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COMBINING DISPLACEMENT AND ACCELERATION DATA FOR STRUCTURAL HEALTH ASSESSMENT

Federico Ponsi[1], Ghita Eslami Varzaneh[1], Veronica Dallari[1], Giorgia Ghirelli[1], Laura Dieci[1], Elisa Bassoli[1] and Loris Vincenzi[1]

[1] Department of Engineering “Enzo Ferrari” – University of Modena and Reggio Emilia
via Vivarelli, 10, 41125, Modena, Italy
{federico.ponsi,ghita.eslami,veronica.dallari,giorgia.ghirelli,laura.dieci,elisa.bassoli,loris.vincenzi}
@unimore.it

Abstract

Traditional vibration monitoring systems often use accelerometers to record structural responses to various excitation sources, with changes in modal parameters indicating potential damage. However, displacement measurements offer more direct and valuable information about structural health, revealing operational conditions and detecting permanent deformations. Direct displacement measurement, though, is challenging and has several limitations tied to the technology used. For example, GNSS (Global Navigation Satellite Systems) receivers are less suitable for dynamic applications due to low sampling rates, while LVDTs (Linear Variable Differential Transducers) require a fixed base, which is often unavailable. Additionally, double integration of acceleration fails to provide accurate quasi-static or residual displacement measurements. An emerging approach to address the limitations of traditional monitoring systems is data fusion, which combines measurements from various sensors to improve accuracy. Typically, accelerations are integrated with data from strain gauges, GNSS, cameras, inclinometers, and radar. This paper explores the potential of data fusion for structural health monitoring by combining displacement data estimated through vision-based techniques with traditional accelerometer-based measurements. This combination leverages the accelerometer ability to measure very small vibrations with high time resolution and the vision-based approach capability to detect residual or quasi-static displacements. The paper presents results from merging vision-based displacement data with co-located accelerations measured on a laboratory scale frame. Data fusion, involving sensors with different sampling rates, is performed using a multi-rate Kalman filter.

Keywords: data-fusion, multi-rate Kalman filter, vision-based monitoring, structural health monitoring.

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1 INTRODUCTION

Accelerometers are essential components in traditional vibration monitoring systems, measuring the structure response to various excitation sources [1]. The extraction of modal features from accelerations [2] and the detection of changes over time are fundamental steps in established damage detection methods [3-5]. However, displacement measurements provide more direct and valuable insights into structural health, acting as an operational condition index and enabling the quick identification of permanent deformations.

Key technologies for direct displacement measurement in structural monitoring include Global Navigation Satellite Systems (GNSS) [6], Linear Variable Displacement Transducers (LVDT) [7], satellite remote sensing [8,9], terrestrial radar interferometry [10,11], and vision-based techniques [12-14]. While each of these methods offers distinct advantages, they also have limitations that restrict their broader use. GNSS receivers typically have low sampling rates, making them less effective for dynamic monitoring; however, multi-constellation, high-frequency GNSS receivers show promise for enhancing three-dimensional displacement tracking. LVDTs require a fixed base for installation, which is often unavailable, especially for monitoring real-scale infrastructure. Vision-based techniques provide low-cost solutions for direct displacement measurement but are sensitive to lighting and weather conditions. To fully unlock their potential, further research is needed.

Double integration of accelerations can also estimate displacements, but it faces challenges such as unknown initial conditions for integration and amplified acceleration noise during the process. To address these issues, stable and accurate filtering methods have been proposed by Lee et al. [15] and Hong et al. [16] to suppress low-frequency noise. However, these filters limit the technique to linear dynamic displacement reconstruction, as they also suppress low-frequency displacement components, including pseudo-static displacements caused by moving loads on bridges or permanent displacements resulting from structural damage.

Among the available technologies for displacement measurement, vision-based monitoring has the potential to reduce reliance on costly industrial equipment [17], demonstrating great capabilities in measuring both static and dynamic structural displacements, even with consumer-grade devices. In addition, vision-based methods offer several advantages, including direct displacement measurement (eliminating the need for double integration of accelerations) and the ability to monitor multiple points with a single device, which can be easily repositioned depending on the application [14].

Despite these numerous benefits—such as cost-effectiveness, time savings, ease of use, and reduced operational and management costs—the accuracy of vision-based displacement measurement is still being explored and remains difficult to quantify. This challenge arises from the fact that accuracy is not solely determined by the camera hardware itself. Calibration and data processing play crucial roles, including the correction of lens distortion in each video frame, perspective adjustments, and the identification of the scale factor necessary to convert displacements from pixel units to physical units. Furthermore, environmental factors are well-known to contribute significantly to errors and uncertainties. These include camera vibrations caused by wind or user interactions, changes in weather conditions, variations in ambient light, and air refraction differences due to temperature fluctuations between the camera and the monitored object [18,19].

The purpose of this paper is to examine the potential of data fusion for structural health monitoring by combining vision-based displacement measurements with measures obtained through a traditional accelerometer-based monitoring system. While vision-based methods may provide less accurate displacement estimates compared to double integration of accelerations, they can play a key role in refining post-processed displacements and reducing the uncertainties caused by the integration process, particularly when combined with a Kalman filter approach. To evaluate the potential of the data fusion approach in structural health monitoring, where detecting residual displacements is essential, tests are conducted on a laboratory scale frame subjected to dynamic excitation alongside a permanent imposed displacement. The frame is equipped with MEMS (Micro-Electro-Mechanical Systems) accelerometers and artificial targets, whose movements can be monitored from consecutive frames of a recorded video. The measured accelerations are transformed into displacements using an improved double integration technique, and then combined with displacements obtained from vision-based tracking.

The paper is organized as follows: section 2 introduces the multi-rate Kalman filter formulation for data fusion while section 3 outlines the vision-based procedure to estimate structural displacements from recorded videos. Laboratory scale frame experiments are presented in section 4 together with the data fusion outcomes. Finally, conclusions are drawn in section 5.

2 DATA-FUSION USING A MULTI RATE KALMAN FILTER

The Kalman filter expression for data fusion is derived by modeling the measurement process in a state-space equation format:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} + \mathbf{w} \tag{1}$$

$$z = \mathbf{H}\mathbf{x} + v \tag{2}$$

where the state vector $\mathbf{x} = [x\ \dot{x}]^{\boldsymbol{T}}$ includes the displacement x and the velocity $\dot{x}$. The variables $z = x_m$ and $u = \ddot{x}_m$ are the measured displacement and acceleration, respectively. The white noise process $\mathbf{w}\sim(\mathbf{0},\mathbf{Q})$ has a covariance matrix $\mathbf{Q}$ and $v\sim(0,r)$ denotes a random variable representing the uncertainty in displacement measurements with variance r. We assume $\mathbf{Q} = \begin{bmatrix} 0 & 0 \\ 0 & q \end{bmatrix}$, where q is the acceleration variance, since the only source of noise in Eq. (1) is the measured acceleration. The coefficient matrices are:

$$\mathbf{A} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \mathbf{H} = [1 \quad 0] \tag{3}$$

Assuming that accelerations are sampled at a rate T_a, Eqs. (1)-(2) are discretized as:

$$\mathbf{x}_{k+1} = \mathbf{A}_d\mathbf{x}_k + \mathbf{B}_d u_k + \mathbf{w}_k \tag{4}$$

$$z_k = \mathbf{H}\mathbf{x}_k + v_k \tag{5}$$

The discretized coefficient matrices are:

$$\mathbf{A}_d = \begin{bmatrix} 1 & T_a \\ 0 & 1 \end{bmatrix}, \mathbf{B}_d = \begin{bmatrix} T_a^2/2 \\ T_a \end{bmatrix} \tag{6}$$

while $\mathbf{H}$ remains unchanged. The covariance matrices for the discrete noise sequences are:

$$\mathbf{Q}_d = \begin{bmatrix} qT_a^3/3 & qT_a^2/2 \\ qT_a^2/2 & qT_a \end{bmatrix}, \mathbf{R}_d = \mathbf{R}/T_a \tag{7}$$

Introducing the state covariance matrix $\mathbf{P}$ and the state estimate $\hat{\mathbf{x}}$, the forward Kalman filter algorithm is summarized as follows:

- Initialization**:**

$$\mathbf{x}_0 = \mathbf{0}; \mathbf{P}_0 = \mathbf{I} \tag{8}$$

- Time update (a priori estimate)

$$\hat{\mathbf{x}}_{k+1|k} = \mathbf{A}_d\hat{\mathbf{x}}_{k|k} + \mathbf{B}_d u_k \tag{9}$$

$$\mathbf{P}_{k+1|k} = \mathbf{A}_d\mathbf{P}_{k|k}\mathbf{A}_d^T + \mathbf{Q}_d \tag{10}$$

- Measurement update (a posteriori estimate)

$$\hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} + \mathbf{K}_{k+1}\left(z_{k+1} - \mathbf{H}\hat{\mathbf{x}}_{k+1|k}\right) \tag{11}$$

$$\mathbf{P}_{k+1|k+1} = (\mathbf{I} - \mathbf{K}_{k+1}\mathbf{H})\mathbf{P}_{k+1|k} \tag{12}$$

where the Kalman gain $\mathbf{K}_{k+1}$ is given by:

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1|k}\mathbf{H}^{T}\left(\mathbf{H}\mathbf{P}_{k+1|k}\mathbf{H}^{T} + \mathbf{R}_{d}\right)^{-1} \tag{13}$$

Since acceleration and displacement are often measured at different sampling rates, with acceleration typically having a higher rate, we define T_a and T_d as the sampling intervals for acceleration and displacement, respectively, with $T_d > T_a$.

In this context, data fusion requires a multi-rate Kalman filter. The full Kalman filter algorithm, including both time updates (Eqs. (9) and (10)) and measurement updates (Eqs. (11) and (12)), is applied when both acceleration and displacement measurements are available When only acceleration measurements are available, between sampling times kT_d and $(k+1)T_d$, with k integer, the time update occurs without the measurement update, and the optimal estimate $\hat{\mathbf{x}}_{k+1|k+1}$ is equal to $\hat{\mathbf{x}}_{k+1|k}$ computed through Eq. (9). Finally, the displacement time series is obtained by applying a smoothing procedure. For more details, refer to [20,21].

3 VISION-BASED DISPLACEMENT ESTIMATION

Vision-based monitoring relies on the fundamental concept that, assuming a stationary camera, changes in the position of artificial targets or distinctive features of the structure between consecutive frames correspond to the displacement of the related point on the structure over time. The estimation of the absolute structural displacement at each monitored position involves two main stages: the vision-based monitoring system setup, which is tailored to the specific structure being observed, and the video post-processing phase, which serves as the essential connection between raw data (represented by a sequence of video frames) and the displacement time series of the targets. Going into more detail, the estimation procedure can be outlined in the following steps:

- **Monitoring campaign setup:** this step focuses on designing the experimental campaign based on the specific application scenario and expected structural movements. It includes defining camera specifications, selecting appropriate lenses, and determining the ideal frame rate. In this study, a consumer-grade camera is used to assess the effectiveness of low-cost monitoring systems for evaluating the dynamic behavior of structures. Additionally, the camera placement and measurement points are determined. In the presented application, artificial targets are placed both on the monitored structure and on the ground to reduce the impact of camera shake.

- **Camera parameter calibration:** this step involves determining various factors, including intrinsic parameters (such as focal length, optical center, and lens distortion), extrinsic parameters (camera position and orientation relative to the scene), and geometric parameters (projection distortions introduced by the camera system). In the vision-based monitoring method described in this paper, camera calibration is carried out using the approach proposed by Geiger et al. [22], implemented in the MATLAB Computer Vision Toolbox. This method is robust to changing imaging conditions, fully automatic, and can be performed with a few images.

- **Feature tracking:** this is a crucial step to accurately estimate displacements from videos in vision-based monitoring systems. This process involves identifying distinct points or patterns in video frames, such as corners or edges, which can be tracked over time. By following these features across consecutive frames, the displacement (in pixels) of specific points on the structure can be determined. The accuracy of displacement measurements heavily depends on the quality and reliability of feature detection, extraction, and tracking. Even small errors in feature tracking can lead to significant inaccuracies, particularly when dealing with minor displacements. Additionally, feature tracking methods must account for variations in lighting, perspective, and other environmental factors. The key features to be tracked can essentially be selected between intrinsic distinctive elements of the structure (such as bolts or holes) and artificial targets installed on the structure. The former results extremely attractive when the structure is preserved as part of the cultural heritage, as well as if it is not easily or safely accessible. On the other hand, the specific geometry and high contrast of artificial targets lead to more accurate results, albeit requiring access to the structure. In this study, high contrast artificial targets with different geometries are installed on the monitored frame as well as on the ground. The results presented below refer to the checkerboard targets, which proved to be the most effective thanks to several factors: (1) the ease of identifying square corners, (2) the possibility to detect multiple square corners for each target, enabling the averaging of the results, and (3) the sub-pixel accuracy achievable in displacement estimation. As far as the last aspect is concerned, the square corners of a checkerboard serve as key features for target detection due to their distinct RGB intensity contrast with neighboring pixels. Sub-pixel precision in corner detection is possible since checkerboard squares typically do not align with integer pixel boundaries. The image gradient, which reflects the change in RGB intensity between adjacent pixels, allows for the identification of corner coordinates with sub-pixel accuracy in each frame [22]. In the present study, the Kanade-Lucas-Tomasi algorithm [23] is employed to track the movement of checkerboard corners over time, initially identified using the Harris-Stephens algorithm [24].

- **Displacement conversion from pixels to real-world units:** this conversion is based on the definition of a scale factor, calculated as the ratio between a known dimension of the monitored object (for example, the size of the artificial target in mm) and the same dimension identified in pixels in the captured image.

- **Filtering camera shake effects:** this step is essential for estimating absolute structural displacements. Indeed, the so-far identified displacements are the relative displacements between the camera and the monitored point on the structure. The evaluation of absolute structural displacements relies on the presence of ground-based targets, which are assumed to be stationary. Any displacements detected for these targets are attributed solely to unintended camera movements, not actual structural motion. By subtracting these undesired movements, the absolute displacements of the structure are captured, free from external noise or camera instability.

Before initiating the target tracking process, a region of interest (ROI) must be defined. This is a rectangular region of the frame within the target features are initially detected. The MATLAB Image Processing and Computer Vision Toolboxes (Mathworks) are used for this purpose. Once defined, the ROI is treated as a multidimensional pixel matrix, where each pixel is characterized by its 2-D coordinates (relative to the upper-left corner of the frame) and its RGB intensity level.

4 STEEL FRAME EXPERIMENTS

4.1 Monitoring systems

This section presents the experiments conducted on the laboratory scale steel frame equipped with both an accelerometer- and a vision-based monitoring system, as shown in Figure 1.

The accelerometer-based system consists of a control unit and two biaxial MEMS accelerometers placed at the top of the frame. Each sensor unit can measure temperature and accelerations with a sampling frequency ranging from 20 Hz to 80 Hz. In this application, the sampling frequency is set to 80 Hz. By employing local digital filtering techniques and oversampling, these units achieve a noise floor of around 0.3 mg, ensuring high reliability [25].

As regards the vision-based monitoring system, artificial targets with different geometries are installed at the top frame, while two circular targets are installed on the ground to remove camera shaking effects. The videos are recorded with a Nikon D7500 camera, capturing in 4K at 30 frames per second (FPS), using a DX 18-140 mm lens, and mounted on a tripod (see Figure 1b).

The laboratory scale frame is composed of steel elements assembled through bolt connections. It is 153 cm high and has 94 cm x 102 cm plane dimensions. The rectangular base of the frame is realized with pairs of L-shaped elements joined together by means of bolts. Columns have a thin rectangular cross section and are connected at their top by paired L-shaped beams that are oriented in the direction of the column maximum stiffness. Single L-shaped profiles ensure the connection of the beams in the orthogonal direction.

During the test, the response of the frame to an external excitation involving both a dynamic and a permanent component is measured. The dynamic excitation consists of the free vibration of the frame in the direction of minimum stiffness after an input excitation, while the permanent displacement is simulated by shifting the frame base during the free vibrations.

(a) (b)

Figure 1: Test configuration of the steel frame experiments.

4.2 Results

The results presented below correspond to Test 1, which involves free vibrations induced by an input force, and Test 2, which combines free vibrations with an imposed displacement of the entire frame.

As far as Test 1 is considered, Figures 2a and 2b show the comparison between the displacement estimated from measured acceleration and from the vision-based approach. The displacements are reconstructed from the measured accelerations through an improved double integration procedure [15]. The applied method is formulated as a regularization problem in which the acceleration is approximated by the second-order central finite difference of displacement. The displacement is reconstructed inside an overlapping time window by minimizing the least-squared error between measured and approximated acceleration. As expected, the results indicate that although there is good agreement between the two time series, the measurement noise is greater for the vision-based displacement than for the estimates derived from acceleration. The fusion of data coming from the two measurement systems allows reducing the noise characterizing the vision-based displacement, as shown in Figures 2c and 2d.

In Test 1, the reliability of the displacement estimated from acceleration is due to the absence of residual or quasi-static displacements. On the contrary, when a residual displacement is present, the double integration of acceleration fails to accurately estimate the structural displacement, as these displacements are filtered out during the integration process. This can be clearly observed from the results of Test 2, shown in Figure 3. The vision-based displacement estimation enables the observation of how the free vibrations of the frame were influenced by an imposed displacement of approximately 110 mm at around 15 seconds, after which the frame continued to oscillate around the new position (see Figure 3a). This effect, however, cannot be observed in the displacement estimated from acceleration, as highlighted in Figure 3b. In contrast, Figures 3c and 3d demonstrate how combining data from the two measurement systems allows for the identification of the residual displacement while mitigating the noise in the vision-based estimation. The latter aspect is clearly visible by comparing vision-based displacements of small amplitude with the corresponding results of data fusion, as carried out in Figure 3d.

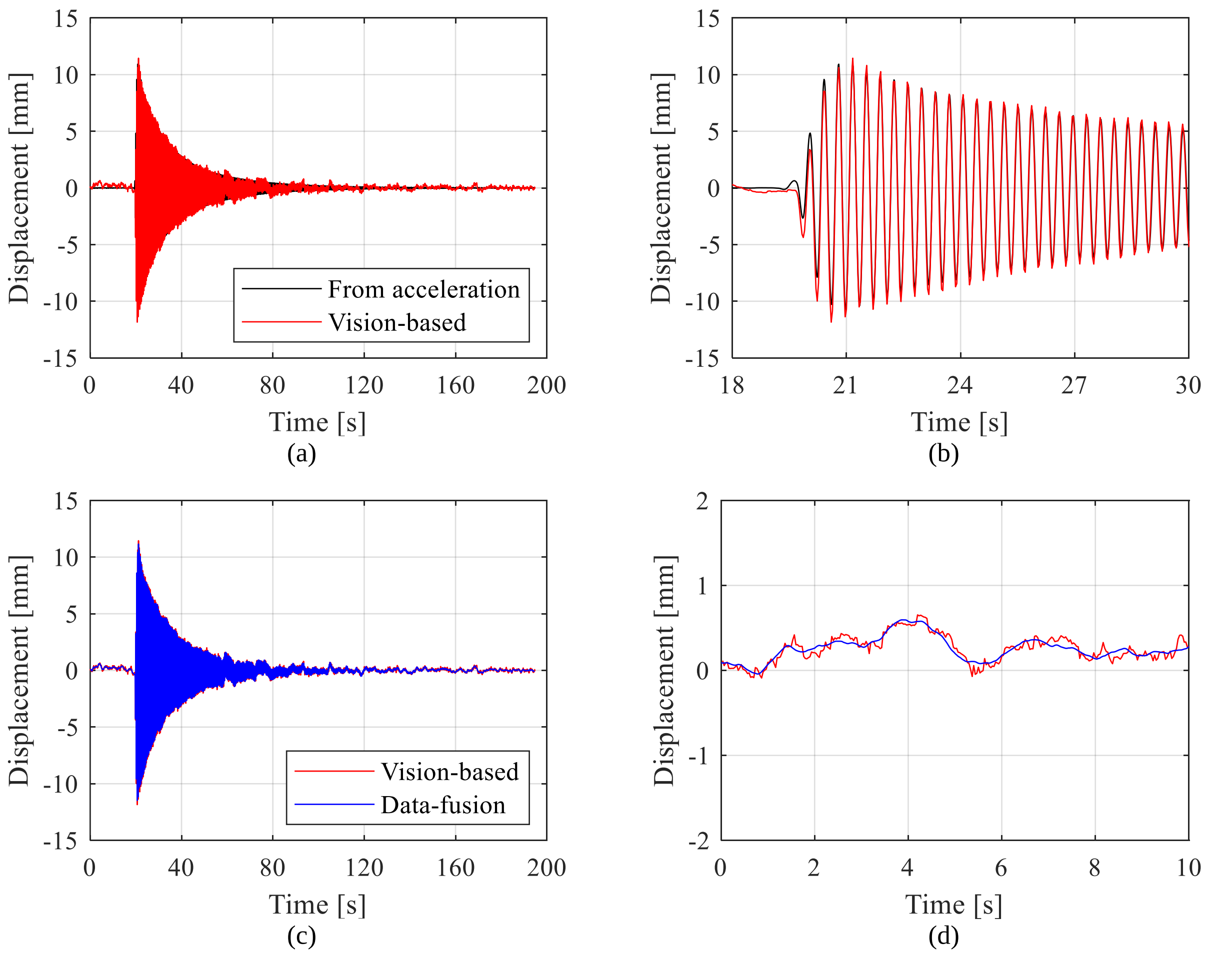

Figure 2: Test 1: (a) displacement estimated from acceleration and from vision-based technique; (b) detail of (a); (c) data-fusion result compared to vision-based displacement; (d) detail of (c).

5 CONCLUSIONS

This paper focused on the application of a data fusion method for structural displacement estimation, using a multi-rate Kalman filter to combine acceleration and vision-based data. This approach aims to address the limitations associated with a single sensor measurement for estimating structural displacements. In the context of structural health monitoring, displacement measurements are highly valuable, as they enable the rapid detection of permanent deformations and serve as an indicator of the structural health condition.

The vision-based method allows for direct displacement estimation, although the resulting displacement is typically affected by non-negligible noise. In contrast, displacement reconstruction from acceleration recordings, while highly accurate, requires the removal of low-frequency noise components. This can be achieved through stable filtering techniques, which simultaneously eliminate low-frequency displacement components, such as quasi-static or permanent displacements.

The potential of data fusion is investigated on a laboratory-scale steel frame. The results confirm that the data fusion approach enhances the accuracy of the vision-based estimation, thanks to the combination with accelerometric data, while also accurately estimating the residual displacement.

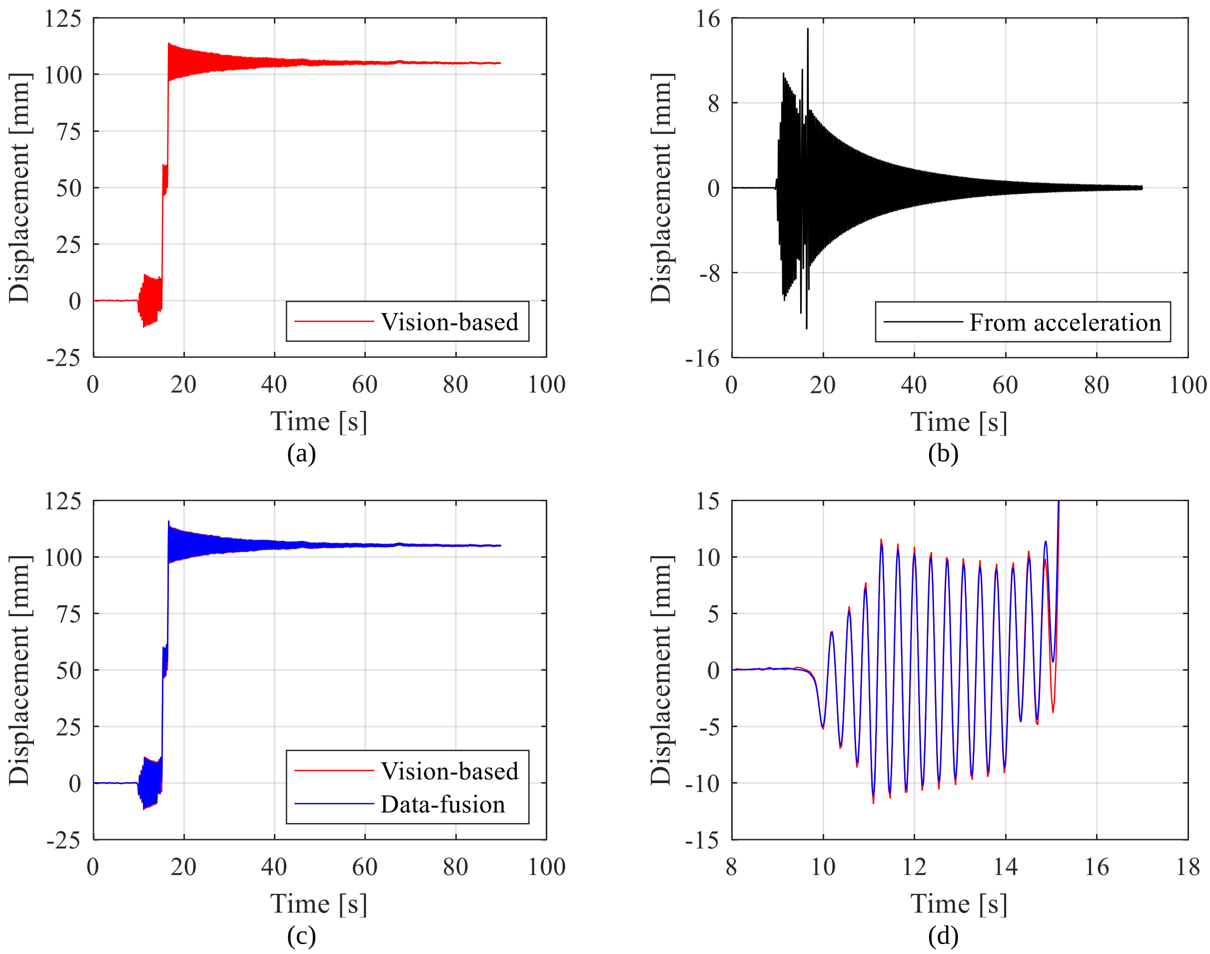

Figure 3: Test 2: (a) displacement estimated from vision-based technique; (b) displacement estimated from acceleration; (c) data-fusion result compared to vision-based displacement; (d) detail of (c).

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