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ADAPTIVE TRACKING OF ROAD VEHICLE ENGINE SPEED BASED ON ACCELERATION MEASUREMENTS

Abstract: The paper presents adaptive approach to a method of vehicle engine speed tracking based on acceleration measurements which are taken in the vehicle body part. Engine-induced vibrations, which are acquired using a vehicle measurement system, as strongly nonlinear can be modelled using multi-notch filter. It was stated the optimal parameter of the multi-notch filter exists; however, solution space function of the optimization problem is significantly nonlinear. For such conditions adaptive LMS algorithm, which includes multi-notch filter, tends to converge to local minimum points of the solution space. Cross-correlation estimation of multi-notch filter output and its delayed version as well as power estimation of engine-induced acceleration signal were used to tune online an adaptation constant of LMS algorithm and bandwidth parameter of multi-notch filter. Results obtained for stationary and non-stationary engine-induced vibrations justified high accuracy of the tracking algorithm.

Keywords: vehicle engine nonlinear vibrations, acceleration sensors, signal frequency tracking, LMS based engine speed estimation, multi-notch filter.

1. Introduction

Nowadays, vehicular control system requires numerous sensors to track multiple parameters and vehicle motion quantities, *e.g.*: progressive velocity or engine speed. Availability of engine speed measurements allows the control system as well as the driver to appropriately utilize engine. However, in some cases measurements of engine speed are acquired with low sample rate which is sufficient for normal vehicle utilization but inacceptable during vehicle based experiments which require additional sensors or estimation methods to be used.

Further analysis is dedicated to all-terrain vehicle which is equipped with accelerometers but offers no access to engine speed sensors. Engine speed of the vehicle is closely related to the frequency of harmonic components of engine-induced vibrations which can be measured using installed sensors. Adaptive frequency tracking algorithms are widely used in automatic control for harmonic detection [1] and measurement noise filtering [2] as well as it can be adapted to the engine speed tracking problem in which additionally significant nonlinearity and multi-harmonics nature of engine-induced vibrations need to be taken into account as referred in [3].

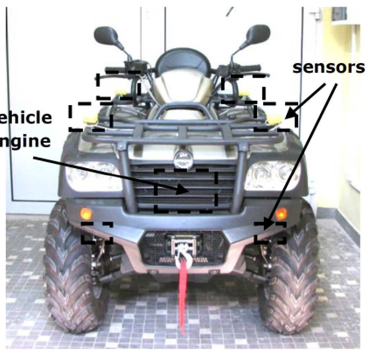
Adaptive LMS (Least-Mean Square) algorithm include reference model which is usually implemented as FIR filter. In case of engine speed tracking the reference model should be suited to the deterministic nature of such signals, which can be satisfied by narrowband filter of two kinds, *i.e.*: zeroing polynomial filter [4] and notch filter [5]. However, single notch filters algorithms are not recommended in case of multi-harmonics analysis so tracking algorithms are extended to cascade multi-harmonics filters [6] or comb filters [7] which are used as reference models. Multi-notch based LMS tracking algorithm can additionally be improved by making dependent of notch filter parameter on LMS adaptation constant [8] or on cross-correlation derived based on filter output and its delayed version [9].

The article is organized as follows. Chapter 2 presents features of experimental vehicle's engine and measurement system which is installed in the vehicle. Chapter 3 describes a solution space of parameter's optimization as well as the LMS based frequency tracking algorithm. In chapter 4 the estimation method is validated. Finally, chapter 5 concludes the results.

2. Characteristics of vehicle engine and measurement system

The frequency tracking method is dedicated to an ATV (all-terrain vehicle) Sweden CF-Moto 500 (Figure 1). The experimental vehicle is a key element of a vehicular vibration control system [10]. Results of vehicle engine speed measurements are displayed on the vehicle dashboard, unfortunately, display update rate is not high enough. The system consists of 8 accelerometers which are located in the vehicle underbody and body parts as well as they acquire acceleration in the frequency band of 0 – 250 [Hz].

(a) (b)



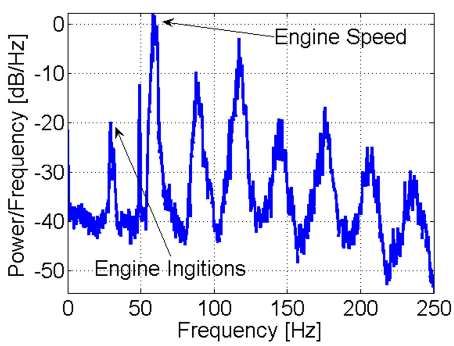


Fig.1. Features of experimental vehicle and measurement system: a) engine and sensors locations; b) power spectral density of the engine-induced acceleration signal for engine speed of 58 [*Hz*]

The experimental vehicle is equipped with four-stroke petrol engine which includes one cylinder, *i.e.*, one ignition occurs in every second engine revolution. Engine-induced vibrations propagate through the construction of the vehicle and can be sensed using vehicle body accelerometers. During normal utilization of the vehicle acceleration measurement signals consists of numerous components such as road-induced or maneuver-induced acceleration. However, it was stated based on measurements, that average power of engine-induced vibrations significantly exceeds power of other measurement components.

Engine-induced acceleration is strongly nonlinear and includes multiple harmonics. It was stated that the first and the second harmonics correspond to engine ignitions and engine speed; further harmonics are derivatives of the first two components. Such observations have been justified based on measurements which have been performed for various engine speed values; in the following an example is presented which corresponds to manually set engine speed of 58 [Hz]. Engine-induced acceleration was acquires during 50 [sec] engine's run with results presented as power spectral density function in Figure 2. Harmonic peaks which correspond to engine ignitions and engine speed are clearly visible in the figure.

3. Modified LMS based frequency tracking algorithm

Non-stationary engine speed estimations needs to be performed online during vehicle ride. An optimal solution is found iteratively using gradient-based method, *i.e.* LMS algorithm. It is widely used in the field of frequency tracking and vibration cancellation due to its simplicity.

3.1. Offline based search of optimal solution

Two kinds of narrowband filter are used to model nonlinear vibrations generated by the vehicle engine, *i.e.*: zeroing polynomial filter and notch filter. Main drawback of zeroing polynomial filters is absence of poles which makes the filter's bandwidth uncontrollable in comparison to notch filters so the latter ones were included in the engine speed estimation method. Centre frequencies of notch sub-filters (included in multi-notch filter) have been made equal to consecutive multiplications of the fundamental frequency parameter; the multi-notch filter is defined as follows:

$$H_{Notch-M}(z, r_H, \omega_H) = \prod_{m=1}^{M} \frac{1 - 2\cos(m\omega_H) z^{-1} + z^{-2}}{1 - 2r_H \cos(m\omega_H) z^{-1} + r_H^2 z^{-2}} \,. \tag{1}$$

Number of notch sub-filters, which are included in the multi-notch filter, is equal $M = 5$. Symbol r_H denotes bandwidth parameter of each notch sub-filter; symbol ω_H corresponds to the frequency parameter of filter (1).

Engine-induced acceleration signal was processed using filter (1) and its output can be estimated as follows:

$$y_{Notch-M}(n, r_H, \omega_H) = h_{Notch-M}(n, r_H, \omega_H) * x(n)\,, \tag{2}$$

where $h_{Notch-M}(n)$ is an impulse response of the multi-notch filter (1) and $x(n)$ is engine-induced acceleration signal. It can be shown that there exists an optimal value of multi-notch frequency parameter which minimizes a certain quality index and corresponds to the frequency of engine ignitions. Quality of multi-notch filter adjustment is estimated based on quality index QI_{FA} as follows:

$$QI_{FA} = MSE[y_{Notch-M}(n, r_H, \omega_H)]\,. \tag{3}$$

Preliminary research has been performed using stationary engine-induced acceleration measurements of length 50 [sec] which corresponds to engine speed of 42 and 67 [Hz]. For such conditions values of the quality function (3) have been estimated for cases which differ in value of r_H parameter, *i.e.*: 0.65, 0.85 and 0.95. Strong nonlinearity of the multi-notch filter characteristics leads to the nonlinearity of quality index function (3) – it includes numerous local minimum points (Figure 2a) – which requires the sophisticated optimization methods to be used.

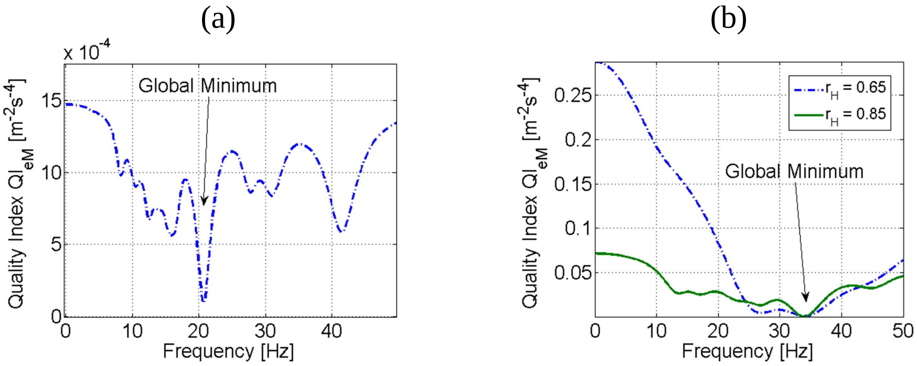


Fig.2. Solution space of QI_{FA} quality index for engine speed and r_H bandwidth parameter of: a) 67 [Hz] and 0.95; b) 42 [Hz] and 0.65, 0.85, respectively

Nonlinearity of the QI_{FA} function leads the minimum search algorithm to converge to local minimum points. Figure 2b presents solution space for two r_H values which shows that the lower value of r_H bandwidth parameter the smoother the solution space. For low value of r_H it is easier to reach the neighbourhood of the global minimum; however result of the optimization is not accurate enough. After coarse value of engine speed fundamental frequency is found, the estimation can be made with higher accuracy by increasing value of bandwidth parameter r_H. For analyzed conditions global minimum points can be noticed in plots presented in Figure 2 which are equivalent to the frequency of engine ignitions equal to 21 and 33 [Hz].

3.2. Utilization of LMS algorithm in online signal frequency tracking

The multi-notch filter (1) was included in the LMS adaptive algorithm as a reference model; dynamics of the algorithm is defined as follows:

$$\omega_H(n+1) = \omega_H(n) - \mu \cdot y_{Notch-M}(n) \frac{\partial[y_{Notch-M}(n)]}{\partial \omega_H}, \tag{4}$$

where symbol μ denotes adaptation constant of the LMS algorithm. A novel LMS based approach to frequency tracking was presented in [9]. Authors have included the multi-notch filter in the LMS algorithm, as presented above, and derived a recursive formula for the gradient of the multi-notch filter output (2) as follows:

$$\begin{aligned} g_m(n) &= g_{m-1}(n) - 2\cos[m\omega_H(n)]g_{m-1}(n-1) + 2m\sin[m\omega_H(n)]y_{Notch-m-1}(n-1) + g_{m-1}(n-2) + \\ &+ 2r_H\cos[m\omega_H(n)]g_m(n-1) - r_H^2 g_m(n-2) - 2r_H m\sin[m\omega_H(n)]y_{Notch-m}(n-1) \end{aligned} \tag{5}$$

for $m = 1,2,\ldots,M$, where

$$g_m(n) = \frac{\partial[y_{Notch-M}(n)]}{\partial \omega_H} . \tag{6}$$

Initial values of g_m and $y_{Notch-m}$, which are used in the recursive formula (5), are defined as follows: $y_{Notch-0} = x(n)$, $g_0(n) = 0$, $g_0(n-1) = 0$, $g_0(n-2) = 0$.

3.3. Improvements of the frequency tracking algorithm

Authors [9] proposed choosing the initial value of bandwidth parameter r_H close to the optimal solution; however it requires an initial coarse search which is inacceptable in non-stationary real-time applications. Additionally it was proposed, due to the complex shape of the solution space function (Figure 2a), that parameter r_H is adaptively tuned during algorithm execution. Parameter r_H should be set to low value if the algorithm has not already converged to the global minimum and if it has, the parameter needs to be increased to make estimation of engine speed accurate. Simultaneously, after algorithm has converged to the optimal solution, the adaptation constant μ is recommended to be decreased to assure the algorithm will remain in the optimal solution. Instantaneous quality of adaptation result is obtained using cross-correlation estimation of the multi-notch filter output $y_{Notch-M}(n)$ (Equation 2) and its delayed version. Additionally, high frequency components of the cross-correlation estimation are suppressed using low-pass filter described with parameter λ_C which results in the following formula of cross-correlation estimation:

$$c_{Notch}(n) = \lambda_C \cdot c_{Notch}(n-1) + (1-\lambda_C) \cdot y_{Notch-M}(n) \cdot y_{Notch-M}(n-1) . \tag{7}$$

Adaptive tuning of parameters r_H and μ is defined according to [9] as follows:

$$r_H(n) = r_{H\,\min} + e^{-\alpha|c_{Notch}(n)|} \cdot (r_{H\,\max} - r_{H\,\min}) , \tag{8}$$

$$\mu(n) = \mu_{\min} + (1 - e^{-\alpha|c_{Notch}(n)|}) \cdot (\mu_{\max} - \mu_{\min}) . \tag{9}$$

Parameters r_H and μ are limited to the chosen range of (r_{Hmin} ; r_{Hmax}) and (μ_{min} ; μ_{max}), respectively. Symbol α denotes saturation rate of parameters defined in (8) and (9); it can be also used as a scaling parameter of cross-correlation estimation c_{Notch}.

3.4. Modified LMS algorithm including input power estimation

Statement was made, based on measurements, that there exists additional dependence of adaptation constant $\mu(n)$ and saturation rate α on power of the engine-induced acceleration signal $x(n)$. Power of the engine-induced signal is estimated using the following expression:

$$v_{Engine}(n) = \lambda_V \cdot v_{Engine}(n-1) + (1-\lambda_V) \cdot x^2(n) , \tag{10}$$

where $v_{Engine}(n)$ is low-pass filtering's (parameter λ_V) result of power estimation of engine-induced acceleration. Corrected adaptation parameter μ_V is inversely proportional to the power estimation (10) and linearly proportional to the original μ parameter as follows:

$$\mu_V(n) = \mu(n) \cdot v_{Engine}^{-1}(n) \ . \tag{11}$$

Formula dedicated to the corrected saturation rate $\alpha(n)$ includes constant scaling parameter α_V and was empirically derived as follows:

$$\alpha(n) = \alpha_V \cdot \log[v_{Engine}^{-1}(n)] \ . \tag{12}$$

It can be also stated, based on measurement, that due to the construction of the experimental vehicle (Figure 1a) the higher engine speed, the higher estimated power (10), which also leads to relations (11) and (12).

4. Experiment's conditions and results of engine speed estimation

Two classes of measurement data analysis are presented, *i.e.*: dedicated to stationary and non-stationary engine-induced acceleration signals. In the non-stationary analysis a specially generated non-stationary measurement signal was composed based on different stationary measurement signals. For both cases experiments were performed using the front right accelerometer which is included in the vehicle measurement system. Acceleration signal was acquired with sample rate of 500 [Hz] for five conditions which differ in value of manually set engine speed, *i.e.*: 33, 42, 50, 58 and 67 [Hz] (revolutions per second) during time period of 50 [sec]. Parameters of the algorithm were obtained and validated experimentally for all measurement data set (Table 1).

Tab. 1. Parameters of LMS based engine speed estimation algorithm

$M = 5$	$r_F = 0.85$	$\lambda_C = 0.995$
$\mu_{min} = 0.01$	$r_{Hmin} = 0.50$	$\lambda_V = 0.999$
$\mu_{max} = 0.1$	$r_{Hmax} = 0.85$	$\alpha_V = 900$

4.1. Analysis of stationary engine-induced acceleration signal

Consequently, engine-induced vibrations are assumed as stationary. The algorithm was executed based on all measurement data set, separately. Desired values of engine speed are compared with estimated values using a relative $QI_{ES\text{-}rel}$ quality index (results listed in Table 2) which is defined as follows:

$$QI_{ES-rel} = \frac{1}{2\pi \cdot N_{ES}} \sum_{n=1}^{N_{ES}} \left[\frac{\omega_F(n) - \omega_D(n)}{\omega_D(n)} \right]^2 \ . \tag{13}$$

Values of quality index are inversely proportional to the accuracy of the estimation algorithm. It can be noted that for desired engine speed values of 33 and 67 [Hz] the algorithm exhibits significantly lower accuracy and needs to be improved. However, there was no possibility to measure actual engine speed during experiments. Engine speed can be set manually with a finite tolerance and assumed as constant during each experiment so significantly high values of quality indices can also partly show the inaccuracy of engine speed control system as well.

Tab. 2. Relative quality index $QI_{ES\text{-}rel}$ for stationary and non-stationary engine-induced acceleration signals

Quality index $QI_{ES\text{-}rel}$ [ ] × 10^{-4}					
Stationary engine speed [Hz]					Non-stationary engine speed
33	42	50	58	67	
11	3.6	9.7	4.2	11	134

4.2. Analysis of non-stationary engine-induced acceleration signal

The algorithm was also validated for specially generated non-stationary engine-induced acceleration signal which consists of all parts of stationary engine-induced signals with length of 10 [sec] each (Figure 3). Such validating signal allows verifying the algorithm while engine speed is changing which is presented. It can be noted (Figure 3) that for most cases the algorithm correctly tracks vehicle engine speed; it converges to the correct value while engine speed is changing. However, some cases require the algorithm to be further developed and improved. Analysis of the algorithm was also performed using quality index (13) presented in Table 2. Values of quality indices are significantly higher in case of non-stationary acceleration signal mainly because of algorithm's temporal inaccuracy which is visible in Figure 3.

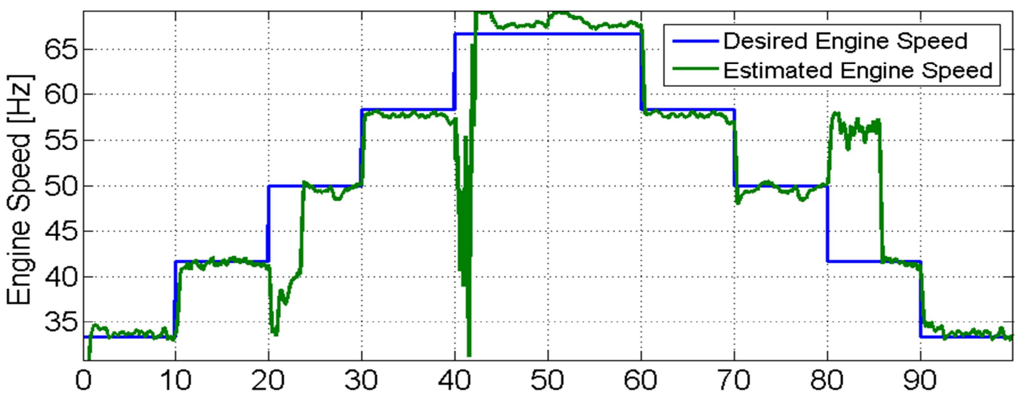


Fig.3. Time-frequency analysis of adaptive engine speed estimation for non-stationary engine-induced acceleration signal

5. Conclusions

Numerous control schemes which are used to control vehicle engine require continuous information about engine state, *e.g.* engine speed. Engine-induced vibrations propagate through experimental vehicle body and can be easily taken using vehicle body accelerometers. The adaptive LMS based algorithm using multi-notch filter was proposed to estimate engine speed online. Validation of the estimation algorithm was performed using various stationary as well as specially generated non-stationary engine-induced acceleration signals and high accuracy of the algorithm was justified.

Further developments of the algorithm needs to be performed to increase its reliability; it can be used for frequency tracking and filtering of engine-induced measurement noise.

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