Design of a Robust Adaptive Vehicle Observer Towards Delayed and Missing Vehicle Dynamics Sensor Signals by Usage of Markov Chains

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***Abstract*— As the influence and thereby the facilities for nowadays Vehicle Dynamics Control (VDC) systems increase by the expansion of actuators in vehicles, the measured vehicle dynamics get more and more relevant as they serve as basis for the controller. The common occurrence of delay or temporary absence of sensor signals raises new safety demands in order to guarantee passenger immunity. In this paper a new method for the handling of delayed and missing vehicle dynamics sensor signals by use of Markov Chains is introduced. The performance of this method in combination with a vehicle observer based on Extended Kalman Filter (EKF) technique is validated by simulation. The results are provided to illustrate the performance of this concept. Here the missing and delayed measurements are realized by a binary switching sequence.**

I. INTRODUCTION

Time delay and missing measurements of vehicle dynamics sensors have received much attention in the last years since time delays and stoppage of signal flow exist in every electric vehicle architecture (e.g. the architecture shown in Fig.1). Often these appearances are the cause for instability or performance degradation of the integrated VDC. The occurrence of communication delay [1], [2] and packet loss [3], [4] is as common as it is random. For example the VDC in an electric vehicle equipped with four individually assessable motors might bring the vehicle in an unstable state due to time delay or absence of important sensor signals. As the complexity and influence on vehicle dynamics of VDC in future will increase [5] the issue of handling time delayed and missing vehicle dynamics sensor signals even gets more important. Consequently this raises new requirements for vehicle safety demands. The currently published ISO 26262 [6] specifies guidelines for necessary software safety mechanisms at the software architecture level. In order to come up to the defined correction mechanisms, this paper presents a novel method for handling delayed and missing sensor signals to guarantee the vehicle and passenger safety.
There was a lot of work dealing with the filtering problems for systems with missing measurements during the past years. Yang et al. [1] and Wang et al. [3] have summarized the research results about H_∞ filtering and control for various time-delayed systems with missing and delayed measurements for single sensors in many published literature.

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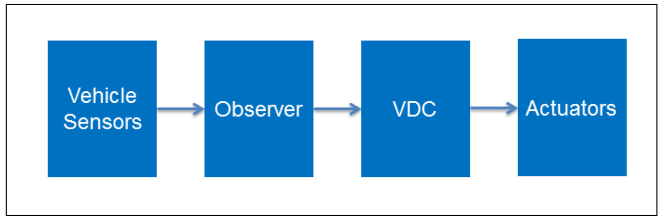

Fig. 1. Signal architecture

Moreover H_2 filtering [7] for multi-sensors in uncertain linear systems and H_∞ filtering concepts [8] for multi-sensors with classes of discrete-time stochastic nonlinear systems have been developed. As the former work of the author is based on the EKF method [9] - and this concept is very suitable for the observation of the nonlinear vehicle dynamics - this method is used here. So far the research for robust kalman filtering techniques was focused on the classic Kalman Filter [10], [11] but not on EKF for the replacement of delayed and missing sensor signals. Up to now either signals were replaced by their last measured values [12], either the output is set to zero [13] or state estimates [14] are used as outputs to the VDC. Actually Kluge et al. [15] analyzed the stochastic stability of EKF with intermittent observations. Unfortunately there is no applicable concept for the replacement of missing and delayed signals that guarantees the correct executing of VDC.
In this paper the use of Markov Chains is proposed to handle delayed and missing sensor signals in order to improve the vehicle state and parameter estimation which is the basic information for the commands of the VDC for the actuators. Here the Markov Chain algorithm was selected since the concept does not make any assumptions about the system behavior in the past and the complexity of the algorithm is still capable for online integration in the vehicle.
The method is tested in simulation within a 14 degree of freedom (DOF) nonlinear vehicle model where the tire forces are calculated with the Pacejka [22]. Similar to [17] and [18] the delays and missing measurements are modeled by Bernoulli distributed white sequences satisfying known conditional probability distributions.
The required basic theory and a descriptive example of Markov Chains is given in section II. In section III the basic approach for the robust filtering is explained. Here the designed vehicle observer is introduced. The dimensioning of the Markov Chains for the replacement of missing and delayed vehicle sensor signals is given in section IV and simulation results from the pure signal replacement and the

overall performance of the vehicle observer in the nonlinear vehicle model are presented in section V. Finally conclusions are given in section VI.

II. MARKOV CHAINS

In this section a general explanation of Markov Chains method is introduced. In 1907 Andrei A. Markov began the study of an important new type of change process. In this process the outcome of a given experiment can affect the outcome of the next experiment. This type of stochastic process is called Markov Chain [19]. The most specific characteristic of Markov Chains is the memorylessness: the next stage depends only on the current state and not on the sequence of events that preceded it. In general, Markov Chains are applicable in discrete and continuous time. As the target hardware is a microcontroller with discrete sample time we focus on the discrete time method.

The assumption for discrete-time Markov Chains is the definition of a limited set of possible states, the bounded state space I. The process starts in one single state $i \in I$ and changes over time. More precisely we assume a finite state space with $I = \{1, 2, \ldots, l\}$ where $l \in \mathbb{N} = \{1, 2, \ldots\}$ is an arbitrary but specified natural number. For every state $i \in I$ the probability α_i that the considered system at instant of time $n = 0$ is in state i is given by:

$$0 \leq \alpha_i \leq 1, \quad with \sum_{i=1}^{l} \alpha_i = 1. \tag{1}$$

The vector $\alpha = (\alpha_1, \ldots, \alpha_l)^T$ of all single probabilities $\alpha_1, \ldots, \alpha_l$ forms the initial distribution of the Markov Chain. Similarly to the initial distribution there is a probability $p_{i,j}$ that the system state changes from state i directly to state j. As this probability exists for every pair of states $i, j \in I$ a l x l matrix can be built. This matrix is called the transition matrix $P = (p_{ij})_{i,j=1,\ldots,l}$ and is given by:

$$p_{ij} \geq 0, \quad with \sum_{j=1}^{l} p_{ij} = 1. \tag{2}$$

For every quantity $I = \{1, 2, \ldots, l\}$ and for every vector $\alpha = (\alpha_1, \ldots, \alpha_l)^T$ there is a respective matrix $P = (p_{ij})$, that fulfills the requirements (1) and (2). The Markov Chain can be defined as follows:

- Unless $X_0, X_1, \ldots : \Omega \rightarrow I$ is a series of stochastic variables that are defined in the same state space (Ω, F, P) and they take their value out of the quantity $I = \{1, 2, \ldots, l\}$.
- Then $X_0, X_1, \ldots$ is called a homogeneous Markov Chain with the initial distribution $\alpha = (\alpha_1, \ldots, \alpha_l)^T$ and the transition matrix $P = (p_{ij})$, if (3) is valid for arbitrary $n = 1, 2, \ldots$ and $i_0, i_1, \ldots, i_n \in I$.

$$\begin{aligned} &P(X_0 = i_0, X_1 = i_1, \ldots, X_n = i_n) \\ &\quad = \alpha_{i_0} p_{i_0 i_1} \cdots p_{i_{n-1} I_n} \end{aligned} \tag{3}$$

Moreover the following points have to be considered:

- A quadratic matrix $P = (p_{ij})$ that fulfills (2) is called stochastic matrix.
- With the following definition the meaning of the intuitive equation (3) is pointed out, especially the notation of initial distribution and transition matrix.

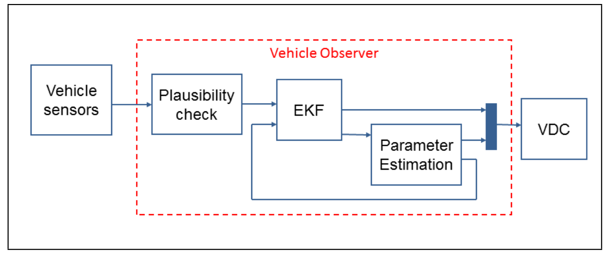

Fig. 2. Structure of the vehicle observer

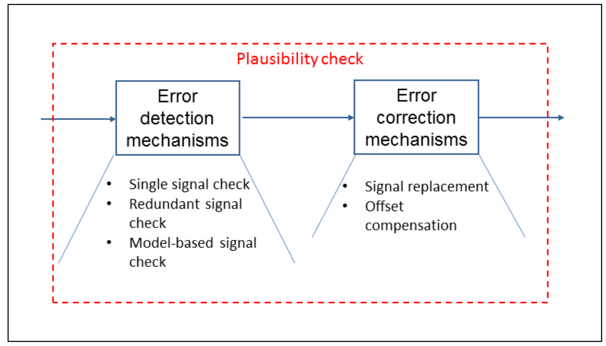

Fig. 3. Structure of the plausibility check

III. BASIC APPROACH FOR ROBUST FILTERING

The Markov Chain algorithm is implemented in the vehicle observer architecture within the plausibility check. In Fig. 2 the different subsystems are displayed.

A. General filtering approach

Here the measured sensor signals are transmitted to the plausibility check first. This subsystem will be explained in detail in the next section. In the EKF subsystem the observation of the vehicle state is executed. In detail the longitudinal and lateral velocity, the longitudinal and lateral acceleration, the yaw rate and the side slip angle of the vehicle are observed. The observation is based on the EKF concept, a nonlinear vehicle model and the usage of the Dugoff tire model [16] to compute the tire forces. In the parameter estimation block, the unknown and variable vehicle parameter mass, road friction coefficient and the effective tire radius are estimated. The estimation has event-seeking characteristic and thus it is robust to noisy measurements. With the feedback of the estimated parameters the equations of the vehicle model in the EKF subsystem are updated. Hence the observation becomes adaptive. More detailed information of the last two subsystems can be found in [9].

B. Plausibility check

As the plausibility check is the first receiver of the sensor signals it has an important role in the complete observer functionality. It verifies the incoming sensor signals and detects faulty or missing signals. The plausibility check can be split in two subsystems of functionality: The error detection mechanisms and the error correction mechanisms (see Fig. 3). The signal error detection mechanism is set out of a single signal check, a redundant signal check and a model-based signal check. The error correction mechanisms include the replacement of signals and an offset compensation during standstill. More information about the plausibility check can be found in [20]. The Markov Chain algorithm, which will be introduced in the next chapter, is integrated in the signal replacement subsystem.

IV. MARKOV CHAINS FOR SIGNAL REPLACEMENT

As the general theory of Markov Chains was introduced in section II, now the specific development of Markov Chains to replace delayed or missing vehicle sensor signals will be explained. First an overview of the build up and functionality is given in subsection A, the calculation of the initial distribution is presented in subsection B and the design of the transition matrices is shown in subsection C. Finally the computation of the state of the Markov Chain is given in subsection D.

A. Build up and functionality

The error correction mechanisms bases on the analysis of the sensor signals by the error detection algorithm. The Markov Chain algorithm will only be executed whenever a sensor signal is detected either as delayed or missing. In order to reduce the computational effort there are several different subsystems containing a specific algorithm of the Markov Chain method. Only one of them will be activated dependent on the information of missing or delayed signal coming from the error detection mechanisms (see Fig. 4). For example the wheel speed subsystem will be enabled whenever the error detection mechanisms detects a delayed or missing wheel speed signal. The signal bus entering the signal replacement subsystem contains the measured sensor signals as well as the results from the error detection mechanisms. Here the Markov chain concept replaces the delayed or missing sensor signals based on the still available sensor signals and the last measured value of the specific signal. The following output signals are transmitted to the shortly presented vehicle observer: the four wheels speeds, the yaw rate, longitudinal and lateral acceleration and the steering angle.

B. Calculation of the initial distribution

The initial distribution for each Markov Chain is based on the last measurement and the current values from the available sensor signals. As the last measurement represents the basis for the initial distribution, the current measurements are taken to estimate the probabilities for the surrounding states. In particular, the initial distribution of the last measured state i is set to 0.5. The remaining 0.5 are allocated by calculating the distributions on basis of the current measurements where every subsystem has its own equation. In general the maximum gradients γ_u for each signal u are compared to the defined interval Δu and thus the number

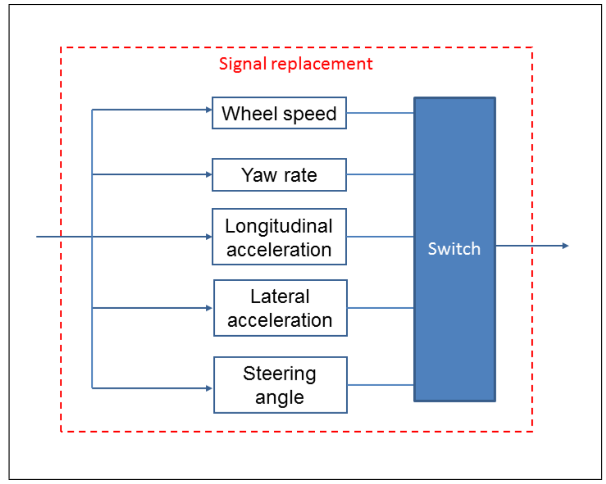

Fig. 4. Structure of signal replacement

of states m that may have a initial distribution greater than zero is calculated by $m = \frac{\gamma_u}{\Delta u}$. The tendency towards which direction of the last measured state the next state will tend is determined by comparison to thresholds for the gradients of the specific measurement. These threshold values were evaluated empirically in simulations with highly dynamical maneuvers and were verified by outcomes of recorded data from real test drives. If the gradients cross this certain threshold, only the distribution of the m states to the left and accordingly right side of the last measured state are upgraded. In case no threshold is crossed, the remaining 0.5 are allocated equally to the $m/2$ entries to each side. The sum to add for each entry is calculated by $d_u = \frac{0.5}{m}$. One example for the remaining initial distribution calculation is given in the following equation for the longitudinal acceleration a_x:

$$u_{a_x} = \begin{cases} (\ldots, 0, u_i, u_{i+1} + d_u, \ldots, u_{i+m} + d_u, 0, \ldots) \\ (\ldots, 0, u_{i-m} + d_u, \ldots, u_{i-1} + d_u, u_i, 0, \ldots) \\ (..., u_{i-m/2} + d_u, ..., u_i + d_u, ..., u_{i+m/2} + d_u, ...) \end{cases}$$

The first row represents the initial distribution in case the gradient of the reconsidered current measurement crosses the positive threshold. In the second row the gradient crosses the negative threshold and in the third row the gradient does not cross the threshold.

C. Design of the transition matrices

The first important task when designing the transition matrices for the Markov Chains is the definition of the bounded state space. As the ranges of the respective sensors are known by their data sheet, the task is to find a good agreement between the wanted accuracy and the restriction of computational effort. In Tab. I the empirical evaluated values for the equally spaced interval Δu, the range given by the data sheet and the arising length of the state space l, which showed good performance, are listed. So each transition matrix P has the size $l \times l$.

Similar to the calculation of the initial distribution, the row entries of the transition matrices are calculated. The most

TABLE I

DISCRETIZATION OF SIGNALS

	Δu	range	l	unit
wheel speed	2.5	250	101	rad/s
yaw rate	0.0175	$\pm$1.750	201	rad/s
long. acc.	0.177	$\pm$17.70	201	m/s^2
lat. acc.	0.177	$\pm$17.70	201	m/s^2
steer. angle	0.0069	$\pm$0.3475	101	rad

important differences are, that the current measurements are not considered and the calculation of the entries is done offline. So the transition matrices are static. The computation for each row j is done with the equation of the third row of the initial distribution. So the entries of the transition matrices are equally distributed.

D. *Computation of Markov Chain state*

Consequently the outputs of the Markov Chains are calculated based on the usage of the online computed initial distribution and the offline calculated transition matrix. As the complete vehicle observer is designed for a sample time of $T_s = 10(ms)$ the equation $uP^{(n)}$ is updated in every execution step. In case of delayed signals this calculation is done for the first power of P and in case of missing signals the power increases with time of signal absence. To reduce the computational effort the row searching is limited to the gradient thresholds. Here the time for replacement of missing signals is bounded to a maximum of $t_{max} = 1\ (s)$. As the safety concept accepts tolerance times of $50(ms)$ to detect false sensor performance the sample time is fast enough to fulfill this requirement.

V. SIMULATION RESULTS

The results are presented in two different ways. First only the signal replacement results for every subsystem are shown in subsection V-A. Afterwards the signal replacement subsystem is implemented in the vehicle observer. The simulation results were created within the complete nonlinear vehicle model and are presented in subsection V-B. The test scenario is for both ways the same. Here the Sine with Dwell scenario was selected since it is a scenario with high vehicle dynamics. In general the driver gives a sinus steering movement but holds the steering angle at its peak after completion of the third quarter-cycle of the sinusoid for $500\ (ms)$. The exact steering input is shown in Fig. 8. The initial speed of the vehicle is $v_{init} = 10\ (m/s)$. Furthermore the driver does not act neither on the acceleration nor on the brake pedal.

A. *Signal replacement*

The simulation was executed for five different missing signal cases as displayed in Fig. 4. Since the replacement of delayed signals is not that critical, only the results for missing signals within a fixed appearing period of $0.5\ (s)$ for the Sine with Dwell driving maneuver are displayed in Fig. 5 - Fig. 8.

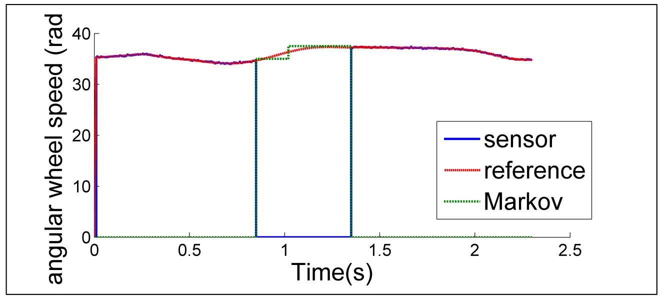

Fig. 5. Signal replacement for wheel speed

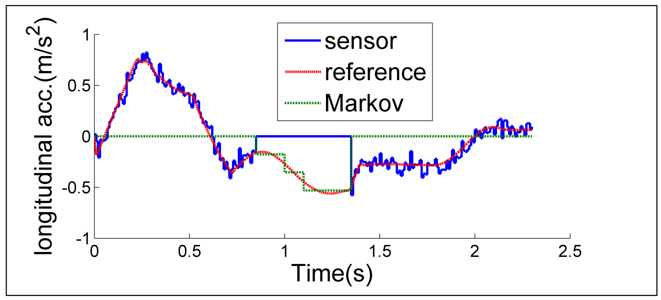

Fig. 6. Signal replacement for longitudinal acceleration

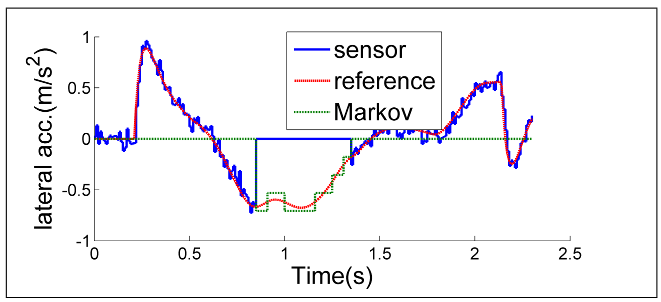

Fig. 7. Signal replacement for lateral acceleration

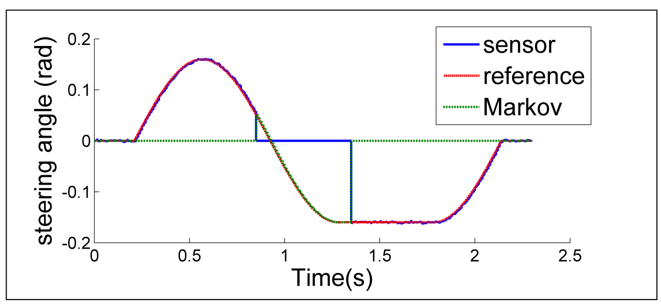

Fig. 8. Signal replacement for steering angle

In all figures the measured sensor signal is plotted with a solid line, the reference signal is plotted with a dashed line and the corresponding Markov Chain state is plotted with a dashed-solid line. During modelling of signal absence the sensor inputs were set to zero for display reasons. Likewise the outputs of the signal replacement block were set to zero when there was a valid sensor signal.

Fig. 5 shows the absence of the angular wheel speed between $t_s = 0.85$ and $t_s = 1.35\ (s)$ of simulation time. The Markov Chain switches state in this period once. The deviation from the reference signal is very small. The missing longitudinal

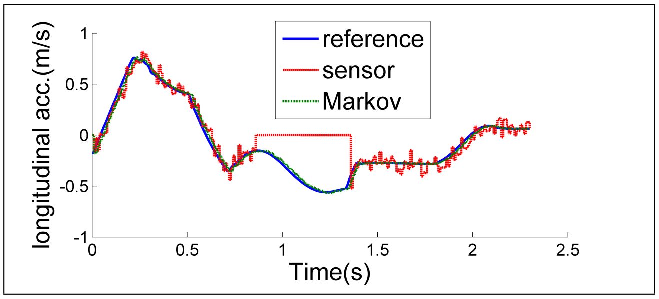

Fig. 9. Observer outputs for long. acceleration

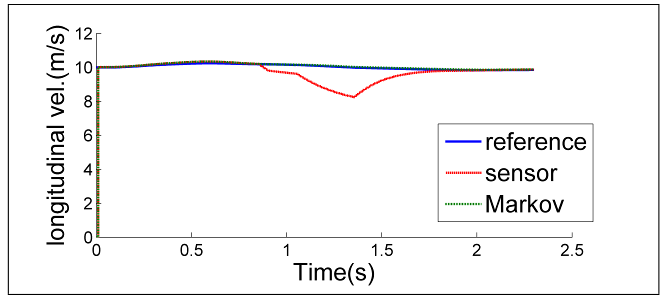

Fig. 10. Observer outputs for long. velocity

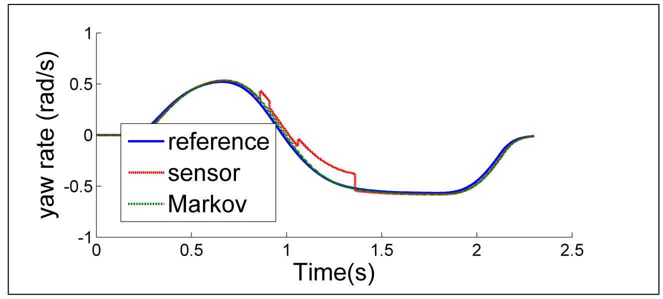

Fig. 11. Observer outputs for yaw rate

acceleration shown in Fig. 6 changes state twice. There is a steady state deviation but this is due to the defined interval Δu. In Fig. 7 the Markov state stays close to the reference signal by switching state five times. But since the lateral acceleration is a very important state for the control of the lateral dynamics, a higher accuracy would be a more beneficial for the VDC. The results for the missing steering angle are shown in Fig.8. Here the deviation between the reference and the Markov signal is very small. The state within the period of sensor signal absence switches many times.

B. Performance within the vehicle observer

The simulation results were created with a nonlinear 14 DOF vehicle model. This model uses six DOF for the movement in space of the Center of Gravity (CoG). Four degrees are used for the vertical movement from the wheels to the chassis which depends on the suspension characteristics. The remaining four degrees are related to the rotational movement of the vehicle wheels. The model is calibrated with real measurement data to represent the eFuture Prototype [21]. As the display of all observer outputs and possible signal absent would cross the limits of this paper, results for the most affected signals for two different missing cases of sensor signals are presented. In chapter V-B.1 the longitudinal acceleration is absence whereas the information of the front left wheel speed is missing in section V-B.2. As in subsection V-A the period of the sensor absence is set to $0.5(s)$ between simulation time $t_s = 0.85\ (s)$ and $t_s = 1.35\ (s)$. Finally the method to analyze the vehicle observer outputs is introduced in subsection V-B.3.

1) Absence of long. acceleration: In case of an absence of the longitudinal acceleration only the longitudinal acceleration output of the vehicle observer is significantly affected. In Fig. 9 the reference signal is plotted with a solid line, the original sensor signal is plotted with a dashed line and the Markov replaced signal is plotted with dashed-pointed line style. It can be seen that the signal replacement during the period of signal absence is close the reference signal. Moreover this replaced signal has even lower deviation from the reference signal then the original signal during normal performance of the sensor.

2) Absence of one wheel speed: In case of missing information about the front left wheel speed the longitudinal velocity, the yaw rate and the side slip angle of the vehicle observer outputs are affected.

In Fig. 10 the longitudinal velocity of the vehicle is displayed. The signals and the line styles are the same as in the previous figure. While the deviation of the replaced sensor signal of the Markov algorithm remains very small the observer output to the reference signal is high. Moreover the period of signal deviation is longer than the signal absence of $0.5\ (s)$ since the algorithm of the vehicle observer needs some adaption time when receiving the sensor signal again.

The yaw rate of the vehicle can be seen in Fig. 11. The deviation of the observer with sensor signal replaced with Markov algorithm is very small. In contrast the deviation of the observer output performing with the sensor signal is temporarily quite high with a relative deviation of almost 50%. When the sensor signal is available again at simulation time $t_s = 1.35\ (s)$ the accuracy of the observer output increases immediatly.

In Fig. 12 the side slip angle of the vehicle is shown. The deviation of the output signal from the reference signal is small during the absence of sensor signal. Furthermore it does not last as long as the period during which the sensor signal is not available. But this might cause huge differences in the ADAS control commands because the side slip angle is one of the most important vehicle states that indicates the vehicle stability. The observer performance with the signal replaced with the Markov algorithm shows good accuracy when compared to the reference signal.

3) Analysis of observation accuracy: As the figures of the different vehicle states are not specific enough for the analysis of the vehicle observer accuracy, the computation of the Root Mean Square Error (RMSE) is inserted. In general the RMSE of a data series is just one value. This method was extended by a sliding window so that the accuracy can be

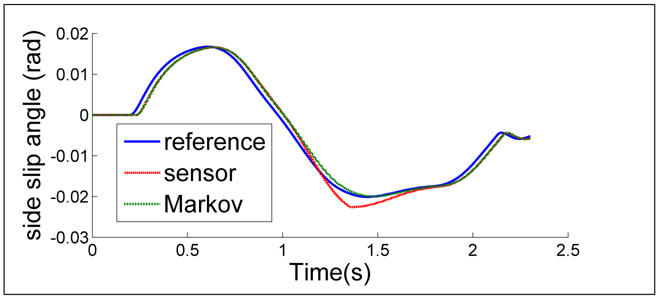

Fig. 12. Observer outputs for side slip angle

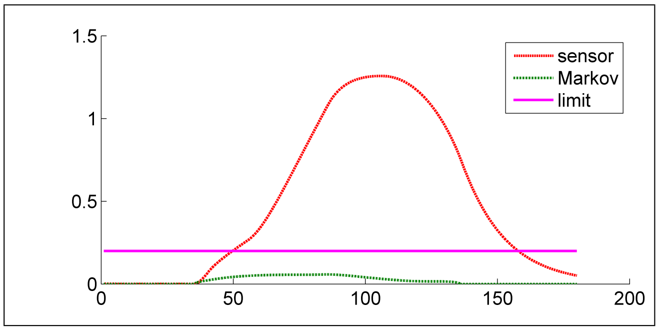

Fig. 13. RMSE error of the longitudinal velocity

analyzed at different moments during the process. Here the length of the sliding horizon was set to $t_{slide} = 0.5(s)$. With a sample time $T_s = 0.01$ (s) the latest 50 values are taken into account to compute the current $RMSE_i$. The equation is given by:

$$RMSE_i = \sqrt{\frac{1}{\Delta T} \sum_{t_i}^{t_i+\Delta T} (x_t - \hat{x}_t)^2}. \tag{4}$$

Where ΔT is the horizon length, t_i is the current simulation time, x_t is the reference value and $\hat{x}_t$ is the observed value. In Fig. 13 the development of the RMSE for the longitudinal velocity in case V-B.2 is shown. The defined limit for the RMSE is plotted with a solid line, the RMSE of the sensor signal is plotted with a dashed line and the Markov RMSE is plotted with a dashed-dot line. Where the RMSE with the replaced sensor signal remains under the limit, the RMSE with the sensor signal exceeds the limit for most of the time.

VI. CONCLUSIONS

The signal replacement shows good performance in the replacement of the wheel speed, yaw rate and steering angle. The replacement of lateral acceleration and longitudinal acceleration is satisfying but shows optimization potential. The overall performance of the vehicle observer with implemented Markov Chain signal replacement algorithm was simulated in many different driving scenarios. Here the improvement to missing or delayed sensor signals was proven. This ensures the correct working of the VDC that guarantees passenger and vehicle safety even in critical driving situations with high dynamics. In the future working on the variable choice for state space intervals promises to enhance the accuracy of the signal replacement. Moreover the concept of signal replacement works even for a single signal absence or delay. Thus this method will be extended towards the replacement of multi-sensor delay or stoppage of signal flow. Finally the algorithm will be flashed to hardware on a prototype in order to validate the simulation results in a real environment.

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