

A fired-induced displacement estimation method for civil infrastructure

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Abstract

The paper presents a new dynamic displacement estimation method for online risk assessment of a structure during fires. The proposed method is developed for smart ball sensors, which are installed on the roof or wall of a structure by firefighters and transmit the safety information of the structure members. The proposed method combines acceleration and velocity data from an accelerometer and a geophone based on a real time data fusion algorithm based on Kalman filter. By recursively integrating acceleration measurements and correcting integration error using velocity measurements, the proposed method can estimate the displacement of the structure without displacement sensors for which it is typically difficult to be applied to fire sites since they require fixed support. The performance of the proposed algorithm was verified by lab-scale tests, in which displacements estimated by the proposed method are compared to reference displacement measured by laser Doppler vibrometer (LDV).

1. Introduction

During fire accidents, it is crucial to assess the condition of structural members in a civil structure accurately for effectively predicting dangerous collapses induced by fire. It is well known that fire on civil infrastructure causes dynamic response such as rapid deflection of beams and rapid buckling of pillars, and final collapse of the major members of the structures [1-3]. To assess the dynamic deformation of each structural member, accelerometers have been widely used and the data from accelerometers are mostly double-integrated to identify the displacements of structural members. However, accumulated bias and error would reduce the reliability of calculated displacement [4-5]. Nevertheless, accelerometer still has their own strengths such as high sampling frequency and direct current (DC) level measurement for health monitoring of civil infrastructure [6].

To resolve the accuracy of acceleration measurements, data fusion techniques based on various velocity, acceleration and displacement sensors have been introduced recently [7]. One good example of these data fusion techniques is Kalman filter based dynamic response estimation technique [4][6]. Typically, the technique shows much precise estimation accuracy by generating dynamic response of a structure using two measurements (i.e. acceleration and displacement) [8-9].

The purpose of this paper is to present a dynamic response estimation method for

online risk assessment of a structure during fire by fusing the acceleration and velocity data from accelerometer and geophone sensor, respectively. The following paragraphs are categorized as three sections; Section 2 proposes theoretical description of the proposed displacement estimation technique, and Section 3 demonstrates experimental verification of the proposed estimation technique, and final conclusions are made in Section 4.

2. Proposed dynamic response estimation technique for civil infrastructure

In Section 2, theoretical background of the proposed technique is offered. The proposed technique consists of (1) state-space model for describing the relation among velocity and acceleration measurements, bias in acceleration measurement and other noise components, and (2) Kalman filter algorithm for estimating dynamic response from the measurements.

2.1. State-space model

The first premise for establishing state-space model for estimation is the assumption of sensor measurement data components. In the proposed estimation technique, acceleration and velocity are utilized as input data, consisting of true response, noise process and sensor bias. Let the measurements of an accelerometer and geophone at time step k be \ddot{x}_m and \dot{x}_m , respectively, the equations for \ddot{x}_m and \dot{x}_m can be described as:

$$\ddot{x}_m(k) = \ddot{x}(k) + w(k) + b_1(k) \quad (1)$$

$$\dot{x}_m(k) = \dot{x}(k) + v(k) + b_2(k) \quad (2)$$

where \ddot{x} and \dot{x} are the true acceleration and the velocity, w and v are zero mean white Gaussian noise processes, and b_1 and b_2 are accelerometer bias and geophone bias, respectively.

Considering the large influence of accelerometer bias accumulation, state vector \mathbf{x} is defined as:

$$\mathbf{x}(k) = \begin{bmatrix} x(k) \\ \dot{x}(k) \\ b_1(k) \end{bmatrix} \quad (3)$$

With this defined state vector, the rectangle integration rule is applied to establish transition equation of the state-space model.

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\ddot{x}_m(k) + \mathbf{B}w(k) \quad (4)$$

where

$$\mathbf{A} = \begin{bmatrix} 1 & \Delta t & 0.5\Delta t^2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 0.5\Delta t^2 \\ \Delta t \\ 0 \end{bmatrix}$$

Velocity measurement can be expressed using the state vector defined in Eq. (3).

$$\dot{x}_m(k) = \mathbf{C}\mathbf{x}(k) + v(k) + b_2(k) \quad (5)$$

where

$$\mathbf{C} = [0 \quad 1 \quad 0]$$

Thus, the final forms of the state-space model are Eqs. (4) and (5).

2.2. Data-fusion technique based on Kalman filter

The whole procedure could be separated into two steps. Figure 1 shows the schematic procedure of proposed data fusion technique based on Kalman filter. The first step is prediction step which incorporates the process for predicting state vector $\mathbf{x}(k+1)$ at the next time step by using the acceleration measurement $\ddot{x}_m(k)$ and the estimate $\hat{\mathbf{x}}(k)$ of state vector $\mathbf{x}(k)$ at the previous time step. The second step is calibration step, which incorporates the process for calibrating the prediction of the state vector $\mathbf{x}(k+1)$ to enhance the accuracy.

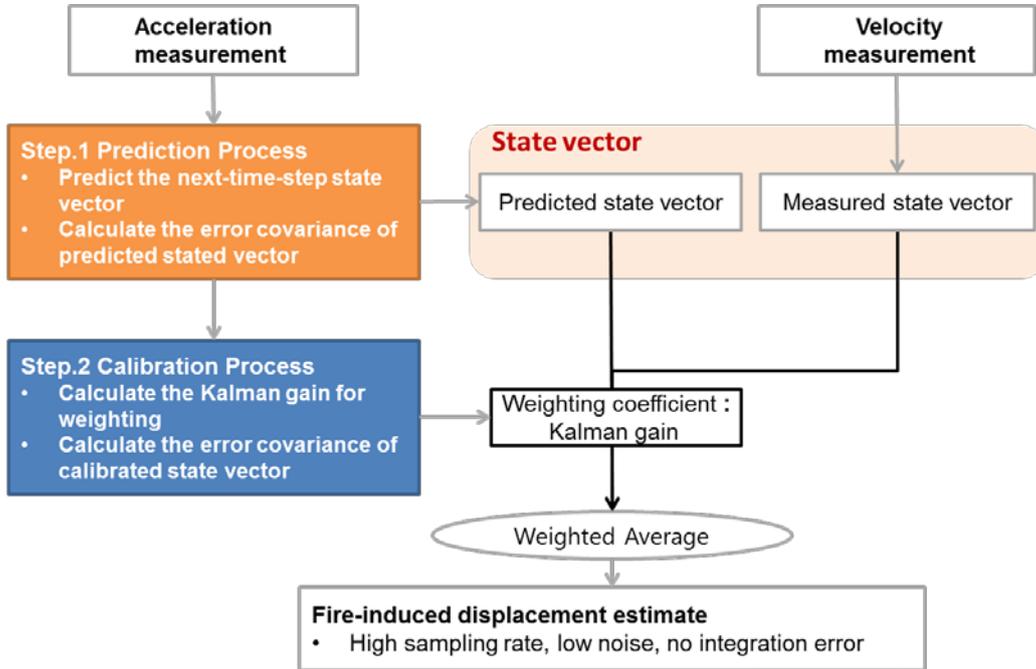


Figure 1. Schematic design of data-fusion technique

2.2.1. Prediction step

The purpose of prediction step is to estimate the state vector $\mathbf{x}(k+1)$ by using $\hat{\mathbf{x}}(k)$ and $\ddot{x}_m(k)$. With stochastic approach, the expectation is applied and the noise effect is removed since the expectation of the noise is zero. The equation (6) describes the predicted state vector.

$$\hat{\mathbf{x}}^-(k+1) = E[\mathbf{x}(k+1)] = \mathbf{A}\hat{\mathbf{x}}(k) + \mathbf{B}\ddot{x}_m(k) \quad (6)$$

where $\hat{\mathbf{x}}^-(k+1)$ is the estimate of $\mathbf{x}(k+1)$ at the prediction step, and $\hat{\mathbf{x}}(k)$ is the estimate of $\mathbf{x}(k)$ at the calibration step at the time step k .

After predicting the state vector, the covariance of error is followed as equation (7):

$$\begin{aligned} \mathbf{P}^-(k+1) &= E[\mathbf{e}^-(k+1)\mathbf{e}^{-T}(k+1)] = \mathbf{A}\mathbf{P}(k)\mathbf{A}^T + \mathbf{B}\sigma_w^2\mathbf{B}^T \\ &= \mathbf{A}\mathbf{P}(k)\mathbf{A}^T + \mathbf{Q} \end{aligned} \quad (7)$$

where e^- is the error of the estimated state vector, σ_w is standard deviation of w , and $\mathbf{Q} = \mathbf{B}\sigma_w^2\mathbf{B}^T$.

2.2.2. Calibration step

The purpose of the calibration step is the accuracy improvement of predicted state vectors by using covariance of error. Due to calculated Kalman gain which results from the calibration step, the calibrated state vector is established by the weighted average between the predicted state vector and the measured state vector. Equation (8) is for Kalman gain calculation

$$\mathbf{K}(k+1) = \mathbf{P}^-(k+1)\mathbf{C}^T\{\mathbf{C}\mathbf{P}^-(k+1)\mathbf{C}^T + \sigma_v^2\}^{-1} \quad (8)$$

where \mathbf{K} is Kalman gain, σ_v is standard deviation of noise v .

$$\mathbf{P}(k+1) = \{\mathbf{I} - \mathbf{K}(k+1)\mathbf{C}\}\mathbf{P}^-(k+1) \quad (9)$$

And the error covariance of calibrated state vector is calculated by using equation (9). This covariance matrix will be utilized for the prediction process of the time step $k+2$.

With Kalman gain $\mathbf{K}(k+1)$, the weighted average between the estimated state vector at the prediction step and the velocity measurement can be implemented for estimation of calibrated state vector by using equation (10)

$$\hat{\mathbf{x}}(k+1) = \mathbf{K}'(k+1)\hat{\mathbf{x}}^-(k+1) + \mathbf{K}(k+1)\dot{x}_m(k+1) \quad (10)$$

where $\mathbf{K}'(k+1)\hat{\mathbf{x}}^-(k+1)$ is expressed as equation (11) in terms of $\hat{\mathbf{x}}^-(k+1)$, $\mathbf{K}(k+1)$, \mathbf{C} , and $b_2(k+1)$. $\mathbf{K}'(k+1)$ could not be independently uncoupled with assumption that $b_2(k+1)$ is not zero. Instead of $\mathbf{K}'(k+1)$, $\mathbf{K}'(k+1)\hat{\mathbf{x}}^-(k+1)$ is calculated for reflecting the constant geophone bias $b_2(k+1)$ term and is directly applied to the weighted average equation (10).

$$\mathbf{K}'(k+1)\hat{\mathbf{x}}^-(k+1) = \hat{\mathbf{x}}^-(k+1) - \mathbf{K}(k+1)\{\mathbf{C}\hat{\mathbf{x}}^-(k+1) + b_2(k+1)\} \quad (11)$$

Thus, the calibrated state vector, which is the accuracy enhanced form, is estimated by the equation (10) of calibration step.

3. Experiment

With an effort for overcoming the realistic limitation about protecting the sensors and igniting at real structures, fire-induced deformation simulation experiment is implemented. The simulation assumption and emphasis reflect the study of National Institute of Standards and Technology (NIST) which have already verified the property of fire-induced deformation [1].

3.1. Experiment Setting

The experiment instruments are separated into the two groups. The first group is composed of three sensors; geophone (ION LF-24), accelerometer (PCB Piezotronics

3713E112G) and laser Doppler vibrometer (Polytec PSV-400) which is for reference velocity measurement. The second group is composed of modal shaker (APS 400 ELECTRO-SEIS) and a controller (Polytec Data Management System / Junction Box / Vibrometer Controller) with performance of data acquisition and signal generation. The concrete arrangement of instruments and schematic design of experiment are described by Figure 2.

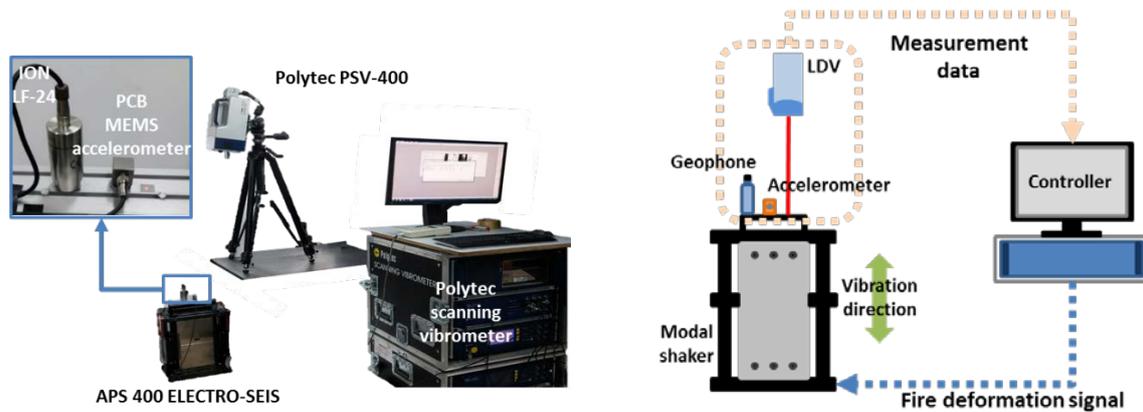


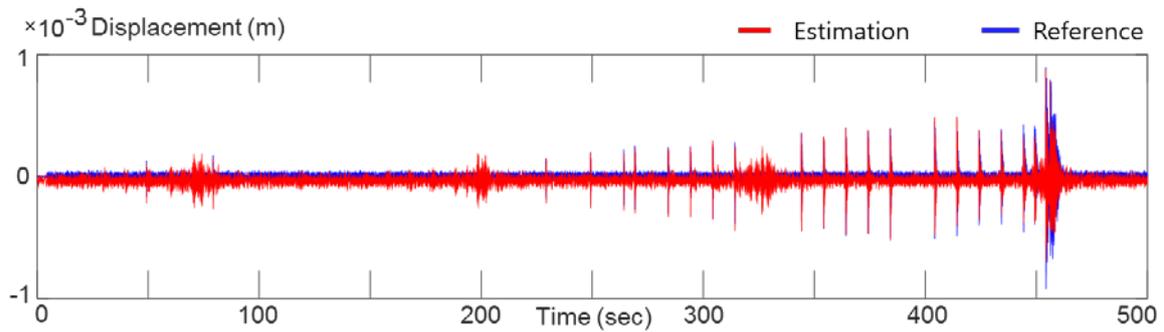
Figure 2. Experiment set up and schematic design

The whole process of experiment could be described as the simulation implementation of the first group and the measurement implementation of the second group. The experiment is initiated with the transmission of the fire-induced signal from controller to modal shaker. After the transmission, the modal shaker simulates the fire-induced deformation with one direction of degree of freedom. Then, the pre-activated sensors (geophone, accelerometer, and LDV) start to measure the deformation and all measured data are transmitted to the controller simultaneously with measurement of sensors.

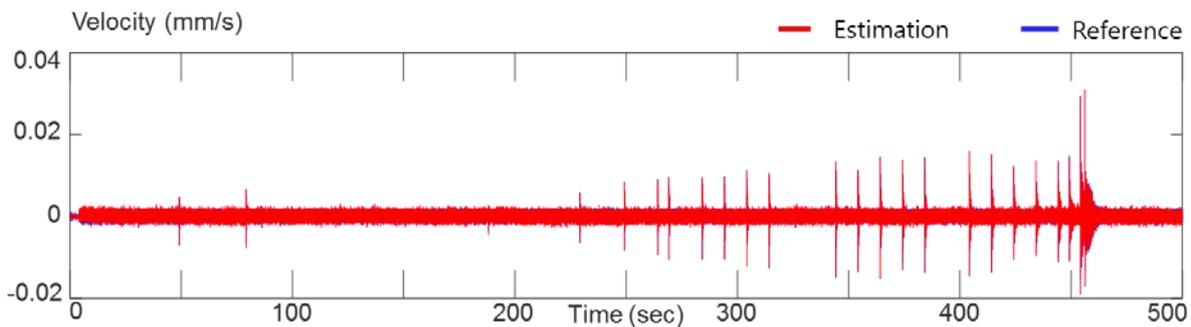
3.2. Experiment Result

With the acquired measurement data, the evaluation of the proposed technique performance is implemented. The reference displacement is drawn by an integration of the reference velocity measurement data from LDV, and the estimated displacement is compared to the reference displacement. Additionally, the estimated velocity is compared to the reference velocity from LDV. The comparison configuration is described at Figure 3.

For quantifying the accuracy of estimation, the root mean square (RMS) error is calculated for both displacement and velocity estimation results. The RMS error of displacement estimation is 0.957 mm and that of velocity estimation is 2.362 mm/s.



(a) The comparison between estimated displacement and reference displacement,
RMS Error = 0.957 mm



(b) The comparison between estimated velocity and reference velocity,
RMS Error = 2.362 mm/s

Figure 3. Comparison between estimation and reference

4. Conclusion

With the notice of importance of monitoring fire-induced deformation with sensors, the accurate estimation technique by using measurement data is required, and this study proposes a novel estimation technique. The technique utilizes both acceleration and velocity data as input and estimates the true velocity and true displacement of structural member. The performance verification of the estimation technique has been implemented by the simulation experiment. As a future study, this estimation technique would be applied to Smart ball which is designed as an immediately attachable multiple sensor including accelerometer and geophone.

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