# Methodology for Real-time State Estimation at Unobserved Locations for Structures Experiencing High-rate Dynamics

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## ABSTRACT

Real-time monitoring, condition assessment, and control of structural systems that experience high-rate dynamics are challenging due to these structures operating at timescales below 10ms. Examples of structures that may experience high-rate dynamics include hypersonic vehicles, space crafts, and barriers with active blast mitigation. The real-time monitoring systems used on these structures could greatly benefit from a robust and effective high-rate state estimation methodology that would enable the state of the structure at any unobserved location to be estimated. Any methodology designed for these high-rate systems must account for the challenges associated with data measurement and processing at the considered timescale. This work presents and experimentally validates a methodology for enabling the real-time state estimation at unmonitored locations on a dynamic system that undergoes system level changes (i.e. damage). In this work, the DROPBEAR experimental test bed at the Air Force Research Laboratory is used to validate the proposed methodology for a one-degree-of-freedom system excited with an impact load where a system level change is realized through the dropping of a magnetically attached mass during testing. Results show that the proposed methodology is capable of accurately estimating the levels of acceleration experienced at two unobserved locations in real-time both before and after the mass is detached. A time interval between state estimations of 7.1 ms was achieved during testing.

## INTRODUCTION

High-rate dynamics are defined as the dynamic responses from a structure that experiences an acceleration of over 100 g (high-amplitude) caused by an event that occurs on the timescale of less than 100 ms (high-rate) [1]. A Structural system experienc-

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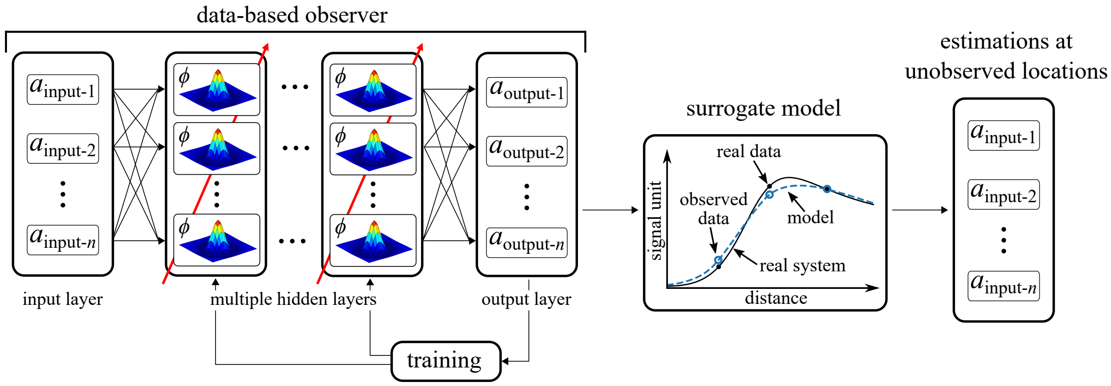


Figure 1. Flowchart of the proposed methodology for obtaining real-time state estimations at unobserved locations of a structure.

ing high-rate dynamics will contain complex inputs and responses, of which the key characteristics can be summarized as: 1) large uncertainties in the system inputs; 2) high levels of non-stationarities and heavy disturbances; and 3) unmodeled dynamics resulting from changes in the structural system [2, 3]. A structural system operating in a high-rate dynamic environment can experience sudden and unmodeled plastic deformation of the structure that may lead to damaged electronics, sensors, and/or delicate payloads. Furthermore, the locations of payloads or electronic packages may prevent the direct monitoring of the structure at key locations. Therefore, a topic of interest is the formulation of a state-estimation methodology that can track these complex dynamic events at unmonitored locations in real-time. This paper proposes and experimentally validates a state estimation methodology that first trains a neural network on experimental data in real-time and then uses this trained network to estimate the accelerations at unmonitored locations using a numerical model.

State estimation of structures experiencing high-rate dynamics is necessitated when the states of the structures cannot be directly measured [1]. Researchers have investigated various state-estimation techniques [4–6]. Advances in computer science, along with the corresponding advances in control theory, have enabled the development of quickly converging, robust observers. These observers have the potential to produce intelligent structural systems that can respond to dynamic events in real-time. This paper introduces a methodology leverages recent advances in data-based observers, surrogate modeling, and real-time computing hardware to generate estimations of structural responses (i.e. acceleration) at unmonitored locations of a structure. In brief, the methodology is as follows. First, a data-based observer is used to obtain a state-estimation of the monitored system, thereafter, a pre-constructed surrogate model of the system is used to obtain a numerical model of the system. This numerical model is then used to estimate the response of the structure at unobserved locations. The proposed methodology was experimentally verified in real-time at the Munitions Directorate of the AFRL using the DROPBEAR (Dynamic Reproduction of Projectiles in Ballistic Environments for Advanced Research) test bed to simulate a high-rate dynamic event [7].

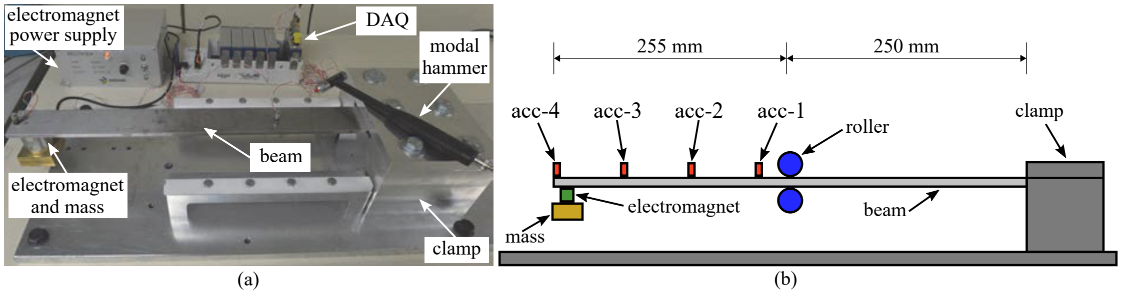


Figure 2. The DROPBEAR test bed used for validation showing: (a) a picture of the test bench (without the rollers installed) with the key components annotated; and (b) schematic of the cantilever beam as tested showing the locations of the rollers, which restrain the cantilever beam in the vertical direction, and the four accelerometers.

## METHODOLOGY

The proposed methodology is presented in figure 1 and detailed as follows. First, a data-based observer is used to obtain a state-estimation of the monitored system. The data-based observer used in this work is based on a simple batch trained neural network with multiple hidden layers using a sigmoid activation function. This observer architecture was chosen for this preliminary work due to its simplicity to implement on field programmable gate arrays (FPGA) and relatively fast training duration. However, other data-based observers including variable input space observer presented by Hong et al [8] and a hybrid model- and data-based observer where a neural network was used to estimate complex nonlinear dynamics presented by Hu et al [9], could also be used. A data-based observer, in comparison to other model based observers [10,11], was selected to develop a mathematical mapping of the structure because of its ability to observe the structure's state without knowledge of system dynamics or the high-rate event that the structure is experiencing. The neural network can be trained using measurable state parameters through backpropagation. Once a mathematical mapping function (the trained neural network) has been obtained, this function can be used to propagate a surrogate model with state-estimations. Thereafter, this surrogate model can be used to provide estimates of the structural system at unmonitored locations.

Experimental validation of the proposed methodology was performed in real-time using the DROPBEAR test bed located at the AFRL Munitions Directorate [7]. Figure 2(a) presents the DROPBEAR test bed while the as-tested configuration is detailed in figure 2(b). The test bed consists of a large aluminum base fastened securely to a table with an aluminum block used to clamp a steel cantilever beam. The steel beam is 51 mm wide with a free length of 505 mm and a thickness of 6.4 mm. The mass of the beam involved in bending is 1.29 kg. A detachable electromagnet was used to add an additional 0.687 kg (electromagnet plus three brass plates) to the tip of the beam. The electromagnet can be disengaged quickly to simulate a high-rate dynamic event (e.g., a sudden detachment of a system component). This test used four accelerometers (PCB-353B17), labeled acc-1 through acc-4, spaced evenly along the beams span, as annotated in figure 2(a). Data collection, computations, and storage were performed using a Windows-based

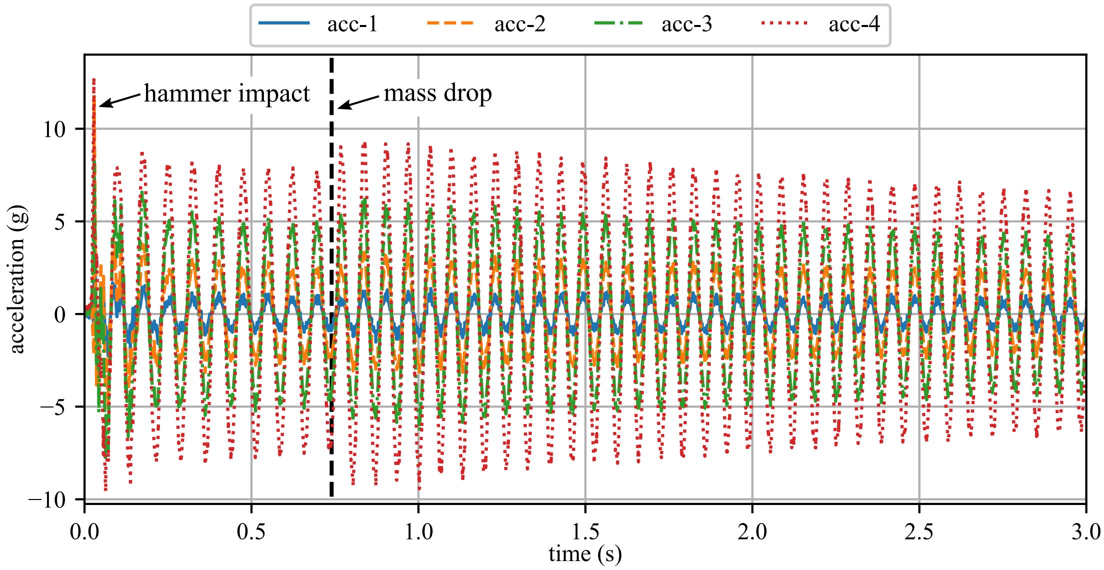


Figure 3. Experimental results showing the temporal results for all four accelerometers.

National Instruments controller (PXIe–8133) with two 14-Bit analog input cards (PXI-6133). One data acquisition card was used to measure the accelerometer response while the other was used to obtain the moment that the electromagnet detaches from the beam, this was obtained through measuring the electrical conductivity between the beam and the electromagnet case.

For the experimental conditions considered here, the data-based observer is formulated as follows. First, ten samples are simultaneously taken from acc-1 and acc-4 at a sampling rate of 12,500 samples per second. Of these ten points, ten are used to batch train the neural network, and the tenth is used as an input to the train network to obtain final prediction(s). As the data must be collected before it is used to train the neural network, the data collection is not continuous and data is only obtained in batches before being feed to the data-based observer. Thereafter, a single hidden layer neural network with 25 nodes is used to build a mapping from acc-1 to acc-4. The network is trained using backpropagation over 50 iterations. Once the mapping is developed, a tenth data point for acc-4 is predicted using the tenth data point from acc-1. Thereafter, this response predicted using the mapping function is applied to a numerical model to produce estimated accelerations at the unmeasured locations. For the simple case of the cantilever beam considered here, a simple linear model is used as the surrogate model. This process is then repeated for the next time step.

## ANALYSIS

Acceleration results obtained during testing are presented in figure 3. The test was initiated with a hammer impact and the mass was released from the beam at approximately 0.74 seconds. In total, the test was allowed to vibrate for 30 seconds, however, only the first three seconds are presented in figure 3. Figure 4 reports the data points for the first positive acceleration peak following the mass drop. The time gap between the sets of data points is allocated to the training of the data-based observer. A visible

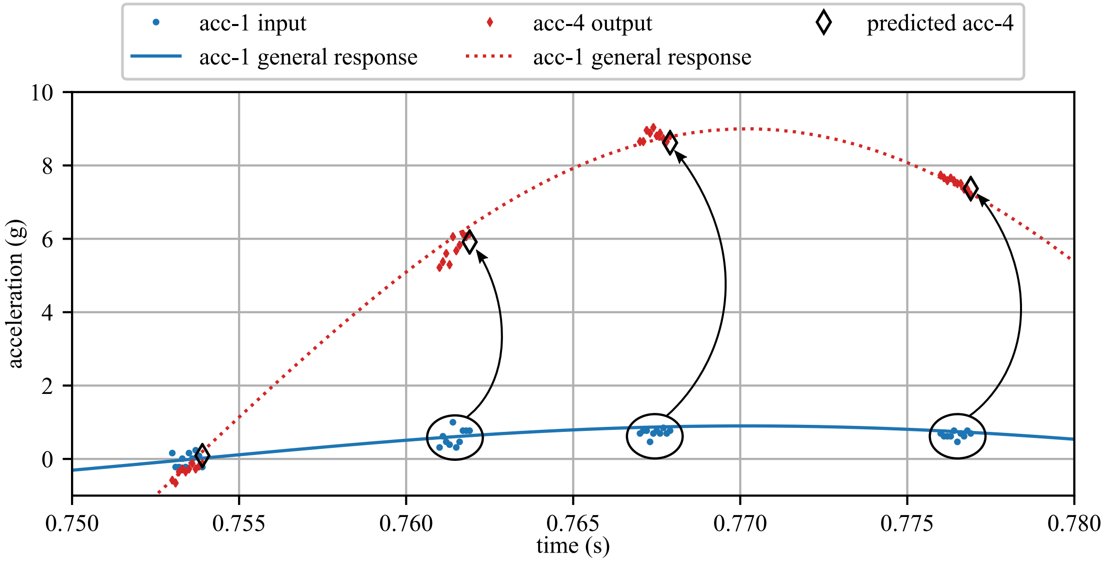


Figure 4. Acceleration data for four prediction cycles showing the data acc-1 and acc-4, as well as the predicted value for acc-4, where the arrow represents the data used in predicting the tenth data point for acc-4.

difference of successive time gaps can be seen in figure 4, these variations are assumed to be cause by background tasks running in the operating system of the hardware, and variations in the complexity of the neural network. In addition to the measured data, figure 4 also reports the value predicted for the tenth data point of acc-4, using the tenth input from acc-1, as a red triangle. Overall, the predicted value was found to be closely correlated with the real value at the time stamp of interest. For the data presented in figure 4, the proposed system was found to be capable of obtaining a new state estimation for the accelerations at acc-2 and acc-3 every 6 to 9 ms. Over the course of the entire test, an average cycle time of 7.1 ms was observed.

Figure 5 reports both the measured (figure 5(a)) and predicted (figure 5(b)) acceleration data. The measured results for the sensors (acc-1 and acc-4) used in training the neural network immediately before and after the mass is dropped from the cantilever beam are presented in figure 5(a). Note the increase in the maximum acceleration and decrease in frequency that occurs after the mass is released from the cantilever beam. In conjunction, figure 5(b) reports the estimated accelerations at acc-2 (orange circles) and acc-3 (green squares) along with the measured accelerometer responses. The data-based observer was found to be capable of tracking the dynamic system through this high-rate dynamic event (mass dropping), a key advantage of the data-based observer over model-based observers. Due mainly to the time delay in training the neural network, a state estimation at an unobserved location was obtained on average 6.1 ms after the data was measured at the observed location. This time lapse could be greatly reduced if the neural network was not retrained at every successive step, however, the reuse of previously trained neural networks was not considered in this introductory work.

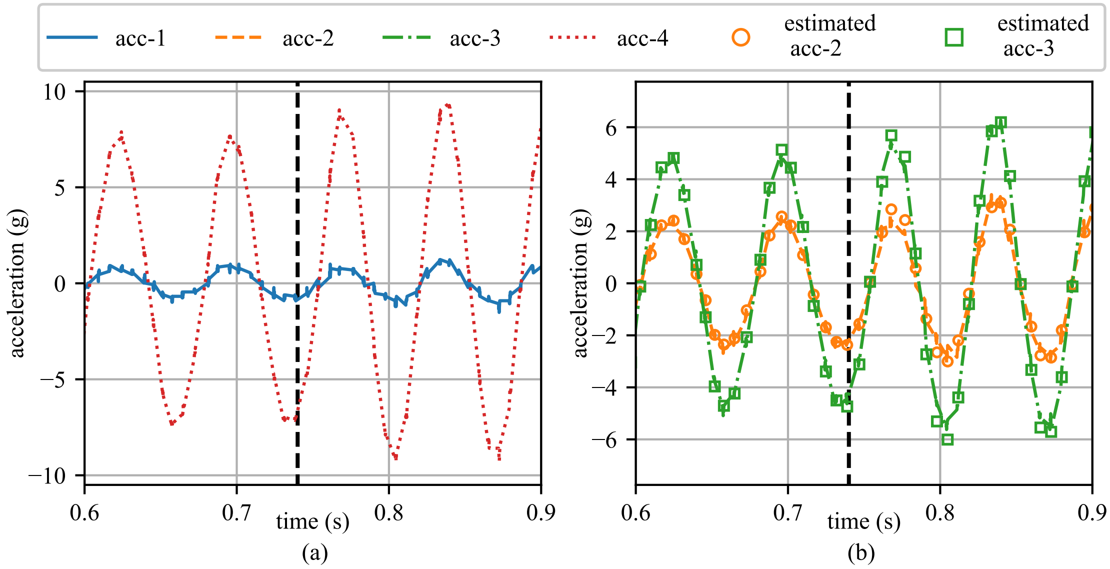


Figure 5. Results showing: (a) responses from acc-1 and acc-4 immediately before and after the mass is dropped; and (b) estimated and measured accelerations at acc-2 and acc-3.

## CONCLUDING REMARKS

This work presented a methodology for real-time state estimation at unobserved locations in a structural system experiencing high-rate dynamics. Experimental results demonstrated that, when implemented on a Windows-based National Instruments controller, the proposed method was capable of operating at 141 Hz. Overall, the proposed methodology was found to be capable of producing accurate real-time state estimation with an error of 1.5%. Future work will develop a feed-forward algorithm to allow the observer to learn from its previous states and create numerical models for the modeling of more complex structures.

## ACKNOWLEDGMENTS

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