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Intelligent Monitoring the Vertical Dynamics of Wheeled Inspection Vehicles

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Abstract: The problem of intelligent monitoring of the vertical dynamics of wheeled inspection vehicles is addressed. With the independent MacPherson suspension system installed, the basic analysis focuses on the evaluation of the parameters of the so-called quarter car model. To identify a physically motivated continuous description, in practice, dedicated integral-horizontal filters are used. The obtained discrete model, which retains the original parameters, is effectively identified using the classic least squares procedure. Using the method of identification in the sense of the least sum of absolute values, the results of such an assessment become insensitive to sporadic outliers in the sampled data. However, the early signs of possible mechanical defects of the suspension can be seen using the forgetting mechanism. This helps to identify failures that can be recognized by changes in system parameters. Ultimately, the quality of the intelligent vehicle suspension monitoring developed is verified by means of numerical simulations.

Keywords: vehicle suspension, quarter car model, continuous system, least squares, least absolute values.

1. INTRODUCTION

In recent years, many autonomous aerial drones, unmanned mobile robots and inspection vehicles have found a variety of practical applications. For example, professional remote-controlled drones are successfully engaged in border patrols, while specific police quadcopters with vision systems ascend to the sky to monitor road traffic. Dedicated untethered robots, in turn, take on difficult diagnostic tasks, mentioning the detection of corrosion attacks inside pipelines or inspection of boiler tubes in power plants. In addition, wheeled or tracking inspection vehicles are extremely practical in discovering unknown areas and play an invaluable role in hazardous rescue operations after mining disasters. It is worth noting that these specific applications bring measurable economic benefits, which clearly justifies the intensive development of unmanned aerial and ground intelligent robots (Kowalczuk and Tatara, 2019).

It is important that all component subsystems of the mobile robot are reliable and efficient enough. In particular, the mechanical efficiency of the suspension system is crucial for successful completion of tasks performed by wheeled inspection vehicles. Thus, the intelligent monitoring of the dynamics of the suspension mechanism is of importance.

Early detection of mechanical damage can be a serious incentive to withdraw the vehicle from the area under exploration. This significantly reduces the risk of losing the vehicle with its load and expensive sensing systems. Therefore, the identification procedure resistant to disturbances and occasional outliers is important to avoid possible misinterpretation of measurement data disturbed by noise or sporadic errors (resulting, for example, from the unexpected maximal compression of the shock absorber).

Therefore, the developed intelligent system that supervises the vertical dynamics of the inspection vehicle should meet the following requirements: (i) numerical processing (signal sampling, data registration) and evaluation of the suspension model parameters takes place in online mode; (ii) the implemented identification procedures enable tracking the evolution of time-variable parameters; (iii) the data processing is to some extent resistant to additive measurement noise and environmental disturbances; (iv) the estimation results are insensitive to occasional outliers in the recorded data; (v) the identification results remain reliable, even if non-linear saturation effects occur in the system (e.g. extreme compression or extension of the shock absorber).

This study discusses the following issues. Section 2 presents the suspension model for a quarter car. Due to the use of integration operators with a finite horizon, the appropriately rearranged description takes the form of an equivalent discrete model that retains the original parameters. Different recursive and iterative estimaation algorithms are introduced in section 3. It is explained that the proposed estimation in the sense of the least sum of absolute values make the identification results robust to occasional outliers in the data being processed, while the least squares estimates are usually heavily influenced by such occasional measurement errors. The results of the numerical test are given in section 4, while section 5 summarizes the research and draws conclusions.

2. VEHICLE SUSPENSION MODEL

2.1 Quarter Car Dynamics

Essentially, a vehicle suspension is a system of tires, shock absorbers (dampers), springs and appropriate mechanical

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couplings that connect wheels and the car body. The main purpose of this system is to guarantee passengers the comfort of traveling. In the case of unmanned vehicles, proper suspension mechanisms should protect the cargo (e.g. expensive sensors or medical material needed in rescue operations), and also prevent vehicle incidents with potentially fatal consequences (e.g. accidents with turnover).

The general dynamics of a moving vehicle are determined by three basic forces: longitudinal, lateral and vertical. Given that these directions are perpendicular, the monitored vertical acceleration is in fact independent of other movements. However, the MacPherson suspension column design (with wheels reacting independently to field impacts) simplifies the problem, taking into account the so-called dynamics of a quarter car (Fig. 1).

The physical model explaining the vertical dynamics of the vehicle is shown in Fig. 2. In this model, the body with passengers and load is represented by the sprung mass (M). Unsprung weight (m), in turn, includes a wheel (tire and rim), wheel hub, rolling bearings, brake blocks, bolts and other structural components not protected by the spring. Parameters K and β describe the spring stiffness and the shock absorber damping of the suspension system, respectively. Analogically, the parameters K_0 and β_0 define the respective properties of the tire (Hassaan, 2014).

The influence of spring stiffness can be described by Hooke's well-known law. According to a suitable rule, the tensile force of an elastic body (a spring or tire) increases linearly with the distance change. In the case of hydraulic dampers, the occurring Stokes viscosity force is proportional to the speed of movement of the shock absorber sleeve. In fact, tire elasticity is usually only relevant in the dynamics of heavy vehicles (buses or trucks). Most often the damping of the tire is radically smaller compared to the damping provided by the shock absorber, so you can simply ignore parameter β_0 in further considerations.

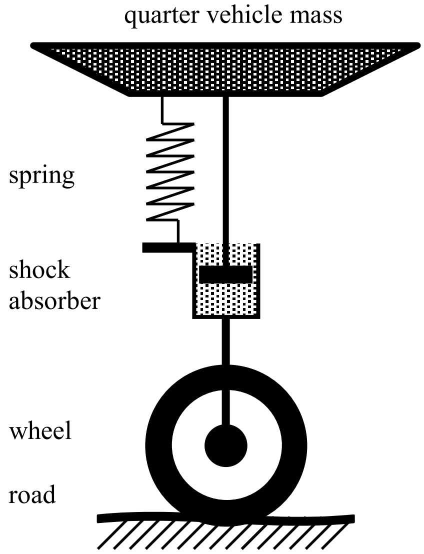

Fig. 1. Quarter car suspension system.

Thus, following the Newton's laws, the differential equations describing the vertical dynamics can be written down as

$$M\,z'' = \beta(w' - z') + K(w - z) \tag{1}$$

$$m\,w'' = -\beta(w' - z') - K(w - z) - K_0(w - \mu) \tag{2}$$

where $z(t)$ and $w(t)$ describe movements of the sprung and unsprung masses, respectively, while the road-tire reaction (i.e. system excitation) is represented by $\mu(t)$. One should also realize that an initial compression of the spring compensates the gravity force acting on the vehicle. Since a certain static equilibrium of the suspension is observed in the motionless vehicle, the gravity can be neglected in (1) – (2).

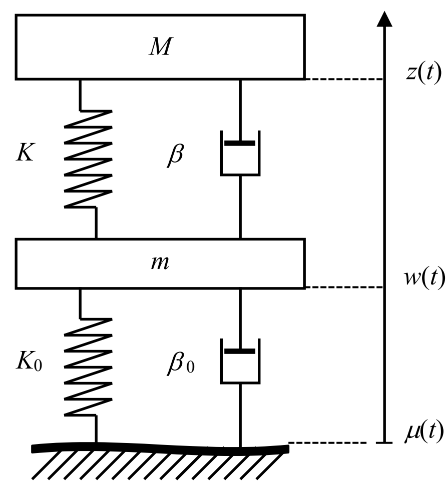

Fig. 2. Physical model of the suspension system.

By introducing an equivalent state-space representation of the mechanical suspension, a possible numerical implementation of the respective dynamics can be facilitated. With the convenient phase variables ($x_1 = z$, $x_2 = w$, $x_3 = z'$, $x_4 = w'$) represented in the state vector

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \tag{3}$$

the state-space representation of the dynamics of the suspension system is given by

$$\mathbf{x}' = \mathbf{A}\,\mathbf{x} + \mathbf{B}\,\mu \tag{4}$$

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ \frac{-K}{M} & \frac{K}{M} & \frac{-\beta}{M} & \frac{\beta}{M} \\ \frac{K}{m} & \frac{-(K+K_0)}{m} & \frac{\beta}{m} & \frac{-\beta}{m} \end{bmatrix} \tag{5}$$

$$\mathbf{B} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{K_0}{m} \end{bmatrix}. \tag{6}$$

Practical methods for discrete approximation of continuous models are discussed in the next section.

2.2 Continuous-Time Modelling

Consider a differential equation model of the linear dynamics

$$y^{(n)} = -a_{n-1} y^{(n-1)} + \ldots - a_0 y + b_{n-1} u^{(n-1)} + \ldots + b_0 u \tag{7}$$

with $u = u(t)$ and $y = y(t)$ standing for the input and output signals, respectively. The system can be subject to certain (usually unknown) initial conditions: $y^{(n-1)}(0)$, … , $y(0)$, and $u^{(n-1)}(0)$, … , $u(0)$. Numerical identification of the parameters a_i and b_i is based on processing of the recorded samples of the input and output signals. This methodology, commonly referred to as discrete identification of continuous models, employs dedicated methods of numerical approximation of continuous quantities (Unbehauen and Rao, 1990). Among different approaches, the idea of linear integral filtering (LIF) in transformation of (7) brings promising results.

The LIF operation (Sagara and Zhao, 1990) subject to an rth derivative of a measurement signal $x(t)$

$$J^n x^{(r)}(t) = \int_{t-h}^{t} \int_{t_1-h}^{t_1} \ldots \int_{t_{n-1}-h}^{t_{n-1}} x^{(r)}(t_n)\, dt_n\, dt_{n-1} \ldots dt_1 \tag{8}$$

is simply represented by the multiple nth order integration of the signal $x^{(r)}(t)$ over an assumed time interval h. By employing the well-known trapezoidal method of numerical integration, the operation (8) can easily be approximated in discrete domain $J^n x^{(r)}(t) \approx I_r^n \cdot x(kT)$ using the FIR filter

$$I_r^n = (\tfrac{1}{2}\, T)^{n-r} (1+q^{-1})^{n-r} (1-q^{-1})^r (1+q^{-1} + \ldots + q^{-L+1})^n \tag{9}$$

where q^{-1} is the delay operator ($q^{-1} \cdot x(kT) = x(kT - T)$) and an integer parameter L expresses the integration horizon h as a multiplicity of the sampling time T (i.e. $h = L \cdot T$). The accuracy of the above processing can be improved by employing more sophisticated rules of numerical integration.

Application of the method of splines, for instance, makes the processing (8) robust to possible accumulation of numerical errors (Kowalczuk, 1993; Kowalczuk and Kozłowski, 2000).

Finally, the discrete model retaining the original parameters represented in (7) takes a convenient regression form

$$\psi(k) = I_n^n y(k) = \boldsymbol{\varphi}^{\mathrm{T}}(k)\boldsymbol{\theta} + e(k) \tag{10}$$

$$\boldsymbol{\varphi}(k) = [\, -I_{n-1}^n y(k) \ldots \, -I_0^n y(k) \;\; I_{n-1}^n u(k) \ldots \; I_0^n u(k)\,]^{\mathrm{T}} \tag{11}$$

$$\boldsymbol{\theta} = [\, a_{n-1} \ldots a_0 \;\; b_{n-1} \ldots b_0 \,]^{\mathrm{T}} \tag{12}$$

with k standing for the sampling moment $k \cdot T$, $\psi(k)$ denoting the reference signal, $e(k)$ being the residual error, and $\boldsymbol{\varphi}(k)$ and $\boldsymbol{\theta}$ representing the regression and parameter vectors, respectively.

It is worth noticing that the described LIF approach to approximation of continuous models brings rational advantages. First, the entries of (11) obtained from the FIR filtering of the measurement signals stay bounded, provided the system (7) is stable (i.e. the input-output signals are bounded). Second, the respectively integrated free response of the system (7) is entirely eliminated after the elapse of time $n \cdot L \cdot T$, and thus the unknown initial conditions of (7) do not influence the results of parameter estimation.

Yet, the bias of estimates influenced by additive noises can significantly be reduced, provided the integration horizon ($h = L \cdot T$) is tuned so that the magnitude characteristics of the identified system (7) and the LIF operator (8) are closely matched (Sagara and Zhao, 1990).

Now, by employing suitable estimation procedures the parameters (12) of the underlying continuous dynamics (7) can easily be identified.

3. ESTIMATION PROCEDURES

3.1 Least Squares Estimator

It is realistic that the monitored vehicle suspension can sometimes be a variable-parameter system. Of course, weight losses resulting from fuel consumption in combustion engines are almost unnoticeable in a short time period. There exist, however, situations in which changes of the sprung mass are evident. This takes place, for instance, when an agricultural vehicle spreads herbicides, pesticides, fertilizers or other chemical agents on the reclaimed soil. What is more, a possible damage of the mechanical system (e.g. oil leak in a hydraulic damper) can also influence variations in the identified parameters. It is therefore practical that estimation procedures utilize a specific forgetting mechanism allowing for on-line tracking the evolution of variable parameters (12).

Most commonly, the weighted least squares (LS) algorithm resulting from minimization of the classical quadratic criterion

$$V_{\mathrm{LS}}(\boldsymbol{\theta}) = \sum_{i=1}^{k} \lambda^{k-i} e^2(i) = \sum_{i=1}^{k} \lambda^{k-i} [\, \psi(i) - \boldsymbol{\varphi}^{\mathrm{T}}(i)\, \boldsymbol{\theta}\,]^2 \tag{13}$$

can be used to identify the parameters of the monitored system. The LS routine in its algebraic form can be shown as

$$\hat{\boldsymbol{\theta}}(k) = \left[\sum_{i=1}^{k} \lambda^{k-i}\, \boldsymbol{\varphi}(i) \boldsymbol{\varphi}^{\mathrm{T}}(i) \right]^{-1} \left[\sum_{i=1}^{k} \lambda^{k-i}\, \boldsymbol{\varphi}(i) \psi(i) \right] \tag{14}$$

where the so-called forgetting factor λ usually falls in the range of 0.9…1. The choice of λ influences the memory length of the LS routine. This length (referred to as an effective number of observations) is given by: $\Gamma = 1/(1 - \lambda)$. In order to overcome the numerically inconvenient matrix inversion, a recursive realization of (14) can be derived using the matrix inversion lemma (Ljung, 1987). This results in

$$\varepsilon(k) = \psi(k) - \boldsymbol{\varphi}^{\mathrm{T}}(k) \hat{\boldsymbol{\theta}}(k-1) \tag{15}$$

$$\mathbf{P}(k) = \frac{1}{\lambda} \left[\mathbf{P}(k-1) - \frac{\mathbf{P}(k-1) \boldsymbol{\varphi}(k) \boldsymbol{\varphi}^{\mathrm{T}}(k) \mathbf{P}(k-1)}{\lambda + \boldsymbol{\varphi}^{\mathrm{T}}(k) \mathbf{P}(k-1) \boldsymbol{\varphi}(k)} \right] \tag{16}$$

$$\hat{\boldsymbol{\theta}}(k) = \hat{\boldsymbol{\theta}}(k-1) + \mathbf{P}(k) \boldsymbol{\varphi}(k) \varepsilon(k) \tag{17}$$

where the covariance matrix $\mathbf{P}(k)$ appearing in (15) – (17) is simply the inverse of the information matrix $\mathbf{R}(k)$ represented in the first brackets of (14). The start-up value of this matrix is usually assumed as $\mathbf{P}(0) = \text{diag}\,(10^5, \ldots, 10^5)$. Note that the LS estimates are consistent provided the regression data $\boldsymbol{\varphi}(k)$ and the residual process $e(k)$ represented in (10) are uncorrelated ($\text{E}[\boldsymbol{\varphi}(k)e(k)] = 0$). This takes place, for instance, when $e(k)$ is a zero-mean white noise sequence. Otherwise (i.e. for correlated noises), the estimates (17) suffer from an asymptotic bias. The instrumental variable method is a good remedy to the bias problem (Söderström and Stoica, 1981).

5.2 Least Absolute Values Estimator

The introduced recursive LS routine is numerically simple and convenient for implementation. Unfortunately, the respective method is very sensitive to possible outliers in measurement data. In order to overcome this problem an estimator in the sense of the least sum of absolute values (LA) can be put into practice (Janiszowski, 1998). Since analytical minimization of the respective goal function

$$V_{\text{LA}}(\boldsymbol{\theta}) = \sum_{i=1}^{k} \lambda^{k-i}\,|\,e(i)\,| = \sum_{i=1}^{k} \lambda^{k-i}\,|\,\psi(i) - \boldsymbol{\varphi}^{\text{T}}(i)\,\boldsymbol{\theta}\,| \tag{18}$$

is problematic, an iterative solution can be proposed. Assuming that approximate values of the residual error $e(k)$ are available (e.g. from a running-in-parallel LS procedure), the LA criterion can be rearranged as follows

$$V_{\text{LA}}(\boldsymbol{\theta}) = \sum_{i=1}^{k} \lambda^{k-i} \frac{e^2(i)}{|\,e(i)\,|} \approx \sum_{i=1}^{k} \lambda^{k-i} \frac{[\,\psi(i) - \boldsymbol{\varphi}^{\text{T}}(i)\,\boldsymbol{\theta}\,]^2}{|\,\hat{e}(i)\,|} \tag{19}$$

what allows for analytical minimization of (19), which gives

$$\hat{\boldsymbol{\theta}}(k) = \left[\sum_{i=1}^{k} \lambda^{k-i} \frac{\boldsymbol{\varphi}(i)\boldsymbol{\varphi}^{\text{T}}(i)}{|\,\hat{e}(i)\,|}\right]^{-1} \left[\sum_{i=1}^{k} \lambda^{k-i} \frac{\boldsymbol{\varphi}(i)\psi(i)}{|\,\hat{e}(i)\,|}\right]. \tag{20}$$

The result (20) can further be improved by performing an iterative processing. With the initial estimates of the residual error $e(i) = \psi(i) - \boldsymbol{\varphi}^{\text{T}}(i)\boldsymbol{\theta}$ obtained from an LS scheme

$$\hat{e}^{/p/}(i) = \psi(i) - \boldsymbol{\varphi}^{\text{T}}(i)\,\boldsymbol{\theta}^{/p/} \tag{21}$$

$$\hat{\boldsymbol{\theta}}^{/p+1/} = \left[\sum_{i=1}^{k} \lambda^{k-i} \frac{\boldsymbol{\varphi}(i)\boldsymbol{\varphi}^{\text{T}}(i)}{|\,\hat{e}^{/p/}(i)\,|}\right]^{-1} \left[\sum_{i=1}^{k} \lambda^{k-i} \frac{\boldsymbol{\varphi}(i)\psi(i)}{|\,\hat{e}^{/p/}(i)\,|}\right] \tag{22}$$

the ultimate iterative procedure (21) – (22) of successive approximations ($p = 0, 1, \ldots$) follows instantly.

It is of fundamental importance that the index (18) is decreasing in consecutive iterations of the above algorithm (Kozłowski, 2003). Therefore the processing (21) – (22) can be terminated, if the observed decrease in minimization of (18) falls below an assumed threshold value (e.g. $\Delta_{\min} = 10^{-6}$)

$$\left|\, V_{\text{LA}}(\hat{\boldsymbol{\theta}}^{/p/}) - V_{\text{LA}}(\hat{\boldsymbol{\theta}}^{/p+1/}) \,\right| < \Delta_{\min}\,. \tag{23}$$

It is natural that the residual errors (21) tend to zero, so the presented iterative solution suffers from the problem of small divisors. In such cases the so-called regularization can be applied in computations. Namely, the close-to-zero absolute values appearing in (22) are substituted with a fixed threshold $\varepsilon_{\min}$ (e.g. $\varepsilon_{\min} = 10^{-8}$).

The LA routine can be simplified, provided the processing (21) – (22) is bounded to a single iteration only. Application of the matrix inversion lemma leads to an approximate recursive LA scheme (Kowalczuk and Kozłowski, 2011)

$$\varepsilon(k) = \psi(k) - \boldsymbol{\varphi}^{\text{T}}(k)\,\hat{\boldsymbol{\theta}}(k-1) \tag{24}$$

$$\mathbf{P}(k) = \frac{1}{\lambda}\left[\mathbf{P}(k-1) - \frac{\mathbf{P}(k-1)\boldsymbol{\varphi}(k)\boldsymbol{\varphi}^{\text{T}}(k)\mathbf{P}(k-1)}{\lambda\,|\,\varepsilon(k)\,| + \boldsymbol{\varphi}^{\text{T}}(k)\mathbf{P}(k-1)\boldsymbol{\varphi}(k)}\right] \tag{25}$$

$$\hat{\boldsymbol{\theta}}(k) = \hat{\boldsymbol{\theta}}(k-1) + \mathbf{P}(k)\boldsymbol{\varphi}(k)\,\text{sgn}[\varepsilon(k)] \tag{26}$$

where, as before, λ stands for the forgetting factor. The derived algorithm has to be initiated. In early instants (for $k = 1 \ldots k_0$), the LS estimates can be used. Then, beginning with $k = k_0 + 1$, the recent covariance matrix $\mathbf{P}(k)$ and the estimate of $\boldsymbol{\theta}$ can be supplied in (24) – (26). This initiation is efficient for the weighted estimator ($\lambda < 1$). This is so, because the finite memory ($\Gamma < \infty$) of the algorithm allows for gradual elimination of the temporary start-up data from the information matrix $\mathbf{R}(k)$ (i.e. $\mathbf{R}(k) = \mathbf{P}^{-1}(k)$). Identically, as before, the correlation $\text{E}[\boldsymbol{\varphi}(k)e(k)]$ influences the consistency of the estimates, so the instrumental variable method can again be helpful to improve the accuracy of estimation.

The described LS and LA algorithms are subsequently used in identification of the suspension model parameters.

4. SIMULATION RESULTS

To determine the dynamics of the suspension system (Fig. 2), the appropriate measurement signals should be selected. In the simplest way, two accelerometers can be used to record the dynamics of both elastic and unsprung masses. Unfortunately, an additional (and usually expensive) in-tire accelerometer is necessary to ensure a reliable measurement of the road-tire reaction. In this study, the model used has been further simplified by ignoring the stiffness of the tire ($K_0 \to \infty$). This assumption is absolutely realistic in the case of unmanned vehicles that use non-pneumatic tires. Of course, rolling resistance is thereby increased, but the risk of losing the vehicle immobilized by tire damage is eliminated.

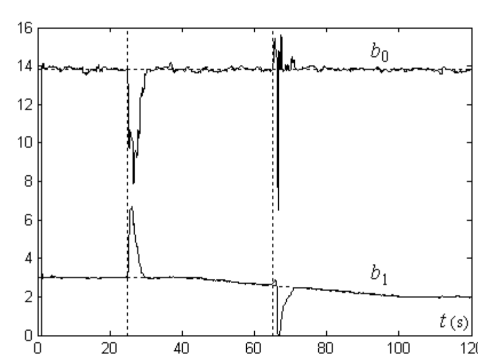

Fig. 3. LS identification of time-variant system parameters (vertical lines indicate the appearance of outliers).

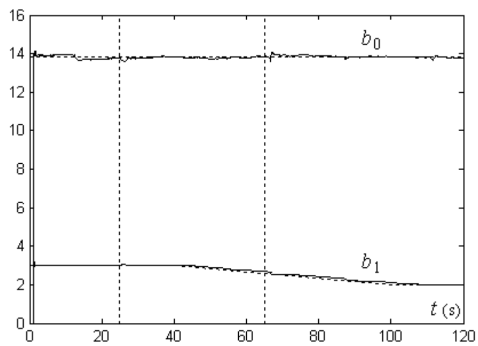

Fig. 4. LA identification of time-variant system parameters (vertical lines indicate the appearance of outliers).

Since the road-tire reaction can then be monitored by the 'wheel accelerometer', the ultimately considered model of the vehicle suspension assumes the following form

$$z'' = b_1(w' - z') + b_0(w - z) \tag{27}$$

with $b_1 = \beta / M$, $b_0 = K / M$, and $w(t) = \mu(t) + R$, where R stands for the radius of the wheel.

Now, with the output $y = z''$ representing the acceleration of the sprung mass, and the input $u = w'' - z''$ being the difference of both the monitored accelerations, the discrete counterpart of (27) can be shown in the regression form

$$\psi(k) = I_2^2 y(k) = \boldsymbol{\varphi}^{\mathrm{T}}(k)\boldsymbol{\theta} + e(k) \tag{28}$$

$$\boldsymbol{\varphi}(k) = [\, I_1^2 u(k) \;\; I_0^2 u(k) \,]^{\mathrm{T}} \tag{29}$$

$$\boldsymbol{\theta} = [\, b_1 \;\; b_0 \,]^{\mathrm{T}} . \tag{30}$$

In the performed numerical tests the mechanical parameters $\beta = 150$ (kg·s^{-1}), $K_0 = 690$ (kg·s^{-2}), and $M = 50$ (kg) define the initial dynamics (27) of the suspension. The road reaction is represented by the function (Fig. 7)

$$\mu(t) = \sum_{i=1}^{4} G_i \left(1 - \cos\tfrac{2\pi t}{T_i}\right) \tag{31}$$

where $G_1 = 1$, $G_2 = 2$, $G_3 = 3$, $G_4 = 4$ (cm), and $T_1 = 1.3$, $T_2 = 1.9$, $T_3 = 2.5$, $T_4 = 2.8$ (rad·s^{-1}).

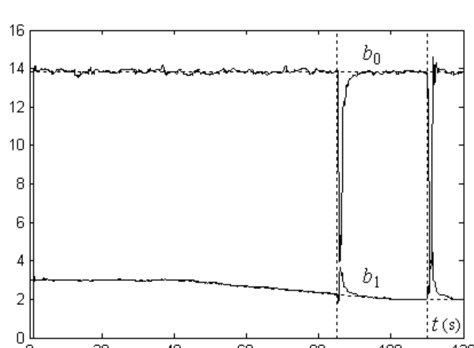

Fig. 5. LS identification of time-variant system parameters (vertical lines indicate the saturation effect).

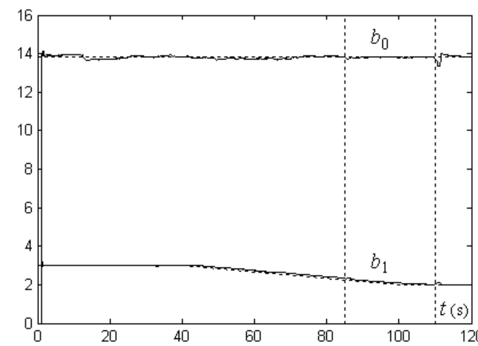

Fig. 6. LA identification of time-variant system parameters (vertical lines indicate the saturation effect).

In experiments (Fig. 3, Fig. 4) the loss of measurement data (i.e. $z(t) = w(t) = 0$ for $25 \le t \le 26$ (s) and for $65 \le t \le 66$ (s)) is supposed to represent occasional measurement faults.

Additionally, a specific component is added to excitation (31) (i.e. $\mu(t) \leftarrow \mu(t) + \delta(t)$) so as to simulate sporadic road bumps influencing saturations of the shock absorber (Fig. 5, Fig. 6)

$$\delta(t) = \sum_{i=1}^{2} H_i \exp\,[-\alpha_i (t - \tau_i)^2]\,. \tag{32}$$

The function $\delta(t)$ is subject to $H_1 = H_2 = 15$ (cm), $\tau_1 = 85$ (s), $\tau_2 = 110$ (s), and $\alpha_1 = \alpha_2 = 22.2$ (s^{-2}).

The sampling time equals $T = 0.02$ (s), while the independent additive noises corrupting the measurements of accelerations are assumed as zero-mean uniformly distributed processes with equal standard deviations ($\sigma = 2.4$).

Yet, a mechanical damage of the shock absorber results in an observed gradual change (i.e. from 150 down to 100 (kg·s^{-1})) of the damping parameter β in the time interval 40…100 (s).

The integration horizon $L = 30$ ($h = L{\cdot}T = 0.6$ (s)) is implemented in numerical realization of the FIR operators (9), and both the employed recursive estimators utilize the forgetting mechanism with $\lambda = 0.98$ ($\Gamma = 1/(1-\lambda) = 50$). The simulation time of a single experiment is equal to 120 (s).

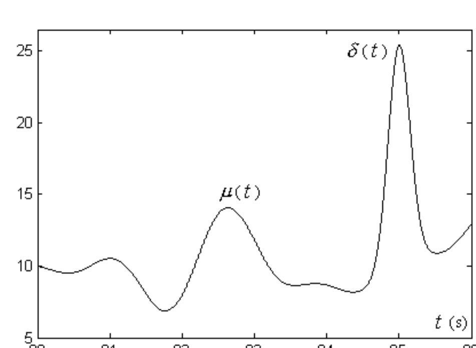

Fig. 7. Simulation of the road reaction $\mu(t)$ and bumps $\delta(t)$ (signals observed in the time interval 80…86 (s)).

It is obvious that the LS identification results are very sensitive to occasional errors in the processed data: outliers (Fig. 3) and saturation (Fig. 5). In contrast, the LA procedure is almost insensitive to such effects (Fig. 4 and Fig. 6). Therefore, the generated estimates are reliable. Apparently, using the mechanism of forgetting, both LS and LA estimation procedures obtain the ability to track variable parameters of the monitored system.

5. CONCLUSIONS

The presented studies use weighted LS and LA algorithms to identify the dynamics of the suspension system in online mode. The conducted numerical tests prove that the implemented forgetting mechanism allows on-line tracking of the parameters evolution of the considered continuous model. The LA procedure shows robustness in case of occasional errors in the data being processed (in relation to outliers in measurements and nonlinear effects attributed to occasional saturations in the shock absorber). In contrast, such undesirable phenomena have a very large impact on the results obtained from the classic LS routine.

The concept of integration with the finite horizon used seems particularly convenient for the numerical mechanization of the continuous description (differential equation) considered. This is because the resulting discrete model retains the original parameters, while the FIR processing of the sampled input-output signals greatly facilitates the final formation of regression data. The solution also guarantees that unknown initial conditions of the system do not falsify the identification results. To improve identification of the model, specific nonlinear system components and surface roughness should be taken into account (Gaspar et al., 2007).

Since basic data processing (FIR filtering) results in the unavoidable coloring of the additive measurement noise, the residual error becomes a correlated process, and the parameter estimates suffer from an asymptotic load. Specific, instrumental variable modifications of the LS and LA procedures can effectively improve the consistency of estimation (Söderström and Stoica, 1981).

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