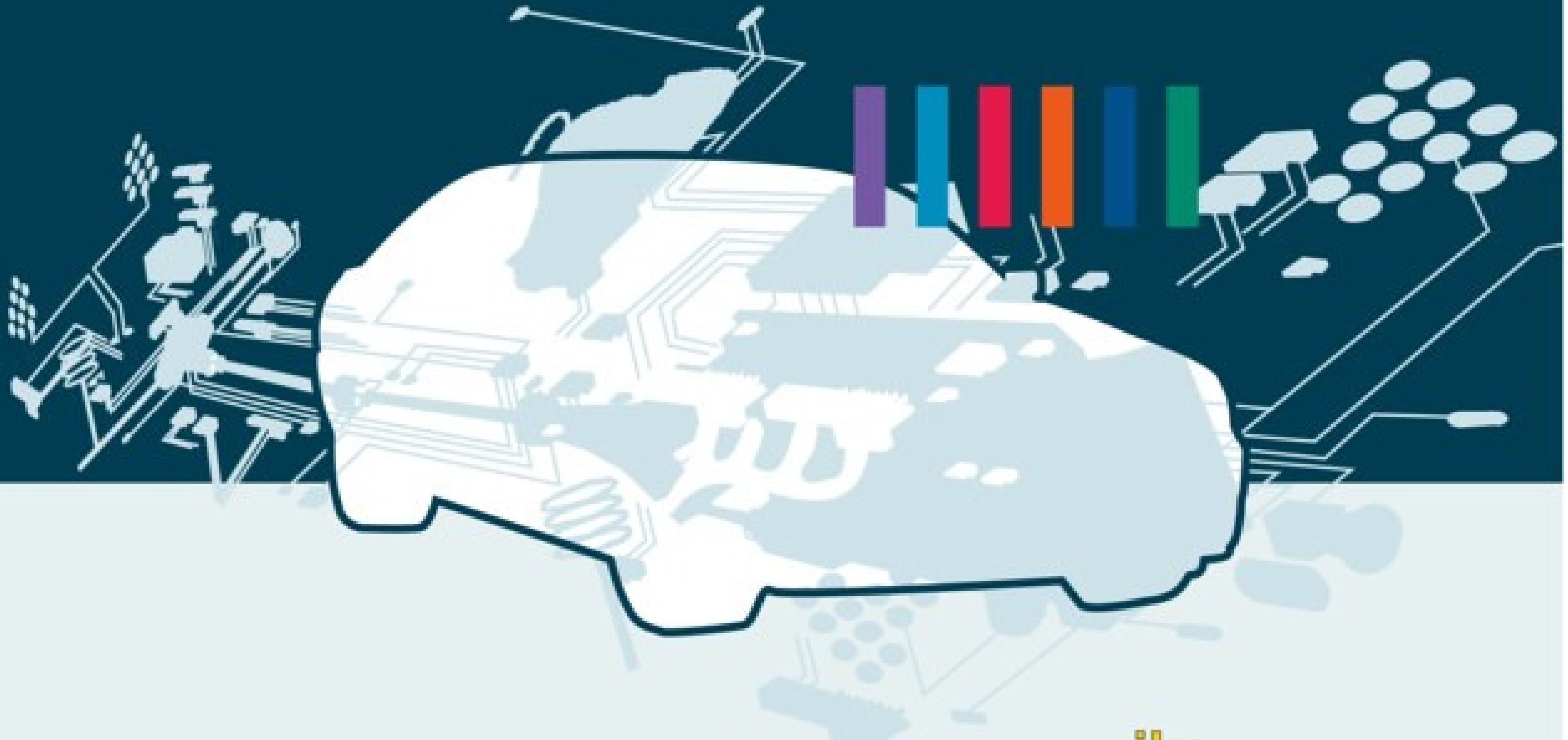
Automobile *verstehen*.



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IQPC Vehicle Dynamics Control

Model Based State Estimation for Vehicle Dynamics Control

Frankfurt, June 12, 2007

Dipl.-Ing. Martin Saeger
Institut für Kraftfahrwesen Aachen - RWTH Aachen

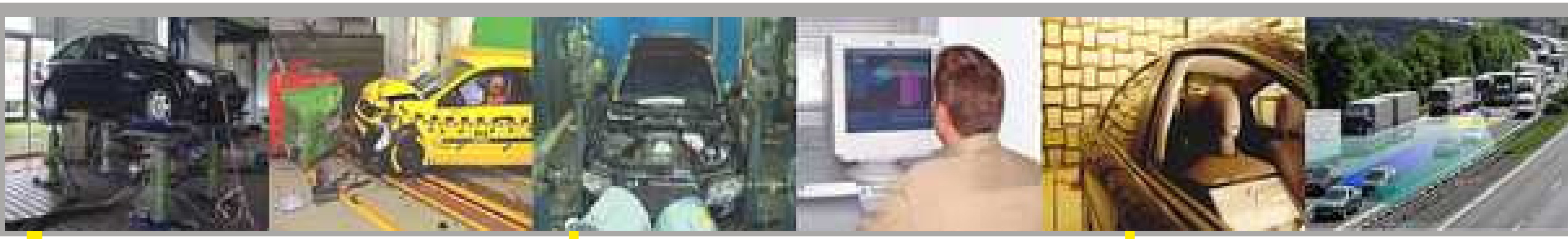
Fields of Competence and Activities of ika / fka

Body
- Passive Sicherheit
- Leichtbau
- Betriebsfestigkeit

Electronics
- Bordnetzentwicklung und Betriebsstrategien
- Mikrocontrollerbasierte Steuergeräte
- Hard- und Softwareentwicklung
- Diagnose

Traffic
- Fahrerassistenzsysteme
- Verkehrssimulation
- Modellierung des Fahrerverhaltens

Strategic Consulting
- Marktanalysen und Trendstudien
- Technologiebewertungen
- Seminare und Tagungen



Chassis
- passive und aktive Fahrwerksysteme
- CAx-Methodenentwicklung
- Funktions- und Reglerentwicklung
- Erprobung und Bewertung
- Reifentechnologie (TiM)

Drivetrain
- Konventionelle und unkonventionelle Antriebe
- Konzept- und Komponentenentwicklung

Acoustics
- Geräusch und Schwingungen
- Antriebstrangschwingungen
- Sound Quality und Psychoakustik

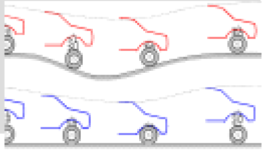
Chassis Departement at ika / fka

Active and Passive Chassis Development

Studies & Concepts
Axle Calculation
Axle System Analysis

Controller and Function Development

Vehicle State Estimation
Control Algorithms
Plausibility Checking

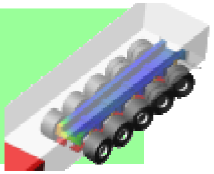


Testing & Assessment

Test Track & Test Benches
Durability Testing
Driver Vehicle Interaction

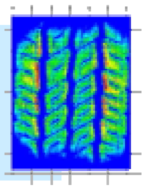
CAx-Method Development

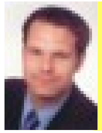
Design & Calculation
Vehicle Dynamics Simulation

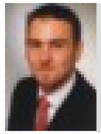


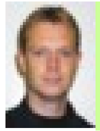
Tyre Technologies (TiM)

Tyre Parameter Fitting
Tyre Sensors

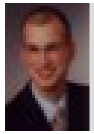


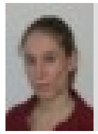

Thomas
Schrüllkamp
Leiter Geschäftsbereich Fahrwerk


Martin
Saeger
Teamleiter
Funktions- und Reglerentwicklung


Mark
Wöhrmann
Teamleiter
CAx-Methodenentwicklung


Ingo
Albers


Jörn
Lützow


Nele
Kennes

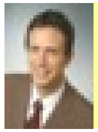

Thomas
Horrmann


Carsten
Hoffmann


Bodo
Kleickmann

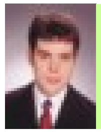

Daniel
Wegener


Christian
Hartweg

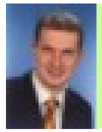

Karsten
Wunram


Matthias
Wilmes


Sebastian
Loos

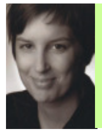

Peter
Rettweiler


Bastian
Schäfer


Christian
Förster


Thomas
Hüsemann


Christian
Bachmann


Susanne
Winter

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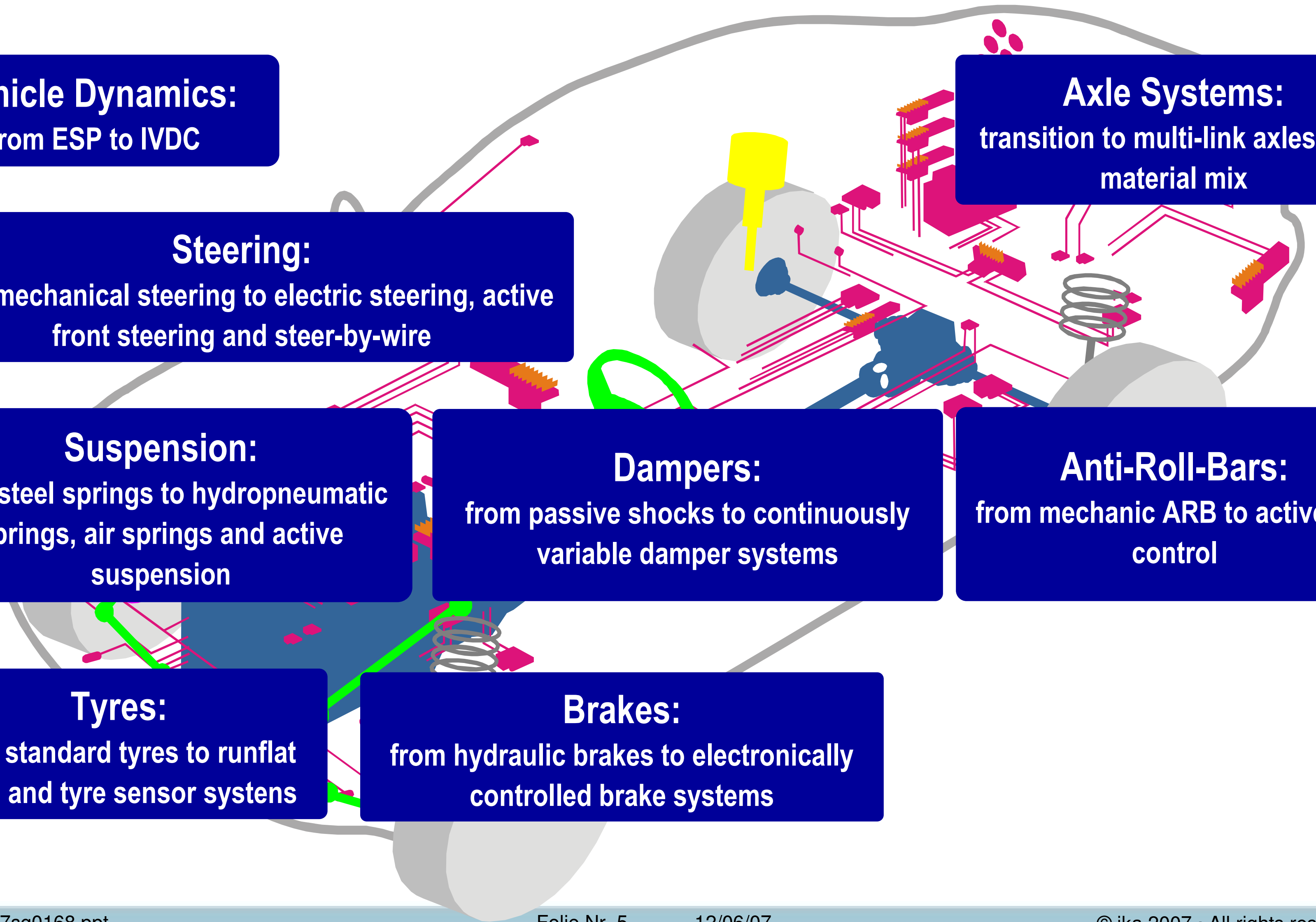
Chassis Department: Activities and Development Fields



Vehicle Dynamics:
from ESP to IVDC

Steering:
from mechanical steering to electric steering, active front steering and steer-by-wire

Suspension:
from steel springs to hydropneumatic springs, air springs and active suspension

Tyres:
from standard tyres to runflat tyres and tyre sensor systens

Dampers:
from passive shocks to continuously variable damper systems

Brakes:
from hydraulic brakes to electronically controlled brake systems

Axle Systems:
transition to multi-link axles and material mix

Anti-Roll-Bars:
from mechanic ARB to active roll control

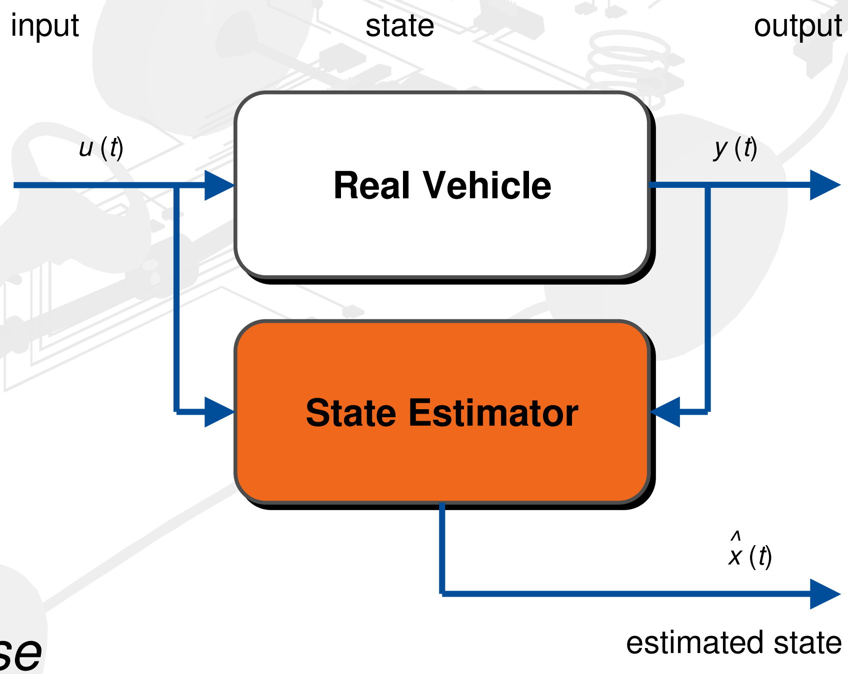
Motivation and Background of State Estimation

- **Direct determination of input signals often not feasible**
  sensors too expensive, relevant data not measurable
- **Necessity to fuse different input signals to one information**
  example: 4 wheel speeds and 1 longitudinal acceleration
- **Integration of measured values**
  - offset and noise cause signal drift
  - low-pass filtering leads to loss of information

utilization of system knowledge:
model based signal processing

Model Based Signal Processing: State Estimation and State Observation

- **Determination of internal state values using system models**
  estimation/observation of a state from input and output data
- **Use of approaches from control engineering**
  state estimators and state observers
- **Observer**
  deterministic design
  e.g., Luenberger observer
- **Estimator**
  stochastisc aproach
  e.g., Kalman filter
  → suitable for measurement noise



The Kalman Filter

- **Stochastic state estimator for dynamic systems**
  first published in 1960 by R. E. Kalman
- **Description of the system in state space**
  additionally considering process and measurement noise
- **Optimal feedback matrix**
  minimal squared error when assuming white noise
- **Application for time-discrete linear systems**
  variants of the filter exist for time-continuous and particularly non-linear systems

Vorhersage ("Predict")

1. *Vorhersage des nächsten Zustands*
   $$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1}$$
2. *Vorhersage der Fehler-Kovarianz*
   $$P_k^- = AP_{k-1}A^T + Q$$

Korrektur ("Correct")

1. *Berechnung der Kalman-Matrix*
   $$K_k = P_k^- C^T (CP_k^- C^T + R)^{-1}$$
2. *Korrektur der Schätzung*
   $$\hat{x}_k = \hat{x}_k^- + K_k(y_k - C\hat{x}_k^-)$$
3. *Korrektur der Fehler-Kovarianz*
   $$P_k = (I - K_k C)P_k^-$$

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State Space Modelling

- **Setting up the system‘s differential equations**
  e.g., equations of motion from Newton-Euler method
- **State space formulation of the model**
  system state x, input values u, output values y

$$\dot{x} = F \cdot x + G \cdot u$$

$$y = C \cdot x + D \cdot u$$

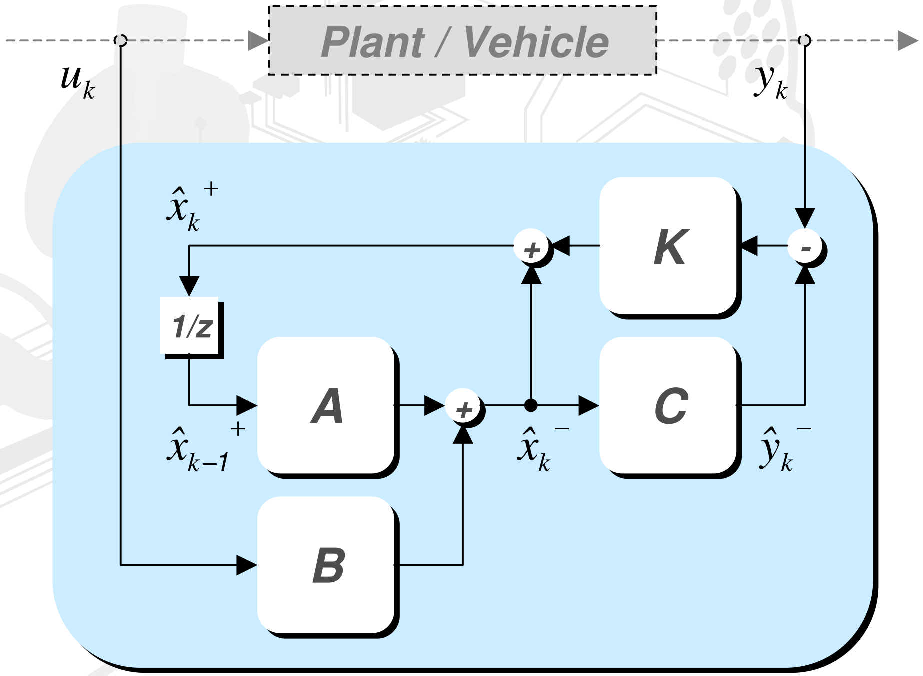
- **Discretising of the model equations in state space**
  assumption of constant gradients and small changes per time interval

$$\hat{x}_{k+1}^{-} = A_k \cdot \hat{x}_k + B_k \cdot u_k$$

$$\hat{y}_k^{-} = C_k \cdot \hat{x}_k^{-} + D_k \cdot u_k$$

Function of a State Estimator

- **Prediction of the state**
  from last state estimate
  and input values
- **Calculation of measurements**
  for the predicted state
- **Comparison of measurements**
  with values measured in reality
- **Calculation of correction vector**
  from residual and K matrix
- **Correction of the state**
  addition of correction vector
  and state vector



Non-linear State Estimation: Extended Kalman Filter and Unscented Kalman Filter

- **Extended Kalman filter: differentiable non-linear systems**
  filter linearizes the system around the current state estimate
- **Differentiation of the system with respect to all state variables**
  - prerequisite: differentiable non-linearities
  - definition of the complete Jacobi matrix necessary

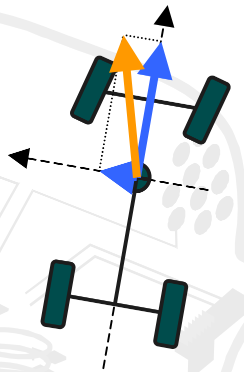
- **Unscented Kalman filter: applicable to any non-linear system**
  - application of the „unscented transformation“ by Julier and Uhlmann
  - relatively new, few applications in automotive engineering
- **Creation of an artificial ensemble of weighted states**
  - given mean and covariance, defined rules for selection
  - calculation of state estimate by weighting from state ensemble
  - calculation of feedback matrix K according to least error squares

General Applications of Kalman Filters

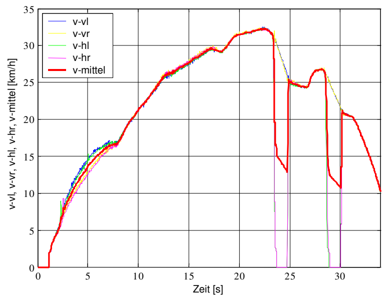
- **Space and aviation (origin of the Kalman filters)**
  e.g., guidance and navigation, auto pilots
- **GPS-based navigation**
  fusion of inertial measurements (accelerations, angular rates) with GPS position data
- **Object tracking**
  radar surveillance, virtual reality systeme
- **Environment detection**
  e.g., in driver assistance systems
- **Weather forecast**
  fusion of different weather measurements and forecasts
- **Economics**
  e.g., estimation/prediction of economic factors

Fields of Application for State Estimation in Vehicle Dynamics Control

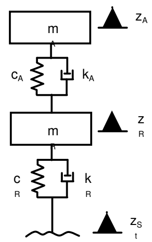
- **Estimation of vehicle sideslip angle**
  - sideslip angle: information of stability
  - optical measurement not feasible for series production
  → various approaches for estimation published



- **Estimation of longitudinal vehicle velocity**
  - wheel speeds contain errors due to slip
  - available: brake pressure, engine torque, a_x
  → determination of reference velocity



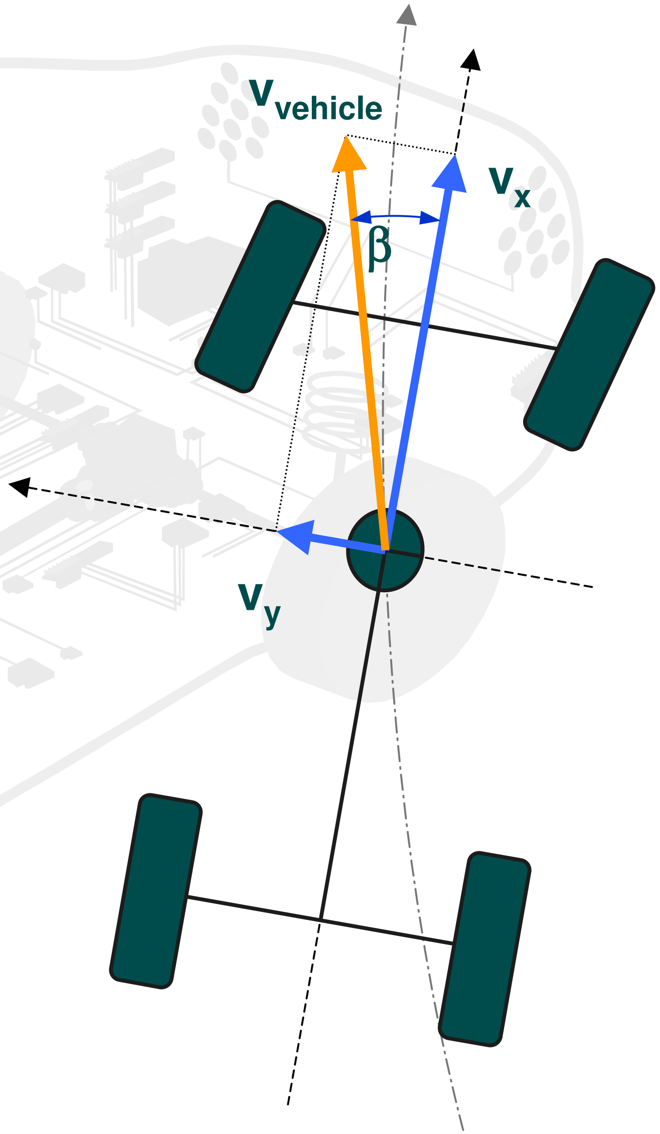
- **Estimation of travel rates in damper control**
  - damper velocity necessary for control
  - measurement of vertical wheel and body accelerations
  → Kalman filter eliminates signal drift



Vehicle Sideslip Angle Estimation

- **Modelling of lateral dynamics**
  e.g., *single-track or two-track vehicle model*
- **Acquisition of input value**
  steering angle
- **Acquisition of output values**
  lateral acceleration, yaw rate
- **Acquisition of variable Parameters**
  e.g., velocity, longitudinal acceleration
- **Estimation of the system state**
  sideslip angle, yaw rate

$$\tan\beta = \frac{v_y}{v_x}$$



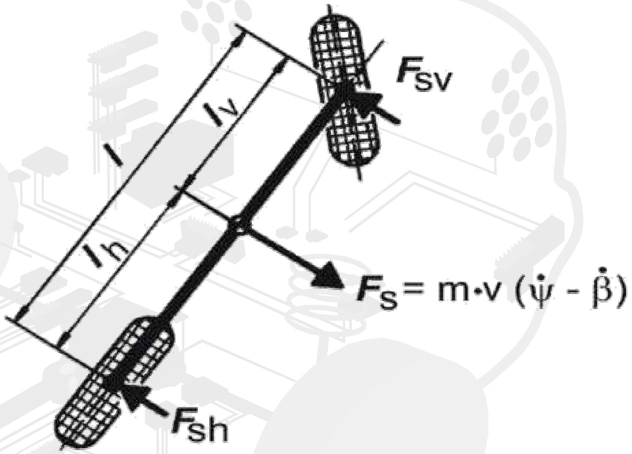
Vehicle Model for Sideslip Angle Estimation: Example Single-Track Model

- **Formulation of differential equations**

$$\dot{\beta} = \left(-\frac{c_{s,v} + c_{s,h}}{m \cdot v} \right) \cdot \beta + \left(-1 - \frac{l_v \cdot c_{s,v} - l_h \cdot c_{s,h}}{m \cdot v^2} \right) \cdot \dot{\psi} + \left(\frac{c_{s,v}}{m \cdot v} \right) \cdot \delta_v$$

$$\ddot{\psi} = \left(\frac{l_h \cdot c_{s,h} - l_v \cdot c_{s,v}}{J_z} \right) \cdot \beta + \left(\frac{-l_v^{\,2} \cdot c_{s,v} - l_h^{\,2} \cdot c_{s,h}}{J_z \cdot v} \right) \cdot \dot{\psi} + \left(\frac{l_v \cdot c_{s,v}}{J_z} \right) \cdot \delta_v$$

$$a_y = \left(-\frac{c_{s,v} + c_{s,h}}{m} \right) \cdot \beta + \left(-\frac{l_v \cdot c_{s,v} - l_h \cdot c_{s,h}}{m \cdot v} \right) \cdot \dot{\psi} + \left(\frac{c_{s,v}}{m} \right) \cdot \delta_v$$



- **State space representation**

$$\dot{x} = A \cdot x + B \cdot u \qquad x = \begin{pmatrix} \beta \\ \dot{\psi} \end{pmatrix} \qquad A = \begin{pmatrix} -\frac{c_{s,v} + c_{s,h}}{m \cdot v} & -1 - \frac{l_v \cdot c_{s,v} - l_h \cdot c_{s,h}}{m \cdot v^2} \\ \frac{l_h \cdot c_{s,h} - l_v \cdot c_{s,v}}{J_z} & \frac{-l_v^{\,2} \cdot c_{s,v} - l_h^{\,2} \cdot c_{s,h}}{J_z \cdot v} \end{pmatrix} \qquad u = \delta_v \qquad B = \begin{pmatrix} \frac{c_{s,v}}{m \cdot v} \\ \frac{l_v \cdot c_{s,v}}{J_z} \end{pmatrix}$$

$$y = C \cdot x + D \cdot u \qquad y = \begin{pmatrix} a_y \\ \dot{\psi} \end{pmatrix} \qquad C = \begin{pmatrix} -\frac{c_{s,v} + c_{s,h}}{m} & -\frac{l_v \cdot c_{s,v} - l_h \cdot c_{s,h}}{m \cdot v} \\ 0 & 1 \end{pmatrix} \qquad D = \begin{pmatrix} \frac{c_{s,v}}{m} \end{pmatrix}$$

- **Discretizing and design of a linear Kalman filter**

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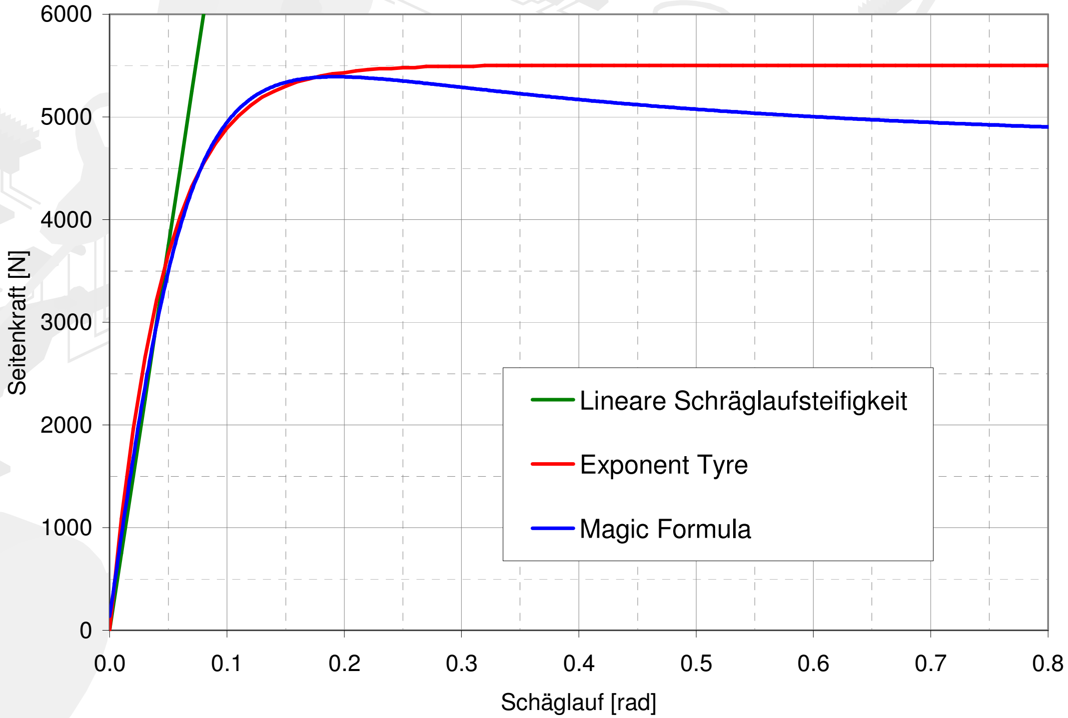
Vehicle Model for Sideslip Angle Estimation: Two-Track Model and Tyre Modelling

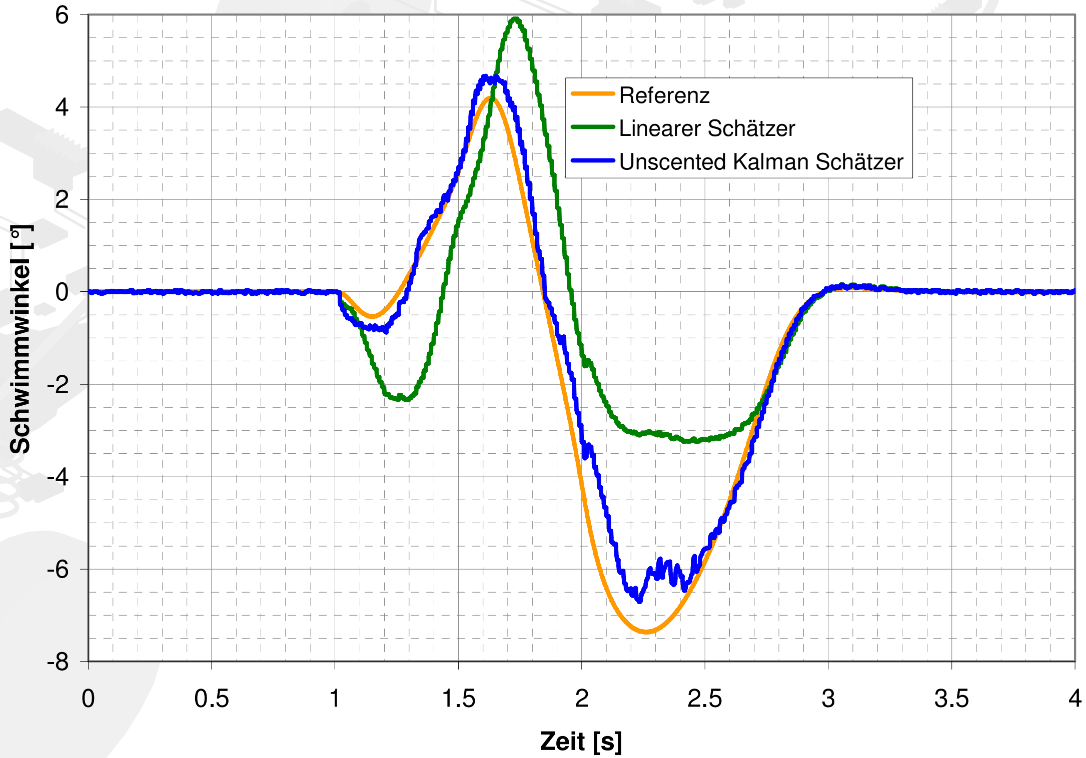
- **Model extension for exact representation of vehicle dynamics**
  - *two-track model: 4 wheels, CoG height, wheel loads*
  - *tyre modelling: non-linear properties*
- **Tyre models**
  - *lateral tyre slip stiffness*
    → linear Kalman filter
  - *exponential tyre model*
    → extended Kalman filter
  - *Pacejka's Magic Formula*
    → Unscented Kalman Filter
- **ika: UKF estimator**
  - *two-track model*
  - *Magic Formula tyres*



Estimation Results: Sideslip Angle

- **Estimation results dependent on tyre and vehicle model**
  linear estimators: sufficient for lower lateral acceleration / dynamics
  nonlinear estimators / complex models: suitable for higher dynamics

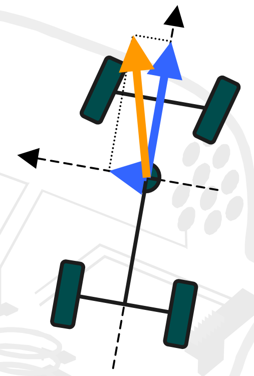
- **Example: Single Sinus**
  transient lateral excitation
  → large tyre and vehicle sideslip angles
  → improved estimation with non-linear model



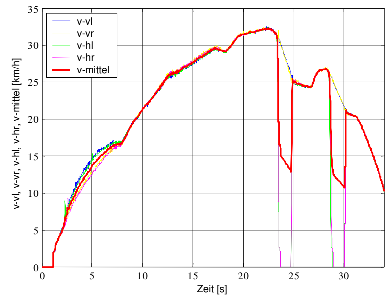
- **Further possibilities**
  estimation of friction,
  road banking,
  tyre forces

Fields of Application for State Estimation in Vehicle Dynamics Control

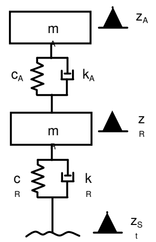
- **Estimation of vehicle sideslip angle**
  - *sideslip angle: information of stability*
  - *optical measurement not feasible for series production*
  - *→ various approaches for estimation published*



- **Estimation of longitudinal vehicle velocity**
  - *wheel speeds contain errors due to slip*
  - *available: brake pressure, engine torque, a_x*
  - *→ determination of reference velocity*



- **Estimation of travel rates in damper control**
  - *damper velocity necessary for control*
  - *measurement of vertical wheel and body accelerations*
  - *→ Kalman filter eliminates signal drift*



Estimation of Longitudinal Velocity

- **Determination of a reference vehicle velocity (e.g., ABS, ESP)**
  „sensor fusion“ of wheel speeds and e.g., longitudinal acceleration
- **Modelling of longitudinal motion**
  simple plant and measurement models

plant: $$\begin{pmatrix} a_x \\ v_x \end{pmatrix}_k = \begin{pmatrix} 1 & 0 \\ t & 1 \end{pmatrix} \begin{pmatrix} a_x \\ v_x \end{pmatrix}_{k-1}$$

measurement: $$\begin{pmatrix} a_x \\ v_{vl} \\ v_{vr} \\ v_{hl} \\ v_{hr} \end{pmatrix}_k = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} a_x \\ v_x \end{pmatrix}_k$$

- **Possibility for improving estimation quality: adaptive filter**
  tuning of process and measurement covariances depending on driving state (e.g., using fuzzy logic)
  → *higher weighting of wheel speeds for low acceleration values*
  (small tyre slip, low quality of acceleration signal)
  → *higher weighting of a_x for acceleration / braking*
  (high tyre slip, better reliability of acceleration signal)

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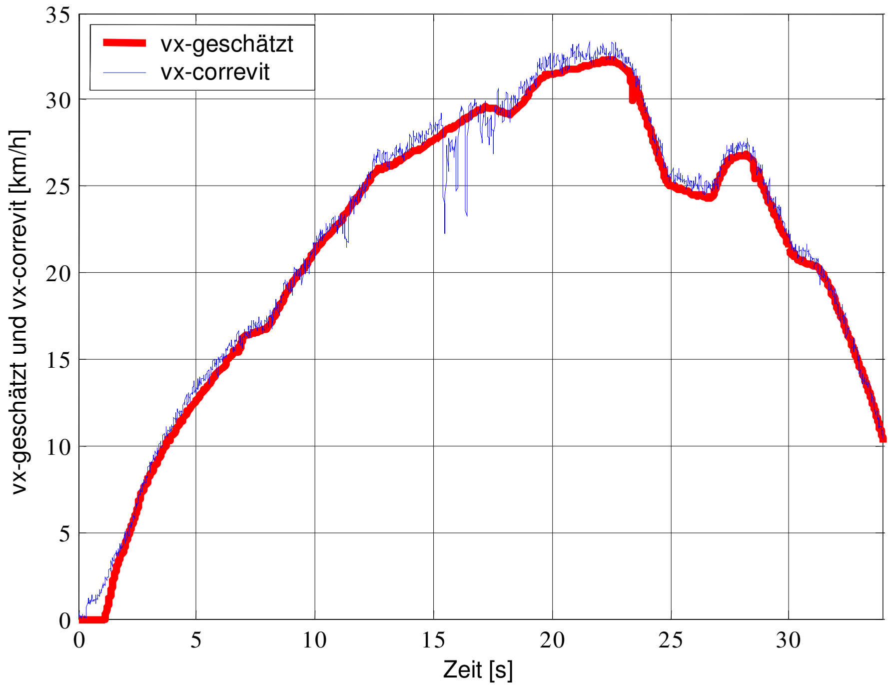
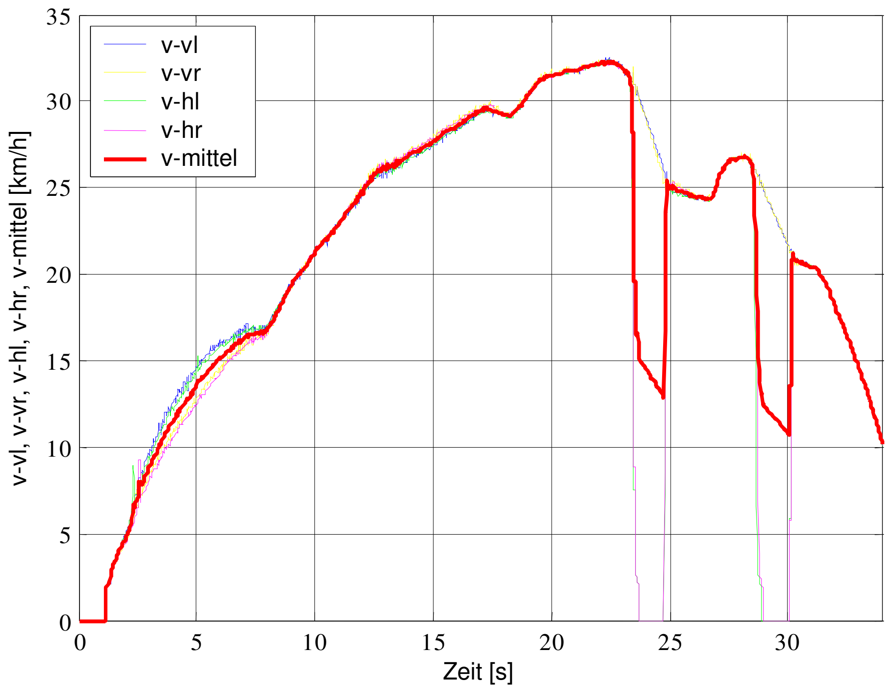
Estimation of Longitudinal Velocity Results

- **Verification in track tests: acceleration / braking on snow**
  comparison of estimate and optical measurement, wheel speeds





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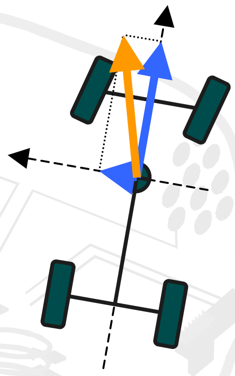
Fields of Application for State Estimation in Vehicle Dynamics Control



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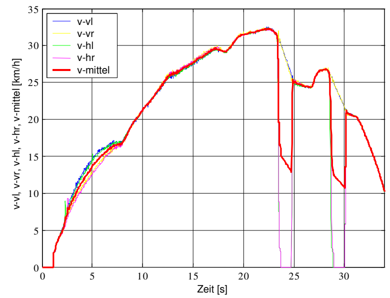

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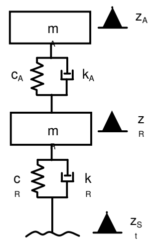

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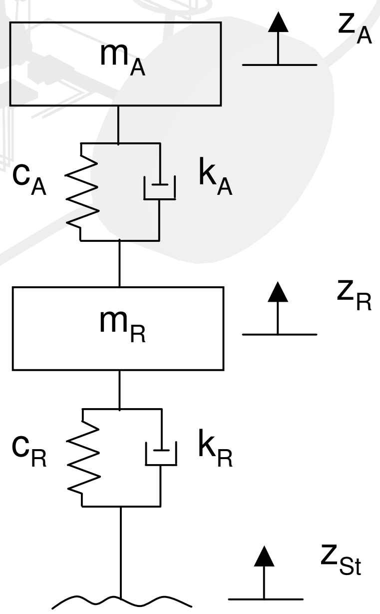
Shock Absorber Velocity Estimation

- **Controllable dampers with proportional valve: v_D required**
  for realisation of force requests from skyhook control
- **Modelling of the suspension as quarter car model**
  state: vertical velocity and position of wheel and body

$$\hat{x} = \begin{pmatrix} z_A \\ \dot{z}_A \\ z_R \\ \dot{z}_R \end{pmatrix} \qquad y = \begin{pmatrix} \ddot{z}_A \\ \ddot{z}_R \end{pmatrix}$$

- **Challenge: input values unknown**
  road excitation to the system
  not available as input data
  → modelling of the quarter car with fixed base point (z_{St} = 0)



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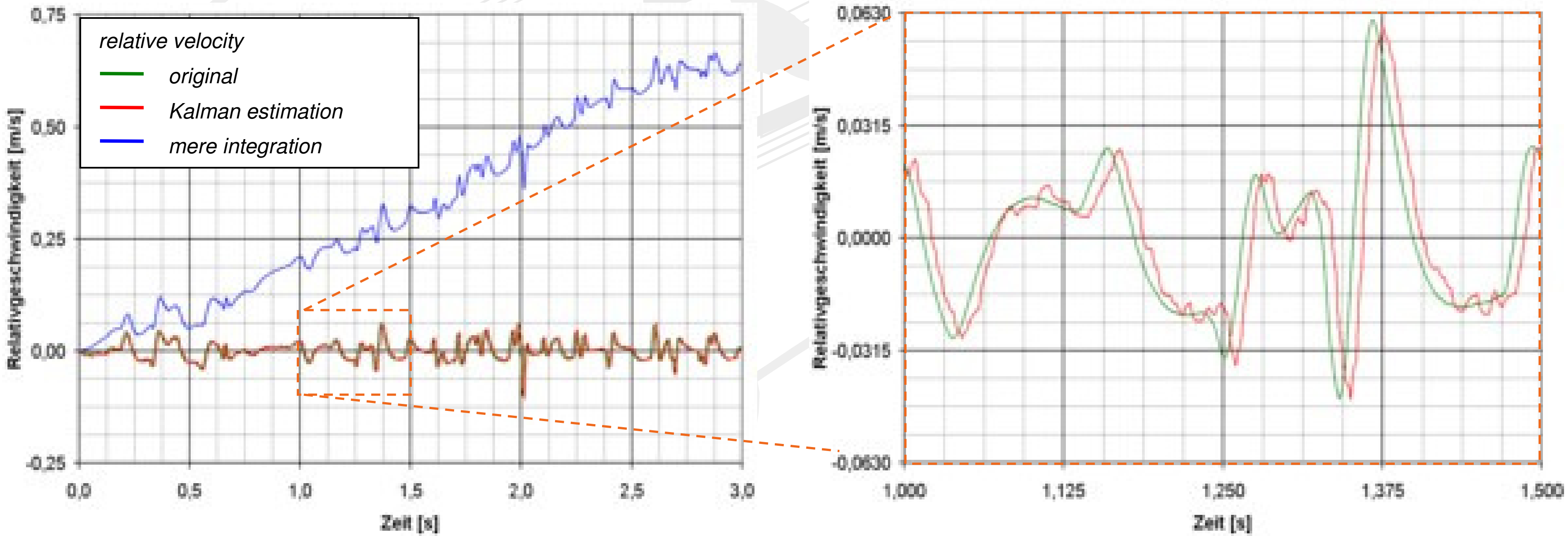
Shock Absorber Velocity Estimation Results

- **Comparison: reference, estimation and mere integration**
  sensor values corrupted with noise, discetising, and quantisation
  → *signal drift is eliminated, time offset due to signal transmission*
- **Exact estimation of damper relative velocity**
  although body and wheel travel are incorrect due to missing excitation



Perspective: State Estimation in Damper Control

ax
ay
3x $a_{z,Aufbau}$
4x $a_{z,Rad}$

State Estimaton
Kalman filter
body dynamics

z_pkt
psi_pkt
theta_pkt
4x z_{Rad}_pkt

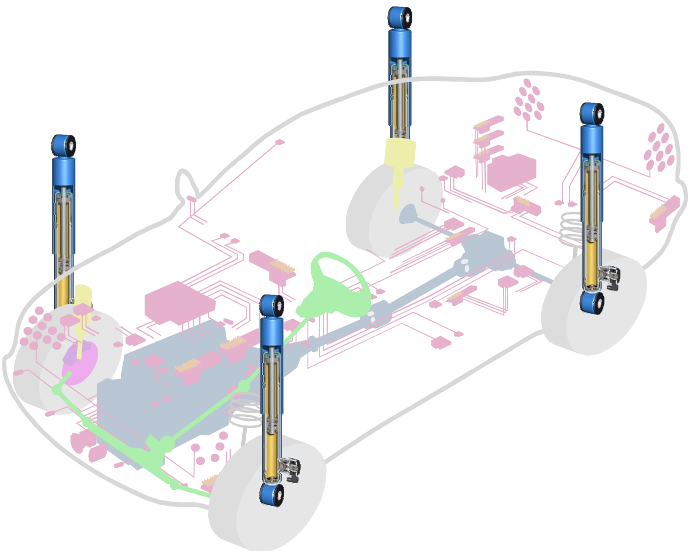
Damper Control
Skyhook algorithm

4x i_{Ventil}

input values vector
sensor signals

estimated state vector
body state of motion

control actions
valve current



Conclusion

- **Growing importance of model based state estimation**
  for different tasks in signal processing in various fields of application
- **Wide spectrum of use in vehicle dynamics control**
  - estimation of states wich cannot be measured
  - stabilizing signal integration
  - fusion of multipe sensor information
- **Development and application of state estimators at ika / fka**
  use of conventional methods and realization of new variants
- **Unscented Kalman filter for vehicle state estimation**
  Realization of a slip angle estimator based on a two-track model with tyres according to Pacejka's Magic Formula
  → improvement particularly in highly dynamic situations

Contact

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