Sensor-Only System Identification for Structural Health Monitoring of Advanced Aircraft

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Purpose

The safety and reliability of aircraft depend on the health of structural components. Environmental conditions, cyclic loading due to takeoff and landing, and aging all contribute to structural wear and degradation, leading to potentially catastrophic events.

Structural health monitoring (SHM) techniques address this need [1]. SHM typically involves ground-based testing, scheduled according to flight history, that is, flight hours and takeoff/landing cycles [2]. This approach allocates maintenance based on statistical models of wear and aging that predict incipient failure modes. However, anomalous failure modes may be difficult to detect between scheduled maintenance.

To overcome these shortcomings, the goal of this project is to develop a new approach to analyzing flight data for SHM called *sensor-to-sensor system identification* (S2SID). This technique can decrease the need for costly maintenance that takes the aircraft out of service, while providing the means for detecting potential failure events that may occur between traditionally scheduled testing.

Background

In standard system identification, measurements of input and output signals are used to fit a model of a chosen structure and dynamic order. In many applications, however, the input signal is unknown, and thus sensor measurements are the only available data. If a statistical description of the unknown input is available, then sensor-only (also called "blind") identification techniques can be used to detect changes in the dynamics of the system [3–6]. For structural dynamics applications, sensor-only identification is known as operational modal analysis (OMA) [7–11].

In contrast to blind identification, S2SID requires no knowledge of the statistical properties of the input. For applications where the excitation is unknown and only sensor measurements are available, S2SID designates one measurement as the pseudo-input and another measurement as the pseudo-output. The identified *pseudo transfer function* (PTF) typically captures information about only the zeros (anti-resonances) of the structure. Although pole locations are generally not estimated, S2SID has the advantage of not requiring knowledge of the system excitation. In fact, the unknown ambient system excitation plays the necessary role of providing excitation that can be used to identify PTFs within S2SID [12, 13]. Extensions to multi-input, multi-output PTF identification, which is necessitated by non-scalar excitation, is considered in [14].

S2SID is related to transmissibility identification [9, 15, 16]. In the simplest situation, measurements of transmissibilities assume that one of the sensors is colocated with the controlled displacement excitation. The resulting transmissibility involves both resonance (pole) and anti-resonance (zero) features of the structure. However, transmissibility identification can also be performed with arbitrary arrangements of sensors, without regard to the location of the external excitation. In this case, only anti-resonance (zero) information is captured, and the goal is to construct a transmissibility that relates one set of measurements to another set so that the resulting transmissibility is independent of the forcing function. This objective is thus a specialization of S2SID to the case of identical sensors (for example, all accelerometers). For the case of more than two sensors, transmissibility identification is described in [15]; however, the construction of the PTF in [15] is incorrect since the structure of the PTF does not correctly cancel the unknown forcing to obtain a transmissibility that is independent of the details of the forcing function. A correct construction is given in [14]. Furthermore, S2SID is more general than transmissibility identification since S2SID is applicable to arbitrary collections of sensors, such as accelerometers, displacements sensors, and strain gauges. Finally, like transmissibility identification, S2SID does not perform modal analysis as in the case of operational modal analysis [7–11]. Instead, S2SID can be applied without knowledge of the structural geometry as long as the sensors are in close enough proximity to facilitate PTF identification.

Impact and Benefits to NASA or Aeronautics

This work is aligned with the Aviation Safety Program (AvSP), whose goals are to predict and prevent safety issues, to monitor for safety issues inflight and mitigate against them should they occur, to analyze and design safety issues out of complex system behaviors, and to constantly analyze designs and operational data for potential hazards. Moreover, AvSP strives to advance state-of-the-art design tools to detect, avoid, and protect against loss-of-control due to potential adverse events including atmospheric and vehicle system factors, and develops advanced capabilities for detection and mitigation of aging-related hazards before they become critical. These goals are addressed in our research by providing in-flight health monitoring without relying on controlled excitation.

This research will provide significant cost and time savings for aircraft health monitoring while improving safety and reliability. In addition, this work will contribute to the following NASA and national goals.

National Security & Homeland Defense R&D Goals & Objectives.

Demonstrate innovative airframe structural concepts for efficient high-altitude flight.

Aviation Safety R&D Goals & Objectives.

Develop technologies to reduce accidents and incidents through enhanced vehicle design, structure, and subsystems.

Approach

The approach taken for this investigation was a government-academia collaboration that consisted of a partnership between NASA DFRC and the Department of Aerospace Engineering at the University of Michigan. The academia partner pledged in-kind money worth approximately $332,000, which included salary support, infrastructure cost, travel for scholarly discussions of research progress, and presentation of results at internationally recognized conferences. Both partners provided the theoretical analysis of the problem, algorithmic development, and validation. In addition, NASA facilitated the strategic research task and provided fight-test data from the SOFIA aircraft for algorithmic validation.

Summary of Research

This project focused on theoretical, algorithmic, and implementation issues that are critical to making *sensor-to-sensor system identification* (S2SID) SHM a viable technology for aircraft SHM. The theoretical and algorithmic issues in S2SID-SHM are described in Aim 1. Aim 2 focuses on validating S2SID-SHM based on simulated data. Aim 3 applies S2SID-SHM to flight data for further validation. These descriptions are taken from the Phase I proposal.

Aim 1: Theoretical and Algorithmic Extensions of S2SID-SHM.

Issue 1: Persistency and identifiability. Since S2SID depends on freely available and unknown ambient excitation, it is necessary to ascertain that this excitation is sufficiently persistent (despite being otherwise unknown) to facilitate estimation of key parameters. In addition, key parameters must be identifiable, that is, estimated without ambiguity. We will address both issues through analysis of the algorithm based on the aircraft's flight envelope and the expected ambient excitation spectrum.

Status: This issue was addressed by analysis of SOFIA data. We performed coherence, correlation, and detrend analysis of the data, and we discovered a direct relationship between correlation and proximity of sensors. Although this finding was not surprising, it demonstrated the integrity of the data, building confidence in its usefulness and limitations for PTF identification. With regard to persistency and identifiability, the data was found to be rich in spectral content, and thus sufficient for use in PTF identification.

Issue 2: Sensor noise. Identification accuracy depends on the ability to obtain *consistent estimates* of key parameters, that is, asymptotically vanishing estimation bias as increasingly larger data sets are used. A technique that ensures consistency was demonstrated in [17]; however, [17] assumes knowledge of the autocorrelation (coloring) of the sensor noise. Our goal is to alleviate the need for this assumption.

Status: Significant effort was devoted to this issue, which is challenging due to the fact that sensor noise is unknown and affects all sensors. Estimation of the impulse response is a well-studied problem; we compared various techniques with regard to their sensitivity to sensor noise in [18]. Analysis of the SOFIA data indicated measurement quantization as a result of sensor resolution constraints, but otherwise the noise statistics are unknown. We performed extensive least-squares fits of sensor data, using both IIR and FIR model structures. The main finding is that the best prediction errors were obtained using an FIR model structure. This finding is consistent with theoretical results that show that transfer function identification with a white input signal and with noise corrupting the output sensor yields consistent estimates of the impulse response. However, in the case of PTFs, the input signal is *not* white, and sensor noise may corrupt both the input and output signals.

Issue 3: Nonlinearity. Thus far, S2SID is based on linear models. Recent work [19] shows that consistent estimates are achievable despite the presence of certain types of nonlinearities. For S2SID, we will investigate the accuracy of the estimated PTFs by developing modifications to the algorithm that ensure that the PTF estimates are independent of the unknown excitation in the presence of nonlinearities. The goal is to demonstrate the robustness of S2SID to nonlinearities in the structural response. Extensions to nonlinear PTFs can also facilitate this goal.

Status: We applied techniques for detecting whether the PTF includes significant nonlinearities. In particular, we applied two different techniques for identifying Hammerstein systems, which are systems involving the cascade of a static input nonlinearity and a linear dynamic subsystem [19]. The static input nonlinearity provides an indication of distortion present in the PTF. These techniques showed that no significant nonlinearity was present in the PTFs between the sensors that were selected.

Aim 2: Validation with Simulated Data. The performance of S2SID-SHM will be assessed and demonstrated by using synthetic data sets generated from simulated mass-spring-damper truth models of various geometries with simulated sensor noise and nonlinearities. For each geometry, we will perform statistical analysis of the accuracy of the method. The estimated PTFs will be compared to the true PTFs to assess the effectiveness of S2SID-SHM. This phase will provide a means for quantifying damage by providing estimates of the structural parameters.

Status: We performed extensive tests of synthetic data sets in conjunction with the analysis of SOFIA data. The approach taken was to apply identification techniques to SOFIA data, and then use synthetic data sets to probe the underlying model properties. Results of this type are described later in this section.

Aim 3: Application to Experimental Flight-Test Data. We will apply S2SID-SHM to experimental flight-test data from NASA DRFC's SOFIA program. The SOFIA data, which were collected to observe structural loads during missions, is ideally suited for assessing how the structural dynamics and parameters change during the aircraft's flight history. In contrast to simulated data, the truth model is unknown, and thus successful demonstration of this approach to the analysis of flight data will serve to validate the utility of S2SID-SHM to NASA for mission readiness and safety assurance.

Status: We applied S2SID to flight data obtained from the SOFIA aircraft located at the NASA Dryden Flight Research Center. SOFIA is a highly modified Boeing 747SP, housing an infrared telescope in the aft fuselage. The telescope is isolated from the onboard scientific staff and equipment by means of a pressure dome, thus allowing a door to open and permit astronomical observations. Due to long flight durations of 10 hours or more and the stress of opening the telescope door in-flight, structural health monitoring of both the aircraft and telescope are of concern. As such, a suite of accelerometers have been placed at various locations throughout the aircraft to provide data for post-flight stress analysis. We obtained three data sets from SOFIA flights.

In particular, experimental flight data were gathered during a routine flight at 12,192–15,240 m (40,000–50,000 ft) to conduct astronomical observations onboard SOFIA. Data were collected by the sensors under ambient conditions during flight. The accelerometer data used in this study were collected from sensors located at the right horizontal stabilizer tip, rear spar (vertical direction), and vertical stabilizer front and rear spars (lateral direction). The sensor data were filtered by a sixth-order antialiasing Butterworth filter with a cut-off at 1 kHz and recorded at 5 kHz. Data were collected while the aircraft operated in the Mach number range $M =$ 0.4–0.7 and dynamic pressures $Q =$ 26–390 psf (pounds per square foot). Data were preprocessed to remove the linear trend, mean, and outliers. The preprocessing step ensured that all unwanted low-frequency disturbances, offsets, trends, and drifts were removed to enhance the accuracy of the identified models. Coherence between signals was studied with and without preprocessing. We applied S2SID with and without preprocessing in order to ascertain the effects of these procedures. We also estimated the level of error in the data due to the sensor resolution. In particular, the output resolution is the smallest distance between signal measurements. Dividing the output range by the output resolution gives the dynamic range, which is the maximum number of distinct sensor output values over the output range.

Accomplishments

Results of PTF Identification

PTF identification is based on least squares optimization in conjunction with specialized model structures. In the following discussion we assume that the system being identified is linear, and we focus on linear model structures for system identification. Although there are various ways to represent systems with inputs and outputs, system identification typically uses discrete-time, time-series models, where the current output is a linear combination of past inputs and outputs. Special cases of these models include moving average (MA) models, autoregressive (AR) models, and autoregressive/moving average with exogenous input (ARMAX) models. Time series models can be represented as transfer functions, where the numerator coefficients weight the past inputs, and the denominator coefficients weight the past outputs. In contrast to state space models, time-series models do not involve an explicit internal state.

Various types of time-series models are used for system identification. Infinite-impulse-response (IIR) models possess an impulse response that requires an infinite number of steps to decay to zero. The impulse response of a time-series model consists of numbers called *impulse response parameters*, which are denoted by $H_1, H_2, \ldots$. Impulse response parameters are also called *Markov parameters*. A specialized form of IIR models is given by the μ-Markov model [18, 20–22], whose numerator coefficients include a collection of impulse response parameters. Finally, a finite-impulse-response (FIR) model is a discrete-time, time-series model with the special property that its impulse response reaches and remains at zero after a finite number of steps. All of the coefficients of an FIR model are Markov parameters. μ-Markov models provide a bridge between IIR models and FIR models in the sense that, as μ increases, the μ-Markov model increasingly mimics the form of an FIR model.

The accuracy of least-squares identification of time-series models depends on various aspects of the problem. For example, the model order may be unknown, and errors may be incurred by over-estimating or underestimating the order. Next, the inputs to the system must be sufficiently persistent to allow estimation of the model coefficients. Furthermore, beyond persistency, for the case in which the input to the system is stochastic, the statistical properties of the input can affect the accuracy of the parameter estimates. And, finally, the nature of the noise corrupting the input and output of the system impacts the accuracy of the parameter estimates. The most challenging situation arises when both the input and output signals are corrupted by noise that is mutually correlated. (We note that "sensor noise" on the input refers to uncertainty about the input signal due to actuator noise.)

In [18] we compared least-squares techniques with various time-series models under different types of inputs and sensor noise. In the case of a persistent but otherwise arbitrary input signal and in the presence of noise on both the input and the output, it is shown in [17] that consistent parameters can be obtained if the statistical nature of the input and output noise is known. However, this knowledge is usually not available in practice. In the more realistic case in which the statistical properties of the input and output noise are unknown, it is shown in [18] that consistency of the impulse response parameters can be achieved using μ-Markov models under more restrictive assumptions, namely, if the input signal is white noise and only output noise is present. This result motivates interest in using μ-Markov models for system identification. If, in addition, input noise is present, then it is shown in [19] that semi-consistency can be achieved, where semi-consistency refers to consistency up to an unknown multiplicative constant. In view of these issues, it is clear that the challenging aspects of S2SID are 1) the input signal is not white, 2) the input and output are corrupted by correlated noise, and 3) the statistical properties of the sensor noise is unknown.

Using SOFIA data to guide the Phase I investigations, we found that the most accurate model fits, as determined by prediction error (cross validation) were obtained from least-squares optimization

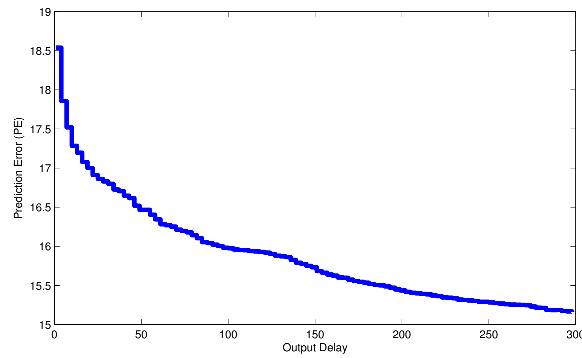

Figure 1: This plot shows the prediction error (cross validation) for FIR model fits as a function of output delay. Delaying the output relative to the input improves the accuracy of the model fit as measured by a prediction error criterion.

of FIR time-series models. However, these investigations provided an unexpected feature illustrated in Figure 1. Specifically, Figure 1 shows that the prediction error decreases as the output delay is increased relative to the input. The reason for this surprising effect becomes clear only upon plotting the impulse response of the FIR model. As shown in Figure 2, the impulse response of the fit model has a significant noncausal component, plotted to the left of the chosen delay step.

To confirm that the noncausal component of the SOFIA impulse response is contributing to the prediction error, we remove the noncausal component and then re-include it one impulse parameter at a time; this is done by including the impulse response parameters one at a time from the left of the chosen delay step in Figure 2. Figure 3 shows that the prediction error decreases as noncausal impulse response parameters are included in the identified FIR model.

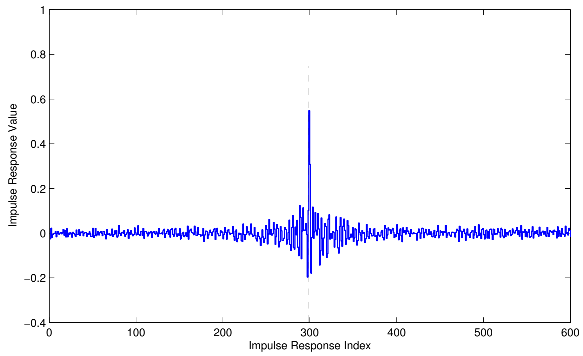

Figure 2: This plot shows the PTF impulse response of the FIR model fit corresponding to a chosen output delay of 298 steps. The surprising feature of this impulse response is that it has a significant noncausal component, which appears to the left of the delay of 298 steps.

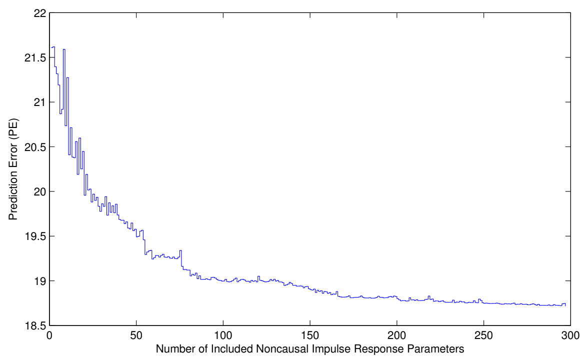

Figure 3: The prediction error is plotted here as an increasing number of noncausal impulse response parameters are included in the model. This plot confirms that the noncausal component of the estimated model contributes to the prediction accuracy.

Source of the Noncausal Impulse Response

As shown above, the noncausal component of the impulse response estimated by identification with an FIR model structure provides a significant improvement to the identification accuracy as measured by the prediction error. This is a surprising observation since it suggests that the PTF between the pseudo-input and pseudo-output is not physically meaningful. To investigate this issue, we constructed synthetic data sets by simulating the lumped mass-spring-damper systems shown in Figure 4. Specifically, we excite this structure with an external force, and we record the velocities of two masses for use in PTF identification. We consider parameters for two cases. In the first case, Figure 5 shows that delaying the pseudo-output does not lead to a noncausal component of the impulse response. However, in the second case, Figure 6 shows that delaying the pseudo-output does in fact produce a noncausal component of the impulse response. The key distinction between the PTFs in these two cases is the fact that in the former case the PTF is stable, whereas, in the latter case, the PTF is unstable.

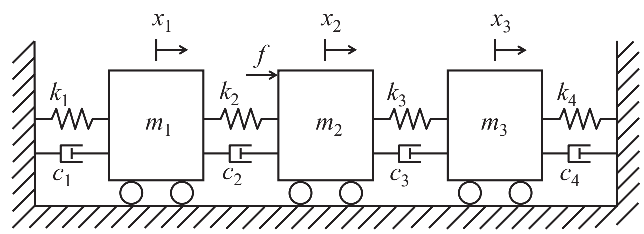

Figure 4: Mass-spring-damper structure. This example is used to produce synthetic data for developing and testing PTF identification methods. By adjusting the parameters, stable and unstable PTFs can be constructed.

Although the mass-spring-damper system is stable, the transfer function from force to a velocity measurement may be nonminimum phase, that is, it may have zeros outside of the unit circle. In this case, the PTF may be unstable, although the pseudo-input and pseudo-output data used to identify the PTF are bounded. Applying system identification to fit the PTF yields an FIR model with a significant noncausal component. This noncausal component is an artifact of the use of an FIR model structure. Although an IIR model structure can be used to avoid the noncausal component, the presence of noise corrupting the sensors yields inaccurate IIR model fits, whereas FIR model fits are significantly more accurate.

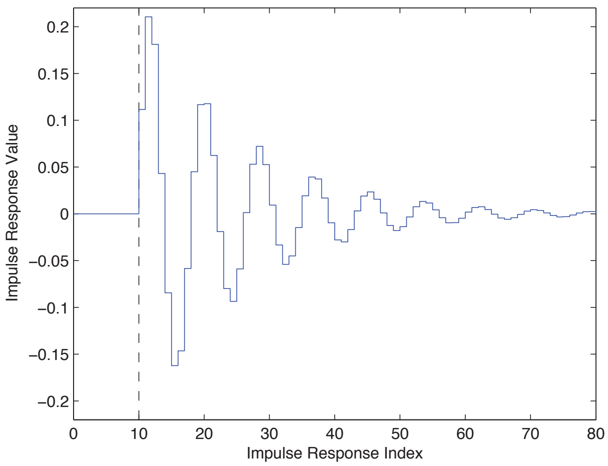

Figure 5: PTF identification is applied to the structure in Figure 4 with the parameters $m_1 = 9$ kg, $m_2 = 4$ kg, $m_3 = 2$ kg, $k_1 = 99$ N/m, $k_2 = 28$ N/m, $k_3 = 310$ N/m, $k_4 = 101$ N/m, $c_1 = 0.9$ N-sec/m, $c_2 = 5.1$ N-sec/m, $c_3 = 0.8$ N-sec/m, $c_4 = 5.2$ N-sec/m and discretization time step of 0.2 sec. A random white noise force excitation is applied to m_2. The pseudo-input is the velocity of m_3, and the pseudo-output is the velocity of m_1. The estimated PTF impulse response is found to be causal.

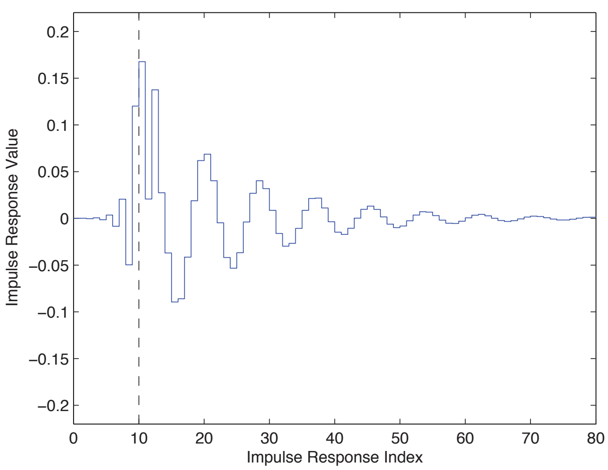

Figure 6: PTF identification is applied to the structure in Figure 4 with the parameters as in Figure 5 except that now $m_3 = 14$ kg. In this case, the estimated impulse response is found to be noncausal. The noncausal component of the impulse response is due to the fact that one of the transfer functions from excitation to measurement is nonminimum phase, and therefore the PTF from the pseudo-input to the pseudo-output is unstable. The instability of the PTF induces a noncausal component in the PTF impulse response.

Next Steps

The proposed Phase II research is aimed at refining and demonstrating this approach, thereby moving S2SID to an enhanced readiness status for transition to NASA applications, with potential applications to non-aerospace structures for infrastructure monitoring. The objectives of the proposed Phase II project are as follows:

Task 1. Refine the prediction error of the identified PTFs. The approach developed in Phase I indicates the ability to construct models that provide high-fidelity predictions of the response of one sensor based on another sensor. Our goal is to continue to improve the accuracy of these predictions, which is essential to the next two objectives.

Task 2. Develop detection metrics to assess PTF structural changes. Once system identification is used to construct an empirical PTF, the next crucial step is to develop metrics for assessing changes to the aircraft that warrant inspection. Metrics can be based on either changes to the PTF or its prediction error. This is the primary objective of Phase II.

Task 3. Apply S2SID to flight data to determine threshold criteria. We plan to continue working with data from SOFIA (Stratospheric Observatory for Infrared Astronomy) [23] along with other aircraft to assess sensitivity to flight conditions and possible long-term changes in the structural dynamics.

Current TRL: 2

Applicable NASA Programs/Projects

The proposed research complements the Vehicle Systems Safety Technologies (VSST) Project, whose goal is to detect, mitigate, and recover from hazardous flight conditions, while maintaining airworthiness and health. These goals will be addressed in our research by providing in-flight health monitoring without relying on controlled excitation.

In addition, we envision our S2SID approach to SHM to be tested and refined inflight on-board the NASA DFRC flexible MUTT research aircraft. The Phase II proposal package includes a letter of support from Mr. John Bosworth, who is the Project Chief Engineer for the X-56A MUTT vehicle.

Publications and Patent Applications

Conference Papers Submitted

C1 K. Aljanaideh, A. Ali, M. Holzel, S.L. Kukreja and D.S. Bernstein. "Sensor-to-Sensor Identification of Hammerstein Systems", Submitted to *In Proc. 51st IEEE Conference on Decision and Control*, pages TBD, Maui, Hawaii, USA, December 2012.

C2 K. Aljanaideh, B.C. Coffer, D.S. Dionne, S.L. Kukreja and D.S. Bernstein. "Sensor-to-Sensor Identification for the SOFIA Testbed", Accepted to *In Proc. AIAA Guidance, Navigation, and Control Conference*, pages TBD, Minneapolis, Minnesota, August 2012.

C3 K. Aljanaideh, M. Holzel, A. Ali, S.L. Kukreja and D.S. Bernstein. "Sensor-to-Sensor Identification of Hammerstein Systems", Submitted to *Proc. Amer. Contr. Conf.*, Montréal, Canada, June 2012.

C4 A. V. Morozov, A. A. Ali, A. M. D'Amato, A.J. Ridley, S. L. Kukreja and D. S. Bernstein. "Retrospective-Cost-Based Model Refinement for System Emulation and Subsystem Identification", *In Proc. 50th IEEE Conference on Decision and Control and European Control Conference*, volume 50, pages 2142 - 2147, Orlando, Florida, December 2011.

C5 A.J. Brzezinski, S.L. Kukreja, J. Ni and D.S. Bernstein. "Identification of Sensor-Only MIMO Pseudo Transfer Functions," *In Proc. 50th IEEE Conference on Decision and Control and European Control Conference*, volume 50, pages 2154 - 2159, Orlando, Florida, December 2011.

Journal Papers Submitted

J1 M. Holzel, A. Asad, A. D'Amato, S.L. Kukreja, and D.S. Bernstein. Semi-Consistent Nonparametric Identification of Hammerstein Systems Using Ersatz Nonlinearities *Automatica*, May 2012 (submitted).

Journal Papers in Progress

J2 A.J. Brzezinski, B.C. Coffer, S.L. Kukreja, J. Ni, and D.S. Bernstein. Sensor-to-Sensor Identification of Pseudo Transfer Functions. In preparation for *Automatica*.

Awards & Honors Related to Seedling Research

N/A

References

[1] W. Staszewski, C. Boller, and G. R. Tomlinson, *Health Monitoring of Aerospace Structures: Smart Sensor Technologies and Signal Processing*. Wiley, 2004, ISBN-10: 0470843403.

[2] A. J. Arietta and A. G. Striz, "Modelling of aircraft fatigue load environment," in *38th Aerospace Sciences Meeting and Exhibit*, Reno, NV, 2000, aIAA-00-0973.

[3] E. Parloo, S. Vanlanduit, P. Guillaume, and P. Verboven, "Increased reliability of reference-based damage identification techniques by using output-only data," *J. Sound & Vib.*, vol. 270, pp. 813–832, 2004, DOI: 10.1016/S0022-460X(03)00494-2.

[4] L. Mevel, A. Benveniste, M. Basseville, M. Goursat, B. Peeters, H. Van der Auweraer, and A. Vecchio, "Input/output versus output only data processing for structural identification–application to inflight data analysis," *J. Sound & Vib.*, vol. 295, pp. 531–552, 2006, DOI: 10.1016/j.jsv.2006.01.039.

[5] M. D. Spiridonakos, A. G. Poulimenos, and S. D. Fassois, "Output-only identification and dynamic analysis of time-varying mechanical structures under random excitation: a comparative assessment of parametric methods," *J. Sound & Vib.*, vol. 329, pp. 768–785, 2010, DOI: 10.1016/j.jsv.2009.10.005.

[6] M. Basseville, A. Benveniste, M. Goursat, L. Hermans, L. Mevel, and H. V. der Auweraer, "Output-only subspace-based structural identification: from theory to industrial testing practice," *ASME Journal of Dyn. Sys., Meas., & Cont.*, vol. 123, no. 4, pp. 668–676, 2001, DOI: 10.1115/1.1410919.

[7] B. Peeters and G. D. Roeck, "Stochastic system identification for operational modal analysis:

A review," *ASME Journal of Dyn. Sys., Meas., & Cont.*, vol. 123, pp. 659–667, 2001, DOI: 10.1115/1.1410370.

[8] C. Rainieri and G. Fabbrocino, "Automated output-only dynamic identification of civil engineering structures," *Mech. Sys. & Sig. Proc.*, vol. 24, pp. 678–695, 2010, DOI: 10.1016/j.ymssp.2009.10.003.

[9] C. Devriendt, G. De Sitter, and P. Guillaume, "An operational modal analysis approach based on parametrically identified multivariable transmissibilities," *Mech. Sys. & Sig. Proc.*, vol. 24, pp. 1250–1259, 2010, DOI: 10.1016/j.ymssp.2009.02.015.

[10] anonymous, "What is operational modal analysis?" www.svibs.com/solutions/what-is-oma.aspx.

[11] G. H. James, T. G. Carne, and J. P. Lauffer, "The natural excitation technique (next) for modal parameter extraction from operating structures," *Modal Analysis: Int. J. Analytical and Experimental Modal Analysis*, vol. 10, no. 4, pp. 260–277, 1995.

[12] A. M. D'Amato, A. J. Brzezinski, M. S. Holzel, J. Ni, and D. S. Bernstein, "Sensor-only noncausal blind identification of pseudo transfer functions," in *Proc. SYSID*, Saint-Malo, France, 2009, pp. 1698–1703, DOI: 10.3182/20090706-3-FR-2004.00282.

[13] A. J. Brzezinski, S. L. Kukreja, J. Ni, and D. S. Bernstein, "Sensor-only fault detection using pseudo transfer function identification," in *Proc. Amer. Conf. Contr.*, Baltimore, MD, 2010, pp. 5433–5438, ISBN: 978-1-4244-7426-4.

[14] ——, "Identification of sensor-only mimo pseudo transfer functions," in *Proc. Conf. Dec. Contr.*, Orlando, FL, 2011, pp. 2154–2159, DOI: 10.1109/CDC.2011.6160978.

[15] C. Devriendt and P. Guillaume, "Identification of modal parameters from transmissibility measurements," *J. Sound & Vib.*, vol. 314, pp. 343–356, 2008, DOI: 10.1016/j.jsv.2007.12.022.

[16] N. M. M. Maia, J. M. M. Silva, and A. M. R. Ribeiro, "The transmissibility concept in multi-degree-of-freedom systems," *Mech. Sys. & Sig. Proc.*, vol. 15, pp. 129–137, 2001, DOI: 10.1006/mssp.2000.1356.

[17] H. Palanthandalam-Madapusi, T. Van Pelt, and D. S. Bernstein, "Parameter Consistency and Quadratically Constrained Errors-in-Variables Least-Squares Identification," *Int. J. Contr.*, vol. 83, pp. 862–877, 2010, DOI: 10.1080/00207170903470666.

[18] M. S. Fledderjohn, M. S. Holzel, H. Palanthandalam-Madapusi, R. J. Fuentes, and D. S. Bernstein, "A comparison of least squares algorithms for estimating markov parameters," in *Proc. Amer. Contr. Conf.*, Baltimore, MD, 2010, pp. 3735–3740, ISBN: 978-1-4244-7426-4.

[19] A. A. Ali, A. M. D'Amato, M. S. Holzel, S. L. Kukreja, and D. S. Bernstein, "Consistent identification of hammerstein systems using an ersatz nonlinearity," in *Proc. Amer. Contr. Conf.*, San Francisco, CA, June 2011, pp. 1242–1246, ISBN: 978-1-4577-0080-4.

[20] T. Van Pelt and D. S. Bernstein, "Least Squares Identification Using μ-Markov Parameterizations," in *Proc. Conf. Dec. Contr.*, Tampa, FL, December 1998, pp. 618–619, DOI: 10.1109/CDC.1998.760748.

[21] M. Kamrunnahar, B. Huang, and D. B. Fisher, "Estimation of Markov Parameters and Time-delay/Interactor Matrix," *Chemical Engineering Science*, vol. 55, pp. 3353–3363, 1999, DOI: 10.1016/S0009-2509(00)00008-7.

[22] R. Venugopal and D. S. Bernstein, "Adaptive Disturbance Rejection Using ARMARKOV System Representations," *IEEE Trans. Contr. Sys. Tech.*, vol. 8, pp. 257–269, 2000, DOI: 10.1109/87.826797.

[23] anonymous, "Sofia: Stratospheric observatory for infrared astronomy," www.nasa.gov/sofia.