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ONLINE OPTIMIZATION OF A PREVIEW CONTROLLER – STRUCTURE AND ALGORITHMS [1]

Joachim Lückel
Eckehard Münch
Henner Vöcking
Thorsten Hestermeyer

University of Paderborn

e-mail: Joachim.Lueckel@mlap.de; muench@mlap.de; Henner.Voecking@mlap.de; Thorsten.Hestermeyer@mlap.de

Active suspension systems are used to increase ride comfort and safety of vehicles. Optimal results can be achieved if disturbances from the track are known in advance. Usually, this causes a problem as track excitations cannot be measured until they take effect on the vehicle. Here, we present an approach to disturbance compensation for railway vehicles coupled in a network. Information on stationary arising track disturbances are gathered by vehicles and stored locally at track sections. By repeated runs over a respective section this information is iteratively optimized and can be used for the disturbance compensation in subsequent vehicles.
The developed optimization algorithm is described. Design criteria are derived from digital control theory. The procedure was implemented on a testbed for a semi-vehicle with three degrees of freedom, where its usability was proved. The results are discussed and, finally, some aspects of generalization are considered.

Key word: mechatronics, learning, distributed optimization, active suspension, railway systems

1. Introduction

Today, active suspension systems are well established in theory and practice. This holds especially true for automotive applications. When looking at

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the railway industry, vehicles with active suspensions are available, but these systems usually focus on the 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 an application example, the system setup of the railway system "Neue Bahntechnik Paderborn", which is described in more detail in Section 2.

Most of the vast 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 article shows that it is possible to reduce body motion by a great extent by using the experience gained by other vehicles. In order to do so, two things are necessary: Firstly, an algorithm is required that determines information about the track excitation and uses this in the control algorithm of the active suspension. Secondly, a collaborative network with communication infrastructure has to be set up. Here, we focus on the first step.

The article is structured as follows:

Section 2 gives a brief overview of an examplary suspension system and its underlying control structure. Section 3 presents the basic idea for the overall system setup including the optimization algorithm in the collaborative vehicle network. With this setup in mind, Section 4 develops the learning algorithm. In order to show the applicability of the algorithm and its benefits, the system was implemented on a suspension test bed described in Section 5, where the results are discussed as well. The article concludes with an outlook in Section 6.

2. Active suspension control

The railway system "Neue Bahntechnik Paderborn" (NBP) (Hestermeyer, 2003) features small autonomous railway vehicles of van size with a fully-active suspension system (Fig. 1). The suspension system is used for both tilting of the car body and for the adjustment of the spring and damper characteristics. The car body and bogie are connected by air springs without any passive dampers. This is for enhancing the comfort as passive dampers harden if their excitation contains high frequencies.

The function of passive dampers is taken on by an active system of hydraulic cylinders that create damping forces by displacing spring bases. The displacement vector x_{active} yields necessary cylinder displacements $l_{cyl,i}$ by computing the inverse kinematics of the cylinder arrangement (Fig. 2). As the

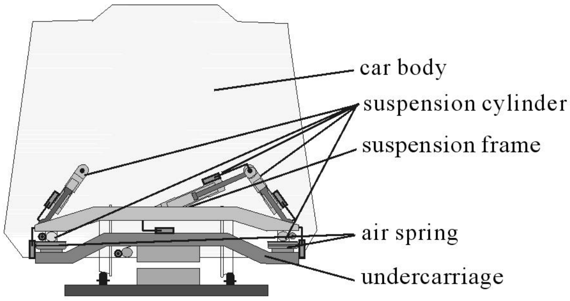

Fig. 1. Structure of active suspension

input for the controller, relative positions with respect to velocities between the car body and the bogie are used, which are gained from the measured lengths of hydraulic cylinders and position sensors in parallel to the air springs. In this way, dynamics of the entire system can be customized arbitrarily by adjusting the parameters of the controller, and therefore the rules for calculating the additional active forces.

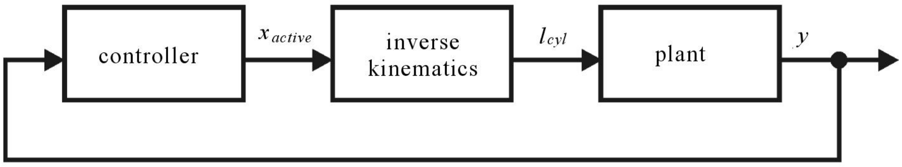

Fig. 2. Control structure for relative damping

3. 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 major role in the success of the system. One important aspect became clear already with first realizations of active suspension systems. The disturbance compensation using information about the ground excitation can improve the ride comfort considerably. Jäker (1990) e.g. used a disturbance compensator as a part of the control law for the active suspension in an off-road truck with great success[2].

[2]The information about wheel excitation was derived from an observer based on signals from accelerometers mounted on the axles.

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 the wheel. This is known as "preview". Preview information for rear wheels can be gained by using information from 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 the internal preview provides only small benefit (Rutz, 1987). The preview information for the front wheels would therefore help to improve ride comfort even more. Unfortunately, looking at a single vehicle, collecting the preview information for the front wheels is an arduous and costly business. (Donahue (2001) e.g. describes a military external preview system with an expensive radar and optical sensors.) A much simpler way to obtain the desired information can be found for vehicles integrated in a network. Ioannou (1998) proposed such an infrastructure-supported network for highway vehicles.

In this work, we concentrate on the railway system "Neue Bahntechnik Paderborn" (NBP) (Hestermeyer, 2003), which supplies perfect infrastructure for the new preview system presented here.

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 frequency converters and computer hardware. The creation of propelling forces requires fast communication between the shuttles and the track. Figure 3 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 (see also Hestermeyer *et al.*, 2004; Münch *et al.*, 2004).

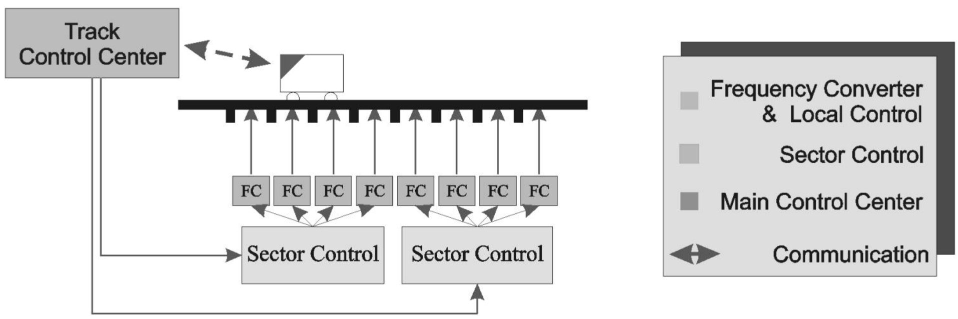

Fig. 3. Communication structure for the railway-system "Neue Bahntechnik Paderborn" (Zanella *et al.*, 2002)

The system structure shown in Fig. 3 suggests the following set-up for the determination of the track excitation.

In the first step, the track is logically divided into different sections, and the agent network is allocated to the track. One track agent is allocated to each section (Fig. 4)[3].

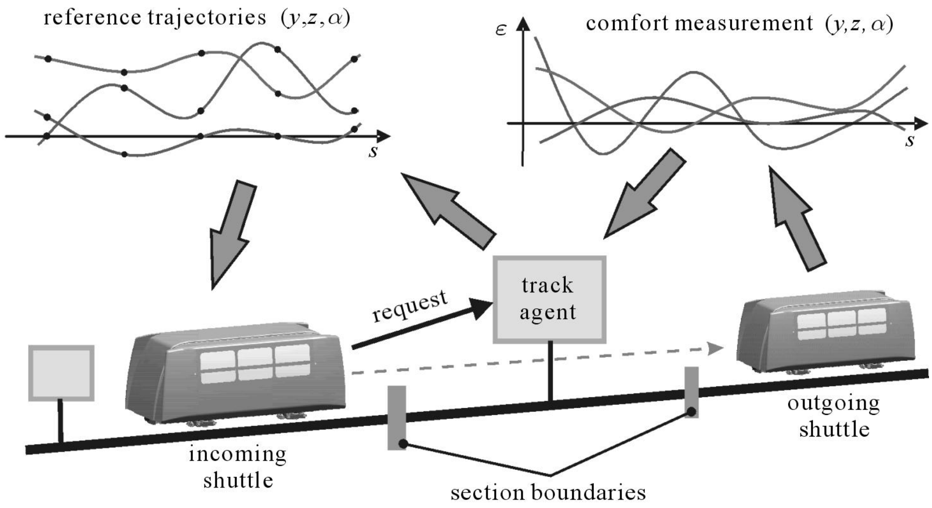

Fig. 4. Determination of preview information by multi-agent optimization

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 the case of a communication error, the disturbance compensation is simply turned off. This results in less comfort but is otherwise uncritical.

Apart from improving the 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 even excluded at all.

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[3]Comparing Fig. 3 and Fig. 4, it seems obvious to select 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]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.

3.1. Extended control structure

As already mentioned in the introduction, the work presented here focuses on the realization of the disturbance compensation and the trajectory optimization disregarding communication issues and questions arising from the multi-agent implementation. Figure 5 shows the structure of the self-learning control system including the learning algorithm.

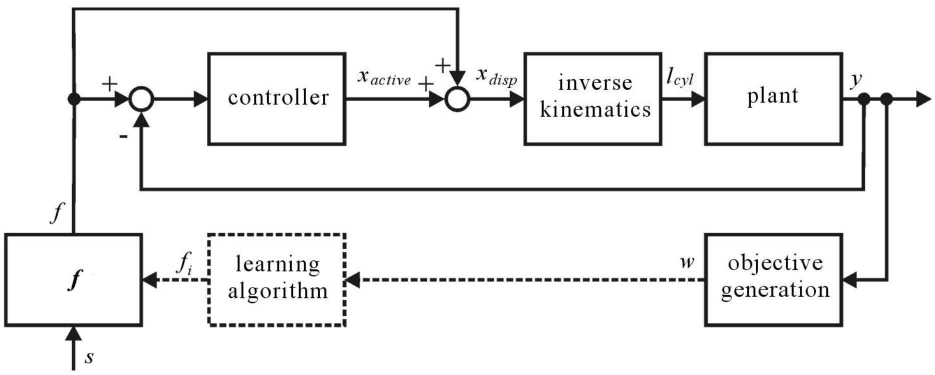

Fig. 5. Control structure featuring learning algorithm

The basis of the active suspension control is a simple feedback law (block "controller") assuring sufficient damping of the car body as described in Section 2.

In order to minimize the absolute movement of the car body, an additional relative displacement signal f is introduced, which includes the reference and disturbance information in function of the shuttle position s (Hestermeyer *et al.*, 2004). The table $\overline{f} = (s_i, f_i)$ determines f from s by interpolation.

Based on the system response evaluated by a block objective generation, the 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.

So far, this concept suggested the usage of the track excitation as disturbance compensation. This requires knowledge of the vehicle and actuator dynamics when using the excitation trajectory in the controller. In the first step, this dynamics was not explicitly considered, so that the car body and actuator dynamics was reflected in 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 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, where k indicates the step number of the learning process and thus the number of shuttles that have crossed the section.

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

4.1. Learning algorithm

As the learning algorithm, a computation instruction of the form

$$f_i^{k+1} = f_i^k - K_a y_j^k \tag{4.1}$$

with

$$j = i + h \tag{4.2}$$

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 dynamics of the car body and indicates a shift of the f_i^k signal with respect 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 the shuttle v.

For the passage over the regarded track section, a constant speed

$$v(t) = \text{const} \tag{4.3}$$

is assumed.

4.2. Convergence analysis

The learning algorithm in Eq. (4.1) is very much similar to the description of discrete controllers. They differ in the meaning of the counting variable k, which describes the progres of time with the discrete controllers. In the presented learning algorithm, 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 shuttle-dynamics by a mathematical model. In order to treat the supporting points independently of 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

$$y_j^k = K_p(f_i^k + u_i^k) \tag{4.4}$$

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

Inserting it into learning algorithm equation (4.1) yields

$$f_i^{k+1} = f_i^k - K_p K_a (f_i^k + u_i^k) \tag{4.5}$$

The use of the Z-transformation with Eq. (4.5) results in a transfer function

$$G(z) = \frac{f_i(z)}{u_i(z)} = \frac{K_p K_a}{1 - K_p K_a - z} \tag{4.6}$$

In order to analyze the stability of the system, poles of (4.6) can be used

$$z = 1 - K_p K_a \tag{4.7}$$

For stable system behaviour, the pole stays within the unit circle

$$0 < K_p K_a < 2 \tag{4.8}$$

In the stability analysis presented above, strong simplifications were made. Dynamic behaviour of the shuttle was reduced to a simple gain factor K_p, whereby the dependencies between neighboured 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 the insensitivity of the feed-forward signal f_i^k to the above mentioned stochastic disturbance is increased.

4.3. Extended convergence analysis

In the following section, an extended convergence analysis is presented, which considers the dependencies of neighboured supporting points by more accurate modelling of the shuttle dynamics.

In order to do this, the response of the shuttle chassis to the supporting points and the track excitation must be described in relation to the current supporting point. This can be achieved by a linear difference equation. The solution to such a difference equation has the form[5]

$$\{y_j\} = Z^{-1}\{Y(z)\} \tag{4.9}$$

The dynamics of the car body in this application scenario can be modelled by a second order system.

$$y_{j+2} + b_1 y_{j+1} + b_0 y_j = g_j \tag{4.10}$$

By assuming of $y_0^k, y_1^k = 0$, the solution to such a system results in

$$y_j = \sum_{\nu=2}^{j} g_{j-\nu} a_{\nu-1} \tag{4.11}$$

with

$$a_j = \frac{\alpha_1^j - \alpha_2^j}{\alpha_1 - \alpha_2} \tag{4.12}$$

(see Bronstein *et al.*, 1995) where α_1 and α_2 are poles of the system, and the track excitation is denoted by g_j.

By selecting the sample rate of the difference equation equal to the clocking of the disturbance compensation, one receives

$$y_j = \sum_{\nu=2}^{j} (f_{j-\nu} - u_{j-\nu}) a_{\nu-1} \tag{4.13}$$

With $u_{-1}^k, u_0^k = 0$ and $f_{-1}^k, f_0^k = 0$, Eq. (4.13) yields a description of the car body position at the supporting points $1, \ldots, n$ with respect to the signal

[5]Here Z^{-1} represents the inverse Z-transformation. In this context, the inverse Z-tranformation of the difference equation in the time domain is meant (see Section 4.2).

vector $\boldsymbol{f}^k$ and the track excitation vector $\boldsymbol{u}^k$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ \vdots \\ y_n \end{bmatrix}^k = \underbrace{\begin{bmatrix} 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 \\ a_1 & 0 & \cdots & 0 & 0 & 0 \\ a_2 & a_1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & 0 & 0 & 0 \\ a_{n-2} & a_{n-3} & \cdots & a_1 & 0 & 0 \end{bmatrix}}_{\mathbf{A}_p} \left(\begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \\ \vdots \\ f_n \end{bmatrix}^k - \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ \vdots \\ u_n \end{bmatrix}^k \right) \tag{4.14}$$

By inserting Eq. (4.14) into Eq. (4.1), one receives a mathematical description for the overall behaviour of the learning algorithm. By choosing an appropriate shift h, it is always possible to insert the matrix $\mathbf{A}_p$ from (4.14) as a lower triangle matrix into this description. Choosing $h = 2$, results in the following set of equations

$$\begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix}^{k+1} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix}^k - K_a \begin{bmatrix} a_1 & 0 & \cdots & 0 \\ a_2 & a_1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ a_n & a_{n-1} & \cdots & a_1 \end{bmatrix} \left(\begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix}^k - \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}^k \right) \tag{4.15}$$

or briefly

$$\boldsymbol{f}^{k+1} = \underbrace{(\mathbf{I} - K_a \mathbf{A}_{p,h=2})}_{\mathbf{A}} \boldsymbol{f}^k + K_a \mathbf{A}_{p,h=2} \boldsymbol{u}^k \tag{4.16}$$

where $\mathbf{I}$ is the identity matrix.

In these equations, the mutual influence of neighboured supporting points is considered by the modelling of the car body dynamics.

In order to examine the convergence and stability of the learning algorithm, the eigenvalues of the system matrix $\mathbf{A}$ are determined. These eigenvalues can be gained from the determinant

$$\det(\mathbf{I} - K_a \mathbf{A}_{p,h=2} - \lambda \mathbf{I}) = 0 \tag{4.17}$$

i.e.

$$\begin{vmatrix} 1 - K_a a_1 - \lambda & 0 & \cdots & 0 \\ K_a a_2 & 1 - K_a a_1 - \lambda & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ K_a a_n & K_a a_{n-1} & \cdots & 1 - K_a a_1 - \lambda \end{vmatrix} = 0 \tag{4.18}$$

The determinant of the lower trinagle matrix is equal to the product of the diagonal elements. So as the eigenvalues of $\mathbf{A}$, we get the n-fold eigenvalue $\lambda_{1,\dots,n}$ with

$$\lambda_{1,\dots,n} = 1 - K_a a_1 \tag{4.19}$$

As one can see from Eq. (4.18),this eigenvalue is independent of the total number of supporting points n.

The eigenvalue $\lambda_{1,\dots,n}$ only depends on the term a_1 from the description of the car body dynamics (see Eq. (4.12)). Comparing Eq. (4.19) and Eq. (4.7) from the simple convergence analysis, one states that with $K_p = a_1$ the two results of the convergence analysis results are identical.

The presented learning algorithm is limited to systems which perform repeativly the same type of movement, i.e., with the same velocity and the same trajectory. Under these circumstances, it is possible to design a stable and convergent algorithm by means of the depicted convergence analysis. The approach is not restricted to small systems since the factor a_1 can always be determined for the linear difference equation. This applies as well to higher order systems (Bronstein *et al.*, 1995).

5. Realisation and results

For a practical test, the approach for the preview control presented here was realised in a simplified environment. In the following, we describe the incorporated testbed and present the implementation of the applied procedure.

5.1. Configuration of the testbed

The control of the damperless suspension/tilt system is described by Hestermeyer *et al.* (2003) for a complete vehicle. To test the active suspension, a testbed was built up in the context of the "NBP". It allowed us to design and test the suspension control (Liu-Henke *et al.*, 2002). Figure 6 shows the testbed. Three lower hydraulic cylinders serve to simulate track excitations and are able to impose forces and 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 2.

With the procedure described here, the control of the relative motion between the car bogie and body is sufficient. In order to achieve an increase in comfort, one might think of damping absolute movements of the carriage body

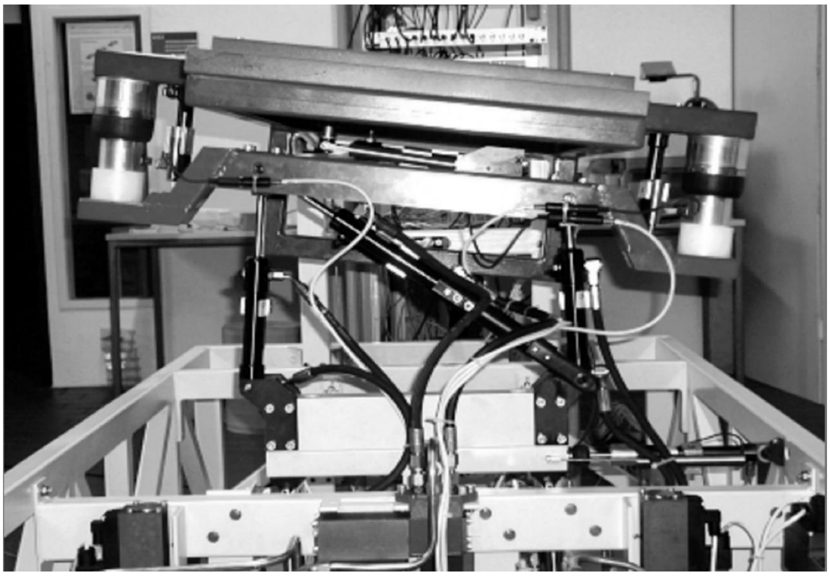

Fig. 6. Suspension-tilt testbed

(skyhook, Hestermeyer *et al.*, 2004), but this was not included in the analysed control because the absolute movements were to be impacted by the preview algorithm.

5.2. Implementation of the optimization algorithm

In order to test the self-optimization approach presented in Section 4 at the testbed, we needed a recurring excitation for simulation of repeated runs along a fixed section. For this purpose, a track course was defined that stretched over a 100 m-long track section. For determining the objective variables, we subdivided the track section into 100 parts of 1 m each; thus for any possible direction of motion an evaluation vector containing 100 elements was recorded for each crossing. For the objective, we used the maximum of deviations from the middle position of the car body in the respective part; it was measured by existing position-measuring sensors. One run over the track section took 10 s at the assumed speed $v = 10\,\mathrm{m/s}$. After each crossing, the evaluation vectors were transmitted to the learning algorithm which defined new trajectories of the disturbance compensation for the next crossing. These trajectories are parameterised over 100 supporting points corresponding to the parts of the respective section. As shown in Fig. 5, the signal f was interpolated between the supporting points. The algorithm required to determine the optimal disturbance compensation was implemented to a real-time hardware, in addition to the testbed control described. Here, the emphasis was put on testing the learning algorithm. Difficulties resulting from the necessary communication between the vehicle and processing of information on the track were ignored. At the time interval where the crossing is finished, the recorded evaluation variables were transmitted to the optimizing procedure which afterwards computed new trajectories of the disturbance compensation at exactly the same time interval and made them available for the next crossing to start at the following time interval.

5.3. Results

This section describes the results of the optimization on the basis of measurements at the testbed. The recurring excitation over the track section in question is displayed in Fig. 7 to Fig. 9 in the top left-hand corner. In the translatory direction, the chassis was at first excited by a sinusoidal signal and subsequently by three steps in the lateral direction, respectively inversely in the vertical direction. Additionally, a superposed sinusoidal rotation around the longitudinal axis of the chassis took effect. The diagrams on the lower left display the disturbance trajectory acquired by repeated runs in the course of optimization. The plot shows the characteristics as follows: at the outset of the optimization as a dotted line, after five crossings as a broken one, and as an unbroken line after 50 crossings. The part on the right displays the corresponding plots of the objective functions w.

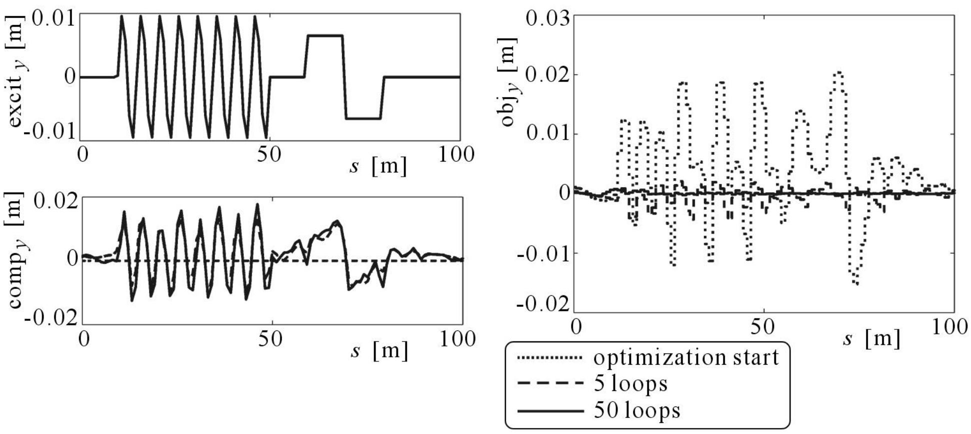

Fig. 7. Evaluation: lateral

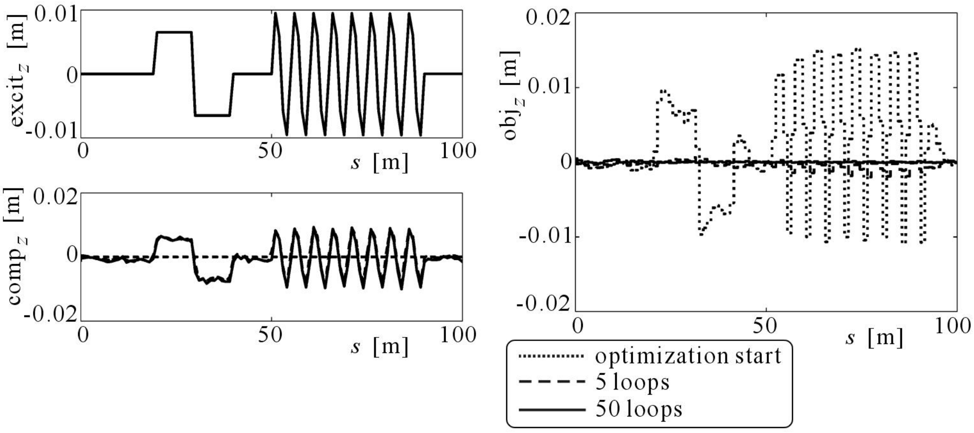

Fig. 8. Evaluation: vertical

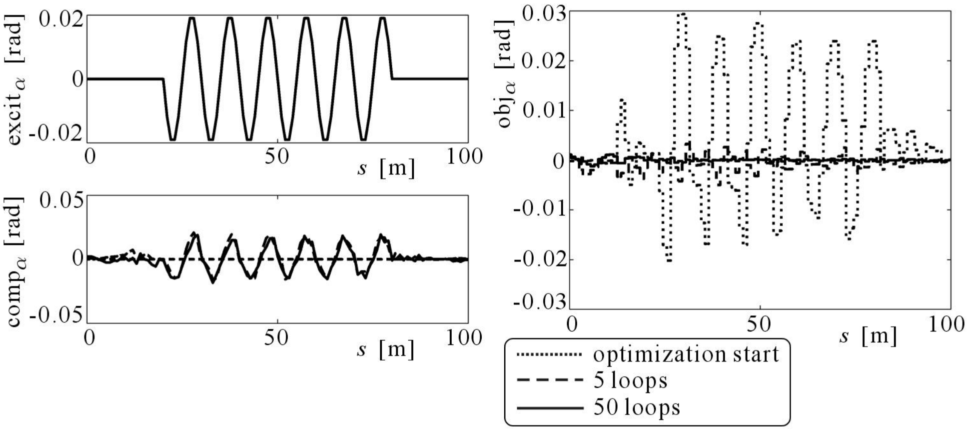

Fig. 9. Evaluation: rotatory

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

Another aspect is made clear in the comparison between the excitation behaviours and the corresponding disturbance compensation. With vertical motion these variables converge closely to the excitation, 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; and vice versa – 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 behaviour shown. On the other hand, the car body motion in the 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.

6. Conclusion

It was shown that the using of the existing data processing infrastructure for the exchange of collected data can be effecive for the compensation of recurring stationary disturbances. The realization at a testbed confirmed the advantages of this approach. However, it must not be ignored that trajectories of the compensation do not represent the disturbances themselves. Rather they are optimized with respect to a particular vehicle. At the testbed, this causes no problem because dynamics 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. Nevertheless, in order to be able to use the presented method, independent information on a vehicle must be stored. For this purpose, 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 to different types of vehicles.

To prove the convergence of the learning algorithm, a simplified convergence analysis was performed by using methods of digital control theory. The disign criteria for the parameters of the algorithm were derived from this analysis, so they can easily be chosen. Thus the method represents a good way to improve dynamic behaviour for repetitive motions. It can also be transferred to other applications which show similar characteristics.

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Bieżąca optymalizacja sterowania typu "preview", jego struktura i algorytmy optymalizacji

Streszczenie

Układy zawieszeń aktywnych stosowane są w celu zwiększenia komfortu i bezpieczeństwa ruchu pojazdów. Optymalne parametry pracy takich zawieszeń uzyskuje się, gdy zaburzenia od drogi znane są z góry. Zwykle jednak zaburzenia te mogą być dopiero zmierzone, gdy zaczynają już oddziaływać na pojazd. W pracy zaprezentowano metodę kompensacji zakłóceń ruchu na przykładzie pojazdów szynowych poruszających się w sieci. Informacje o nierównościach toru pojawiających się stacjonarnie zbierane są i przechowywane dla poszczególnych sekcji toru. Poprzez kolejne przejazdy pociągów wzdłuż tych sekcji informacje są iteracyjnie optymalizowane tak, aby mogły zostać wykorzystane przez następny pociąg. W artykule opisano zaproponowany algorytm optymalizacji. Kryteria strukturalne procedury zaczerpnięto z teorii sterowania cyfrowego. Algorytm wdrożono do stanowiska doświadczalnego modelu pociągu o trzech stopniach swobody. Badania pokazały skuteczność wprowadzonej metody sterowania. Rezultaty badań przedyskutowano także pod kątem możliwości ich uogólnienia na inne typy pociągów.

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