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Robust Variable Input Observer for Structural Health Monitoring of Systems Experiencing Harsh Extreme Environments

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Abstract

Systems experiencing events in the order of 10μs-10ms timescales, for instance highrate dynamics or harsh extreme environments, may encounter rapid damaging effects. If the structural health of such systems could be accurately estimated in a timely manner, preventative measures could be employed to minimize adverse effects. Previously, a Variable Input Observer (VIO) coupled with a neuro-observer was proposed by the authors as a potential solution in monitoring their structural health. The objective of the VIO is to provide state estimation based on an optimal input space allowed to vary as a function of time. The VIO incorporates the use of mutual information and false nearest neighbors techniques to automatically compute the time delay and embedding dimension at set time intervals. The time delay and embedding dimensions are then used to vary the input space to achieve optimal performance for the estimator based on the observed measurements from sensors. Here, we augment the VIO with a smooth transitioning technique to provide enhanced robustness. The performance of the algorithm is investigated using experimental data obtained from a complex engineering system experiencing a harsh extreme environment. Results show that the enhanced VIO incorporating a smooth transitioning input space outperforms the previous VIO strategies which allowed rapid input space adaptation.

Disciplines

Civil Engineering | Dynamics and Dynamical Systems | Structural Engineering | VLSI and Circuits, Embedded and Hardware Systems

Comments

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ABSTRACT

Systems experiencing events in the order of 10μs-10ms timescales, for instance high-rate dynamics or harsh extreme environments, may encounter rapid damaging effects. If the structural health of such systems could be accurately estimated in a timely manner, preventative measures could be employed to minimize adverse effects. Previously, a Variable Input Observer (VIO) coupled with a neuro-observer was proposed by the authors as a potential solution in monitoring their structural health. The objective of the VIO is to provide state estimation based on an optimal input space allowed to vary as a function of time. The VIO incorporates the use of mutual information and false nearest neighbors techniques to automatically compute the time delay and embedding dimension at set time intervals. The time delay and embedding dimensions are then used to vary the input space to achieve optimal performance for the estimator based on the observed measurements from sensors. Here, we augment the VIO with a smooth transitioning technique to provide enhanced robustness. The performance of the algorithm is investigated using experimental data obtained from a complex engineering system experiencing a harsh extreme environment. Results show that the enhanced VIO incorporating a smooth transitioning input space outperforms the previous VIO strategies which allowed rapid input space adaptation.

INTRODUCTION

The harsh extreme environments pertinent to the dynamic systems of interest is defined as environments comprised of high-rate and high-amplitude events [1]. Some examples of these systems include active blast protection systems for civil structures, smart automotive collision safety systems, in-flight structural health monitoring, and rapid guidance adaptability for space shuttles, aircrafts, and/or hypersonic airframes.

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Due to the extreme environments these systems are subjected to, there is great potential for catastrophe. Precise and on-time health monitoring of these systems is a necessary first step towards ensuring safety.

Structural health monitoring of systems experiencing harsh extreme environments is a complex task. Research has shown these systems include multiple system complexities such as highly nonlinear and nonstationary behaviors [2] for which fixed observers are difficult to apply [3] An alternative is to use adaptive observers, but at the cost of slower convergence rates. Literature focuses on accelerating the convergence of adaptive observers, with the vast majority of efforts on the state estimation function. See refs. [4, 5, 6] for instance. Instead, the authors have proposed to use an adaptive input space to accelerate convergence, a strategy termed VIO [1, 2].

The concept of the VIO is to generate the inputs to an adaptive observer using a delay vector constructed based on Takens' embedding theorem [7]. Prior work from the authors on the VIO demonstrated its potential on a two degrees-of-freedom (2DOF) system, where the VIO was combined with a time delay function for state estimation [1]. The VIO was improved in [2] by using a wavelet neuro-observer instead of a time-delay function and implemented on realistic data, which produced a better set of dynamic functions for the representation. This method was compared with a fixed input strategy. It was shown that the VIO outperformed the fixed input observer by 22% in terms of the overall 2-norm error. However, instabilities were noted in the estimation from rapid input space adaptations.

This study further improves the VIO by integrating a smooth transitioning of the input space by limiting how much the input space can adapt to eliminate or minimize the instabilities caused by rapid input space adaptations. We propose using a smooth adaptation approach of the input space by restricting speed of variation, producing a more robust VIO, here termed robust VIO (RVIO).

VARIABLE INPUT OBSERVER ALGORITHM

The principle of the VIO is to construct a delay vector $\boldsymbol{\nu}$ to be used as the input space to a state estimation function

$$\boldsymbol{\nu}(k) = \begin{bmatrix} y(k) & y(k-\tau) & y(k-2\tau) & \cdots & y(k-(d-1)\tau \end{bmatrix} \tag{1}$$

where y is the time series of a measurement, k a discrete time step, τ the time delay expressed in discrete time steps, and d the embedding dimension. From the Embedding Theorem, there exists an optimal vector $\boldsymbol{\nu}^*$ constructed with the optimal values τ^* and d^* that preserves the system's essential dynamics. Here, it is argued that such vector $\boldsymbol{\nu}^*$ can be used to minimally represent the dynamics of the observed system, therefore yielding an optimized observer with faster convergence capabilities. The Embedding Theorem applies to stationary systems. Because our problem of interest is nonstationary due to the excitations and possible damage, the construction and adaption of $\boldsymbol{\nu}$ is done in real-time, with τ and d selected based on the mutual information (MI) and false nearest neighbors (FNN) algorithms, respectively. The VIO algorithm is diagrammed in fig. 1. Measurements are collected from a system experiencing high-rate dynamic events. The most recent measurements of user-defined

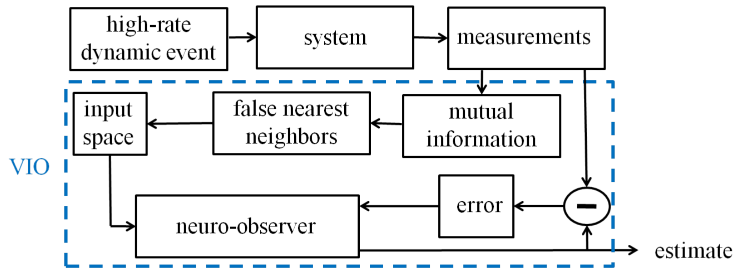


Figure 1: Schematic of the VIO.

length is input into the MI algorithm which calculates the appropriate τ value. The τ value along with the measurements are sent to the FNN algorithm which calculates the optimal d value. The calculated τ and d values are used to build an input space according to eqn. 1. The input space is fed into a neuro-observer with the error feedback to improve the representation.

Neuro-observer formulation

The VIO is formulated with a neuro-observer

$$\hat{y}_k = \sum_{j=1}^{h} \gamma_j \phi_j(\boldsymbol{\nu}) \tag{2}$$

where $\hat{y}_k$ is the state estimate, h the number of nodes, γ the nodal weight of node j, and ϕ the activation function taken as a Mexican hat wavelet

$$\phi(\boldsymbol{\nu}) = \left(1 - \frac{\|\boldsymbol{\nu} - \boldsymbol{\mu}\|^2}{\boldsymbol{\sigma}^2}\right) e^{-\frac{\|\boldsymbol{\nu}-\boldsymbol{\mu}\|^2}{\boldsymbol{\sigma}^2}} \tag{3}$$

where $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ are the center and bandwidth of the wavelet, respectively, and $\|\cdot\|$ is the 2-norm. We selected a single-layer wavelet neural network due to its universal approximation capability [8]. Our neuro-observer is also capable of sequential adaptation to cope with the nonstationary nature of the dynamic systems of interest. A self-organizing mapping architecture [9] is implemented to keep the network representation minimal by adding new nodes when new observations fall outside an Euclidean distance threshold D to the closest available node. When a new node ϕ_j is added, it is given a weight $\gamma_j(0)$ initially equal to zero, a center $\boldsymbol{\mu}_j(0)$ at the location of the new observation, and a user-defined bandwidth $\boldsymbol{\sigma}_j(0)$. After, the network is put in an adaptation mode, where the weights and bandwidths are adapted following a back-propagation rule [10]:

$$\begin{aligned} \gamma_j[k+1] &= \gamma_j[k] - \Gamma_{\gamma_j}\phi_j(\boldsymbol{\nu})\tilde{y} \\ \sigma_j[k+1] &= \sigma_j[k] - \Gamma_{\sigma_j}\gamma_j\left(\frac{1}{\sigma_j^5}\mathrm{e}^{\frac{-\|\boldsymbol{\nu}-\mu_j\|^2}{\sigma_j^2}}(4\sigma_j^2\|\boldsymbol{\nu}-\mu_j\|^2 - 2\|\boldsymbol{\nu}-\mu_j\|^4)\right)\tilde{y} \end{aligned} \tag{4}$$

where $\tilde{y} = \hat{y}_k - y_k$ is the observation error between the estimation and the measurement, and Γ_γ and Γ_σ are the learning rates for γ and σ, respectively.

Input Space formulation

The traditional approach to embedding measurements is through the use of fixed values for τ and d. Based on the work of Cellucci *et al.* [11], the best results were obtained through the MI and FNN test algorithms for identifying τ and d, respectively.

The MI test [12] is written

$$\mathrm{MI}(x,y) = \sum_{x,y} \mathrm{p}(y[k], y[k-\tau]) \log \frac{\mathrm{p}(y(k), y(k-\tau))}{\mathrm{p}(y(k), \mathrm{p}(y(k-\tau)))} \tag{5}$$

where $y(k)$ and $y(k-\tau)$ are discrete observations, $\mathrm{p}(\cdot)$ indicates a probability and $\mathrm{p}(\cdot,\cdot)$ indicates a joint probability. The MI test is used to find the value τ which produce the highest level of novelty in the information, associated with the first local minima in the MI values. The resulting τ value is used to create embedding vectors and find the best embedding dimension d using the FNN test. The algorithm uses the approach described in Kennel *et al.* [13]. The distances between the rth neighboring points of a vector are calculated for a given dimension d, and recomputed after increasing the dimension to $d+1$ to find if points that were neighbors remained neighbors. The number of false neighbors is calculated as a function of embedding dimensions d. The smallest d for which the percentage of false neighbors is below a user defined threshold is taken as the optimal embedding dimension.

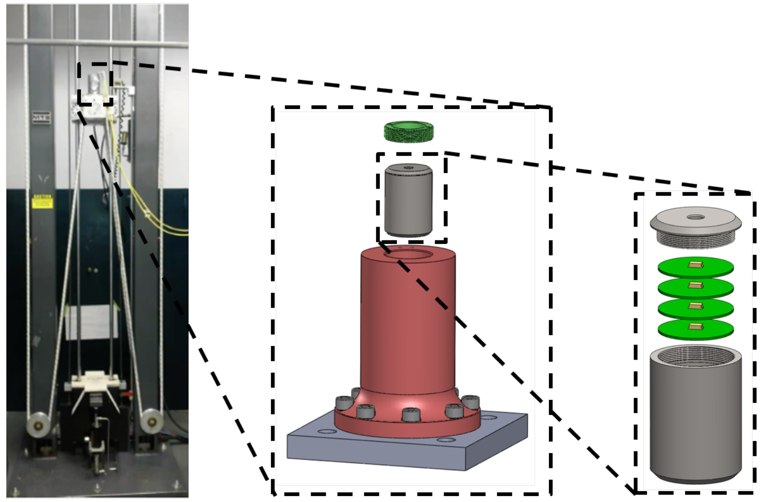
The previous VIO took in a measurement, calculated the time delay τ using the MI algorithm, calculated the embedding dimension d using τ and the FNN algorithm, built the input space vector using the newly calculated τ and d values, and made estimations based on this input space vector. These steps are repeated for each new measurement. The RVIO algorithm adds additional steps. The algorithm starts adapting the input space when it first experiences a change of deceleration greater than 100 g_n. The initial τ and d values are set to 10 steps and a dimension of 2, respectively. The values for τ and d are allowed to vary by ± 10 and ± 1, respectively, with $\tau \leq 1$ and $2 \leq d \leq 10$. The data history length is set at $d(\tau+10)$.

NUMERICAL SIMULATIONS

The neuro-based VIO was numerically simulated on data obtained from a system experiencing a high-rate dynamic event. The dynamic event was generated in a laboratory setting from an accelerated drop tower. Performance of the RVIO is compared against the VIO.

Experimental Setup

Experimental data was collected from a shock test of an electronics package subjected to an impact generated using a MTS-66 drop tower. Inside the electronics package are four high g_n shock accelerometers each secured to a printed circuit board. The electronics package is mounted to the table of the drop tower which is accelerated by stiff bungee cables to create an impact event. The experimental setup is illustrated in fig. 2. For simplicity, only the data from two accelerometers (accel 1 and accel 4) are



(a) (b) (c)

Figure 2: Experimental setup: a) drop tower; b) electronics package mounting fixture; c) electronic package.

used. An input-output type scenario is created using accel 1 as the input and accel 4 as the output. The simulation goal was to determine the set of dynamic functions between the two accelerometers that yielded the best estimation.

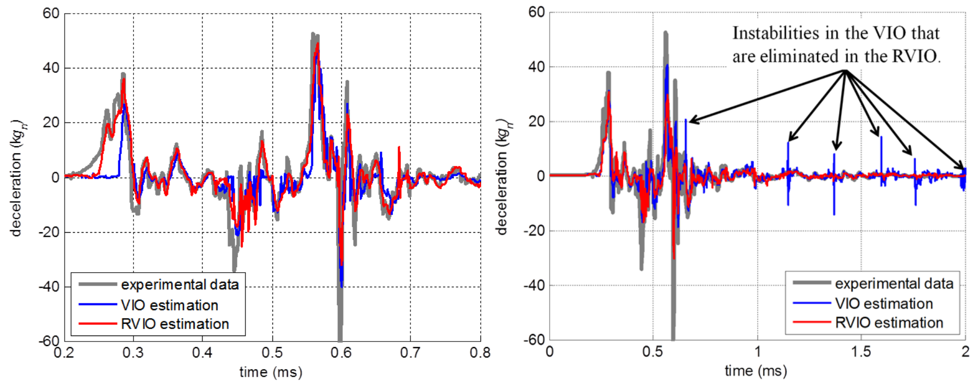
Data was acquired using a Precision Filters signal conditioning system coupled with a National Instruments data acquisition (DAQ) system. The signal was first conditioned using a Precision Filter 28144A Quad-Channel Wideband Transducer Conditioner in constant voltage excitation mode with an anti-aliasing filter set at 204.6 kHz. A National Instruments PXI-6133 acquisition cards sampling at 1 Msa/s was used to digitize and store the data.

This laboratory experiment bears the characteristics of a high-rate dynamic event mainly due to the large uncertainties and high nonlinearities. The large uncertainties are due in part to the input to the system not being readily available. The input is only characterized through the response of accel 1. The high nonlinearities are due to the large external loads which change the mechanical response of the system from a regular strain rate to a high strain rate region. Additionally, noise is introduced to the system through cable movement (cable from sensor to DAQ) and vibration of metal interfaces.

The VIO, similar to other observers, requires tuning, which can require a heuristic approach. Here, we attempt to utilize the VIO and RVIO with minimal tuning. Ten simulations were conducted with varying Γ_γ, Γ_σ, and $\sigma(0)$ to assess robustness. The same parameters for both the VIO and RVIO are used to make a comparison. The parameters for the ten different numerical simulation are shown in Table 1. The values for R_{tol}, A_{tol}, FNN percentage, and data length (VIO only) are taken as 1, 0.1, 20%, and 2000, respectively. These values were kept constant between simulations.

Table 1: Parameter values for the VIO and RVIO

Parameter	Sim 1	Sim 2	Sim 3	Sim 4	Sim 5	Sim 6	Sim 7	Sim 8	Sim 9	Sim 10
Γ_γ	0.1	0.1	0.2	0.2	0.1	0.08	0.08	0.07	0.05	0.05
Γ_σ	0.5	0.3	0.3	0.3	0.3	0.3	0.2	0.4	0.4	0.3
$\sigma(0)$	5	5	5	4	4	4	4	4	4	3



(a) (b)

Figure 3: Time series results (a) zoom on 0.2-0.8 ms, simulation 4; and (b) annotated instabilities, simulation 1.

Simulation Results

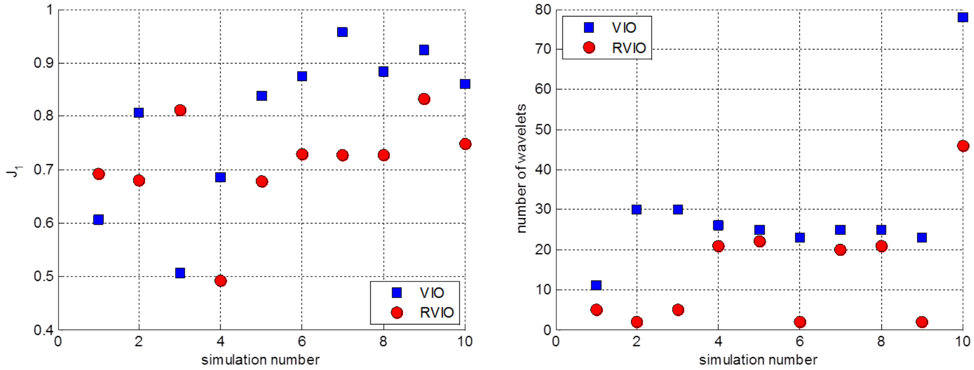
In what follows, we demonstrate the superior performance of the RVIO through the estimation of the time histories, the minimization of instabilities, the 2-norm error for the ten different simulations, and the number of wavelets representing the dynamics between accel 1 and 4.

The time histories of typical simulation results are plotted in fig. 3, with fig. 3(a) showing a zoomed result from simulation 4 and fig. 3(b) showing instabilities in simulation 1. The plots show that estimation of the RVIO is more accurate compared with the VIO throughout the time series, and that instabilities present in simulation 1 are minimized through the input space's smooth transition technique.

The performance of the estimators was quantified by the 2-norm error metric J_1,

$$J_1 = \frac{||(\hat{\boldsymbol{y}} - \ddot{\boldsymbol{x}}_4)||}{||\ddot{\boldsymbol{x}}_4||} \tag{6}$$

with $\hat{\boldsymbol{y}} = \hat{\ddot{\boldsymbol{x}}}_4$ being the estimation of accel 4 measurements, $\ddot{\boldsymbol{x}}_4$. Results for J_1 are plotted in fig. 4(a). The 2-norm errors were significantly reduced using the RVIO for eight out of ten simulations. On average, the RVIO showed an improvement of 21% over the VIO. The number of wavelets (nodes) for each simulation is plotted in fig. 4(b). Results show that the RVIO uses fewer wavelets for a better estimation, therefore providing a more optimal representation.



(a) (b)

Figure 4: (a) Performance J_1; and (b) number of wavelets (nodes).

CONCLUSION

The objective of this research was to investigate methods to engineer safer and smarter systems which require real-time observability for instantaneous and precise decision making capabilities. In our previous studies, we developed the variable input observer (VIO) concept. The VIO was simulated and compared with a fixed input observer and the advantages of using a varying input space through the estimation process demonstrated. However, due to the rapid adaptations of the input space, instabilities or noise were added to the estimation.

In this study, we varied the input space using smooth transitions to avoid rapid and discontinuous changes in the input space. The time delay τ was restricted to varying within ± 10 steps per time step, and the embedding dimension d restricted to a unit change per time step. We termed the new technique the robust variable input observer (RVIO). By limiting the input space adaptation, we demonstrated that the instabilities noticed in the VIO were minimized. In addition, we observed an average improvement in the RVIO's performance by 21% in the 2-norm error of the estimation, and using significantly fewer wavelets for building the representation. Results presented in this paper demonstrated the feasibility of the RVIO at yielding faster and more accurate state estimation.

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REFERENCES

1. Jonathan Hong, Simon Laflamme, and Jacob Dodson. Variable input observer for structural health monitoring of high-rate systems. *Quantitative Nondestructive Evaluation*, 43, 2016.
2. J. Hong, L. Cao, S. Laflamme, and J. Dodson. Variable input observer for state estimation of high-rate dynamics. *Proc. SPIE 10168, Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*, 101680S, 2017.
3. Yan Wang, Rajesh Rajamani, and David M Bevly. Observer design for differentiable lipschitz nonlinear systems with time-varying parameters. In *53rd Annual Conference on Decision and Control (CDC)*, pages 145–152. IEEE, 2014.
4. Mohammad Shahrokhi and Manfred Morari. A discrete adaptive observer and identifier with arbitrarily fast rate of convergence. *IEEE Transactions on Automatic Control*, 27(2):506–509, 1982.
5. Karim Khayati and Jiang Zhu. Adaptive observer for a large class of nonlinear systems with exponential convergence of parameter estimation. In *International Conference on Control, Decision and Information Technologies (CoDIT)*, pages 100–105. IEEE, 2013.
6. Witold Byrski and Jedrzej Byrski. On-line fast identification method and exact state observer for adaptive control of continuous system. In *11th World Congress on Intelligent Control and Automation (WCICA)*, pages 4491–4497. IEEE, 2014.
7. F. Takens. Detecting strange attractors in turbulence. *Dynamical Systems and Turbulence, Warwick*, pages 366–381, 1980.
8. A. Zhang, Q. amd Benveniste. Wavelet networks. *Neural Networks, IEEE Transactions on*, 3(6):889–898, 1992.
9. Teuvo Kohonen. The self-organizing map. *Neurocomputing*, 21(1–3):1–6, 1998.
10. Simon Laflamme, JJ E Slotine, and JJ Connor. Self-organizing input space for control of structures. *Smart Materials and Structures*, 21(11):115015, 2012.
11. C. J. Cellucci, A. M. Albano, and P. E. Rapp. Comparative study of embedding methods. *Physical Review E*, 67:1–13, 2003.
12. A.M. Fraser and H.L. Swinney. Independent coordinates for strange attractors from mutual information. *Physical Review A*, 33(2):1134–1140, 1986.
13. M.B. Kennel, R. Brown, and H.D.I. Abarbanel. Determining embedding dimension for phase-space reconstruction using a geometrical construction. *Physical Review A*, 45(6):3403–3411, 1992.