Semi-Active Suspension Control Design via Bayesian Optimization

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Abstract: The fine tuning of semi-active suspension control systems for road vehicles is usually a costly and burdensome task, needing control expertise and many hours of professional driving. In this paper, we propose a data-driven tuning method enabling the automatic calibration of the parameters of the suspension controller using a small number of experiments and exploiting Bayesian Optimization tools. The effectiveness of the proposed approach is validated on a commercial multi-body simulator. As a side contribution, the approach is shown to be robust with respect to variations of the testing conditions.

Keywords: Semi-active suspension, Vehicle dynamics, Bayesian optimization, Calibration

1. INTRODUCTION

End-of-Line (EoL) calibration of semi-active suspension systems for road vehicles is known to be a costly and heavy task, usually needing a close collaboration among professional drivers, control system experts and test engineers, as well as many hours of driving. For this reason, in Milikken et al. [1995], the tuning of the damper was defined as a black art.

A popular option to make EoL calibration an easier and more efficient task is to rely upon Hardware-in-the-Loop (HiL) simulators, where the driver seats in the car cockpit and drives within a virtual environment, while the variations of the road profile are emulated by a robotic arm, see Schuette and Waeltermann [2005]. Another alternative to real-world tests is the so-called 4-poster test system, where the car is placed on four moving platforms that emulate the road excitation, Chindamo et al. [2017]. Despite their major advantages in terms of costs and repeatability of the tests, such procedures are clearly limited by the lab environment and still require domain experts to perform a suitable calibration.

For the above reasons, in this paper we propose a data-driven calibration method, in which the problem is formulated as a sequential decision making task, see Barto et al. [1989], allowing the test engineer to perform fully automatic tuning of the suspension system. The input of the algorithm will only be the data measured by on-board sensors, while the control parameters will be returned as outputs with no need of human intervention, by minimizing a pre-defined performance-oriented objective function (e.g., addressing comfort or road handling) via Bayesian Optimization, see Snoek et al. [2012], Klein et al. [2016]. We will argue that, using the latter tool, only a limited amount of driving time is required, thus making real experimental tests cost-competitive with respect to HiL and other indoor alternatives. This would not be true for other global optimization approaches, e.g., Particle Swarm or Genetic Algorithms, since they require a high number of experiments, as discussed in Alkhatib et al. [2004]. For more details on Bayesian Optimization, see the surveys in Shahriari et al. [2015], Frazier [2018].

To summarize, the novelty of this work consists of a fully automatic calibration protocol of a fixed structure suspension controller for a road vehicle. The protocol defines the working conditions which the test must follow, the definition of an objective function corresponding to the major key performance index and a smart sampling strategy based on Bayesian Optimization, suggesting the calibration parameters which shall be tested to rapidly converge to the optimum.

The remainder of this paper is as follows. In Section 2, the calibration problem is formally stated for a parametric semi-active suspension controller and a specific layout is selected to illustrate the performance of the proposed algorithm. The automatic tuning algorithm based on Bayesian Optimization is illustrated in detail in Section 3. Simulation results, including a sensitivity analysis with respect to small variations of the testing conditions, are reported in Section 4. The paper is ended by some concluding remarks.

2. PROBLEM STATEMENT

Suspendeds represent a key technology in road vehicles for both comfort and performance, see Savaresi et al. [2010]. A suspension device typically consists of a spring and a damper connected between the wheel and corner of the vehicle. In semi-active suspensions, the damping coefficient can be adjusted in real-time. This allows to combine the superior high-frequency filtering of a low-damping configuration and the good vehicle stability of a stiff damper.

A semi-active damper is a strictly passive system (i.e., no energy is fed into the system) characterized by a controllability region defined in the I and III quadrants of the Force - Speed plane, as in Figure 1. This region defines...
the boundaries of the minimum and maximum damping force $F_d$, which the device can exert as a function of the elongation rate $\Delta \dot{z}$. The damping force is therefore given by

$$F_d = C_{ref} \Phi_{\text{max}}(\Delta \dot{z}) + (1 - C_{ref}) \Phi_{\text{min}}(\Delta \dot{z}),$$

(1)

where $\Phi$ is a non-decreasing function which shapes the damping characteristics (intrinsic to the physical hardware) and $C_{ref}$ is the control signal which denotes the damping coefficient defined in the range $[0, 1]$ (interpolating between minimum and maximum). Ideally, $\Phi$ should be linear in $\Delta \dot{z}$; however for an actual physical device the damping characteristics looks more similar to the function shown in Figure 1.

The objective of the controller consists in choosing the damping coefficient achieving the optimal comfort at any given time. The most popular control algorithm in the semi-active suspension control literature is the so-called skyhook, see Karnopp [1995], which is here presented in its variant described by:

$$C_{ref} = C + K \dot{z}_c \Delta \dot{z},$$

(2)

where $\dot{z}_c$ represents the vertical speed of the chassis. The performance of the control algorithm thus depends on the control parameters $(C, K)$, where the former specifies a nominal damping ratio, whilst the latter the sensitivity to the road excitation. Notice that if $K = 0$, the damper behaves as a passive suspension. As the control law is formulated in (2), the parameters $(C, K)$ are adimensional.

The aim of this paper is to present a calibration procedure which allows to find the optimal values of the pair $(C, K)$ from on-board measurements only, with limited experimental effort. In general, the proposed methodology could be applied to any parametric control law other than (2).

2.1 The Considered Key Performance Index

The main purpose of a suspension system is filtering vibrations due to the road excitation. The quality of the ride depends on the bandwidth where these vibrations occur, and there exists a major trade-off in the calibration of a suspension system with respect to its filtering capabilities.

In Figure 2, the spectrum of the vertical accelerations, relative to an experiment on a test road, is displayed for three configurations: passive low-damping, passive high-damping and semi-active damping.

The low-damping configuration achieves the best high-frequency filtering effect, but is poorly stable around the body resonance (around $2 \text{Hz}$). On the contrary, the high-damping shows a good damping effect, but to the detriment of high-frequency vibrations. The skyhook logic, when accurately calibrated, can achieve the best compromise between the two extreme passive configurations.

The manner in which vibrations affect comfort is dependent on the vibration frequency spectrum. In ISO 2631-1:1997 [E], an evaluation of human exposure to whole-body vibrations is presented. The standard defines a complex key performance index consisting of tri-axial (longitudinal, lateral and vertical) and rotational (roll, pitch and yaw) accelerations; each component is weighted to take into account the range of frequencies which can be perceived by the human body. Eventually, the aforementioned terms are combined in a weighted summation whose result is the final ISO Index, defined as:

$$J = \sqrt{\sum_i (k_i J_i)^2},$$

(3)

where

$$J_i = \sqrt{\frac{1}{T} \int_0^T A_{i\omega}^2(t)^2 \, dt}$$

$$A_{i\omega}^2(t) = W_i(j\omega) A_i(t).$$

In the above expressions, $A_i$ is the $i^{th}$ acceleration (longitudinal, lateral, vertical and rotational), $W_i$ is the frequency weight associated to that term, $J_i$ the root mean square of $A_{i\omega}^2$ and $J$ the ultimate condensed ISO Index. The reader is referred to ISO 2631-1:1997 [E] for the exact expressions of the frequency weights $W_i$ and gains $k_i$.

The quality of a given calibration of the suspension controller will be evaluated from now on after an experiment over a test road as specified by (3).
3. THE PROPOSED DATA-DRIVEN APPROACH

This section introduces the proposed Bayesian Automatic Calibration (BAC) protocol for a parametric suspension control system like the skyhook controller of (2).

3.1 Experimental Protocol

The experiments shall be performed on a single test road representative of the dynamics of interest. This is a critical point, since the result of the optimization strongly depends on the road excitation; in other words, the optimal configuration for a driving cycle on a highway and off-road are expected to differ significantly. Hence, the choice of the road profile has an important impact on the outcome of the optimization and shall be carefully evaluated in the design phase.

In particular, each experiment must be performed over the same road segment at constant velocity in order to ensure the same frequency excitation.

3.2 Performance Evaluation

The evaluation of each experiment is assessed at the end of the experiment itself, based on the ISO Index sensed on the driver seat via an inertial measurement unit (IMU). It is important to remark that any other index based on sensors data could be employed to target a different objective.

The objective of the calibration consists in finding the optimal configuration for the control parameters, which minimizes the ISO Index (thus maximizing the riding comfort) in the least possible number of iterations.

3.3 Methodology

An effective technique to solve these problems would be to formulate an optimization problem including the model of the vehicle and the information about the road profile. However, models are always only an idealization of the real system. For this reason, we will follow a different, purely data-driven rationale, consisting of two main ingredients: a surrogate function to estimate the objective function from data, and an acquisition function to sample the next observation, see Bemporad [2019].

The surrogate function shall be ideally model-free or non-parametric, unless one desires to constrain the objective function to a certain class (e.g., quadratic). In Bayesian Optimization (BO), the objective function is assumed to be drawn from a Gaussian Process (GP), where each observation is a random variable normally distributed and jointly Gaussian with one another. In particular, each pair of observations is bonded by a covariance function encoding the belief that closer points shall have higher correlation than those far apart; typical choices are the Gaussian and Matérn kernels.

Hence, given a set of observations, it is possible to fit a GP whose posterior mean is the expected estimation of the objective function, and its variance represents a confidence interval for the estimation. This means that, for any given set of control parameters, it is possible to compute the estimated ISO Index and a goodness indicator of this estimate.

Given this posterior model, there are several options for the acquisition function which aims at sampling the next observation where there is a higher probability to find a minimum, according to the posterior mean and variance. The most popular algorithms are Expected Improvement and Upper Confidence Bound which can be found declined in different variations to tackle the so-called exploration-exploitation trade-off.

3.4 Algorithm

A pseudocode summarizing this procedure is shown in Algorithm 1. The initialization is performed by picking at random (or any best guess policy) a set of control parameters \((C, K)\), which are evaluated by performing an experiment and then computing the ISO Index defined in (3). The objective function is then estimated by fitting a Gaussian Process (GP). Eventually, the next set of control parameters are chosen by maximizing the expected improvement (EI), which identifies the region in the parameters space, where it is most likely to find the minimum according to such an acquisition function; the parameters are then evaluated by performing another experiment and the ISO Index is computed and updated accordingly.

This class of optimization problems does not rely upon a stopping condition since they are based on the assumption that the evaluation of an experiment is expensive and, thus, there shall be a budget cap to the maximum number of experiments to be performed. Hence, the procedure in Algorithm 1 is repeated until the allowed maximum number of iterations is reached.

Algorithm 1 Bayesian Automatic Calibration (BAC)

\[
(C^{obs}, K^{obs}) \leftarrow \text{random} \\
\text{Perform Experiment and Evaluate } J^{obs} \\
\text{while } i < \text{MaxIterations do} \\
\mu, \sigma \leftarrow \text{fitGP}(C^{obs}, K^{obs}, J^{obs}) \\
(C^{next}, K^{next}) \leftarrow \text{argmax EI}(\mu, \sigma) \\
\text{Perform Experiment and Evaluate } J^{next} \\
\text{Update } (C^{obs}, K^{obs}, J^{obs}) \\
(C^{opt}, K^{opt}) \leftarrow \text{argmin}(\mu)
\]

4. SIMULATION RESULTS

In this section, different data-driven calibration strategies are compared: i) Grid Search, ii) Random Search and iii) Bayesian Automatic Calibration (BAC). These strategies are the best candidates to solve the global optimization problem in the scenario described here, where the evaluation of an experiment is an expensive task.

Grid Search represents the current calibration paradigm where the engineer tests each possible combination of the control parameters; it is the least efficient strategy which requires many experiments if the parameters space is fitted on a thin grid. Random Search is a standard benchmark.
Fig. 3. The luxury sedan vehicle employed in the simulations of Section 4.

in literature, where the parameters are sampled at random from a uniform distribution in the parameters space; it is more efficient than Grid Search, but the optimum is not guaranteed to be found. BAC is the candidate framework proposed in this paper introduced in Section 3.

4.1 Simulation Setup

The experimental simulation of the proposed framework is performed on a full-fledged commercial vehicle simulator which can model complex multi-body dynamics.

The target vehicle is the luxury sedan illustrated in Figure 3, where the main parameters of interest are:

- sprung mass: 1370 Kg
- unsprung mass: 160 Kg
- spring stiffness: 153 N/mm

The vehicle is modeled as a MIMO system whose inputs are the damping forces at the four corners and the outputs are the accelerations the vehicle is subject to (used for the ISO Index evaluation), the elongation rates $\Delta \dot{z}$ and the vertical corner velocities $\dot{z}_c$ (used for feedback in control).

The control system is implemented in a Matlab/Simulink environment following Equations (1)-(2).

The candidate road profile is representative of a rough pavement with low-frequency valley, exciting a broad range of frequencies, traveled at the constant speed of 80 km/h.

4.2 Main Results

The utilization of a simulation environment made it possible to find the actual true minimum of the objective function via Gradient Descent. This is useful for benchmarking the different global optimization strategies.

The Grid Search strategy consisted in testing $C$ in [0, 1] with step 0.05, and $K$ in [0, 50] with step 1; therefore, the grid accounts for 1071 cells, corresponding to the equivalent number of experiments to be performed in order to find the optimal value. A projection of the ISO Index evaluated at each point of the grid is shown in Figure 4, where the green cross represents the true optimum computed via Gradient Descent.

In Random Search, $C$ and $K$ are drawn from uniform distributions, in [0, 1] and [0, 50], respectively. The maximum number of iterations has been set to 30; after performing 30 experiments, the one whose ISO Index is smaller is chosen as the best calibration.

The proposed BAC strategy can identify the region where the optimum is located after only 30 experiments. The chronicle of the observations follows Algorithm 1, and it can be interpreted as follows: at first, pairs at the boundaries of the parameters space are evaluated to learn the approximate shape of the objective function; then, the observations are sampled in the neighborhood of the region where the optimum is most likely to be located. Figure 5 shows the ISO Index estimated after 30 iterations; the observations are represented by yellow dots and are arranged close to the estimated minimum.

The algorithm assigns an indicator for the goodness of the estimation, indicated by $\sigma$ in Algorithm 1, shown in Figure 6: the points where the objective function has been observed are assigned a low uncertainty (ideally this should be zero for a deterministic process), whereas areas far apart from an observation are more uncertain. The main feature of BAC consists in an efficient sampling strategy, which does not consider the areas where the minimum is
5. CONCLUSIONS

This paper presented a novel approach for the automatic calibration of a fixed structure parametric suspension control system. It is shown that the proposed BAC protocol, based on Bayesian Optimization, requires (one to two orders of magnitude) less iterations than Grid Search to reach the region of convergence where the optimum lies.

Future research will be devoted to an experimental validation of the proposed approach.
Table 1. Optimal suspension control parameters found by each strategy, after the specified number of iterations.

|             | True | GS  | RS  | BAC | RS  | BAC |
|-------------|------|-----|-----|-----|-----|-----|
| Iterations  | -    | 1071| 30  | 30  | 100 | 30  | 30  |
| C           | 0.03 | 0.05| 0.01| 0.07| 0.03| 0.01| 0.03|
| K           | 8.49 | 8.00| 17.89| 8.99| 9.74| 2.31| 20.91|
| ISO Index   | 0.82 | 0.82| 0.84| 0.83| 0.82| 0.89| 0.84|
| Median       |      |     |     |     |     |     |     |
| Worst Case   |      |     |     |     |     |     |     |

Fig. 8. Three random realizations of the perturbed road profile.

Fig. 9. ISO Index estimated in the perturbed scenario. The yellow dots represent the points of the parameters space explored via closed-loop experiments.

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