A state observer for the Virgo inverted pendulum


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I. INTRODUCTION

In order to detect gravitational waves (GW), the displacement of the test masses of modern interferometers, such as the Virgo experiment\(^1\) and the Laser Interferometer Gravitational-wave Observatory (LIGO),\(^2\) has to be reduced to the challenging level of \(10^{-18} \text{ m/}\sqrt{\text{Hz}}\) in the 10 Hz–10 kHz detection band. For second generation detectors\(^3\)–\(^4\) the requirements are even more compelling. Since the seismic noise is the dominant low frequency noise source for terrestrial GW detectors, the performance, and reliability of seismic attenuation systems play a critical role.

Two approaches are typical in the design of seismic attenuation systems: active seismic attenuators heavily rely on control systems to reduce the ground motion, while passive isolators exploit the fundamental property that the response of a harmonic oscillator to seismic excitation is equivalent to a second-order low pass filter.

The Virgo superattenuator (SA) (Ref. 5) is an example of this latter approach and is capable of providing more than 10 orders of magnitude of seismic isolation in all six degrees of freedom above a few Hz. The SA mechanical structure, shown in Fig. 1, consists of three fundamental parts:

- the inverted pendulum (IP);
- the chain of seismic filters;
- the payload.

The IP (Ref. 6) is constituted of three 6 m-long hollow legs, each one connected to the ground through a flexible joint and supporting an interconnecting structure (the top ring) on its top. As shown in Fig. 2, the top ring, which is a mechanical support for an additional seismic filter, called filter 0, similar to those used in the chain, is equipped with a set of sensors and actuators, placed in a pinwheel configuration, that are used to actively damp the IP resonance modes. Two kinds of sensors, linear variable differential transformers (LVDTs) and high sensitivity accelerometers specifically designed for Virgo, and two sets of actuators, coil-magnets, and motor-springs, are used.

The chain of seismic filters is suspended from the filter 0 and is constituted by an 8 m-long set of five cylindrical passive filters, each one designed to reduce the seismic noise by 40 dB, starting from a few Hz, in both horizontal and vertical directions.

The payload is suspended from the last seismic filter of the chain and consists of the marionette (an anvil-shaped element, designed to steer the mirror), the reference mass, and the mirror.

The position and acceleration sensors on the top ring provide a signal proportional to a superposition of all SA mechanical resonances and the IP control is currently implemented by diagonalizing the sensor-actuator space in order to obtain three single-input single-output (SISO) systems. It would be useful to monitor and control each mode of the structure independently. For this reason we have developed a Kalman state observer based on a set of state-space models calculated from experimental data using system identification techniques. In Secs. II–III we will briefly discuss the theory involved and analyze the results obtained.

II. THEORY

A. IP linear model

In general, an \(n\)-degree of freedom mechanical system with viscous damping subject to holonomic constraints can be written in the small oscillation regime in the linear form:\(^7\)

\[
\mathbf{M}\ddot{\mathbf{q}}(t) + \Gamma\dot{\mathbf{q}}(t) + \mathbf{K}\mathbf{q}(t) = \mathbf{F}(t),
\]  

(1)
FIG. 1. Left: view from top of the VIRGO superattenuator. Right: detail of the VIRGO IP. We can distinguish, from top to bottom, the three legs of the inverted pendulum, the filter 0, the top ring, the passive filters 1 to 4, and the mirror control system. This last stage, constituted by the steering filter, the marionetta, and the reference mass, is dedicated to the control of the mirror position for frequencies $f > 100$ mHz.

FIG. 2. View from top of the filter 0 mechanical support. The sensors and actuators are placed in a triangular configuration on the top ring, with the sensing axes tangent to the top table. For clarity only one LVDT and one set of actuators are shown.

where $q(t) = [q_1(t), q_2(t), \ldots, q_n(t)]^T$ and $q_k(t)$ are the generalized coordinates, $M$ is the mass matrix, $\Gamma$ is the damping matrix, $K$ is the stiffness matrix, and $F(t)$ is a vector of generalized non-conservative forces. It can be easily shown that, introducing the state vector $x(t) = [q^T(t), \dot{q}^T(t)]^T$, with dimension $N = 2n$, and the output vector $y$, we can write Eq. (1) in state-space representation as

$$\dot{x}(t) = Ax(t) + BF(t),$$

(2)

$$y = Cx(t) + DF(t),$$

(3)

with

$$A = \begin{pmatrix} 0_{n \times n} & I_n \\ -M^{-1}K & -M^{-1}\Gamma \end{pmatrix}$$

(4)

and

$$B = \begin{pmatrix} 0_{n \times n} \\ M^{-1} \end{pmatrix}.$$  

(5)

We are now going to write a simple model of the IP control system. In order to obtain a state-space representation of
the IP equations of motion, we assume the system in small oscillation regime and approximate the dissipation mechanisms of the elastic elements with viscous damping. Moreover, since the frequencies of vertical, pitch, and roll IP modes are well above the unity gain bandwidth of the control loop, we consider only the Cartesian coordinates $x$, $z$, and $\theta_y$ where the $x$, $z$ axes are aligned with the interferometer arms on the horizontal plane. Using generalized coordinates, we can therefore define the state vector of the IP control system as

$$\xi = (x, z, \theta_y, \dot{x}, \dot{z}, \dot{\theta_y})^T.$$  

(6)

Considering the coil currents as the system input vector $u_A$ and the accelerometer signals as the output $y_A$, we can write the IP equations of motion in the form

$$\dot{\xi} = A_A \xi + B_A u_A + w_A,$$  

(7)

$$y_A = S_A \dot{\xi} + S_T \xi + v_A,$$  

(8)

where $S_A \dot{\xi}$ represents the IP center of mass acceleration projected along the accelerometers sensitivity axis and $S_T \xi$ is the top table tilt with respect to the horizontal direction. The vectors $w_A$ and $v_A$ represent the process and measurement noise, respectively. In a similar way, using the IP position measurements, provided by the LVDTs, as the system output $y_L$, we have

$$\dot{\xi} = A_L \xi + B_L u_L + w_L,$$  

(9)

$$y_L = S_L \dot{\xi} + v_L.$$  

(10)

Substituting Eqs. (7) into (8) and (9) into (10), we can rewrite both models in the standard form:

$$\dot{\xi} = A \xi + B u + w,$$  

(11)

$$y = C \xi + D u + v,$$  

(12)

with $A = A_A$, $B = B_A$, $C = S_A A_A + S_T$, $D = S_A B_A$, and $u = u_A$, $y = y_A$, $w = w_A$, $v = v_A + S_A w_A$ for the accelerometers model and $A = A_L$, $B = B_L$, $C = S_L A_L$, $D = S_L B_L$, and $u = u_L$, $y = y_L$, $w = w_L$, $v = v_L + S_L w_L$ for the LVDTs model.

B. System identification

The matrices of Eqs. (11) and (12) can be obtained from experimental data using subspace system identification. This technique allows to estimate a state-space representation of a given order $N$ from the observed data of a multiple-input multiple-output (MIMO) system in the time domain. In particular, we used the MATLAB® system identification toolbox n4sid command, that is a numerical implementation of the Overschee and Moore subspace identification method.

The estimated state-space representations are, in general, not written in form (4). For this reason we scaled the models, in order to reduce their numerical range and sensitivity, and transformed them in modal representation, a canonical form in which the real eigenvalues of the $A$ matrix appear on its diagonal and the complex conjugate eigenvalues appear in $2 \times 2$ blocks on its diagonal. This transformation is always possible if, as in our case, the eigenvalues of $A$ are all distinct.

For a system with $k$ real eigenvalues $\lambda_1, \ldots, \lambda_k$ and $s$ complex eigenvalues $\sigma_1 \pm i \omega_1, \ldots, \sigma_s \pm i \omega_s$, with $k + s = N$, we have

$$A_m = \begin{pmatrix} \lambda_1 & \sigma_1 & \sigma_1 & \cdots & 0 \\ -\sigma_1 & \lambda_2 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ -\sigma_s & 0 & 0 & \cdots & \sigma_s \\ 0 & -\omega_s & 0 & \cdots & \sigma_s \end{pmatrix}.$$  

(13)

This form can be obtained using the matrix $P$ defined as

$$P = \begin{pmatrix} I_k \\ 1 & 1 \\ i & -i \\ \vdots & \vdots \\ 1 & 1 \\ i & -i \end{pmatrix},$$  

(14)

where $A_1, \ldots, A_N$ are the eigenvectors of matrix $A$. The state-space equations (2) and (3) become

$$\dot{x}_m = P^{-1} A P x_m + P^{-1} B u,$$  

(15)

$$y_m = C P x_m + D u,$$  

(16)

and we can define the new matrices $A_m = P^{-1} A P$, $B_m = P^{-1} B$, $C_m = C P$, $D_m = D$. In our case, the outputs $y_m$ provide the positions/accelerations along the generalized coordinates of the suspension.

C. Kalman filtering

We have now to verify that all the state vector components of the estimated models are observable. This can be done by calculating the observability gramian matrix $O$ of the system

$$O = \int_0^\infty e^{A_t} C C^T e^{A^T_t} dt.$$  

(17)

If $O$ is non singular, a state observer capable of providing outputs proportional to each mode of the system can be implemented.

The most common state estimator used in control theory is the Kalman filter. It is essentially a recursive linear filter based on a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance. Assuming the noises $w$ and $v$ are white and Gaussian distributed with zero mean and covariance matrices $R$ and $Q$, the Kalman filter estimates a process by using a form of feedback control: it calculates the process state at some time and then obtains feedback in the form of noisy measurements.

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FIG. 3. Comparison between the transfer function matrix obtained from the LVDTs measurements (black curves) and the frequency response of the linear models calculated using subspace system identification (gray curves). The rows represent the excitations (xCorr, zCorr, tyCorr), while the columns are the sensors (xLvdt, zLvdt, tyLvdt). The top $3 \times 3$ matrix shows the results obtained with the west end IP, while the bottom matrix is relative to the west input IP.
Using the subspace system identification method it is possible to extract some characteristics of the process and measurement noises $w$ and $v$. In particular, we can calculate the matrix $K$ that transforms the measurement noise into the process noise, $w = KV$, and the covariance matrix $Q$. Combining $K$ and $Q$ with the Eqs. (15) and (16), we can rewrite our modal state-space representation in the form

$$
\dot{x}_m = A_m x_m + B_m u + K Q e(t), \quad (18)
$$

$$
y_m = C_m x_m + D_m u + e(t), \quad (19)
$$

where $e(t)$ is a normalized noise source. In this way a Kalman state estimator for this system can be obtained simply using identity covariance matrices.

### III. EXPERIMENTAL RESULTS

The measurements consisted of three open-loop experiments for each selected SA. We excited the IPs of the west end (WE) and west input (WI) suspensions with band-limited white noise using the three coil-magnet actuators placed on the top ring in succession and we measured the LVDTs and accelerometer signals. In each experiment, we shook for 1800 s and acquired the LVDTs and accelerometer signals with 50 Hz sampling frequency.

We calculated three state-space representations of the LVDT model (Eqs. (9) and (10)) one for each excitation, with order $N = 30$. Therefore, we obtained the estimates $\hat{A}_i, \hat{B}_i, \hat{C}_i, \hat{D}_i$ with $i = 1, 2, 3$, where each $\hat{A}_i$ is $30 \times 30$, $\hat{B}_i$ is $30 \times 1$, $\hat{C}_i$ is $3 \times 30$, and $\hat{D}_i$ is $3 \times 1$. The results are shown in the block diagram of the three discrete Kalman filters shown in Fig. 5.
in Fig. 3, where the black curves represent the measured transfer function matrices of the west end (top) and west input (bottom) IPs and the gray curves are the frequency responses of the identified state space models. Even though the quality factors of some modes are overestimated, a good level of agreement is reached.

The value of $N$ has been chosen to have the minimum order that gives an accurate fit of the experimental data over the desired frequency range. Looking at the experimental transfer functions of Fig. 3, we see that, in the band $0.01 \text{ Hz} < f < 2.5 \text{ Hz}$, there are $\sim 15$ resonances in both the WE and WI data. To test this hypothesis, we estimated a high order model for each data set and calculated its Hankel singular values $\sigma_i$. These parameters, that are commonly used in control theory for model reduction, provide a measure of the energy of each state components of a linear model. They are defined as the square root of the eigenvalues of the product between the controllability and the observability gramian matrices

$$
\sigma_i = \sqrt{\lambda_i(CO)},
$$

where $C$ is given by

$$
C = \int_0^\infty e^{NA}BB^T e^{NA^T} dt.
$$

Figure 4 shows the Hankel singular values of a model of order $N = 70$ calculated with WE and WI data. As expected, the last significant drop in the singular values corresponds to $\sim 30$ dominant modes in the system.

After applying the procedure described in Subsection II B to the estimated state-space models and verifying their observability, we calculated three discrete Kalman filters, one for each degree of freedom excited (see the block diagram of Fig. 5). Every estimator has 4 inputs, constituted by the excitations ($x$Corr, $z$Corr, or $ty$Corr) and the measurements ($x$Lvdt, $z$Lvdt, and $ty$Lvdt) and 33 outputs, formed by the 30 estimated state vector components ($\hat{x}_m$) and the 3 estimated outputs ($x$Lvdt, $z$Lvdt, and $ty$Lvdt).

In Fig. 6 we show the transfer functions between the state outputs of one observer, relative to the main resonance modes ($x_1, x_2, x_3, x_1, x_2, x_3$), and its actuator signal input. The geometrical orientation of ($x_1, x_2, x_3$) is, in general, not aligned with ($x, z, \theta$) but depends on random factors such as the asymmetric stiffness of the IP flex joints. The choice of the filter is arbitrary since the coil-magnets are not diagonalized and therefore each of them excites all the modes of the system. Looking at Fig. 6 we can notice that, as expected, the position transfer functions (blue, red, and green curves) have an approximate $1/\omega^2$ high frequency trend, while the velocity transfer functions (magenta, black, and brown curves) tend to zero for low frequencies and goes as $1/\omega$ for high frequencies.

IV. CONCLUSIONS

We successfully applied system identification and Kalman filtering techniques to the Virgo IP mechanical system. A state observer capable to estimate, using time domain data, every resonance mode of the system independently has been developed.

A first possible application would be the implementation of a closed-loop monitoring tool that provides the real-time position and velocity of the Virgo inverted pendulum along its normal modes. In this way any drift in the mechanical characteristics of the IP, due, for example, to environmental noise, can be detected and studied. This work will be the subject of a forthcoming paper.

Kalman filters are commonly used for the development of MIMO optimal dynamic regulators through the linear quadratic Gaussian (LQG) design. Therefore, since a plant state observer is available, we could substitute the classical SISO design approach, currently used in the Virgo IP control, with a multivariable feedback technique such as the LQG. In this way the control diagonalization would no longer be required, and consequently it would be possible to optimize the loop parameters for both the mixed and diagonal terms elements of the sensor/actuator transfer function matrix.