An Approach for Automatic Riding Skill Identification
Overview about the Methodology and first Results
Overview

Structure:

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

Vehicle

- Sensors
- Motion data

Rider Model
- Use Cases?

Safety Structure

- Safety systems (ABS, TCS, MSC)
- Future ARAS
- Mental workload
- Risk awareness
- Individual knowledge and skills
- Road & environment condition
- Emergency infrastructure (E-Call)
Introduction

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?
State of the Art

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
Segmentation based concept for Rider Skill Identification

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)
Probabilistic Segmentation

Definition of Maneuver Primitives (MP)

<table>
<thead>
<tr>
<th>ID</th>
<th>Name</th>
<th>No.</th>
<th>Previous</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>Straight driving</td>
<td>1</td>
<td>6,9</td>
</tr>
<tr>
<td>SR</td>
<td>Stationary right</td>
<td>2</td>
<td>4,5,8</td>
</tr>
<tr>
<td>SL</td>
<td>Stationary left</td>
<td>3</td>
<td>5,7,8</td>
</tr>
<tr>
<td>RI</td>
<td>Roll-in right</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>LR</td>
<td>Roll left to right</td>
<td>5</td>
<td>3,7,8</td>
</tr>
<tr>
<td>RO</td>
<td>Roll-out right</td>
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<td>3,8</td>
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</tr>
</tbody>
</table>

- Sequential Order of Maneuver Primitives!
Probabilistic Segmentation

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

Observation to hidden states

- Measurements → GMM → Observation Probabilities → HMM → Maneuver Primitives
Probabilistic Segmentation

Results:

- **Algorithm vs. human reference**
  - | Maneuver primitive specific |
  - | Tot. | m | m₁ | m₂ | m₃ | m₄₋₆ | m₇₋₉ |
  - | 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 |
  - | 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 | 0.81 |
  - | Sub.4 | 1 | 0.80 | 0.83 | 0.81 |
  - | Sub.5 | 1 | 0.81 |

Evaluation Criteria:

- **Absolute match rate:**
  \[ m_i = \begin{cases} 
  0 & \text{if } l_{\text{human},i} \neq l_{\text{algorithm},i} \\
  1 & \text{if } l_{\text{human},i} = l_{\text{algorithm},i} 
\end{cases} \]
  \[ m = \frac{1}{n} \sum_{i=1}^{n} m_i \]

- **State transition points**
  - [Graph showing roll-angle and roll-rate with TP and TN transitions]
Rider Skill Indicator

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)
Rider Skill Indicator

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 $\approx$ constant $\approx 0 \rightarrow B_{1\ SR,SL} = \sigma(\dot{\phi}) \approx 0$
  - Problem: Short and very smooth driven curves produce $\sigma(\dot{\phi}) >> 0$
  - roll rate can follow a linear model
  - $B_{2\ SR,SL} = \text{RMSE}(\dot{\phi} - \dot{\phi}_{\text{lin}}) \approx 0$
Rider Skill Indicator

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

<table>
<thead>
<tr>
<th>Rider</th>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
<th>F5</th>
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</thead>
<tbody>
<tr>
<td>category</td>
<td>professional</td>
<td>experienced</td>
<td>experienced</td>
<td>experienced</td>
<td>novice</td>
</tr>
<tr>
<td>Riding experience in km</td>
<td>Test rider of Honda R/D Germany</td>
<td>&gt; 40.000</td>
<td>&gt; 100.000</td>
<td>&gt; 20.000</td>
<td>&lt; 3.000</td>
</tr>
<tr>
<td>Riding experience in years</td>
<td></td>
<td>&gt; 10</td>
<td>&gt; 20</td>
<td>&gt; 5</td>
<td>&lt; 1</td>
</tr>
</tbody>
</table>
Results stationary segments

Cumulative Distribution of $B_2$ in stationary segments SL and SR

- CDF Plot x-Axis: score $B_2$, y-Axis: probability that score is $\leq B_2$.
  - slope $\sim$ Variance, $p_{0.5} = \text{Median} \rightarrow$ desired: high slope & most left.
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

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

![Graph showing roll rate over time for different riders](image-url)
Conclusion

Conclusion:

- We analyze motorcycle rider performance duringcornering 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.
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.
Methodology

General Concept of Rider Performance Evaluation

- **Sensor Data**
  - Orientation
  - Rotation rates
  - Acceleration
  - Velocity
  - Position

- **Segmentation**
  - Orientation
  - Rotation rates

- **Maneuver Primitives**
  - Cornering & Straight Driving Maneuver
  - Sequence of Maneuver Primitives

- **Feature Extraction**
  - Statistics
  - Pattern representing riding errors

- **Performance Classificator**
  - SVM
  - ANN

- **Rider Skill Classification**
  - SVM
  - ANN
### Probabilistic Segmentation Models

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- **Sequential Order of Maneuver Primitives !!!**
- **Modeling as n\textsuperscript{th}-order Markov-Chain possible**
Segmentation Results

Absolute match rate

<table>
<thead>
<tr>
<th>Total</th>
<th>Maneuver primitive specific</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>m</td>
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<tr>
<td>HS-HMM</td>
<td>0.886</td>
</tr>
<tr>
<td>B-HMM</td>
<td>0.884</td>
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</tbody>
</table>

State transition points / segmentation points

- 83% to 90% true positive rate in interval 0.2 – 0.5 second
Rider Skill Indicator

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:
Rider Skill Indicator

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)
- Scoring: \( S_{SR,SL} = \sigma(HP(\phi, f_c)) \)
State of the Art

Input | Processing | Output

<table>
<thead>
<tr>
<th>Sensor Data</th>
<th>Distribution Model</th>
<th>Driver Comfort Limits</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Velocity</td>
<td>• Maneuver Detection</td>
<td>• Manoever Score</td>
</tr>
<tr>
<td>• Longitudinal Acc.</td>
<td>• Maneuver Score</td>
<td>• Explicit Metric</td>
</tr>
<tr>
<td>• Lateral Acc.</td>
<td>• Overall Driver Skill Score</td>
<td></td>
</tr>
<tr>
<td>• Rotation rates</td>
<td></td>
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</tbody>
</table>

<table>
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<tr>
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K. Yoneta (2012)
P. Brombacher (2016)
State of the Art

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

Frequency based approach on maneuver level (only turning)

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

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 90% true positive rate in interval 0.2 – 0.5 second