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Application of Response estimation on Bottom-Fixed Offshore Structures

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ABSTRACT

Offshore structures are subjected to non-zero mean random inputs. For a better Structural Health Monitoring solutions, response at most of the locations are required. In the case of fatigue estimation stress time history is required. Strain measurements are generally employed to obtain the stress time histories. In cases of complex civil structures like offshore structures subjected to complex loading requires strain measurements at several expected critical locations, it is practically and economically challenging to install strain gauges at all required locations. Thus, only limited physical sensor distribution is possible and a response estimation algorithm is necessary to obtain strain time history at other critical locations. This paper investigates a combined response and fatigue estimation technique based on the Kalman state estimator to combine multi-sensor data under non-zero mean input excitations. The performance of the response estimation approach is verified numerically, showing that it can successfully estimate strain responses at unmeasured locations.

1. INTRODUCTION

Monitoring underwater structures is challenging in Structural Health monitoring field. These structures are subjected to tidal current which can easily cause sensor malfunctioning. Estimating structural responses at unmeasured important locations can be a powerful alternative to the direct measurement when it becomes unavailable. This paper targets on Bottom-fixed offshore structures such as monopiles, tripods, jackets, and gravity-based structures, have been widely utilized for the purpose of extracting oil and gas, supporting metrological towers and multi-purpose ocean science platforms, and they are expanding their applications for supporting ocean energy facilities (OEFs) including offshore wind turbines and tidal stream turbines.

Response estimation at unmeasured locations from a small number of measurements has been attractive to the researchers who seek to overcome the limited instrumentation. Various efforts for response estimation has been made such as

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finite element model updating with modal expansion (Iliopoulos et al. 2014), natural input modal analysis (Hjelm et al. 2005), time varying auto-regressive model (Yazid et al. 2012), and the model-based Kalman state estimator. Among these efforts, the Kalman state estimator associated with the FE model has been known as an effective tool to estimate the unmeasured responses. Papadimitriou et al. (2009) used strain measurements in the numerical simulation to obtain strain in the entire body, which is subsequently utilized to estimate fatigue remaining life of the structural model. Smyth and Wu (2007) used the Kalman filter to fuse acceleration and displacement with different sampling rates to produce more accurate displacements. Based on the idea that multi-sensor data has the potential to improve the performance of response estimation (Park et al. 2013, Soman et al. 2014, Park et al. 2014, Cho et al. 2014), Jo and Spencer (2014) numerically verified that the combination of acceleration and strain in conjunction with the Kalman filter better estimates unmeasured strains compared to the sole use of acceleration or strain. Yet, the response estimation on offshore structures using the model-based Kalman filter with multi-sensor data has not been fully explored but limited to ideal numerical simulations with analytical FE models, the sole combination of acceleration and strain, and zero-mean random inputs.

2. Formulation

The kalman filter is a linear quadratic estimation algorithm (Kalman (1960)), used for accurate estimation of unknown variables which are actually not accurate with single measurement alone. In this case Kalman filter requires two major inputs i.e. System state and limited physical measurements. The limited physical measurements can be processed to obtain input and measurement noise covariance (Vinay A. Bavdekar (2011) and E Lourens (2012)).

1.1 State space model:
The system state is provided by the state space model, which is derived as follows. Equation of motion of linear dynamic system is given as

$$\mathbf{M}\ddot{u}(t)+\bar{\mathbf{C}}\dot{u}(t)+\mathbf{K}u(t)=p(t) \tag{1}$$

where $u(t)$ is the displacement; it's time derivatives $\dot{u}(t)$ and $\ddot{u}(t)$ are velocity and acceleration vectors, respectively; $\mathbf{M}$, $\bar{\mathbf{C}}$, and $\mathbf{K}$ are the mass, damping and stiffness matrices of the dynamic system, respectively; and $p(t)$ is the input force vector.

Let $x(t)$ be the state vector given as

$$x(t)=\begin{Bmatrix} u(t) \\ \dot{u}(t) \end{Bmatrix} \tag{2}$$

Then, equation of motion is expressed in the state-space form as

$$\dot{x}(t)=\mathbf{A}x(t)+\mathbf{B}p(t)+\mathbf{G}w(t) \tag{3}$$

$$y(t) = \mathbf{C}x(t) + \mathbf{D}p(t) + \mathbf{H}w(t) + v(t) \tag{4}$$

where the matrices $\mathbf{C}$ and $\mathbf{D}$ in Eq. (4) are selected depending on the output of interest $y(t)$; Process and measurement noises $w(t)$ and $v(t)$ are assumed to be stationary, mutually uncorrelated stochastic process following the normal probability distribution. $w \sim N(0,\mathbf{Q})$ and $v \sim N(0,\mathbf{R})$, respectively; the matrices $\mathbf{G}$ and $\mathbf{H}$ are the coefficients of process noise. The system matrices $\mathbf{A}$ and $\mathbf{B}$ are defined as:

$$\mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\bar{\mathbf{C}} \end{bmatrix} \tag{5}$$

$$\mathbf{B} = \begin{bmatrix} \mathbf{0} \\ \mathbf{M}^{-1} \end{bmatrix} \tag{6}$$

For example, if all the displacement and acceleration are to be estimated, the matrices $\mathbf{C}$ and $\mathbf{D}$ can be defined as:

$$\mathbf{C} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\bar{\mathbf{C}} \end{bmatrix} \tag{7}$$

$$\mathbf{D} = \begin{bmatrix} \mathbf{0} \\ \mathbf{M}^{-1} \end{bmatrix} \tag{8}$$

With the above state space model Kalman state estimator (Palanisamy et al. 2015) is constructed as

$$\dot{\hat{x}}(t) = \mathbf{A}\hat{x}(t) + \mathbf{L}(z - \mathbf{C}\hat{x}(t)) \tag{9}$$

$$y(t) = \mathbf{C}\hat{x}(t) \tag{10}$$

where z is the measured responses and Kalman gain $\mathbf{L}$ can be expressed as

$$L = \left[P^{*}\mathbf{C}^{T} + \mathbf{BQD}^{T}\right]\left[\mathbf{R} + \mathbf{DQD}^{T}\right]^{-1} \tag{11}$$

where the error covariance P^{*} is obtained by minimizing the steady state error covariance.

$$P^{*} = \lim_{t\to\infty} E\left(\{x - \hat{x}\}\{x - \hat{x}\}^{T}\right) \tag{12}$$

P^{*} is obtained by solving the algebraic Riccati equation which uses the modified noise covariance $\mathbf{Q}$. It is important to note that for a given non-zero mean input, the response/output is expected to be non-zero mean which may include multiple steady state and transition stages in time domain. In order to estimate such a complex response, the error covariance P^{*} in Eq. (11) should minimize the steady state error covariance at all the stages in the response. The modified process noise $\mathbf{Q}$ enables

P^* to minimize steady state error covariance at all the stages in the response; this enables the formulation to handle non-zero mean input and responses properly. From Eq. (9), it can be inferred that value of filter gain $\mathbf{L}$ determines the priority between model and measurements in response estimation. From Eq. (11) for a given model (**A**, **B**, **C**, and **D**) and process noise $\mathbf{Q}$, the filter gain $\mathbf{L}$ is inversely proportional to the measurement noise covariance $\mathbf{R}$. Thus, estimation using sensors with lower noise level will depend more on measured responses than the given model and vice versa for sensors with higher noise floor. Thus, using sensors with lower noise floor gives better estimation in situations where available numerical model is not accurate.

3. Numerical Validation

In this section a numerical model of a bottom fixed offshore structure is considered (see Fig. 1) and kalman filter based state estimation technique is adopted to estimate strain response using limited measurements.

3.1 Simulation setup:

The model is composed of twenty four frame elements each of which has the length of 0.2 m as shown in Fig. 1. The columns has a circular cross-section of radius 3 cm. The Young's modulus and density of the material were selected as 1000 MPa and 953 kg/m^3 respectively. Four Frame members on top of the columns has Young's modulus and density of 210 GPa and 7850 kg/m^3

The developed numerical model was used in MATLAB Simulink to simulate the acceleration and strain responses of the beam under a non-zero mean input. Responses are sampled at 302 Hz with elliptic AA filter were used as reference response. The accelerations and strains from a few selected nodes were contaminated by white noise. Accelerations are contaminate by 2% noise in root mean square (RMS), while the strains are contaminated by 10% noise in RMS based on the experience of higher noise on the actual strain measurement. These limited responses are used in input covariance estimation and response estimation.

The limited strain measurements along with numerical model is used to estimate the input covariance.

Four simulation cases are considered here, in each case, one of the strain responses is estimated with the help of other strain and acceleration responses. For example in case 1, strain measurements near the root of column 2, 3 and 4 and acceleration on top (Ref. Fig.1) are used to estimate the strain response in column 1.

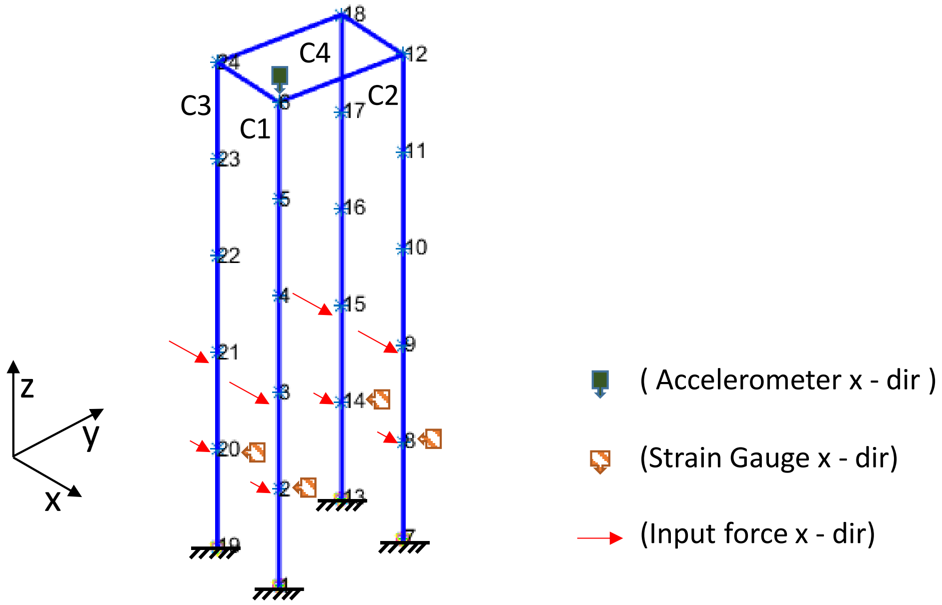
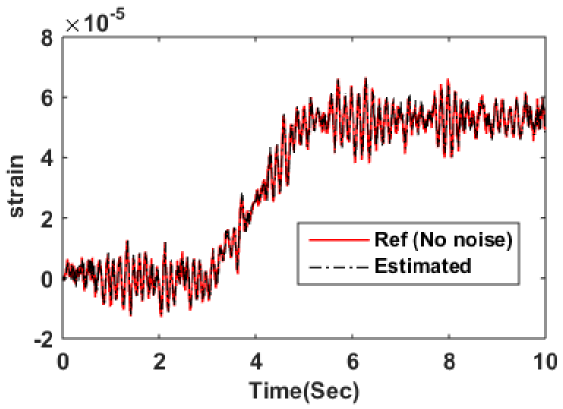


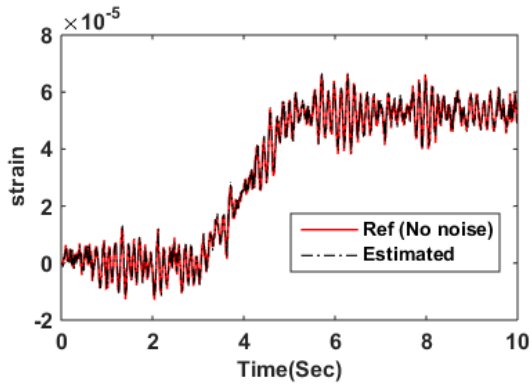
Fig. 1. Numerical model

3.2 Results:

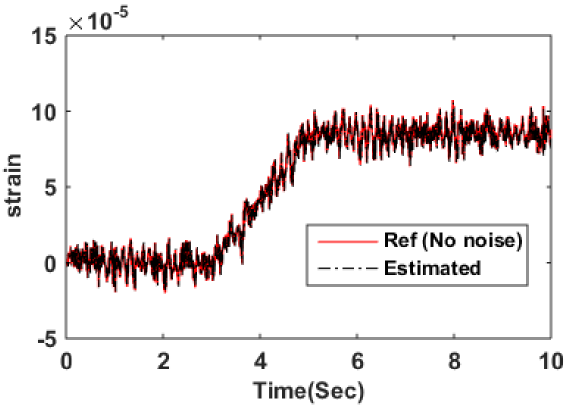
Fig. 2 shows the estimated strain in each case. Each case is processed in two steps. Step 1: estimate the input covariance. Step 2: use the estimated input covariance and limited measurements in Kalman filter based state estimator to estimate the unmeasured response. In case 1, strain response from nodes 8, 14 and 20 with acceleration response from node 6 are used to estimate strain at node 2. From the Fig.2 estimated non-zero mean strain at each column is in good agreement with the reference strain. Column 3 and 4 experience higher strain due to upstream force compared to column 1 and 2. Fig. 3 shows the capability of algorithm to estimate the dynamic component of response in column 1 during 5 to 9 sec.



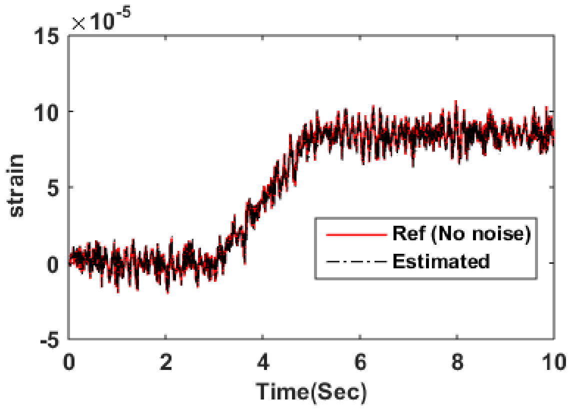
(a) Case 1



(b) Case 2



(c) Case 3



(d) Case 4

Fig. 2. Estimated and reference strain response in time domain

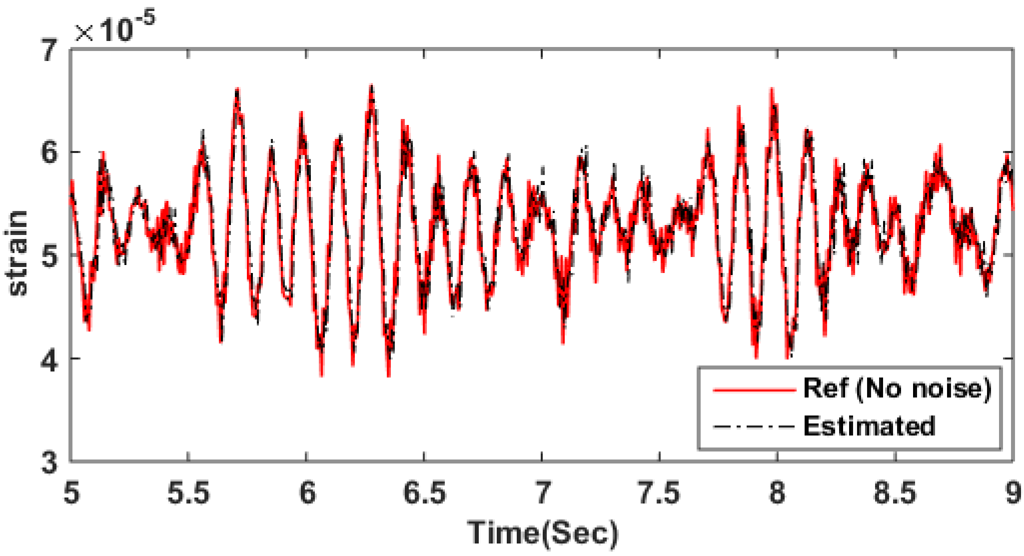


Fig. 3 Estimated and reference strain response in column 1 (between 5 and 9 sec)

The results are also investigated on frequency domain. Fig. 4 shows the comparison of estimated and reference strain power spectra. From the Fig. 4, it can be observed that the estimated strain is in a good agreement with the reference strain. Their strong agreement near 0 Hz shows the capability of algorithm to handle non-zero mean responses.

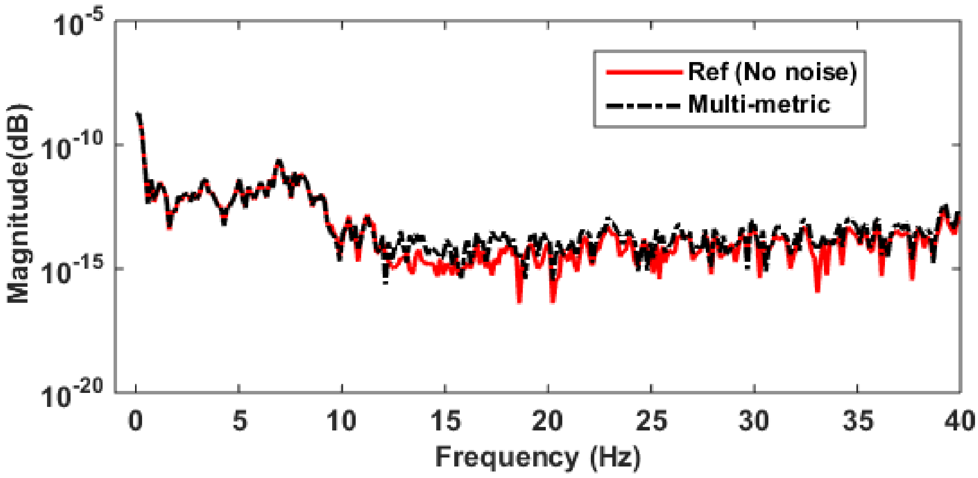


Fig. 4. Estimated and reference strain response in frequency domain.

4. CONCLUSIONS

Kalman filter based response estimation technique is adopted here to estimate strain response at unmeasured location. Following considerations are successfully validated numerically

1. Handling a more reliastic non-zero mean input situation.
2. Implementing data-fusion to enhance the accuracy of estimation.
3. Accurate response estimation over complex 3D offshore structure.

5. ACKNOWLEDGEMENT

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