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Wavefront Sensor Fusion via Shallow Decoder Neural Networks for Aero-Optical Predictive Control

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ABSTRACT

Sensor limitations often result in devices with particularly high spatial-imaging resolution or high sampling rates but not both concurrently. Adaptive optics control mechanisms, for example, rely on high-fidelity sensing technology to predictively correct wavefront phase aberrations. We propose fusing these two categories of sensors: those with high spatial resolution and those with high temporal resolution. As a prototype, we first sub-sample simulations of the Kuramoto-Sivashinsky equation, known for its chaotic flow from diffusive instability, and build a map between such simulated sensors using a *Shallow Decoder Neural Network*. We then examine how to fuse the merits of a common sensor in aero-optical sensing, the Shack-Hartmann wavefront sensor, with the increased spatial information of a Digital Holography wavefront sensor, training on supersonic wind-tunnel wavefront data provided by the Aero-Effects Laboratory at the Air Force Research Laboratory Directed Energy Directorate. These maps merge the high-temporal and high-spatial resolutions from each respective sensor, demonstrating a proof-of-concept for wavefront sensor fusion for adaptive optical applications.

Keywords: aero-optics, optics, photonics, neural networks, Kuramoto-Sivashinsky

1. INTRODUCTION

Aero-optical systems face challenging sources of error as the wavefront, or laser beam, passes through turbulent regions. Adaptive Optic (AO) control mechanisms must be augmented by robust predictive controllers that are fast enough for real-time, in-flight applications. We describe a path forward in predictive control via deep learning, by improving the quality of sensor data used as an input. In this experiment, we attempt to fuse together Shack-Hartmann (SH) wavefront sensor data with more spatially-resolvent but temporally slower, in this setup, Digital Holography (DH) sensor data.[1]

We explore Shallow Decoder Neural Networks (SDNNs) to build a map from the SH to DH wavefront sensor. Limited by the number of usable snapshots in our aero-optical experiment data, we first elect to prototype a sensor fusion model on sub-sampled Kuramoto-Sivashinsky (KS) equation simulations acting as a surrogate sensor dataset. The chaotic flow of the KS equation provides an analogue to the turbulent flow captured by the SH and DH wavefront sensors. Demonstrating the ability of the SDNN to fuse low-spatial/high-temporal resolution data with high-spatial/low-temporal resolution data on the KS equation, we return to our investigation of sensing in aero-optics. Further work with data augmentation and regularization techniques are discussed to overcome the challenges in this experimental aero-optical dataset.

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1.1 Background on Aero-Optics

Airborne optical systems that move rapidly through the atmosphere are subject to varying air density, which translates to changes in the index of refraction in the medium surrounding the aperture. Just as in optical fiber systems where careful engineering and control schemes are necessary to propagate a useful signal, aero-optical systems need to correct for these refractive index deviations for applications requiring high-fidelity communication, tracking, and directed-energy transmission. In an airborne laser system, the beam not only encounters atmospheric turbulence but it also passes through a turbulent boundary layer at the interface with the aircraft.[2,3] This aero-optical effect (AOE) noticeably distorts the signal as Mach number increases and is especially deleterious for supersonic flow. To describe the aberrations, consider that they come from a fluctuating index of refraction, n, described by

$$n(x, y, z) = 1 + K_{GD}(\omega)\rho(x, y, z) \tag{1}$$

where the Gladstone-Dale coefficient, K_{GD}, is a function of frequency ω and ρ is the fluid density.[4] The deviations of a wavefront from an otherwise planar wavefront may be quantified by its optical path difference (OPD),

$$\mathrm{OPD}(x, y, t) = \int_{z_1}^{z_2} n(x, y, t)\mathrm{dz} - \left\langle \int_{z_1}^{z_2} n(x, y, t)\mathrm{dz} \right\rangle \tag{2}$$

where the angle brackets denote a spatial average. Once the wavefront data are measured by a wavefront sensor, the data can be fed into an AO control mechanism to counteract the AOE.[3] Unfortunately, with many AO applications, latency in the control loop can severely limit the ability for the system to adequately compensate the distortions as it experiences supersonic OPD fluctuations that have frequencies in the range of several kHz.[5] Furthermore, the fluid flow around turrets with flat or conformal windows results in complicated structural phenomena - horn vortices, flow separation, shear layers, Kelvin-Helmholtz vortices, re-circulation, and von Karman vortex shedding - making the AOE highly spatially dependent and requiring fast predictive adaptive optical controllers.[6,7]

Experimental wavefront transmission data in transonic to supersonic flow allows researchers to better develop predictive controllers for AO systems. The Airborne Aero-Optics Laboratory Transonic (AAOL-T),[8] which involves in-flight transmission data from a pair of in-flight Falcon 10 aircraft travelling at transonic speed, is a widely used dataset in such studies. More recently, the Aero-Effects Laboratory (AEL) at the US Air Force Research Laboratory Directed Energy Directorate has conducted high-fidelity supersonic wind tunnel optical transmission experiments at Mach 2.0.[1] A notable inclusion in this dataset, which provides more advanced aero-optical data than its predecessors, is the simultaneous use of both a Shack-Hartmann wavefront sensor (SH WFS) and a digital holography wavefront sensor (DH WFS). The SH sensor uses intensity information to reconstruct a wavefront from local spot displacements across its grid of subapertures and is a mainstay of optical measurement in this context. The DH WFS, however, provides a means to record optical phase information as well, creating a powerful tool for metrology.[9,10] Using the dynamic mode decomposition algorithm as a basis for predictive control on both the AAOL-T and AEL datasets, leveraging SH and DH WFS data respectively, has shown promise in building low-latency AO predictors.[7,11,12] However, fusing the results of both a SH and DH WFS for aero-optical application has yet to be studied, and such sensor fusion may provide a stronger basis for forecasting and control as well as a means to perhaps use a SH WFS with all the advantage of a DH WFS algorithmically added on.

2. SENSOR FUSION AND APPLICATION

Sensor fusion is the process of algorithmically synthesizing signals from multiple sources or measurement devices. Many engineering applications, such as the guidance and navigation systems found in aircraft, have access to or require a large amount of information from various sensors, yet these data are often similar and need to be processed into a single, useful signal for use in control systems. Sensor data fusion can be approached via probabilistic models, least-squares methods such as Kalman filtering, or intelligent methods such as neural networks or genetic algorithms.[13]

We propose sensor fusion[13] between the SH and DH WFS devices in order to reveal greater detail and lead to more robust predictive AO control. As depicted in Figure 1, deep learning methods can train a neural network

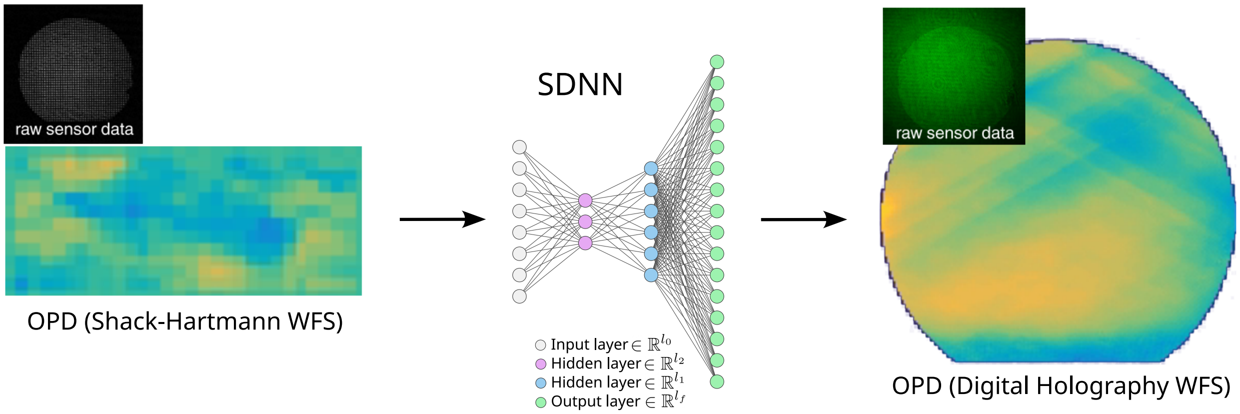

Figure 1. A shallow decoder to map the relatively low-spatial/high-temporal resolution SH input to the relatively high-spatial/low-temporal resolution DH WFS.

mapping from SH to DH WFS and generate the basis for highly temporal and spatially-resolvent predictors for the OPD. Such a predictor would be ideal for in-flight applications, where low-latency is a requirement and greater spatial accuracy is in demand. Modern implementations of shallow neural networks (NN)[14] appear suited to the task, because of their accuracy, interpretability, and - most importantly - low computational overhead and fast training.

The AEL data are split into training and validation sets, whereupon a hyper-parameter search for OPD phase reconstruction ought to provide a pathway forward. For future work, variations to the NN architecture, such as adaptations to the present convolutional layers or skip-connections to enforce physical properties,[15] may be considered. Future enhancements could also be performed as a super-resolution problem.[16]

3. DATASETS

We train our shallow decoder network for wavefront sensor fusion on two model datasets. The first is spatio-temporal data generated from simulations of the Kuramoto-Sivashinsky equation, allowing us a flexible surrogate model to engineer our algorithm. The second is AEL wind tunnel data which corresponds to the real-case scenario desired for the wavefront sensor fusion in an aero-optical environment.

3.1 Kuramoto-Sivashinsky simulation

The 1-D Kuramoto-Sivashinsky equation,

$$\frac{\partial u}{\partial t} = -\gamma \partial_x^4 u - \partial_x^2 u - u \partial_x u \tag{3}$$

where γ serves as a viscosity parameter, is a nonlinear scalar wave partial differential equation originally derived to model the thermal instability in laminar flame fronts. When considered on the periodic domain $0 \leq x < L$, chaotic dynamics with a cascade of period-doubling bifurcations occur as L increases. The KS equation simulation we use involves an $L = 2\pi$ periodic domain along which we sample 2048 spatial points. It is generally accepted to use a multiple of 2π when studying KS simulations. We run the simulation from $0 \leq t \leq 10$ with $100,000$ snapshots after seeding it with random noise, discarding the first 2000 snapshots to dispose of any transient effects. We then sub-sample the simulation to create analogues of two sensor readings: a 32×98000 set with high temporal resolution and a 2048×12250 set with high spatial resolution.

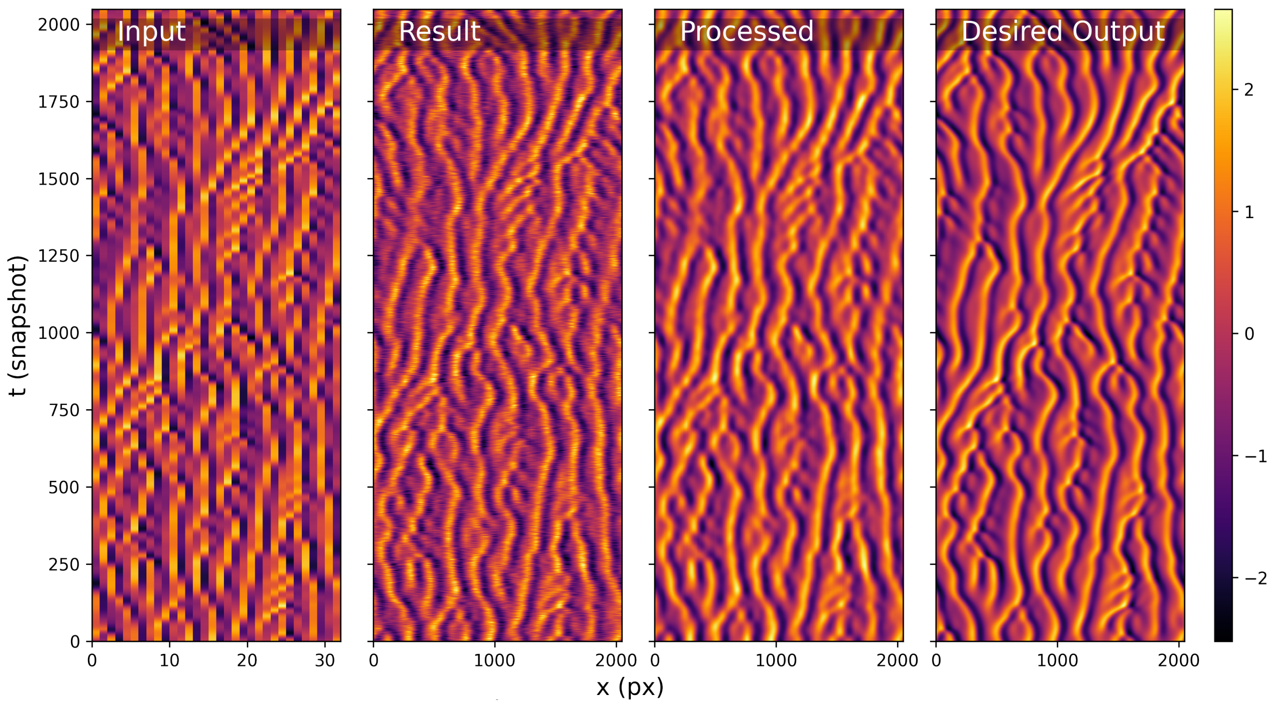

Figure 2. KS sensor fusion from 32 to 2048 spatial dimensions. Pictured is the entire validation set with each row depicting a 1-D snapshot, the result after mapping, post-processing, and the desired truth data. The input data is transformed to the Fourier domain such that the inverse transformed result maintains a periodic spatial dimension.

3.2 AEL aero-optical wind tunnel data

The AEL optical metrology system simultaneously uses three sensors: a SH WFS, a DH WFS, and Schlieren imaging to measure the wind tunnel supersonic flow in the test section.[1] For the purposes of this sensor fusion attempt, we focus on the first two sensors, as they perform a quantitative measurement of the wavefront in terms of phase using the same laser source used to illuminate the test section of the wind tunnel.

The data used in our study included over a second of SH WFS recording at 16×16 spatial resolution per frame with a framerate of 310kHz. Simultaneously, DH WFS information has been captured at 176×176 resolution at a framerate of 30kHz. In essence, the spatial resolution of DH is two orders of magnitude greater than the SH WFS, while its temporal resolution is an order of magnitude lower. Note that the frame-rates of 310kHz and 30kHz form an incommensurate ratio. Ideally, we want to match training snapshot pairs of input data and desired output to the exact same moment in time. The sampling rates in our data therefore provide a challenge in constructing a legitimate training and validation set for deep learning. For these reasons, we elected to construct a dataset where we form unique snapshot pairs that are within a microsecond of one another, which reduced our baseline dataset to $3,000$ snapshots. Because of the shock formation within the wind tunnel data seen in Figure 1, we crop the SH and DH data in, respectively, a 7×11 and 24×38 pixel window of the shock-free region. In future experiments, we intend to better match the framerates and that recommend experimental exploration take this into account.

4. SHALLOW DECODER NEURAL NETWORK

For the task of reconstructing a high spatial resolution flow pattern from sparse sensor inputs, we consider a shallow decoder neural network (SDNN) architecture. A shallow network is one that is assumed to consist of relatively few hidden layers, which we favor due to the decreased complexity in training time and fewer tuning requirements.

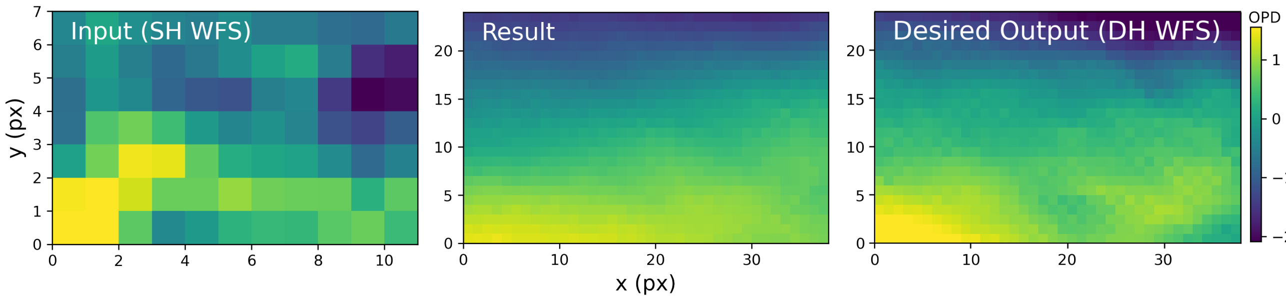

Figure 3. Wavefront sensor fusion on a subset of the AEL data, taking SH WFS input with low-spatial/high-temporal resolution and constructing a map via the SDNN to mimic high-spatial resolution DH WFS output with the same high-temporal resolution as the WH WFS. Pictured is a single 2-D input, mapped output, and desired output from the validation set.

Even the shallowest of NN architectures may approximate our desired mapping, which is the same path chosen by Erichson et. al. as recent as 2020.[14] Their assumptions included a sparse set of sensors to characterize an otherwise high-dimensional flow field, which is often the case in application, for example in sensor distribution problems for oceanographic activity.[17] For their shallow NN, a three-layer setup was used to act as a decoder $\mathcal{F}$ between a sensor vector $\vec{s}$ and the expected state $\vec{x}$ so that $\mathcal{F} : \vec{s} \mapsto \vec{x}$,

$$\mathcal{F}(\vec{s}) = \vec{\Omega}(\vec{\nu}(\vec{\psi}(\vec{s}))) \tag{4}$$

The authors provide an interpretation for the network: ψ describes measurement features, ν provides modal coefficients, and Ω provides a modal basis for the field. As a modern network, the implementation includes dropout[18] and batch normalization[19] and far exceeds the flow field reconstructions of vortex shedding past a cylinder given by standard and improved Proper Orthogonal Decomposition methods, even when confronted with signal-to-noise ratios of 10. The efficacy of this shallow decoder proves usable for estimating isotropic turbulent flow from a coarse grid of sensor measurements, reminiscent of a super-resolution framework like that performed contemporaneously by Fukami et. al. via a convolutional NN and a hybrid down-sampled skip-connection multi-scale model.[16]

5. RESULTS ACHIEVING WAVEFRONT SENSOR FUSION

We employ a SDNN with two hidden layers, both fully connected at 512 and 1024 neurons respectively and each followed by a probability 0.5 dropout layer. The Adam optimizer is used during training with a weight decay of 10^{-4}. Results for the KS sensor simulation and mapping are shown in Figure 2, while preliminary results for the AEL data are shown in Figure 3. A notable difference between these two datasets is in their dimensionality; each KS snapshot is a 1-D vector, while each OPD snapshot from the AEL data has been flattened from a 2-D array. As such, in Figure 2 we are visualizing the entire validation set while in Figure 3 we show results for a single frame from the validation set. Being able to visualize the whole validation set in Figure 2 allows us to perform a diffusion filtering step along the temporal direction in post-processing, further honing the accuracy of the result. Both datasets demonstrate that a shallow decoder network can be trained to map low-resolution measurements to high-resolution measurements at fast sampling rates.

6. CONCLUSION

The emergence of sensor networks for measuring complex physical systems, including aero-optic systems, requires new mathematical techniques that are capable of maximally exploiting multiple sensor modalities for state estimation and forecasting. Emerging algorithms from the machine learning community can be integrated with many traditional scientific computing approaches to enhance sensor fusion capabilities. To partially address this challenge, we proposed a SDNN that maps low spatial-resolution with fast temporal sampling sensors to high spatial-resolution with slow temporal sampling sensors. Thus a low-resolution sensor, such as a windowed

SH WFS operating at a high framerate, can be used in this wavefront sensor fusion modality to produce high-resolution estimates from a trained SDNN model, a priori, and used to enhance the performance of an AO system.

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REFERENCES

[1] Wilcox, C. C., Healey, K. P., Agena, B. D., and Tuffli, A. L., "Air force research laboratory aero-effects laboratory optical metrology system and performance," *Applied Optical Metrology III* **11102** (2019).

[2] Jumper, E. J. and Gordeyev, S., "Physics and Measurement of Aero-Optical Effects: Past and Present," *Annual Review of Fluid Mechanics* **49** (2017).

[3] Wang, M., Mani, A., and Gordeyev, S., "Physics and Computation of Aero-Optics," *Annual Review of Fluid Mechanics* **44** (2012).

[4] Gladstone, J. H. and Dale, T. P., "Researches on the Refraction, Dispersion, and Sensitiveness of Liquids," *Philosophical Transactions of the Royal Society of London* **15** (1863).

[5] Li, Z., Li, Y., Xing, B., Zhang, B., Tuo, H., and Liu, H., "OPD analysis and prediction in aero-optics based on dictionary learning," *Aerospace Systems* **2** (2019).

[6] Goorskey, D. J., Schmidt, J., and Whiteley, M. R., "Efficacy of predictive wavefront control for compensating aero-optical aberrations," *Optical Engineering* **52** (2013).

[7] Burns, W. R., Jumper, E. J., and Gordeyev, S., "A Robust Modification of a Predictive Adaptive-Optic Control Method for Aero-Optics," in [*47th AIAA Plasmadynamics and Lasers Conference*], American Institute of Aeronautics and Astronautics (2016).

[8] Jumper, E. J., Gordeyev, S., Cavalieri, D., Rollins, P., Whiteley, M., and Krizo, M., "Airborne Aero-Optics Laboratory - Transonic (AAOL-T)," in [*53rd AIAA Aerospace Sciences Meeting*], American Institute of Aeronautics and Astronautics (2015).

[9] Wilcox, C. C., Radosevich, C., Healy, K., Tuffli, A., Agena, B., Spencer, M., and Wittich, D. J., "Digital holography wavefront sensing with a supersonic wind tunnel," in [*Holography: Advances and Modern Trends VI*], Fimia, A., Hrabovský, M., and Sheridan, J. T., eds., SPIE (2019).

[10] Sulaiman, S., Gibson, S., and Spencer, M., "Predictive dynamic digital holography and image sharpening," *Journal of the Optical Society of America A* **35** (2018).

[11] Sahba, S., Sashidhar, D., Wilcox, C. C., McDaniel, A., Brunton, S. L., and Kutz, J. N., "Dynamic mode decomposition for aero-optic wavefront characterization," *Optical Engineering* **61** (2022).

[12] Shaffer, B. D., McDaniel, A. J., Wilcox, C. C., and Ahn, E. S., "Dynamic mode decomposition based predictive model performance on supersonic and transonic aero-optical wavefront measurements," *Applied Optics* **60** (2021).

[13] Sasiadek, J., "Sensor Fusion," *Annual Reviews in Control* **26** (2002).

[14] Erichson, N. B., Mathelin, L., Yao, Z., Brunton, S. L., Mahoney, M. W., and Kutz, J. N., "Shallow Neural Networks for Fluid Flow Reconstruction with Limited Sensors," *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* **476** (2020).

[15] Erichson, N. B., Muehlebach, M., and Mahoney, M. W., "Physics-informed Autoencoders for Lyapunov-stable Fluid Flow Prediction," arXiv:1905.10866 (2019).

[16] Fukami, K., Fukagata, K., and Taira, K., "Super-resolution reconstruction of turbulent flows with machine learning," *Journal of Fluid Mechanics* **870** (2019).

[17] Clark, E., Askham, T., Brunton, S. L., and Nathan Kutz, J., "Greedy Sensor Placement With Cost Constraints," *IEEE Sensors Journal* **19** (2019).

[18] Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., and Salakhutdinov, R., "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," *The journal of machine learning research* **15** (2014).

[19] Ioffe, S. and Szegedy, C., "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift," in [*International conference on machine learning*], PMLR (2015).