SELF-LEARNING DISTURBANCE COMPENSATION FOR ACTIVE SUSPENSION SYSTEMS

Eckehard Münch, Henner Vöcking, Thorsten Hestermeyer
University of Paderborn
Pohlweg 98, D - 33098 Paderborn

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Abstract: Ride comfort and safety of vehicles can be increased by active suspension systems. A problem is the detection of disturbances which can generally not be measured until they impact the chassis. Provided guidance and disturbance are known in advance, a controller can use this information to achieve considerably improved behavior. This paper presents an approach in which railway vehicles coupled in a network, in repeated runs over the same track section, learn a disturbance compensation that can almost entirely compensate for stationary disturbances, i.e., disturbances that occur at the same spot in equal measure. Here information on the respective track section is sampled, stored locally at the track, and retrieved by the succeeding vehicle which will use them for an improved compensation for the occurring disturbances and again store information there. This iterative procedure results in an optimal compensation.

The algorithm is described and criteria for its design are derived from digital control theory. The procedure was implemented on a testbed for a semi-vehicle with three degrees of freedom. The results of the measurements are displayed and evaluated in this paper.

1 INTRODUCTION

Today, active suspension systems are well established in theory and practice. This holds especially true for automotive applications. When looking at the railway industry, vehicles with active suspension are available, but these systems usually focus on tilt and centering of the coach body rather than on ride comfort. However - even if rare - , there has also been some work on active damping in industry (Streiter et al., 2001) and public research. This work uses as application example the system setup of the railway system ”Neue Bahntechnik Paderborn”, which is explained in more detail in section 2.

Most of the vast number of literature on the control of active suspension systems focuses on single vehicles. Collaborative vehicle networks, however, offer a promising way to improve ride comfort even further: This paper shows, that it is possible to reduce the body motion by a great extent by using the experience gained by other vehicles. In order to do so, two things are necessary: First, an algorithm is required, that determines information about the track excitation and uses this in the control algorithm of the active suspension. Second, a collaborative network with communication infrastructure has to be set up. This paper focuses on the first step.

The paper is structured as follows:
Section 2 presents the basic idea for the overall system setup in the collaborative vehicle network. With this setup in mind, section 3 describes an example suspension system and the control structure including a learning algorithm. Section 4 develops this learning algorithm. In order to show the applicability of the algorithm and its benefits, the system was implemented on a suspension test rick described in section 5. Section 6 discusses the results. The paper concludes with an outlook in section 7.

2 PREVIEW SYSTEMS FOR ACTIVE SUSPENSIONS

When designing an active suspension it is important to put special care on the employed sensor concept and the control strategy as both play a mayor role in the success of the system. One important aspect became clear already with first realizations of active suspension systems: Disturbance compensation using

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information about the ground excitation can improve the ride comfort considerably. (Jäker, 1990) e.g. used a disturbance compensator as part of the control law for the active suspension in an off-road truck with great success[1].

The way in which the ground excitation is determined has significant influence on the compensation result. Due to actuator dynamics it is vital to know the ground excitation as early as possible. In the optimal case the excitation is known before it actually hits a wheel. This is known as ”preview”. Preview information for the rear wheels can be gained by using information from the front wheels (so called ”internal preview”). This is quite a convenient way for disturbance compensation in trains, where the locomotive can collect track information and transfer it to the carriages. In short vehicles like cars however, the influence of the front wheels on comfort is very high and internal preview provides only small benefit (Rutz, 1987). Preview information for the front wheels would therefore help to improve ride comfort even more. Unfortunately, looking at a single vehicle, collecting preview information for the front wheels is an arduous and costly business. [2] A much simpler way to obtain the desired information can be found for vehicles integrated in a network. (Ioannou, 1998) proposes such an infrastructure supported network for highway vehicles. This paper focuses on the railway system ”Neue Bahntechnik Paderborn” (NBP) (Hestermeyer, 2003), which supplies a perfect infrastructure for the new preview system presented here:

The railway system NBP features small autonomous railway vehicles of van size with a fully-active suspension system. The shuttles are propelled by a double- fed asynchronous linear motor. For the implementation of the motor, the track is divided into sectors, which are equipped with their own computer hardware. The creation of the propelling forces requires fast communication between the shuttles and the track. Fig. 1 shows the information and communication structure of the NBP-system (Zanella et al., 2002). The available computation power and communication infrastructure can be used to set up a preview system for the active suspension (Hestermeyer et al., 2004; Münch et al., 2004).

The system structure shown in Fig. 1 suggests the following set-up for the determination of the track excitation:

[1]Information about the wheel excitation was derived from an observer based on signals from accelerometers mounted on the axles.

[2](Donahue, 2001) e.g. describes a military external preview system with expensive radar and optical sensors.

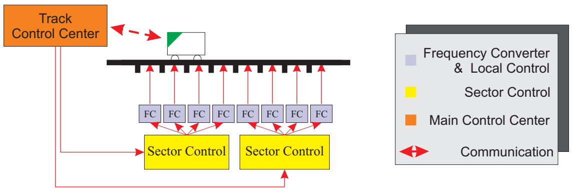

Figure 1: Communication structure for the railway-system ”Neue Bahntechnik Paderborn” (Zanella et al., 2002)

In a first step, the track is logically devided into different sections and an agent network is allocated to the track. One track agent is allocated to each section (Fig. 2).[3]

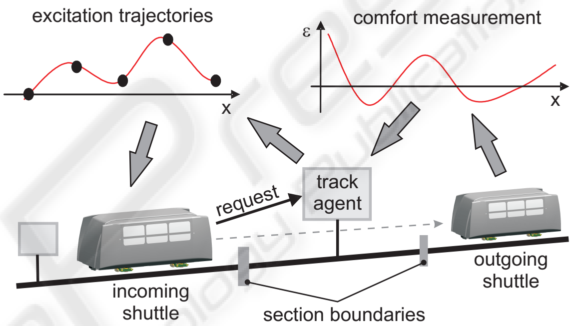

Figure 2: Determination of preview information by multi-agent optimization

When a shuttle wants to enter a special section, it contacts the track agent and receives in return an estimation of the track excitation it can use for disturbance compensation[4] After completing the section the shuttle answers with a performance rating, which is used by the track agent to optimize the trajectory. In case of a communication error, disturbance compensation is simply turned off. This results in less comfort but is otherwise uncritical.

Next to the benefit of improving ride comfort by optimal disturbance compensation, this method offers an excellent way of monitoring the track quality, as the track information is continously updated with each shuttle. Special measurement runs can be reduced or maybe even totally stopped.

[3]Comparing Fig. 1 and 2 it seems obvious to select the sections according to the motor sectors and download the track agent software on the available sector hardware. However, this is not a prerequisite. The multi-agent software can also be run on centralised hardware.

[4]The dynamics of the respective shuttle has to be considered when using the preview information. Otherwise the optimization of the preview information in the track agent might yet converge, but is now valid only for shuttles with similar dynamics.

3 ACTIVE SUSPENSION CONTROL

Suspension System Before discussing the envisioned control system in more detail, it is first necessary to have a look at the physics of the regarded active suspension system (fig 3): Car body and bogie are connected by air springs. The function of passive dampers is taken on by an active system of hydraulic cylinders that creates damping forces by displacing the spring bases. The displacement vector x_{disp} yields the necessary cylinder displacements $l_{cyl,i}$ by computing the inverse kinematics of the cylinder arrangement.

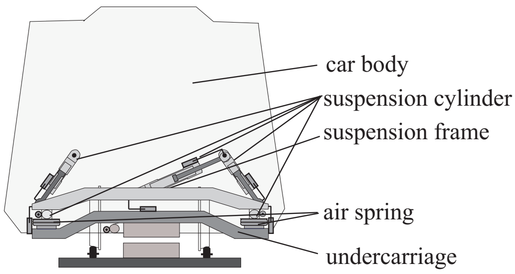

Figure 3: Structure of active suspension

Control Structure As already mentioned in the introduction, this paper focuses on the realization of the disturbance compensation and the trajectory optimization of the distributed control system envisioned in section 2. Communication issues and questions arising from the multi-agent implementation are disregarded. Fig. 4 shows the structure of the self-learning control system including the learning algorithm.

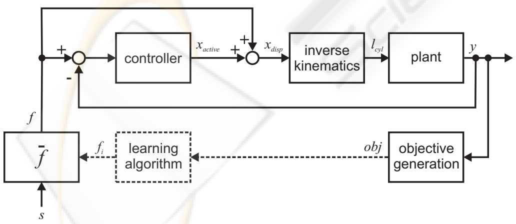

Figure 4: Structure of learning algorithm

The basis of the active suspension control is a simple feedback law (block "controller") assuring sufficient damping of the car body. The control law uses the relative position y between body and bogie to compute the necessary displacement x_{active}.
In order to minimize the absolute movement of the car body, an additional relative displacement signal f is introduced, which includes reference and disturbance information in dependance of the shuttle position s (Hestermeyer et al., 2004). The table $\bar{f} = (s_i, f_i)$ determines f from s by interpolation.
Based on the system response,evaluated by the block objective generation, a superposed learning algorithm computes a trajectory that reduces the influence of disturbances in the track by adding the signal f to the relative displacement between body and bogie.

Section 2 suggested the usage of the track excitation as disturbance compensation. This requires knowledge of vehicle and actuator dynamics when using the excitation trajectory in the controller. In a first step, this dynamics was not explicitly considered in this paper, so that car body and actuator dynamics were reflected in the determined trajectories.

4 LEARNING ALGORITHM

During the run over a track section different disturbances affect the chassis of a shuttle. These disturbances can be distinguished into stochastic disturbances and stationary disturbances, which recur at the same place of the track section. The learning algorithm presented here identifies and compensates these stationary disturbances on the chassis. The objective here is to keep the car body of the shuttle as still as possible, in order to improve the comfort of passengers.

As described in section 3 the learning algorithm determines a trajectory as a sequence of numbers f_i^k. k indicates the step number of the learning process and thus the number of shuttles that have crossed the section.

The shuttle measures the movements of the car body during the passage over the track section. Afterwards the data is given back to the learning algorithm, which determines the new sequence f_i^{k+1}.

Learning Algorithm As learning algorithm a computation instruction of the form

$$f_i^{k+1} = f_i^k - K_a \cdot y_j^k \tag{1}$$

with

$$j = i + h \tag{2}$$

was chosen. The value K_a gives the learning factor of the algorithm and y_j^k the deviation of the car body position. The value h reflects the dynamics of the car body and indicates a shift of the f_i^k signal compared to the associated measuring point. This shift is chosen according to the cut-off frequency of the car body dynamics T and the travel speed of shuttle v.

For the passage over the regarded track section a constant speed

$$v(t) = const. \tag{3}$$

is assumed.

Convergence Analysis The learning algorithm in equation (1) has great similarities to the description of discrete controllers. They differ in the meaning of the counting variable k, which describes the progressing of the time with discrete controllers. In the learning algorithm presented in this paper the variable k indicates a new run over the respective track section.

It is obvious to analyze the convergence characteristics of the learning algorithm by means of well-established digital control-engineering methods (Hanselmann, 1984). Therfore it is necessary to describe the shuttle-dynamics by a mathematic model. In order to treat the supporting points independently from each other, some simplifications must be made for the convergence analysis of the learning algorithm. For the feed-forward signal a simple step-function in place of the interpolation function is used. Furthermore an ideal reference reaction of the car body is assumed. The system response of the shuttle can be described with the simple model

$$y_j^k = K_p \cdot \left(f_i^k + u_i^k\right) \tag{4}$$

in which u_i describes the track disturbance at the supporting point i.

Inserting into the learning algorithm equation (1) yields

$$f_i^{k+1} = f_i^k - K_p \cdot K_a \cdot \left(f_i^k + u_i^k\right) \tag{5}$$

The use of the Z-transformation with equation (5) results in the transfer function:

$$G(z) = \frac{f_i(z)}{u_i(z)} = \frac{K_p \cdot K_a}{1 - K_p \cdot K_a - z} \tag{6}$$

In order to analyze the stability of the system, the poles of (6) can be used.

$$z = 1 - K_p \cdot K_a \tag{7}$$

For a stable system behavior the pole stays within the unit circle.

$$0 < K_p \cdot K_a < 2 \tag{8}$$

In the stability analysis presented above strong simplifications were made. The dynamic behavior of the shuttle was reduced to a simple gain factor K_p, whereby the dependencies between neighbored supporting points were eliminated. If one selects this gain K_p to be the overshoot of the car body response to a unit step, then one receives a useful estimation for the feasible range of the learning factor K_a. In practice the convergence will be assured by reducing the learning factor to a relative small value. On the one hand this leads to a decreased learning speed, on the other hand the insensitivity of the feed-forward signal f_i^k to the above mentioned stochastic disturbance is increased.

5 REALISATION

For a test in practice, the approach for a preview control presented here was realised in a simplified environment. In the following, we will expound the configuration of the testbed and present the implementation of the procedure described.

Configuration of the Testbed The control of the damperless suspension/tilt system is described in (Hestermeyer et al., 2003) for the complete vehicle. To test the active suspension of the entire vehicle a testbed was built up in the context of the ”Neue Bahntechnik Paderborn”. This testbed allowed us to design and test the suspension control (Liu-Henke et al., 2002). Fig. 5 shows the testbed. Three lower hydraulic cylinders serve to simulate track excitations and are able to impose forces resp. torques in horizontal, vertical, and rotatory directions on the car body. The upper part represents the suspension/tilt module as it might be mounted aboard the vehicle. The mass of the carriage is supported exclusively by airsprings, as described in section 3.

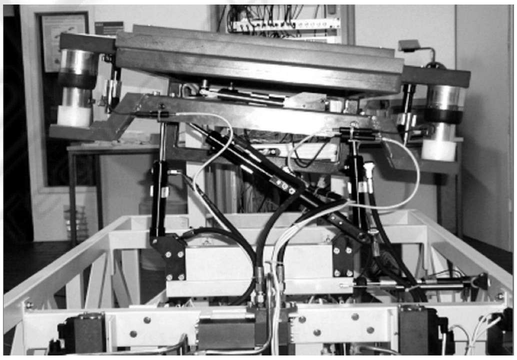

Figure 5: Suspension-tilt testbed

With the procedure described here a control of the relative motion between chassis and carriage body is sufficient. In order to achieve an increase in comfort one might think of damping the absolute motions of the carriage body [5], but this was not included in the present control because the absolute motions are to be impacted by the preview algorithm.

Implementation of the Learning Algorithm In order to test the self-optimisation approach presented in section 4 at the testbed we needed a recurring excitation for a simulation of repeated rides along a fixed section. For this purpose a track course was defined that stretched over a 100-m-long track section. For

[5]This method known as ”skyhook damping” (Hestermeyer et al., 2004)

determining the objective variables we subdivided the track section into 100 parts of 1 m each; thus for any possible moving direction an evaluation vector comprising 100 elements was recorded for each crossing. For an objective we used the maximum of deviations from the middle position of the car body in the respective part; it was measured by the existing position-measuring sensors. One run over the track section in view takes $10s$ at an assumed speed $v = 10m/s$. After each crossing the evaluation vectors are transmitted to the learning algorithm which defines the new trajectories of the disturbance compensation for the next crossing. These trajectories are parameterised over 100 supporting points corresponding to the sections. As shown in fig. 4 the signal f is interpolated between the supporting points. The algorithm required to determine an optimal disturbance compensation was implemented on a dSPACE real- time hardware, in addition to the testbed control described. Here the focus was on testing the learning algorithm. Difficulties resulting from the necessary communication between vehicle and processing of information on the track were ignored here. At the time interval where the crossing is finished the detected evaluation variables are transmitted to the optimising procedure which then computes the new trajectories of the disturbance compensation at exactly the same time interval and makes them available for the next crossing that begins at the next time interval.

6 RESULTS

This section describes the results of the optimisation on the basis of measurements at the testbed. The recurring excitation over the track section in question is displayed in Fig. 6 to 8 at the top. In translatory direction the chassis was at first excited by a sinusoidal signal and subsequently by three steps in lateral direction resp. inversely in vertical direction. Additionally a superposed sinusoidal rotation around the longitudinal axis of the chassis took effect. The middle diagrams display the disturbance trajectory acquired by repeated runs in the course of optimisation. The plot shows the characteristics as follows: at the outset of the optimisation as a dotted line, after five crossings as a broken one, and as an unbroken line after 50 crossings. The lower part displays the corresponding plots of the evaluation functions.

All in all the optimisation method has proved its ability to compensate the car body movements almost in full for the periodically recurring excitations. After only five crossings the amplitudes of the body motion fell below 10%. After 50 crossings the carriage body is nearly in a position of rest in spite of the excitation.

Another aspect is made clear in a comparison of the excitation behaviors and the corresponding disturbance compensation. With a vertical motion these variables converge while with torsion and lateral motion there remain significant differences even after 50 repetitions. This is due to the coupling of motions. A lateral excitation will always bring about a torsion in the car body; vice versa, a rotation of the chassis around the longitudinal axis will always affect the lateral motion of the car body. This is why the disturbance compensation has to take into account these couplings, the result being the behavior shown. On the other hand, the car body motion in vertical direction is decoupled from the other degrees of freedom; thus the disturbance compensation will only have to deal with the excitation portion in this direction.

7 CONCLUSION

It was shown that using existing data processing infrastructure for the exchange of collected data can be effective for the compensation of recurring stationary disturbances. The realization at the testbed confirmed the advantages of this approach. However it may not be ignored that the trajectories of the compensation do not represent the disturbances themselves. Rather they are optimized with respect to the particularly regarded vehicle and its velocity. At the testbed this causes no problem, because the dynamics and the assumed velocity of the testbed does not change during a test. Of course in reality different vehicles must be considered. In this case the compensation adapted to a particular vehicle cannot be used. In order to be able to use the presented method nevertheless, vehicle and velocity independent information must be stored. For this purpose the actual track characteristics are ideal which can be determined by observation from the respective system response of an individual vehicle. In this way the approach introduced here can be generalized on different types of vehicles.

Thus the method represents a good way to improve the dynamic behavior for repetitive motions. It can also be transferred to other applications, which show similar characteristics.

To prove the convergence of the learning algorithm a simplified convergence analysis was performed by using methods derived from digital control theory. An enlargement of the convergence model in view of a concurrent analysis of several supporting points is possible and will be object of future research.

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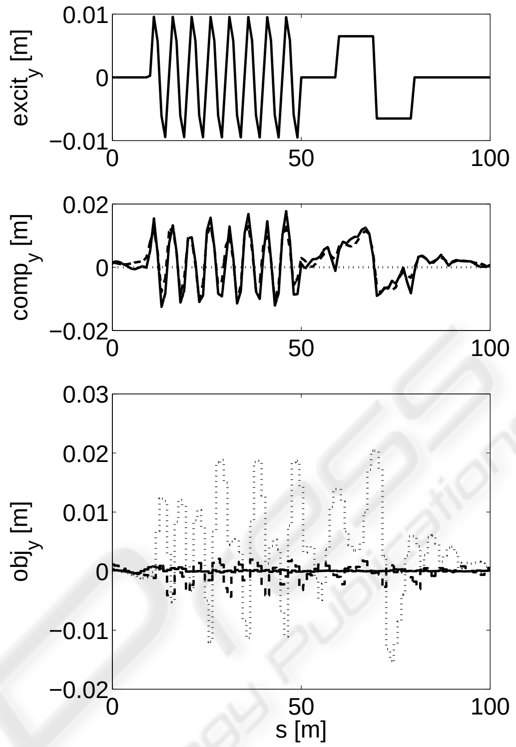

Figure 6: Evaluation: lateral

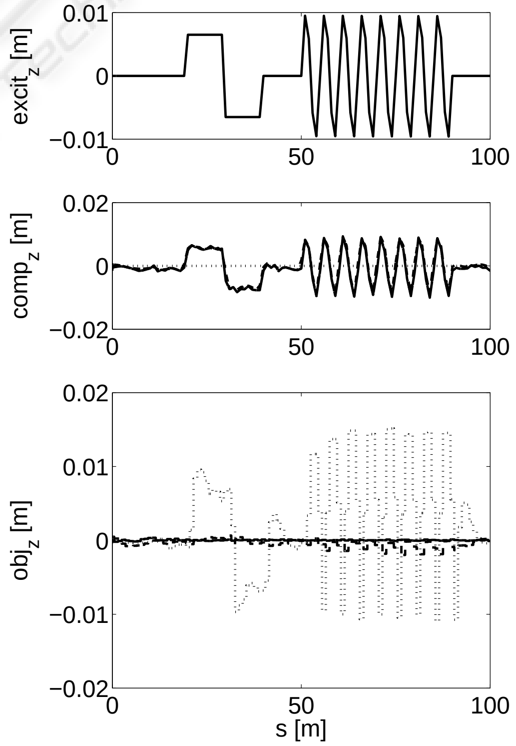

Figure 7: Evaluation: vertical

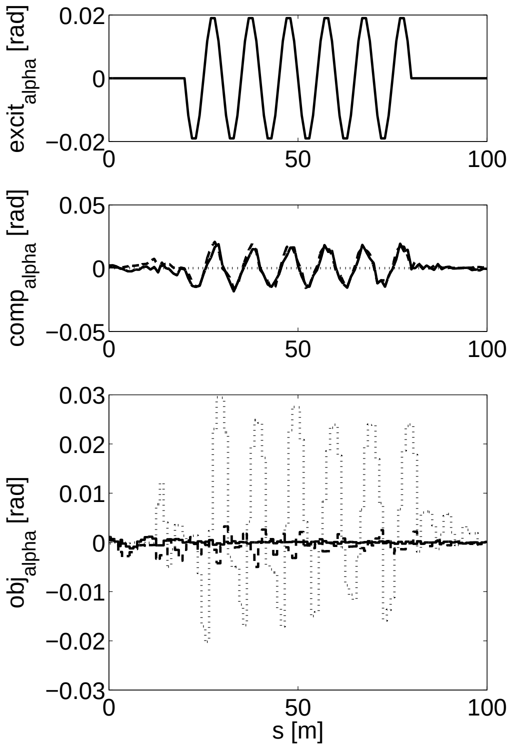

Figure 8: Evaluation: rotatory