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A Robust Preview Feedforward Approach For Vehicle Semi Active Suspension Control Problem

Asma Achnib and Olivier Sename

Abstract—This paper focus on the road adaptation for vehicle semi-active suspension system using preview robust control approach. This approach aims to improve the performance of control systems by using future knowledge of road disturbances. The objectives are to minimize a quadratic criterion on the system output and at the same time to maintain the control signal at a satisfactory level. The proposed solution combines a robust feedback controller with a preview feedforward filter. The feedback controller's purpose is to assure robustness of the closed-loop system to model uncertainties. This new method is developed to synthesize the preview feedforward filter in order to limit the control force damper demand and improve its reliability in an automotive suspension system, and is implemented on the INOVE testbench from GIPSA-lab (1/5-scaled real vehicle) for real-time performance assessment. Experimental results demonstrate the effectiveness of the proposed controller to determinate the damper force in realtime face to measurement noises and road disturbances.

Index Terms—Semi-active suspension, road profile, robust control, discrete-time systems, preview feedforward control, control applications.

I. INTRODUCTION

Due to the need for performance and safety improvement, automotive control requirements are increasing and leading to more and more complex control challenges. Suspension system is one of important components in vehicles due to its potentiel with regard to ride comfort and road handling against the road disturbances. Semi-active suspensions are today more and more used in automotive industry because of their efficiency, while being less expensive and consuming less energy than pure active suspensions [7]. However, in practice, suspension performance can be degraded when a large road disturbance appears or because of uncertainties when are not particulary addressed.

To fulfill the demand, a preview feedforward control associated with a feedback control (used for stabilizing the system and satisfaction some robustness requirements as well as saturating limitations in the meantime) is needed. Preview control history dates back to the late 1960s. The concept of this control approach was proposed initially by Sheridan in 1966 [12]. It aims to improve the performance of control systems by using future knowledge of reference signals and/or disturbances.

Recent developments of automotive industry are often based on recognition of vehicle surroundings using sensors. Several advanced driver assistance systems, which are scanning the surroundings of the vehicle, are already available in modern cars and sensor recognition technologies for self-driving cars represent an important area of research today [5], [13]. These sensors can also be used to measure the road profile in front of the car. Other research has focused on the designed of preview controllers in the context of vehicle suspension systems [4], [6], [9].

Nevertheless, only a few number of research articles have attempted to deal with the problem of robust anticipative control in discrete-time. In [2] an anticipative control problem is considered in the context of active vehicle suspension. The proposed solution is based on $\mathcal{H}_\infty/\mathcal{GH}_2$ design methodology. \mathcal{H}_∞ -norm is used wherever minimisation is required, and generalised \mathcal{H}_2 is used to care for the constraints on suspension stroke; however, uncertainties are not taken into account in the design of the preview feedforward filter.

In this paper, we aim to extend the discrete-time preview robust controller synthesized for optimal tracking of future references in [1] to discrete-time preview robust controller for optimal rejection of future road disturbances for vehicle semi-active suspension systems. The objective is to use the road profile information to limit the control action while helping the rejection of the disturbance effect. In the context of preview systems, it is supposed that future values of the road disturbance signal are available a number of time steps ahead. The method aims to design a control algorithm that minimizes a quadratic criterion on the system output, the optimal solution needs to take into account the known future values of the road disturbances. Furthermore, it is desired to maintain the control signal at a satisfactory level. Therefore, anticipation allows the control input to eliminate the impact caused by measured disturbance on the process output. In the suspension framework, this new method is developed to synthesize the preview feedforward filter in order to limit the control force damper demand and improve its reliability while helping the rejection of the disturbance road effect.

The two major contributions of this paper are as follows:

- A two degrees of freedom feedback-feedforward control schema represents the basis for the proposed controller. A feedforward filter with preview be-

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haviour is introduced to take into account future values of the road disturbances signal. It is supposed that the time window of known future road disturbance values is known. The window's length of the preview feedforward filter can be adjusted accordingly. The feedforward part is obtained by solving a frequency domain optimisation problem with mixed \mathcal{L}_2 performance and \mathcal{L}_∞ constraints for robustness. It is worth noting that the preview feedforward action can be added on top of any robust feedback controller.

- The proposed preview feedforward–feedback controller has been implemented on a real scaled-vehicle test bench, through MATLAB/Simulink Real-Time Workshop. The controller performances are then assessed with experimental tests.

The structure of the paper is given as follows. Section II provides an overview of the required preliminaries. The problem considered in this paper is formulated in section III. Section IV discusses the obtained results after implementation of this method to the available INOVE Platform. Finally, some conclusions are drawn in the section V.

II. PRELIMINARIES

A. Notations

As mentioned in the introduction, this paper deals with the design of discrete-time robust preview control algorithms for road disturbances rejection for semi-active suspension vehicle systems.

Let denote discrete-time transfer function by upper-case letters and signal vectors by lower-case letters in the time domain and upper-case letters in the frequency domain. The unit delay operator q^{-1} is used in the time domain, while q_f^{-1} is used in the frequency domain. The unit advance operator q is used in the feedforward filters to represent the preview action. The sampling period is denoted by T_s , while the sampling frequency is represented by f_s .

B. Feedback–feedforward control description

Consider the feedback–feedforward control schema used for rejection known future road disturbances described by figure 1

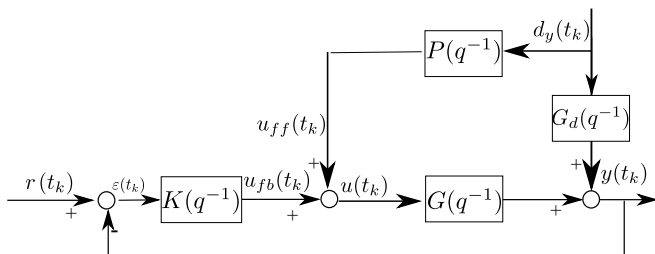


Fig. 1: Feedback–Feedforward control schema used for rejection known future disturbances.

In Fig.1, $G(q^{-1})$ represents the true plant model with uncertain parameters. It is supposed (without loss of generality) that the uncertainty bounds of the parameters are known. The true plant model can be considered as belonging to a set of models, denoted by \mathcal{M}_G , defined using the uncertainty bounds. The objective of robustness can be redefined as robustness to all the models in the model-set;

$G_d(q^{-1})$ is referred to as the disturbance model;

$K(q^{-1})$ is the robust feedback controller;

$r(t_k)$, $u_{ff}(t_k)$, $u_{fb}(t_k)$, $u(t_k)$, $y(t_k)$ and $d_y(t_k)$ represent, respectively, the reference input, the feedforward control, the feedback control, the control input, the system output, and the disturbance signal.

$P(q^{-1})$ is the preview feedforward filter for rejection disturbance that needs to be designed by minimising ∞ -norm of the closed-loop sensitivity function from the disturbance to the output.

The term "preview" is used to indicate that the filter has terms depending on future values of its input. The interpretation of "preview" is better understood in the time-domain, where $P(q^{-1})$ has terms in q^{-1} and also in q which depend on future values of this filter's input.

In this paper, the preview action is introduced using preview finite impulse response (FIR) filters defined as

$$X(q^{-1}) = q^{-n_X} x_{-n_X} + \dots + x_0 + q^1 x_1 + \dots + q^{m_X} x_{m_X}. \quad (1)$$

where, $x_{-1}, \dots, x_{-n_X}, x_0, x_1, \dots, x_{m_X}$ are the coefficients of the filter and n_X is its order.

In the previous equation, $m_X T_s$ determines the window of future time samples. FIR filters are preferred due to their inherent stability and ease of manipulation.

From Fig. 1, two closed-loop transfer functions are of interest. Let us define the transfer function from disturbance $d_y(t_k)$ to system output $y(t_k)$, in the frequency-domain, as ¹

$$\frac{Y(q_f^{-1})}{D_y(q_f^{-1})} = H_{y d_y}(q_f^{-1}) = \frac{G_d + P G_k}{1 + K G_k}, \quad (2)$$

and the transfer function from disturbance $d_y(t_k)$ to control input $u(t_k)$, also in the frequency-domain, as:

$$\frac{U(q_f^{-1})}{D_y(q_f^{-1})} = H_{u d_y}(q_f^{-1}) = \frac{-K G_d + P}{1 + K G_k}, \quad (3)$$

where $Y(q_f^{-1})$, $D_y(q_f^{-1})$ and $U(q_f^{-1})$ are the Z-transforms of $y(t_k)$, $d_y(t_k)$ and $u(t_k)$ respectively; $G_k \in \mathcal{M}_G$.

¹In some of the following equations, the parenthesis (q_f^{-1}) will be dropped to save space.

III. FORMULATION PROBLEM

A. Feedforward filter design

Feedforward filter designs are usually based on some type of inversion of a plant model; however, in real applications, plant models are uncertain and present also non invertible parts. For this reason, the nominal model G_{nom} is decomposed into the invertible G_l and non invertible G_h parts.

$$G_{nom}(q^{-1}) = G_h(q^{-1})G_l(q^{-1}), \quad (4)$$

where $G_l(q^{-1})$ includes the low frequency stable poles and minimum phase zeros of $G_{nom}(q^{-1})$. All the other poles and zeros of $G_{nom}(q^{-1})$ are included in $G_h(q^{-1})$. The separation between low and high frequency parts is based on the bandwidth of the system.

To easily introduce the invertible part G_l and also an anticipative action, the feedforward filter $P(q^{-1})$ is defined as

$$P(q_f^{-1}) = P_0(q_f^{-1})T_P(q_f^{-1}). \quad (5)$$

The P_0 factor is used to compensate the low frequency stable and minimum phase zeros of the nominal model G_{nom} . It is computed as:

$$P_0(q_f^{-1}) = G_d(q_f^{-1})G_l^{-1}(q_f^{-1}). \quad (6)$$

$T_P(q_f^{-1})$ is the preview filter. It is chosen as an anticipative FIR filter of the form:

$$T_P(q_f^{-1}) = t_{P-h}q_f^{-h} + \dots + t_{P_0} + \dots + t_{P_a}q_f^a. \quad (7)$$

Due to $T_P(q_f^{-1})$, both past and future data are used when filtering a signal through $P(q_f^{-1})$. h represents the number of data that have to be saved in the memory of the filter. The parameter a gives the anticipation. A larger a means that information further in the future is needed. While the choice of the parameter h is limited only by the available memory, a has to be adjusted taking into account the time window of available future reference values. In practice, a and h have to be adjusted in accordance to the desired dynamics of the controlled system and the desired closed-loop response time.

Let denote

$$\theta_P = [t_{P-h}, \dots, t_{P_{-1}}, t_{P_0}, t_{P_1}, \dots, t_{P_a}]^T, \quad (8)$$

the parameters vector of the unknown filter $T_P(q_f^{-1})$.

B. Optimization problem

The problem of finding the optimal estimation $\hat{\theta}_P$ is considered. Let select a model G_k from the model-set \mathcal{M}_G . To reduce the effect of the disturbance, the ∞ -norm of the system output $y(t_k)$ is minimized:

$$J_P(\hat{\theta}_P) = \sup_{t_k} |y(t_k)| = \sup_{t_k} |H_{y d_y}(q^{-1})d_y(t_k)|. \quad (9)$$

For finite energy disturbance signals $d_y(t_y)$, a least upper bound of the previous objective function can be obtained by using the system \mathcal{L}_2 norm (see [3])²

$$J_P(\hat{\theta}_P) \leq \left\| H_{y d_y}(e^{-j2\pi f/f_s}) \right\|_2 \|d_y(t_k)\|_2^2. \quad (10)$$

As stated in section II, the dynamics that generate $d_y(t_k)$ are unknown, as such the previous objective should be satisfied for any $d_y(t_k)$, thus only the first term in the right-hand side of the inequality (10) can be optimised. The following minimization problem is proposed for the unknown parameters θ_P :

$$\hat{\theta}_P = \min_{\theta_P} \left\| H_{y d_y}(e^{-j2\pi f/f_s}) \right\|_2. \quad (11)$$

In the frequency-domain, the optimal vector $\hat{\theta}_P$ is defined by the constraint minimization problem:

$$\hat{\theta}_P = \min_{\theta_P} \left\| H_{y d_y}(e^{-j2\pi f/f_s}) \right\|_2, \quad (12a)$$

$$\text{s.t. } \left\| W_{u d_y}(e^{-j2\pi f/f_s}) H_{u d_y}(e^{-j2\pi f/f_s}) \right\|_\infty \leq 1, \quad (12b)$$

$$f \in \left[0, \frac{f_s}{2} \right] \quad (12c)$$

where the weighting function $W_{u d_y}(q^{-1})$ (12b) is used to introduce a frequency constraint on the control input u_{ff} .

$H_{y d_y}(\theta_P, z^{-1})$ and $H_{u d_y}(\theta_P, z^{-1})$ are given by

$$\frac{Y(q_f^{-1})}{D_y(q_f^{-1})} = H_{y d_y}(\theta_P, q_f^{-1}) = \frac{G_d + P(\theta_P)G_k}{1 + KG_k}, \quad (13)$$

and

$$\frac{U(q_f^{-1})}{D_y(q_f^{-1})} = H_{u d_y}(\theta_P, q_f^{-1}) = \frac{-KG_d + P(\theta_P)}{1 + KG_k}, \quad (14)$$

where $G_k \in \mathcal{M}_G$.

C. Extension with robustness considerations

The proposed approach also accounts for robustness constraints in the design of the anticipative feedforward filter. The closed-loop transfer functions $H_{y d_y}(\theta_P, q^{-1})$ and $H_{u d_y}(\theta_P, q^{-1})$ that appear in the optimization problem (12) need the true plant model G for their computation. As this is not known exactly, it should be replaced by the models from the model-set. Thus, the optimization problem (12) is redefined using (15) and (16) so that $\hat{\theta}_P$ should satisfy the criterion and the constraints for all $H_{y d_y}$ and $H_{u d_y}$ in the given sets

$$H_{y d_y}(\hat{\theta}_P, q_f^{-1}) = \left\{ \frac{G_d + P(\hat{\theta}_P)G_k}{1 + KG_k}, \forall G_k \text{ in } \mathcal{M}_G \right\} \quad (15)$$

²In the frequency domain, the q^{-1} operator becomes $e^{-j\omega T_s} = e^{-j2\pi f/f_s}$.

and

$$H_{ud,y}(\hat{\theta}_P, q_f^{-1}) = \left\{ \frac{-KG_d + P(\hat{\theta}_P)}{1 + KG_k}, \forall G_k \text{ in } \mathcal{M}_G \right\}. \quad (16)$$

The problem is of infinite dimension since we must consider the whole model set \mathcal{M}_G . In practice, it is possible to select only a smaller number of models from the model-set that contain the necessary information about the variations of the true plant for the design of the robust controller.

IV. APPLICATION TO AUTOMOTIVE SUSPENSION

In this section, to assess the effectiveness of the approach presented in section III, it is implemented on INOVE test bench at GIPSA-lab, Grenoble. The quarter-car model with the semi-active ER suspension system is introduced in subsection IV-A. The design method is presented in subsection IV-B. The obtained experimental results for preview feedforward- feedback controller are discussed in subsection IV-C.

A. Semi-Active Suspension Modeling

This section describes the quarter-car model with the semi-active ER suspension system [10]. The simplified quarter vehicle model involved here consists of the sprung mass (m_s), the unsprung mass (m_{us}), the suspension components located between (m_s) and (m_{us}) and only catches vertical motions (z_s , z_{us}). The tire is simply modeled by a spring with stiffness (k_t) linked to the road (z_r) (see Fig. 2).

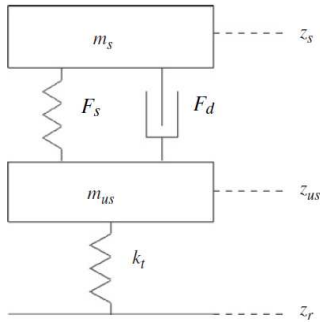


Fig. 2: Quarter car model.

From the Newton's second law of motion, the system dynamics around the equilibrium are given as [8]:

$$\begin{cases} m_s \ddot{z}_s = -F_s - F_d \\ m_{us} \ddot{z}_{us} = F_s + F_d - F_t, \end{cases} \quad (17)$$

where $F_s = k_s(z_s - z_{us})$ is the spring force; $F_t = k_t(z_{us} - z_r)$ is the tire force; the damper force F_d is modelled as follows [14]:

$$\begin{cases} F_d = k_0(z_s - z_{us}) + c_0(\dot{z}_s - \dot{z}_{us}) + F_{er} \\ F_{er} = u, \end{cases} \quad (18)$$

where c_0 , k_0 are constant parameters; z_s and z_{us} are the displacements of the sprung and unsprung masses, respectively. z_r is the road displacement input. $\dot{z}_{def} = \dot{z}_s - \dot{z}_{us}$ and $z_{def} = z_s - z_{us}$ are the deflection velocity and deflection position between the sprung and unsprung mass.

Here the control input u is controlled part of the semi-active ER damper. In practice, it is the duty cycle of the PWM signal that controls the electrical field of such a damper.

Moreover the measured output used in the real-time observer scheme is $y = \ddot{z}_s$ which is easily obtained from on board sensor (accelerometer), and low cost.

The involved model parameters are given in Table I.

Parameter	Value	Description
m_s	2.58 kg	Sprung mass
m_{us}	0.25 kg	Unsprung mass
k_s	1396 N/m	Spring stiffness
k_0	170.4 N/m	Passive damper stiffness coefficient
c_0	68.83 N.s/m	Viscous damping coefficient
k_t	12270 N/m	Tire stiffness

TABLE I: Testbed model parameters values.

The dynamics equation (17) is compactly expressed in state space form with

$$\dot{x} = A_c x(t) + B_c u(t) + B_c^{dist} d_y(t), \quad (19)$$

where $x = [z_s, \dot{z}_s, z_{us}, \dot{z}_{us}]^T \in \mathbb{R}^4$ are the system states, $d_y(t) = z_r$ is the disturbance input from the road profile. The system matrices A_c , B_c and B_c^{dist} are the system matrix, input matrix and disturbance matrix respectively (they are known). The continuous time state space model is transformed to discrete time system with a zero order hold (ZOH) sampling method with a sampling period of $T_s = 0.005$ sec.

B. Design method

In our case and from Fig. 1, the system output $y(t_k)$ and the disturbance signal $d_y(t_k)$ correspond respectively to the chassis acceleration $\ddot{z}_s(t_k)$ and the road profile $z_r(t_k)$. The plant model $G(q^{-1})$ and the road profile model $G_d(q^{-1})$ are given respectively by the following transfer functions in discrete-time.

$$G(q^{-1}) = \frac{0.387 - 1.24q^{-1} + 1.64q^{-2} - 1.10q^{-3} + 0.31q^{-4}}{1 - 2.52q^{-1} + 2.34q^{-2} - 1.02q^{-3} + 0.210q^{-4}}, \quad (20)$$

and

$$G_d(q^{-1}) = \frac{2902q^{-1} - 8397q^{-2} + 8083q^{-3} - 2588q^{-4}}{1 - 2.523q^{-1} + 2.343q^{-2} - 1.021q^{-3} + 0.2102q^{-4}}. \quad (21)$$

The robust feedback controller $K(q^{-1})$ has been designed following the \mathcal{H}_∞ robust control approach presented in [11]-chapter 7. It is given as follows:

$$K(q^{-1}) = \frac{15.21 - 37.31q^{-1} + \dots + 14.49q^{-5} - 2.456q^{-6}}{1 - 1.197q^{-1} - \dots - 1.216q^{-5} + 0.372q^{-6}}. \quad (22)$$

The results shown hereafter correspond to 40 parameters of $T_p(q^{-1})$ filter with an anticipation order of $a = 20$ (corresponding to 0.1 second). The expressions of G_h and G_l are given, respectively, by

$$G_h(q^{-1}) = 0.3876q^{-1} - 0.3876q^{-2}, \quad (23)$$

and

$$G_l^{-1}(q^{-1}) = \frac{1 - 2.523q^{-1} + 2.343q^{-2} - 1.021q^{-3} + 0.2102q^{-4}}{1 - 0.9028q^{-1} + 1.008q^{-2}}. \quad (24)$$

A frequency constraint $W_{udy}(q^{-1}) = 7000$ has been imposed to the control input sensitivity.

The coefficients of the $T_p(q^{-1})$ filter are found by solving the optimization problem (12). This has been done by using the Yalmip toolbox for MATLAB together with the MOSEK solver.

The preview FIR filter $T_p(q^{-1})$ is obtained as

$$T_p(q^{-1}) = 0.003151q^{-19} + \dots + 12.37 + \dots - 0.001948q^{20}. \quad (25)$$

C. Experimental Validation

To validate the effectiveness of the proposed approach, realtime experiments have been performed on the 1/5 car scaled car INOVE available at GIPSA-lab, shown in Fig. 3.



Fig. 3: The experimental testbed INOVE at GIPSA-lab (see www.gipsalab.fr/projet/inove).

This test-bench contains 4 semi-active Electro-Rheological (ER) dampers (from Fluidicon) controlled in real-time using MATLAB Real-Time Workshop and a host computer. The target PC is connected to the host computer via Ethernet standard communication. Also, INOVE testbed is fully equipped with sensors to measure and analyse its vertical motion. At each corner of the system, a DC motor is used to generate the road profile.

In this section, we compare the performance of the robust preview feedback-feedforward control approach (FBFF) with that of the robust feedback control alone approach (FB).

The robust preview control algorithm is applied for the rear-left corner using one sensor: the sprung mass \ddot{z}_s accelerometer. An ISO 8608 road profile signal (Type A) is used for validation approach (see Fig.4).

The experimental results of chassis acceleration \ddot{z}_s , control input u and the diagrams of force/deflection speed are presented in Fig.5 - Fig.7. They show the accuracy and efficiency of the proposed approach. To

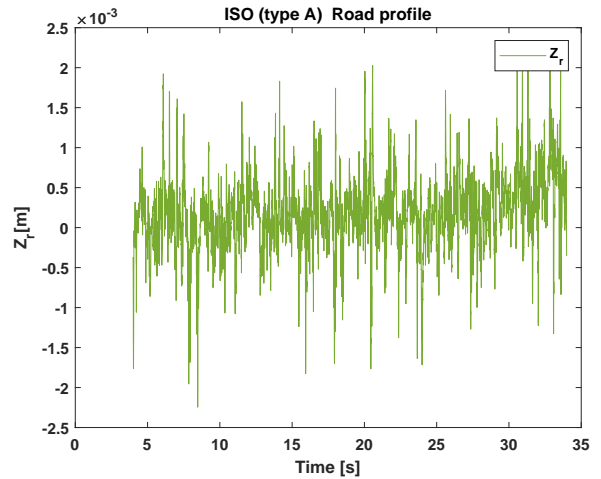


Fig. 4: ISO 8608 road profile signal (Type A).

further describe this accuracy, Table II gives the Root-Mean-Square errors of the system output and the control energy used for feedback control alone (FB) and for preview feedback-feedforward control (FBFF).

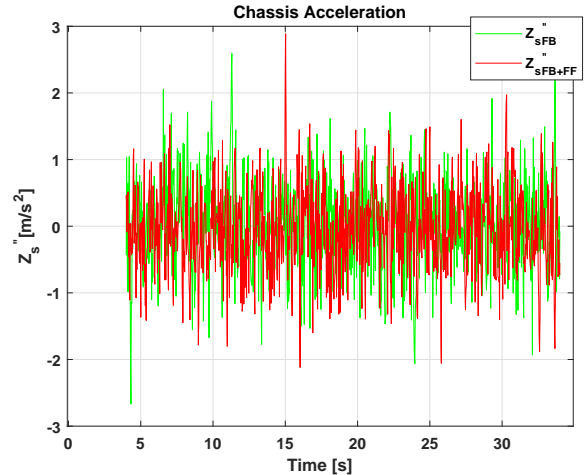


Fig. 5: Sprung mass acceleration (\ddot{z}_s).

In Fig. 8 the duty cycle of the PWM control signal of the real ER damper is shown for both strategies. In the real testbench this real damper control input is obtained using an nonlinear inverse model of the ER damper. It can be seen that the PWM control signal of the feedback-feedforward strategy is much less saturated than the one without the anticipation.

In Table. II, $\ddot{z}_{s_{RMS}}$ and E_c are given by (26) and (27).

$$\ddot{z}_{s_{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^N |\ddot{z}_{s_i}|^2}, \quad (26)$$

$$E_c = \sum_{i=0}^{N_s} u(i)^2, \quad (27)$$

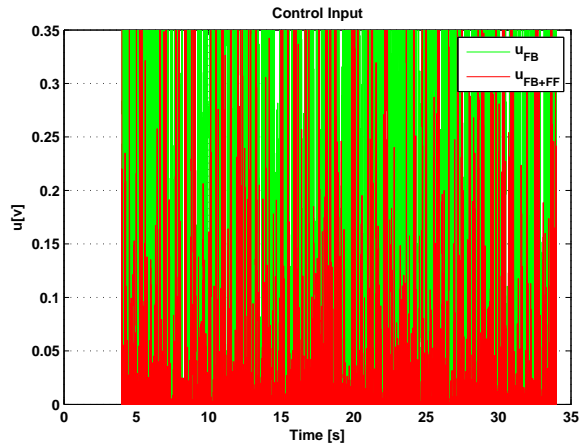


Fig. 6: Control input evaluation.

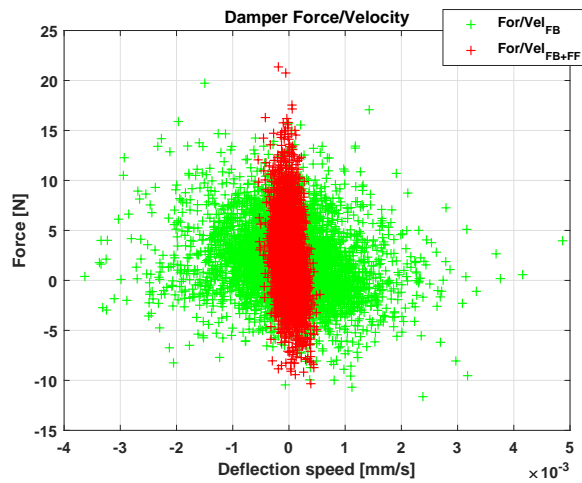


Fig. 7: Force/deflection speed diagrams.

where N_s and u represent respectively the simulation time, the duty cycle applied to the car.

To browse the entire simulation interval, N_s is set to 6001 for the both criteria.

TABLE II: Performance assessment.

	Control type	
Criteria	FB	FBFF
\ddot{z}_s_{RMS}	0.6021	0.5739
E_c	15.9846	7.3625

The obtained results show that in terms of rejection disturbances road the most suitable control approach is the preview feedforward-feedback control approach. Furthermore, it can be observed that the control effort is considerably reduced compared to the results found with the feedback approach alone (50%). This shows the advantage of the optimal preview effect. This is crucial to limit the control force damper demand and improve its reliability.

V. CONCLUSIONS

In this work, a discrete-time preview robust control was designed for road rejection disturbances for the vehicle semi-active suspension system. A preview feedforward filter was optimized in the frequency domain using a mix \mathcal{L}_2 performance and \mathcal{L}_∞ constraints to ensure rejection of future disturbances road. The experimental results demonstrate the effectiveness of the presented approach.

It is true that quarter-car models are popular, simple, unidirectional in kinematics and enable quicker computation than full-car models. However, they do not account for roll and pitch models that are important for car stability. So, it is interest in future works to extend the proposed approach for full-car models.

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