

Incorporation of Adaptive Grid-Based Look-Up Tables in Adaptive Feedforward Algorithms for Active Engine Mounts

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Active engine mounts make an important contribution to ensure the comfort in vehicles with emission-reducing engine technologies, e.g., cylinder-on-demand (COD). To control active engine mounts either adaptive filtering or map-based feedforward control is commonly employed. This contribution proposes two methods to combine both control strategies in order to overcome their respective disadvantages. Adaptive look-up tables are incorporated into a Multiple-input-multiple-output-Newton/FxLMS adaptive feedforward control algorithm in two ways: as parameter-maps or parallel-maps. The proposed control strategies are experimentally compared in a vehicle with a V8-COD-engine. While both methods significantly reduce the convergence time of the adaptive filter, the parallel implementation additionally improves the tracking behavior during fast engine run-ups.

Topics / Integrated chassis control systems, Sensors and actuators, Other related topics in vehicle control

1. INTRODUCTION

Active engine mounts (AEMs) provide an effective contribution to further improve the acoustic and vibrational comfort of passenger cars. To control AEMs, two approaches are widely used. On the one hand, adaptive filters are applied to compensate for the disturbing engine vibration with a control signal of equal amplitude and opposite phase. Especially the use of finite impulse response (FIR) filters whose coefficients are adapted with the filtered-x least-mean-squares (FxLMS) algorithm [1] or one of its variants [2, 3] is common practice. Since adaptive feedforward control employs an accelerometer at the chassis, it guarantees full vibration compensation, despite any changes in the primary transfer paths or engine disturbances. However, due to its adaptive nature, adaptive feedforward control always exhibits a certain convergence time after its activation and may possess a poor tracking behavior. On the other hand, map-based feedforward control has been proposed for the control of AEMs. In this case, data maps obtained from prior measurements [4] or an analytical engine model [5] are used to generate an appropriate control signal. Besides its general advantage, that no error sensor is necessary, map-based feedforward con-

trol exhibits no convergence time until full vibration compensation is achieved. However, as map-based feedforward control is non-adaptive, it is unable to track any changes in the transfer paths. In addition, extensive measurements are necessary to identify appropriate data maps or engine models for feedforward control.

This article proposes methods that combine adaptive and map-based feedforward control in order to overcome their respective disadvantages. First, a variant of the Narrowband-FxLMS algorithm is extended with online-adapted grid-based look-up tables. Two control structures are presented and their inherent properties are discussed. Finally, the proposed methods are experimentally validated in a vehicle with a V8-COD-engine.

2. ACTIVE ENGINE MOUNTS

Fig. 1 shows the AEM that has been employed for this study. The upper fluid chamber is bounded by the main rubber spring which supports the static engine weight. Fluid is forced through the fluid channel into the lower chamber, when the main spring is compressed. The fluid's inertia acts like a tuned mass damper and provides additional damping to counteract low frequency (< 20 Hz) engine vibrations induced by road dis-

turbances. A diaphragm separates the upper from the lower fluid chamber. A moving coil actuator is attached to the diaphragm. Through the control of the actuator, the pressure in the upper chamber can be influenced and therefore a force is generated in order to cancel high frequency engine disturbances (> 20 Hz).

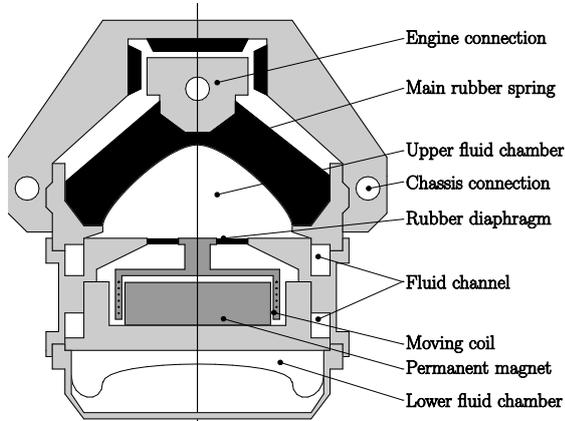


Fig. 1 Schematic diagram of an active engine mount.

The passenger car that has been used for this study is equipped with two AEMs and two accelerometers located at the chassis. The vehicle's V8-COD-engine deactivates half of its cylinders in driving situations where only little torque is necessary. The partial deactivation of the cylinders results in a change of the dominant engine order as well as the excitation level of the disturbing engine vibration. The AEMs are activated to compensate for these changes. Due to the frequent activation and deactivation of the employed control algorithm, a short convergence time is necessary.

3. ADAPTIVE FEEDFORWARD CONTROL ALGORITHM

In this study, a multiple-input-multiple-output (MIMO)-implementation of the complex Narrow-band-FxLMS algorithm is employed. A general block diagram of the algorithm is shown in Figure 2.

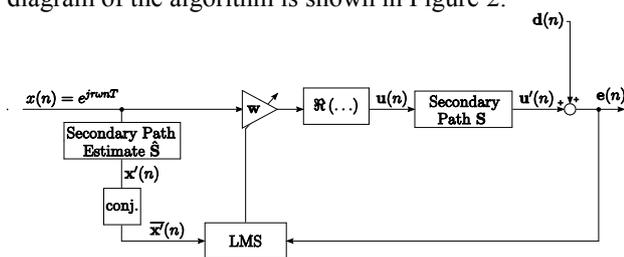


Fig. 2 Block diagram of the complex Narrow-band-FxLMS algorithm.

The vector of error signals measured at the chassis side can be written as

$$e(n) = d(n) + S(n) * u(n), \quad (1)$$

where $d(n)$ is the vector of disturbance signals to be cancelled, $u(n)$ is the control output vector and $S(n)$ is a $[2 \times 2]$ -matrix of impulse responses of the secondary paths $S_{tm}(z)$ between the M control signals and the output of the T accelerometers.

Engine vibrations normally consist of several narrow-band components, so called engine orders, whose frequencies are directly related to the engine speed ω . A complex reference signal $x(n)$ is generated with the engine speed obtained from a crankshaft tachometer and the engine order r , to be canceled. In order to compensate for the dynamics of the secondary paths $S(z)$, the complex reference signal has to be filtered with a matrix $\hat{S}(z)$ of secondary path estimates $\hat{S}_{tm}(z)$. The computational effort for generating the filtered reference signals is reduced by expressing the secondary path estimates by their respective amplitude $A_{tm}(r\omega)$ and phase $\varphi_{tm}(r\omega)$ at the current operating frequency of the adaptive feedforward control algorithm. In this case, the vector of complex filtered reference signals is given by

$$x'(n) = \hat{S}(r\omega)x(n) = \hat{S}(r\omega)e^{jrn\omega T} \quad (2)$$

where

$$\hat{S}_{tm}(r\omega) = A_{tm}(r\omega)e^{j\varphi_{tm}(r\omega)} \quad (3)$$

$$t = 1, 2, \dots, T$$

$$m = 1, 2, \dots, M$$

is the tm -th entry of $\hat{S}(r\omega)$.

According to [6], the complex conjugate $\bar{x}'(n)$ of the reference signal vector $x'(n)$ has to be applied in the weight update equation of a complex-valued LMS algorithm. The complex filter weight vector $w(n)$ is updated according to

$$w(n+1) = w(n) - \mu \hat{S}^H(r\omega)e^{-jrn\omega T} e(n), \quad (4)$$

in order to minimize the mean square of $e(n)$ in Eq. (1). The convergence rate and stability of the algorithm are determined by the step-size parameter μ . Finally, the control signal vector is obtained by multiplying the complex filter weight vector with the complex reference signal and taking the real part of the signal

$$u(n) = \Re\{w(n)x(n)\}. \quad (5)$$

It has been shown in [7] that the convergence properties of the adaptive algorithm in Eq. (4) are determined by the eigenvalue spread, i.e. the ratio of the largest and the smallest eigenvalue, of the matrix product $\hat{S}^H(r\omega)S(r\omega)$. Due to the dynamic characteristics of the secondary paths, the entries of $\hat{S}^H(r\omega)$ and $S(r\omega)$ vary in the operating frequency range of the adaptive algorithm, resulting in an unequal convergence rate at different operating frequencies.

Therefore, in order to obtain an equal convergence rate in the frequency range of interest, the following Newton LMS update equation is employed in this work

$$w(n+1) = w(n) - \mu \hat{S}^{-1}(r\omega)e^{-jrn\omega T} e(n). \quad (6)$$

In this case, the relevant matrix product is $\hat{S}^{-1}(r\omega)S(r\omega)$ which becomes the identity matrix provided a perfect estimation of the secondary paths exists. Thus, the convergence rate is independent of the current operating frequency, since the eigenvalue spread is always equal to one.

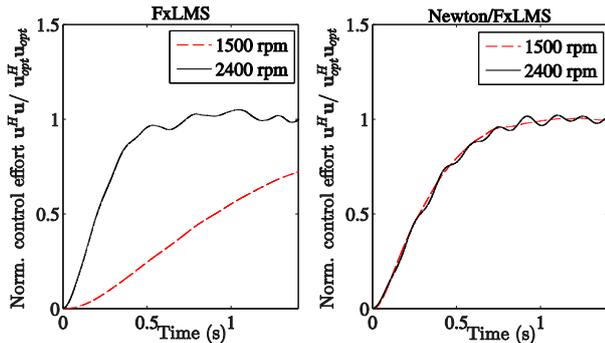


Fig. 3 Normalized control effort of the conventional and the Newton/FxLMS-algorithm.

Figure 3 shows the convergence of the normalized total control effort for the adaptive algorithms in Eq. (4) and (6) activated at two different engine rotation speeds. While the algorithm of Eq. (6) shows an equal rate of convergence in both cases, the algorithm of Eq. (4) exhibits a significantly slower convergence at low engine speeds compared to higher engine speeds.

Although the matrix inversion $\widehat{\mathcal{S}}^{-1}$ in Eq. (6) has been realizable in the rapid control prototyping unit used for this study, its computational load might be too large for practical applications in mass production processors. In this case, several methods are applicable:

- If the secondary paths do not change significantly over time, their inverse could be determined *a priori* offline and stored into look-up tables [8]. The look-up table values are scheduled with the current engine rotation speed.
- If the matrix of secondary path estimates $\widehat{\mathcal{S}}$ is diagonally dominant, its inversion could be approximated by normalizing the step-size μ in Eq. (4) with an adequate normalization matrix, e.g., proposed in [9].
- The expression $\widehat{\mathcal{S}}^{-1}(r\omega)e(n)$ in Eq. (6) could be determined iteratively by a second subsidiary adaptive algorithm.

4. INCORPORATION OF ADAPTIVE GRID-BASED LOOK-UP TABLES

The convergence rate of the adaptive feedforward control algorithm proposed in Sec. 3 is mainly determined by its step-size μ . A larger step-size generally leads to a reduced convergence time. However, the step-size is limited by stability constraints and a larger step-size reduces the algorithm's robustness to errors in the secondary path estimate [7]. In addition, Snyder [10] showed that a large step-size may lead to an undesired amplification of uncorrelated signal components passing from the error signals to the control outputs.

To overcome these drawbacks of limited convergence time and tracking speed, this section proposes two methods to incorporate grid-based look-up tables in adaptive feedforward algorithms. In contrast to the work by Shin [11] the look-up tables are trained online in order to avoid any prior measurements.

4.1 Control structures

In general, the weight adaptation in Eq. (6) starts with the initial condition $\mathbf{w}(0) = \mathbf{0}$. However, the convergence time could be significantly reduced, if prior information of the final weight values was available. Engine vibrations arise from oscillating parts and the combustion process. It is a valid assumption that their amplitude and phase depend on the current engine speed and torque. Assuming that the engine vibration's amplitude and phase angle reach approximately constant values for steady state engine operation, the filter weight vector of the adaptive algorithm converges to constant values, too. By using the crankshaft angle $\varphi_{CS}(n)$ instead of discrete integration of the engine's rotational frequency $\omega(n)$ to generate the reference signal in Eq. (5) and (6), a fixed relationship between the reference signal $x(n)$ and the disturbing engine vibration $\mathbf{d}(n)$ is obtained. In this case, the steady state filter weight vector values are reproducible for constant engine operation points.

The preceding assumptions lay the foundations for the following control structures which incorporate grid-based look-up tables in the adaptive feedforward algorithm of Sec. 3. The independent dimensions of the two-dimensional look-up tables are the engine speed $n_{eng}(n)$ and the engine torque $M_{eng}(n)$. An additional torque sensor is unnecessary, since an estimate of the engine torque is generally available on the vehicle bus system. The look-up tables contain the real and imaginary parts of the complex filter weight vector $\mathbf{w}(n)$ for compensating the vibrations of the particular engine order at the current engine operating point. In order to compensate for any changes in the transfer paths or the engine disturbance during vehicle operation, the look-up tables are extended by an adaptation process which is described in Sec. 4.2.

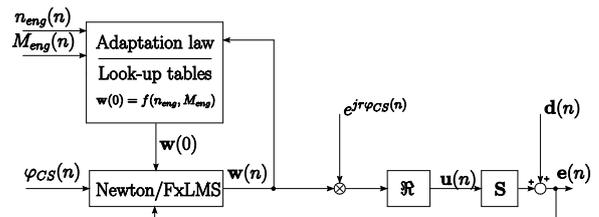


Fig. 4 Newton/FxLMS algorithm with parameter-map.

According to the classification of [12], two control structures are possible for the present application. The control structure of Figure 4 has already been proposed in [13]. The look-up tables are parameter-maps, which store the real and imaginary parts of the complex filter weight vector as initial conditions for the adaptive feedforward control algorithm. Prior to the activation of the adaptive feedforward control algorithm, the initial conditions $\mathbf{w}(0)$ of the current engine operating point are passed from the look-up tables to the adaptive control algorithm. Since the look-up table's information is only accessed before the activation of the adaptive feedforward algorithm, this control structure improves the convergence behavior while the tracking perfor-

mance remains unchanged. During the operation of the adaptive feedforward control algorithm the current complex filter weight vector $\mathbf{w}(n)$ is used as a training signal for the adaptation process of the look-up tables. In this control structure, the map access and the map adaptation are never carried out simultaneously.

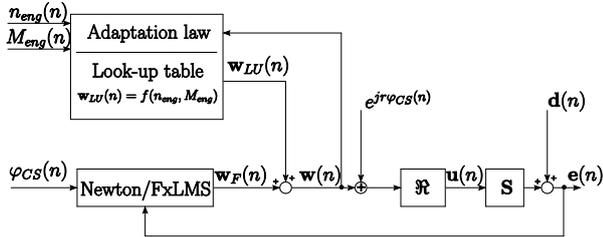


Fig. 5 Newton/FxLMS algorithm with parallel-map.

An alternative structure to incorporate grid-based look-up tables into adaptive feedforward control is shown in Figure 5. The look-up table is applied in parallel to the adaptive algorithm and their respective complex outputs $\mathbf{w}_{LU}(n)$ and $\mathbf{w}_F(n)$ are summed to a superimposed complex filter weight $\mathbf{w}(n)$. The control signal is obtained by multiplication with the complex reference signal. This control structure is comparable to the method proposed in [11]. However, in the present case, the look-up tables are adaptable. The complex filter weight vector $\mathbf{w}(n)$ resulting from the overall superposition is used as a training signal for the adaptation of the look-up tables. The map access and the map adaptation are carried out simultaneously in this control structure. As will be shown in Sec. 4.4 this is crucial for the choice of the step-size parameters of both adaptation algorithms. Besides its ability to reduce the convergence time of the adaptive algorithm, this structure promises an additional improvement of the tracking behavior.

4.2 Online adaptation of grid-based look-up tables

Grid-based look-up tables are the most common type of nonlinear static models in practice. Especially in modern combustion engine control a vast number of one- and two-dimensional look-up tables is employed [14]. The two-dimensional look-up tables used in this paper contain a set of scalar data points approximating the nonlinear dependency between the complex filter weight vector $\mathbf{w}(n)$ and the look-up table's input signals engine torque $M_{eng}(n)$ and engine speed $n_{eng}(n)$, respectively. For each engine mount and engine order to be canceled, two look-up tables are necessary to store the real and imaginary part of the corresponding entry of $\mathbf{w}(n)$.

Fig. 6 shows a method to calculate the table's output value for the current operating point which has been initially proposed in [15]. After determining the four surrounding nodes of the current operating point, the table's output is calculated by weighting the data values at the interpolation nodes with the corresponding opposite areas $A_{k,l}, A_{k,l+1}, \dots$ divided by the total area A of one cell:

$$w_{LU} = (\theta_{k,l}A_{k+1,l+1} + \theta_{k+1,l}A_{k,l+1} + \theta_{k,l+1}A_{k+1,l} + \theta_{k+1,l+1}A_{k,l})/A \quad (6)$$

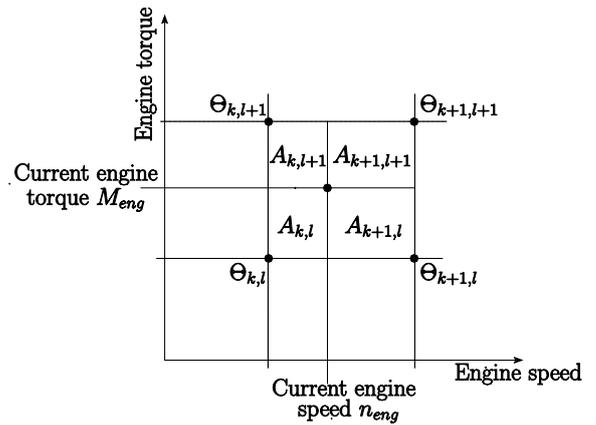


Fig. 6 Interpolation within a two-dimensional look-up table [14,15].

The look-up table data values are adapted online according to the method described in [16]. Converting Eq. (6) into a general basis function formulation leads to:

$$w_{LU} = \sum_{k=1}^K \sum_{l=1}^L \theta_{k,l} \Phi_{k,l}(\mathbf{y}, \mathbf{c}) \quad (7)$$

The vector of input signals (engine torque, engine speed) is expressed by \mathbf{y} and the positions of the interpolation nodes is described by \mathbf{c} . For each input vector, only four basis functions $\Phi_{k,l}(\mathbf{y}, \mathbf{c})$ are nonzero. The vector of table data values at the interpolation nodes

$$\mathbf{v} = [v_1 \dots v_M]^T = [\theta_{1,1} \dots \theta_{K,L}]^T \quad (8)$$

is adapted online with the normalized LMS (NLMS) algorithm [16]:

$$v_i(n+1) = v_i(n) + \mu_{LU} \frac{e_{LU}(n)\Phi_i(\mathbf{y}(n), \mathbf{c})}{\sum_{j=1}^{K \cdot L} \Phi_j^2(\mathbf{y}(n), \mathbf{c})} \quad (9)$$

$$i = 1, 2, \dots, K \cdot L$$

The error e_{LU} describes the difference between the look-up table's output w_{LU} , which equals to the real or imaginary part of one of the complex filter weight vector entries, and the corresponding correct value of the training signal w . The step-size μ_{LU} should not be confused with the step-size μ of the adaptive feedforward algorithm in Eq. (6).

With respect to the additional computational effort of the map adaptation in Eq. (9), it has to be noted, that only the four surrounding data values of the current engine operation points are updated in each adaptation step. In the present application, the current engine operation point is the input vector \mathbf{y} to all implemented data maps. Therefore, the calculation of the basis functions is independent of the number of maps and needs to be performed only once for each adaptation step. Finally, the map adaptation must not necessarily be carried out with the sample rate of the adaptive feedforward algorithm.

4.3 Choice of step-sizes

Through the incorporation of adaptive look-up tables in adaptive feedforward algorithms two step-size parameters μ and μ_{LU} have to be chosen. This section describes some guidelines for the appropriate choice of these step-sizes. In addition the differences between the two proposed control structures are shown.

Both control structures employ the filter weight vector $\mathbf{w}(n)$ as a training signal for the map-adaptation. Since the look-up tables should only be adapted to long-term changes, temporary variations in the filter weight vector have to be suppressed. Generally, LMS algorithms become insensitive to uncorrelated disturbances by choosing low step-sizes. However, a low value of μ degrades the convergence and tracking behavior of the vibration compensation algorithm. Hence, a step-size $\mu_{LU} < 0.0005$ is chosen for the map-adaptation in order to suppress short-term variations of the training signal $\mathbf{w}(n)$. As will be shown in Sec. 5.2, the resulting slow adaptation of the look-up table data proved to be unproblematic, since sufficiently filled look-up table data can be attained within short time periods.

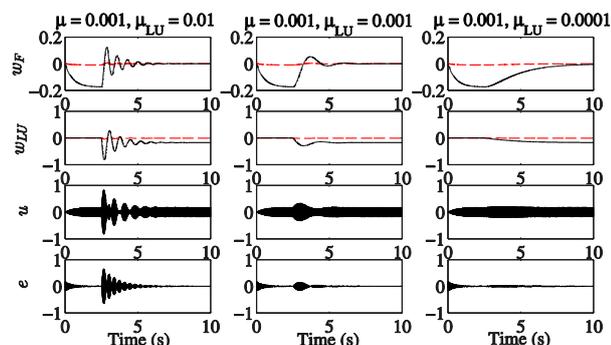


Fig. 7 Comparison of the choice of step-sizes for the adaptive feedforward algorithm with parallel-map.

In contrast to the control structure of Fig. 4, where the map access and the map adaptation are never carried out simultaneously, in the parallel structure of Fig. 5 the step-size parameters μ and μ_{LU} cannot be chosen independently. This is illustrated in the simulation example of Fig. 7 where the Newton/FxLMS algorithm with parallel map is employed to compensate a stationary single-frequency disturbance in a SISO system. The figure shows the real and imaginary parts of the filter weight $w_F(n)$ and the look-up table output $w_{LU}(n)$, respectively, the control signal $u(n)$ and the error signal $e(n)$ for three different choices of μ and μ_{LU} . In each case, the filter weight of the adaptive feedforward algorithm converges to its stationary value, before the adaptation of the corresponding look-up table entries is activated. The simulation illustrates, that the step-size μ_{LU} has to be chosen considerably lower than μ , in order to avoid any oscillating behavior resulting from the simultaneous map access and map adaptation.

5. EXPERIMENTAL RESULTS

In-vehicle tests have been carried out to evaluate the performance of the proposed control structures. First, the results of the online-adaptation of the look-up tables are shown. Afterwards, the improvements in convergence and tracking behavior are illustrated.

5.1 Online-adapted look-up tables

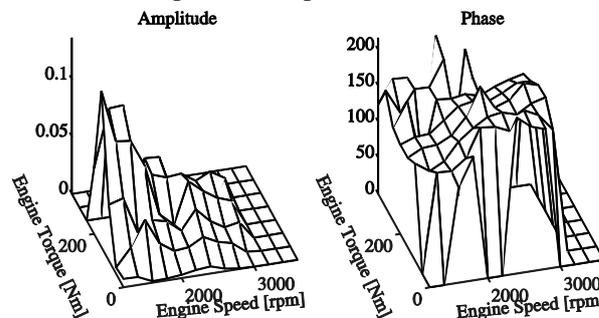


Fig. 8 Online adapted map data (2nd order, left AEM).

The map-adaptation of Sec. 4.2 has been tested in a 30 minute driving cycle of city traffic, country road and highway. Fig. 8 shows the resulting online adapted look-up tables to control the left AEM in order to achieve the compensation of the dominant second engine order. The complex values are shown in terms of their amplitude and phase, in order to improve their physical interpretability. The highest control amplitude can be observed at high loads and low speeds, since in this area the engine excitation is at its highest level. The control signal amplitude decreases with decreasing engine load and increasing engine speed, respectively. The results demonstrate that using the step-size choice of Sec. 4.3 already after a short drive a sufficiently filled look-up table can be attained. Hence, neither prior parameterization nor offline measurements are necessary.

5.2 Convergence behavior

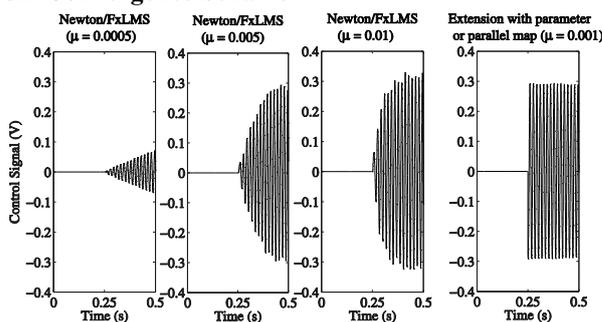


Fig. 9 Convergence of the control signal for the FxLMS algorithm and the proposed methods.

It has been stated in Sec. 4.1 that both control structures are capable to reduce the convergence time without a further increase of the step-size parameter μ . The diagrams of Fig. 9 compare the convergence behavior of the proposed methods with that of the Newton/FxLMS algorithm for different step-sizes μ . The time series of the left actuator's control signal is shown. The AEMs are activated at 0.25 seconds in each case.

The convergence time of the adaptive feedforward algorithm can be reduced with an increased adaptation step-size. However, this may lead to instability or a decreased robustness of the algorithm. The incorporation of parameter maps and parallel maps, respectively, significantly reduces the convergence time while the step-size can be kept at low levels.

5.3 Tracking behavior

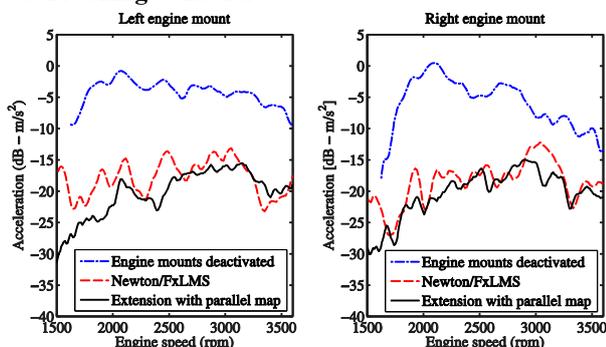


Fig. 10 Cuts of the 2nd engine order of the acceleration at the left and right engine mount position.

Generally, tracking describes the adaptive filter's ability to track variations in the signal statistics. In the present application, these variations occur during changes of the engine speed leading to a modified frequency content of the reference signal $x(n)$ and the error signal vector $e(n)$. To evaluate the tracking behavior of the proposed methods, fast engine run-ups in 3rd gear acceleration have been carried out. Fig. 10 shows the achieved compensation of the 2nd engine order for the Newton/FxLMS algorithm and its extension with parallel maps. The step-size parameter of the adaptive feedforward algorithm has been set to $\mu = 0.001$ in both experiments. Due to the improvement of the tracking behavior, the proposed method further reduces the acceleration at the left and right engine mount position. However, this is only valid for the extension with parallel maps, since the extension with parameter maps has no impact on the tracking behavior of the adaptive feedforward algorithm.

6. CONCLUSION

Methods to combine two commonly used strategies to control AEM, which are adaptive feedforward control and map-based feedforward control, have been proposed. Online adapted look-up tables were incorporated as parameter- or parallel-maps, respectively, into a Newton/FxLMS adaptive feedforward control algorithm. In-vehicle experiments showed that sufficiently filled look-up tables can be obtained within a short driving time. Hence, no prior measurements are necessary in order to obtain appropriate map data. Once the look-up tables are adapted, both methods achieved a substantial reduction of the convergence time. In addition, an improvement of the tracking behavior during fast engine speed changes has been observed when implementing the adaptive feedforward control and the map-based feedforward control in parallel.

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