Sensorless Control with Kalman Filter in an Active Engine Mount System

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Abstract—An active engine mount (AEM) system presented in this paper used to isolate the engine vibration to the chassis and to minimize the effect of such disturbances in the passenger cabin, besides supporting the static load by an engine weight. To accomplish this goal, a feed forward control algorithm will be employed in the currently developed AEM system. The engine mount system developed up to date uses sensors to measure the current states of engine vibration. However, it is expensive to use sensors in the engine mount system, and cutting down the number of sensors provides a major cost reduction. The Kalman filter has a good dynamic behavior and disturbance resistance, and it can work even in a discontinuous position. A procedure for selecting an optimal integral gain will be proposed, and the proposed estimator will be compared to the well-known passivity-based state estimator.

Keywords—engine mount; modeling; vibration; feedforward control; kalman filter; estimator

I. INTRODUCTION

An engine mount are rather significant for vibration insulation during engine power stroke in order to improve the comport of driver and passengers [1-3]. One of the characteristics that define the quality of a vehicle is the amount of noise-vibration-harshness in the cabin. An automobile’s engine, body, and chassis system are susceptible to undesirable vibrations, due to two sources of excitation: the unbalance of the reciprocating engine and the road disturbances. In the automotive industry, the two main functions of an ideal engine mount are to isolate the vibrations and to prevent engine bounce from the vehicle frame excitation. The stiffer engine mount is of benefit to preventing transient process of the engine, while the softer one is helpful for vibration insulation to the vehicle body. To resolve this problem, various semi active and active vibration control techniques have been applied to the engine mount designs [1-5, 9-18]. In an active vibration control, a counteracting dynamic force is created by an actuator in order to suppress the transmission of a disturbance force in the system. A typical active mount system consists of a passive mount (elastomeric or hydraulic) system and one or more actuator systems to generate dynamic forces. In order to perform the control method, an accurate modeling of the engine mount systems is required for calculation of the reference signals.

An Engine Mount and its cross-section used in this research are depicted in Fig. 1. The engine mount consists of a primary rubber, four chambers with different volumes (the upper, working, air, and lower chambers), and the first and secondary orifices. The main rubber provides support force for the engine static weight. It has two mounting brackets: one for the engine and the other for the chassis. The two orifices are used to connect the upper chamber with the oscillating chamber and the lower chamber separately, while a decoupler divides the oscillating and the air chamber. The plate-type decoupler is able to deform slightly due to the pressure difference of the oscillating chamber and the air chamber. The solenoid valve which is installed at the air chamber port can alternatively connect the air path from the air chamber to atmosphere or vacuum so as to reduce the engine mount dynamic stiffness.

Since the vibration on the engine mount which typically contains loading frequencies in the range of 20-200Hz with amplitudes generally less than 0.3 mm and the chassis vibration which the amplitudes are greater than 0.3 mm [5-7] transferred from the engine to the chassis can be determined by engine motions, information on the states of engine motions has a significant importance in such systems. However, these states are usually hard to measure because sensors for these measurements are too complicated and expensive to implement. Therefore, it is necessary to estimate all of the states from easily measurable signals such as the angular speed of crankshaft. Furthermore, cutting down the number of sensors provides a major cost reduction. The Kalman filter has a good dynamic behavior and disturbance resistance, and it can work even in a discontinuous position [8, 9]. In this paper, a procedure for selecting an optimal integral gain will be proposed, and the

Figure 1. A cross-section of the engine mount
The bulge stiffness element is deformed in proportion to the active engine mount (AEM) is described in Fig. 2. The main and bulge stiffness elements are denoted by \( k_m \) and \( k_p \), respectively. The areas of two orifices are denoted by \( A_1 \) and \( A_2 \), the equivalent piston area of the bulge stiffness is denoted by \( A_p \). The fluid flows through two orifices are modeled as equivalent masses \( m_1, m_2 \) damping coefficients \( c_1, c_2 \), and bulge stiffness \( k_1, k_2 \), respectively. As shown in the Fig. 3, the engine mount has four inputs of \( x(i) \), \( x_p(i) \), \( x_1(i) \) and \( x_2(i) \). The output is a force transmitted to the chassis \( F_1(i) \), which is the sum of forces due to engine vibration \( k_m x(i) \), and decoupler vibration \( A_p P(i) \). The pressure \( P(i) \) in the upper chamber is changed by the vibration of the decoupler and this pressure will exert a force on the chassis. Therefore, the force transmitted to the chassis can be expressed as follows.

\[
F_1(i) = k_m x(i) + A_p P(i) \tag{1}
\]

The fluid is assumed to be incompressible, so the continuity equation is

\[
A_p x_p(i) = A_1 x_1(i) + A_2 x_2(i) \tag{2}
\]

The bulge stiffness element is deformed in proportion to the pressure in the upper chamber, so we obtain the equation of equilibrium,

\[
-P(i) A_p = k_p [x_p(i) - x(i)] \tag{3}
\]

The pressure also forces the fluid in the orifices to flow from chamber to chamber, so the equations of motion for two orifices are given by the following equations. The first orifice

\[
m_1 \ddot{x}_1(t) + c_1 \dot{x}_1(t) + k_1 x_1(t) = A_1 P(t) \tag{4}
\]

\[
m_2 \ddot{x}_2(t) + c_2 \dot{x}_2(t) + k_2 x_2(t) = A_2 P(t) \tag{5}
\]

The Kalman filter provides a solution that directly cares for the effects of the disturbance noises. The errors in the parameters will normally be handled as noise. The system can be written with the following equations

\[
\dot{x} = Ax + Bu + r \tag{6}
\]

\[
y = Cx + \rho \tag{7}
\]

where \( r \) and \( \rho \) are the system and the measurement noise. Now, assume that these noises are stationary, white, uncorrelated and Gauss noises, and their expectation is 0.
The covariance matrices of these noises can be defined by [9-11]

\[ \text{cov}(r) = E[rr^T] = Q \]  \hspace{1cm} (8)

\[ \text{cov}(\rho) = E[\rho\rho^T] = R \]  \hspace{1cm} (9)

where \( E[.] \) denotes expected value.

The structure of the Kalman filter can be shown in Fig. 4. The system equations are also the same as

\[ \dot{x} = (A - KC)x + Bu + Ky \]  \hspace{1cm} (10)

The matrix of the Kalman filter is denoted by \( K \) and will be calculated based on the covariance of the noises. We will first build the measure of goodness of the observation, which is the following:

\[ J = \sum_{j=1}^{n} E[z_j^2] \]  \hspace{1cm} (11)

This depends on the choice of \( K \). \( K \) has to be chosen to make \( J \) minimal. The solution of this is the following:

\[ K = PC^TR^{-1} \]  \hspace{1cm} (12)

where \( P \) can be calculated from the solution of the following equation,

\[ PC^TR^{-1}CP - AP - PA^T - Q = 0 \]  \hspace{1cm} (13)

\( Q \) and \( R \) have to be set up based on the stochastic properties of the corresponding noises. Since these are usually unknown they are used as weight matrices in most cases. They are often set equal to the unit matrix, avoiding the need of the deeper knowledge of noises.

Since \( P(t) \) in Eq. (1) is calculated using the measured signals \( x(t) \) and \( F_\gamma(t) \) which are assumed involves white Gaussian noise, the signal \( A_iP(t)/m_i \) also involves white Gaussian noise \( v_i(t) \) inherited from the measured signals. Then, Eqs. (4)-(5) can be rewritten as

\[ \ddot{z}_{1i}(t) + \frac{1}{m_i}z_{1i}(t)z_{4i}(t) + \frac{1}{m_i}z_{2i}(t)z_{3i}(t) = A_i(F_{\gamma}(t) - k_r x(t))/A_pm_i + v_i(t) \]  \hspace{1cm} (18)

In the state space form, Eq. (18) becomes

\[ \begin{bmatrix} \ddot{z}_{1i}(t) \\ \ddot{z}_{2i}(t) \end{bmatrix} = \begin{bmatrix} \frac{z_{2i}(t)}{m_i} \\ \frac{z_{1i}(t)z_{4i}(t) + z_{2i}(t)z_{3i}(t)}{m_i} \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} v_i(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} A_i(F_{\gamma}(t) - k_r x(t))/A_pm_i \]  \hspace{1cm} (19)

The observation equation is

\[ y_i(t) = z_{1i}(t) + v_i(t) \]  \hspace{1cm} (20)

where \( v_i(t) \) is an observation noise which is assumed as a white Gaussian noise.
IV. PREPARE YOUR PAPER BEFORE STYLING

To simulate the force acting on the chassis, here we assume that the vibration source comes only from the engine. This vibration typically contains the loading frequency in the range of 20-200 Hz with amplitudes less than 0.3 mm. In the simulation of EM system with the proposed control algorithm, the engine vibration is represented by sinusoidal function \( x(t) = 0.1 \sin(50 \pi t) \) with amplitude of 0.1 mm and loading frequency of 25 Hertz. In Eqs. (1)-(5), the coefficients \( k_p, A_p, A_t, A_2, m_1, \) and \( m_2 \) are known: \( k_p \) is obtained from experiment and all others are calculated using the geometry of the upper chamber, orifices and liquid properties. Unknown coefficients are \( k_p, c_1, c_2, k_1, \) and \( k_2 \).

Since \( x(t) \) and \( F_1(t) \) are measured, \( P(t) \) is calculated using Eq. (1). In this section, \( x_1(t) \) and \( x_2(t) \) in Eq. (2) and \( c_1, c_2, k_1, \) and \( k_2 \) in Eqs. (4)-(5) are estimated using parameter identification technique. The estimated variables \( x_1(t) \) and \( x_2(t) \) are shown in Fig. 4 while \( c_1, c_2, k_1, \) and \( k_2 \) approximately estimated as 0.042, 0.0011, 1.89, and 0.12, respectively. By substituting the estimated variables \( x_1(t) \) and \( x_2(t) \) to Eq. (2), the variable \( x_p(t) \) in Eq. (2) can be estimated and the result is shown in Fig. 5. Therefore, applying the value \( x_p(t) \) to Eq. (3), the bulge spring constant \( k_p \) is finally calculated approximately 19412 N/m whereas the remaining parameters were obtained from experimental and manufacturer. The validity of the model derived in Eq. (6) was checked: The engine excitation and the actuator vibration independently contribute to the transmitted force. As a result, both the passive transfer function Eq. (7) and the active transfer function Eq. (8) were estimated separately.

Fig. 6 compares the output of the experimental data and the model of the hydro-mount one. The predicted dynamic stiffness and loss angle spectra of the hydro-mount system for low frequency are given in Fig. 7. Although there are small differences in amplitude and time delay, the overall results in Fig. 6 and Fig. 7 show that the force transmitted to the chassis obtained from simulation match with that from measurements reasonably, which validate the proposed hydro-mount system models in Eq. (7).

V. CONCLUSION

In this study, based on the mathematical model, the performances between the passive engine mount system and the active engine mount system were compared. To improve the vibration isolation performance of the AEM system, an adaptive feed forward control method was developed to control the actuator so that the actuator could reduce the
force transmitted to the chassis. The simulation results show that the AEM system with the adaptive feed forward controller is able to significantly reduce the vibration transmission. This proposed algorithm can also reduce the response time of control signal by improving the inherent delayed control output in the feedback algorithm.

REFERENCES


