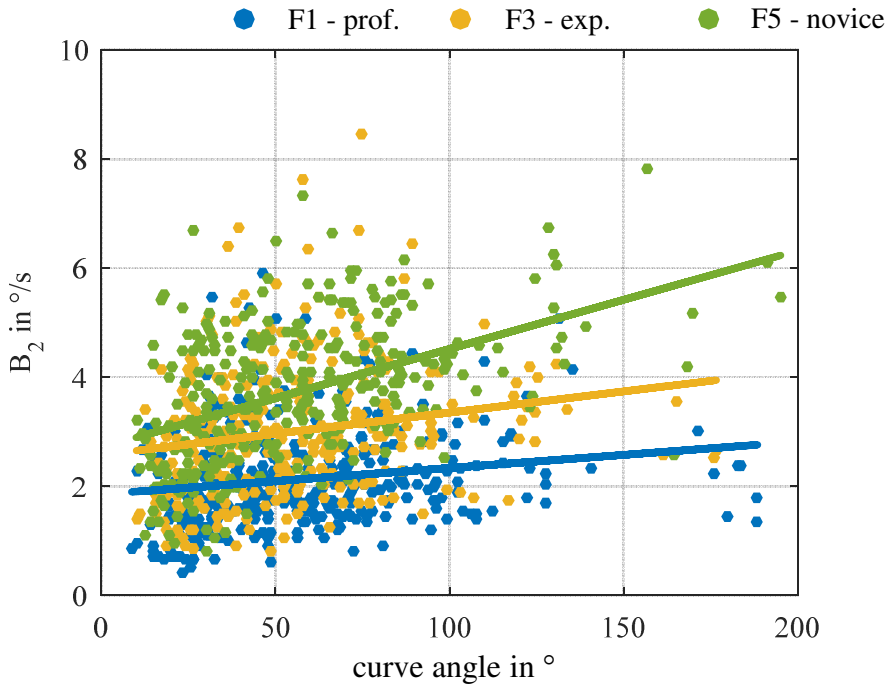
Results

Scatter Plots Curve angle vs. B_2

- **Curve angle: heading change during segment w/o roll-in and roll-out.**



- **stronger dependency of scores for riders with less experience ?**

Preliminary Results

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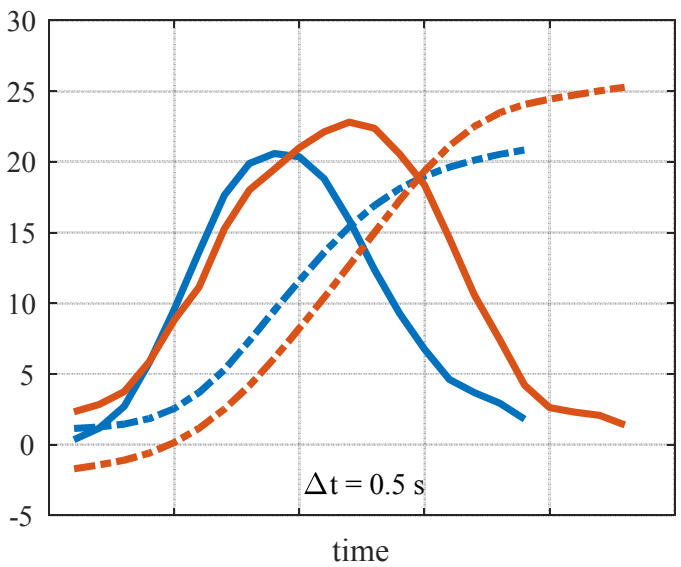
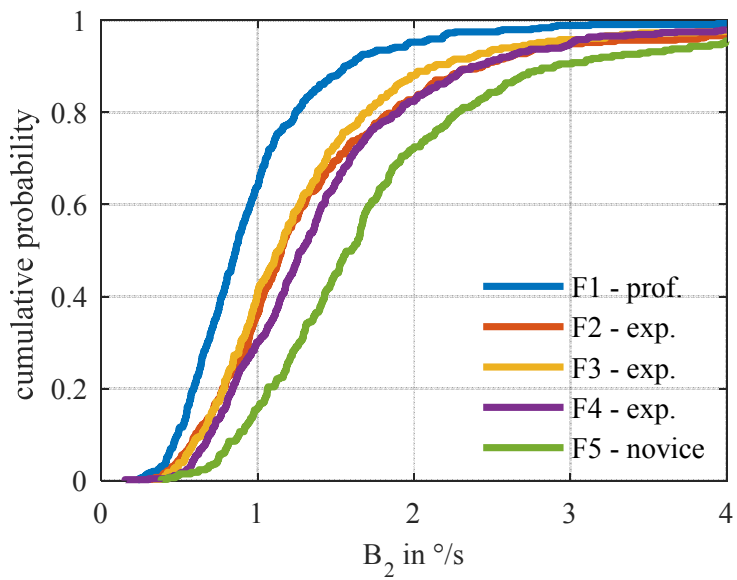
Evaluation of non-stationary cornering segments

- **The roll-in segment is mainly influenced by the steering impulse and the riders' body motion (leaning)**
- **Hypothesis: The shape of the roll rate during roll-in / roll-out segments contains information whether the rider did the correct path planning and applied the right steering action.**



Using a bell curve as shape template



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Conclusion

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Conclusion:

- **We analyze motorcycle rider performance during cornering maneuver based on a segmentation into maneuver primitives which correspond to a certain control behavior.**
- **We showed that a GMM-HMM performs comparable to human visual segmentation by using roll angle and roll rate as input dimension**
- **We introduced a scoring method for stationary cornering segments based solely on roll rate.**
- **The scores can be used to estimate riding experience.**

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Outlook

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Using a shape similarity based classification approach for segments

- **Identify driving errors through distance measure to explicitly predefined riding error templates.**
- **Benefit: Knowledge about what went wrong instead of something went wrong**
  - **e.g.: overshoot the needed roll angle ⟶ approaching lane marks.**

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FZD

INNOVATION DURCH VERSTÄNDNIS

Methodology

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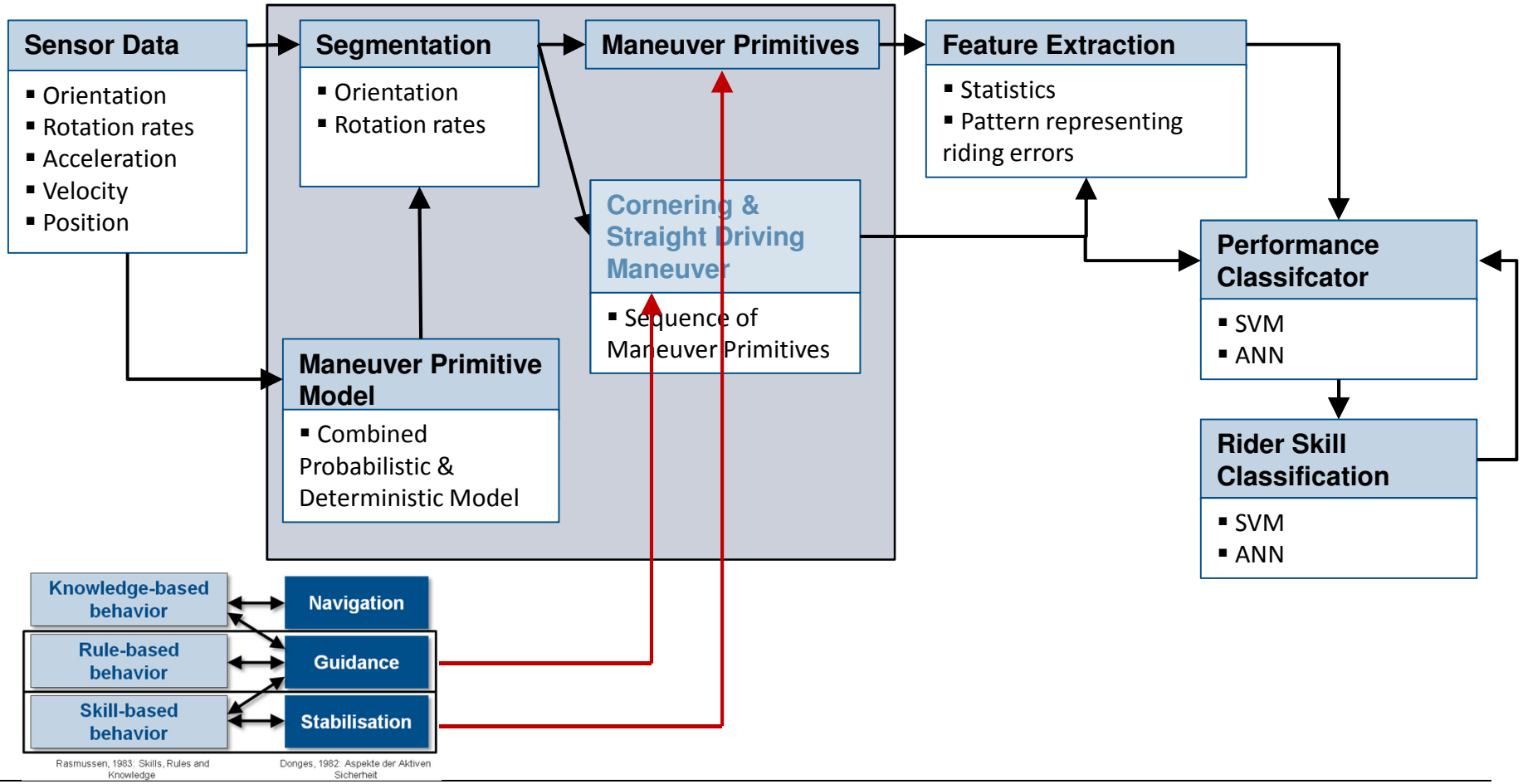
General Concept of Rider Performance Evaluation



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Probabilistic Segmentation Models

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Definition of *Maneuver Primitives (MP)*

Category	ID	Name	No.	Previous ID
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	LI	Roll-in left	7	1
	RL	Roll right to left	8	2,4,5
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- **Sequential Order of Maneuver Primitives !!!**
  - **Modeling as n^{th}-order Markov-Chain possible**

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Segmentation Results

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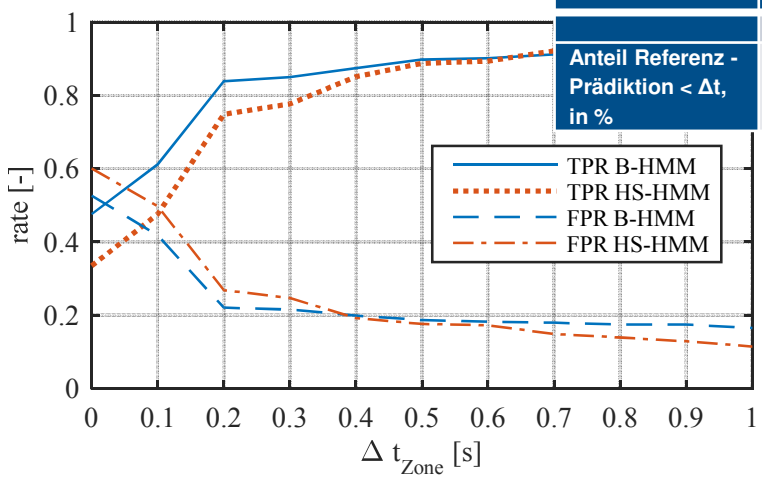
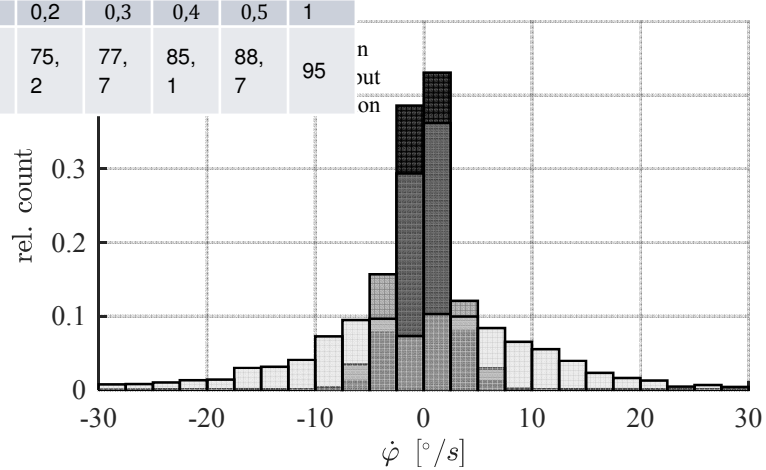
Absolute match rate

	Total	Maneuver primitive specific				
	m	m_1	m_2	m_3	$m_{4\text{-}6}$	$m_{7\text{-}9}$
HS-HMM	**0.886**	**0.945**	**0.864**	**0.909**	0.893	0.889
B-HMM	0,884	0.917	0.805	0.807	**0.960**	**0.941**

State transition points / segmentation points

	Δt in s					
	0,1	0,2	0,3	0,4	0,5	1
Anteil Referenz - Prädiktion < Δt, in %	47,8	75,2	77,7	85,1	88,7	95





- **83% to <u>90 %</u> true positive rate in interval 0.2 – 0.5 second**

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Rider Skill Indicator

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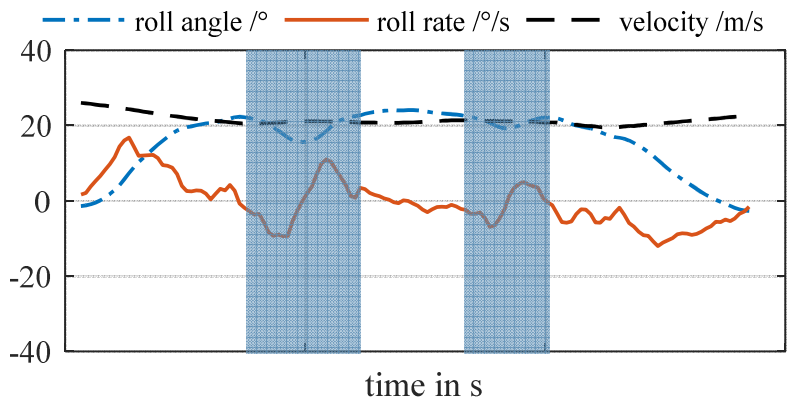
Evaluation of stationary cornering segments

- **Simple cornering maneuvers (roll-in, stationary cornering, roll-out)**
- **Assumptions:**
  - **Road curvature has no sudden changes and oscillations**
  - **High frequency variations of the roll angle result from instabilities (stabilization level) and wrong path planning (guidance level)**
- **Example:**



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Rider Skill Indicator

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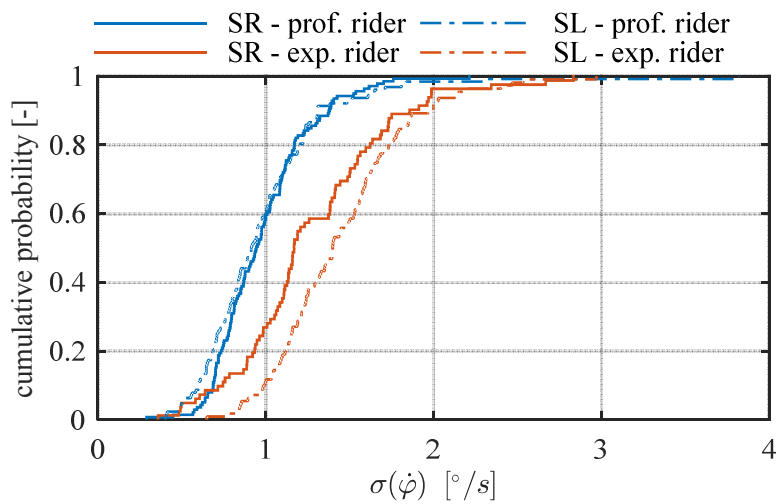
- **Assumptions:**
  - **Road curvature has no sudden changes and oscillations**
  - **High frequency variations of the roll angle result from instabilities (stabilization level) and wrong path planning (guidance level)**
- **Scoring:** $S_{SR,SL} = \sigma(HP(\dot{\varphi}, f_c))$



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State of the Art

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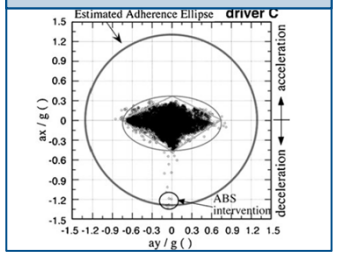
Input	Processing	Output

Sensor Data
- Velocity
- Longitudinal Acc.
- Lateral Acc.
- Rotation rates

Distribution Model



Driver Comfort Limits

Maneuver Detection

Maneuver Score

Explicit Metric

Overall Driver Skill Score

Simulator Data
- Velocity
- Longitudinal Acc.
- Lateral Acc.
- Rotation rates

Feature Extraction

Classificator

Driving Skill Classification

Driving Style Classification

K. Yoneta (2012)
F. Biral (2013), R. Lot (2010)
Y, Zhang (2008,2010), X Tang (2009)
P. Brombacher (2016)

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State of the Art

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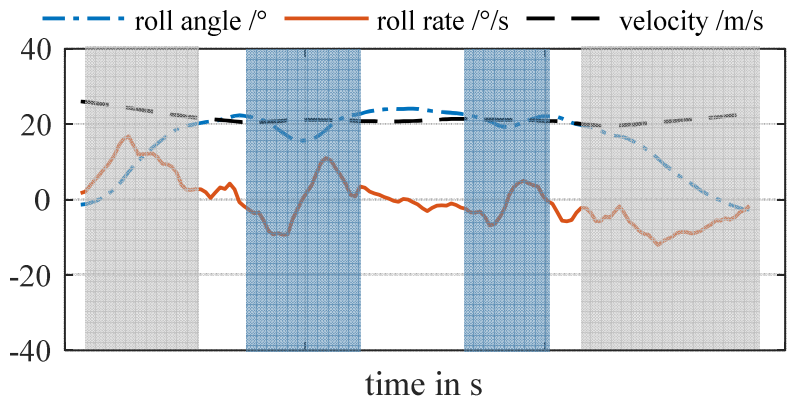
Limitation of State of the Art approaches / applications

- **Rider performance is not analysed in the scenario**
  - **Distribution of roll angle or acceleration reflect risk rather than vehicle control skills [F. Biral (2013), R. Lot (2010); P. Brombacher (2016)]**
- **Methods designed for very specific scenarios → don‘t work in general**
  - **Y. Zhang (2008,2010), X. Tang (2009); K. Yoneta (2012)**

Frequency based approach on maneuver level (only turning)



Problem: Overlapping frequency range from corrective action and turn-in / turn-out

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Segmentation Results

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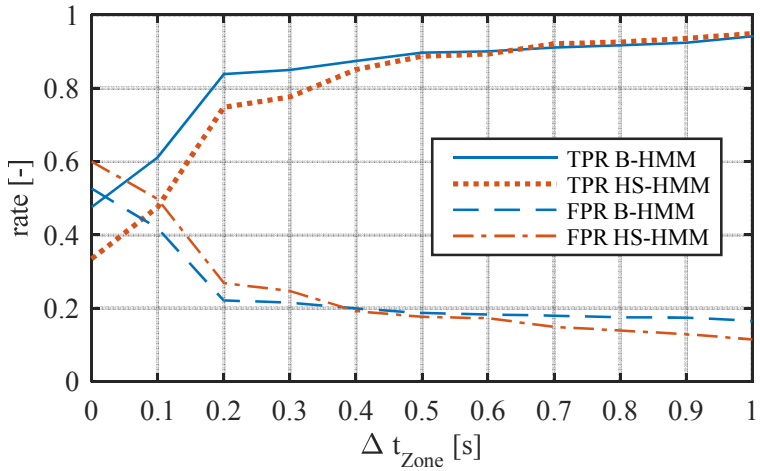
Absolute match rate

- 89 % overall match between prediction and reference annotations
  - Batch-HMM match better for dynamic maneuver primitives
  - HS-HMM match better for stationary maneuver primitives

State transition points / segmentation points



- 83% to <u>90 %</u> true positive rate in interval 0.2 – 0.5 second

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