

Video-Based Roll Angle Estimation for Two-Wheeled Vehicles

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→ Problem statement

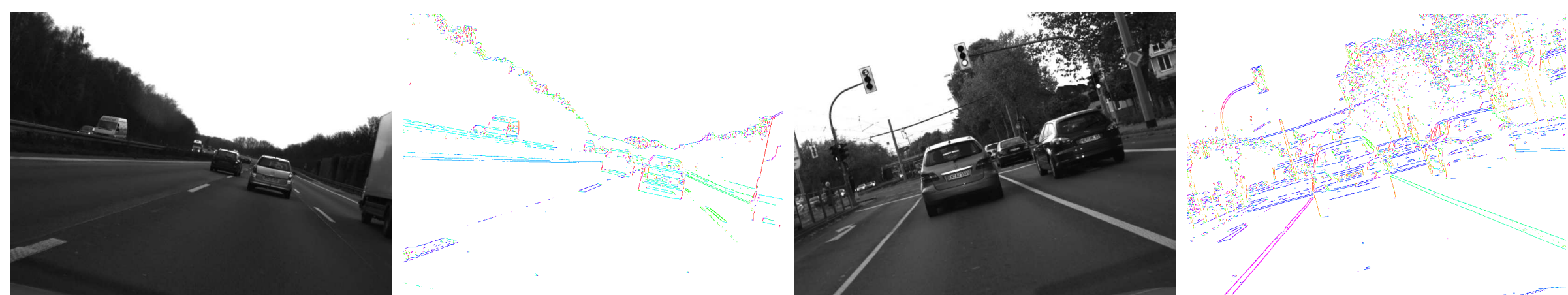
Applications for lane detection, traffic sign recognition, and collision avoidance have been successfully deployed in cars and trucks. State-of-the-art algorithms rely on machine learning and therefore depend on invariance conditions, e.g. a fixed image perspective.

In order to apply current video-based assistance modules in two-wheeled vehicles one needs to determine the roll angle, i.e. the angle between the road plane and the slanted vehicle. It can either be used for parametrisation of the algorithms or for rotation of the video image back to a horizontal alignment. Using an inertial measurement unit to acquire this data is unreasonably expensive.

Estimating the roll angle / rate from video only, would enable us to employ established video-based assistance modules for two-wheeled vehicles without any additional hardware expense.

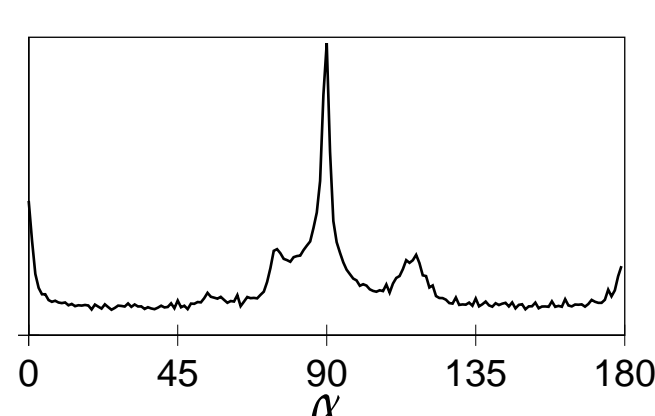
→ Histogram representation

We propose the approach of estimating the roll angle / rate from gradient information of grey-value images only. Looking at road scenes one can find typical compositions and shapes that produce major gradients in the recorded images, e.g. horizon, vehicles, housing, lane borders and markings.



Example images of different scenes and their colour-coded gradient orientations.

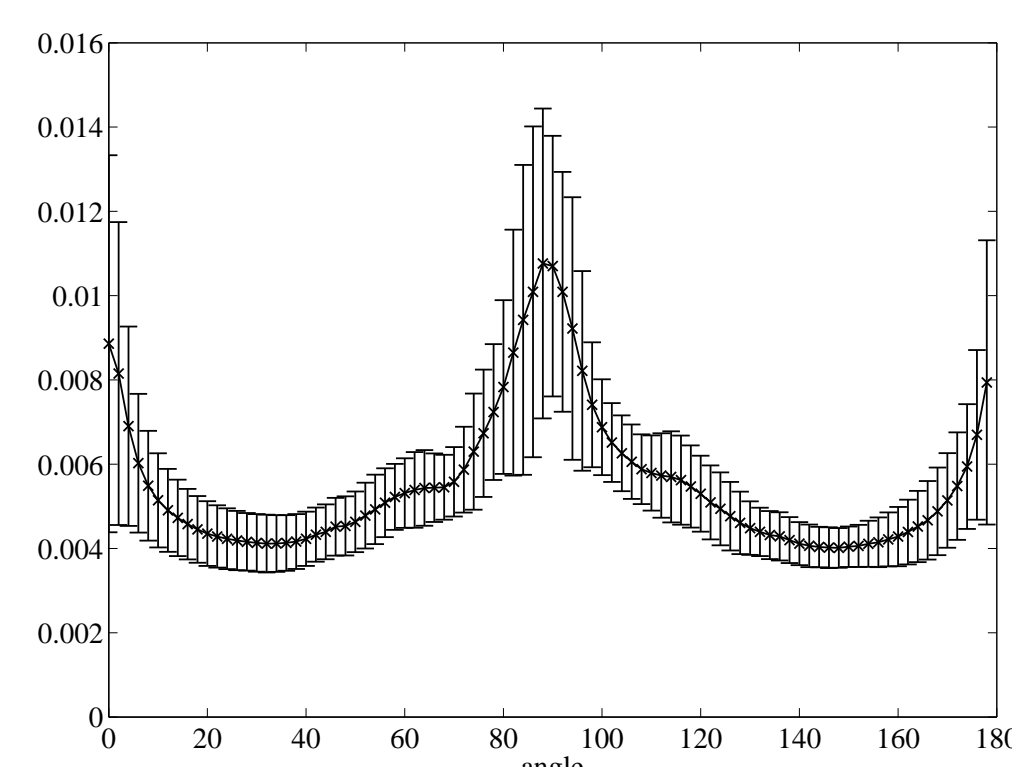
Their orientations result in a characteristic gradient angle histogram, which is similar for most images from a vehicle-mounted camera.

$$h(\alpha) = \frac{\sum_i \begin{cases} \|\vec{g}_i\|, & [\angle(\vec{g}_i)] = \alpha \\ 0, & \text{otherwise} \end{cases}}{\sum_i \|\vec{g}_i\|} \quad \alpha \in \mathbb{N}_0$$


→ Roll angle

Learning statistics from numerous training images enables us to correlate the histogram of a single test image with several translations of the learnt statistics. The current estimate γ_{estim} is the one maximising the auto-correlation measure.

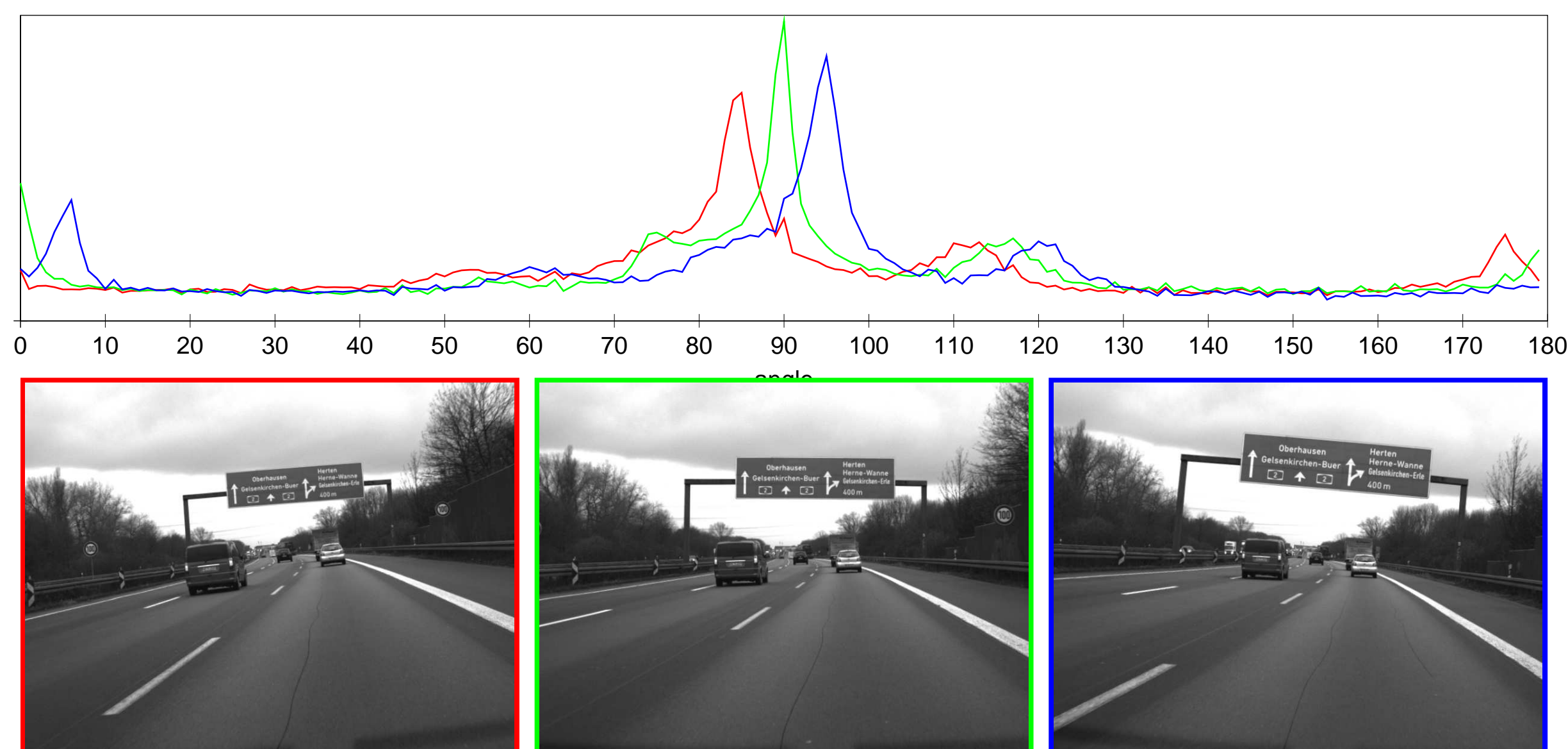
$$\gamma_{\text{estim}} = \arg \max_{\gamma} \sum_{\alpha} \frac{h_{\text{test}}(\alpha + \gamma) - \mu(\alpha)}{\sigma(\alpha)} \quad , \gamma \in [-35^\circ, 35^\circ]$$



Learnt mean and standard deviation for each orientation histogram bin (one degree).

→ Roll rate

In a second step we independently estimate the roll rate γ' , i.e. the roll angle's change per second, by maximising the correlation of orientation histograms from two subsequent images.



$$\gamma'_t = \frac{1}{\Delta t} \arg \max_{\beta} \text{sim}(h_t(\alpha + \beta), h_{t-\Delta t}(\alpha))$$

→ Integration

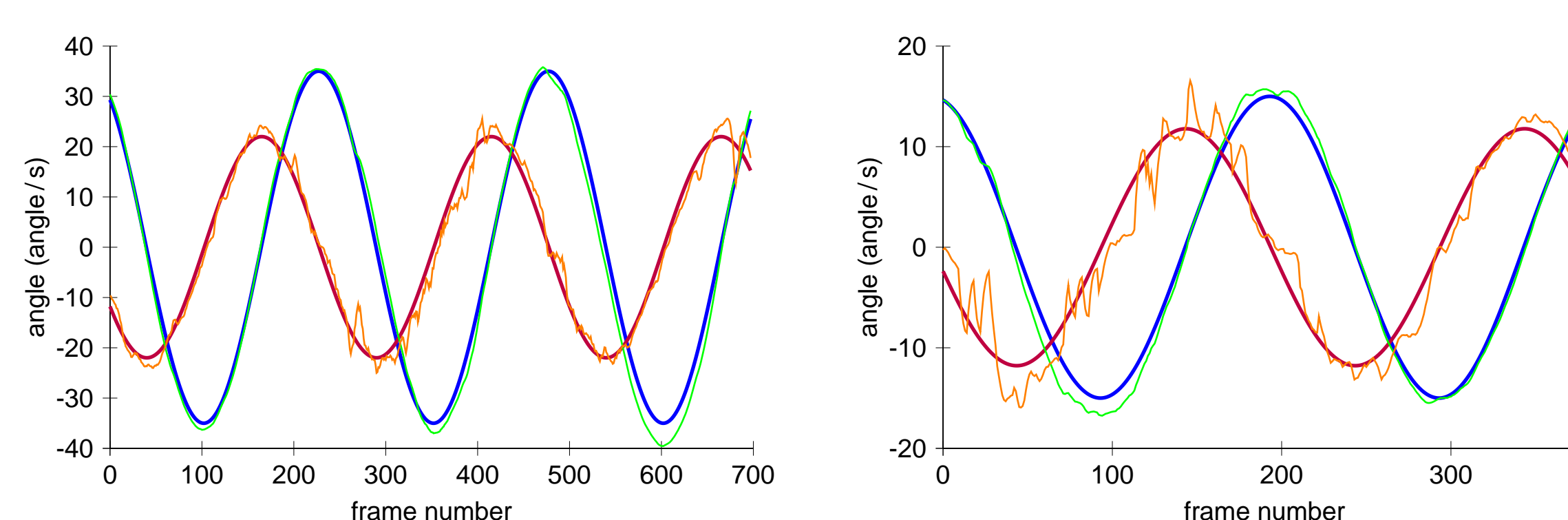
Finally both angle and rate are fed into a linear Kalman filter for robust integration over time. The filter is initialised with physically reasonable dynamics and noise covariances.

→ Experimental results

We performed experiments on real-world video data covering different scenarios. The roll angle was simulated in order to allow for a systematic evaluation with ground-truth data.



Recorded scenarios: Motor way, country road, and urban.



Results from a country road (left) and motor way (right) sequence. Estimated vs. ground-truth angle (green/blue) and rate (orange/purple).

Mean squared errors by road scenarios and correlation methods (normalised cross-correlation, sum-of-absolute-differences, sum-of-weighted-differences):

| Scenario | NCC | SAD | SWD |
|--------------|------|------|------|
| Motor way | 1.82 | 1.96 | 2.47 |
| Country road | 2.40 | 2.47 | 2.43 |
| Urban | 2.12 | 2.04 | 2.41 |
| All | 2.09 | 2.15 | 2.44 |

⇒ Low mean error of about 2 degrees

⇒ Good generalisation behaviour

⇒ Low computational complexity / Fully real-time capable