Closed-Loop Until Further Notice: Exploring Predictive Control Methods in Closed-Loop

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Abstract

For future extremely large telescopes, error in adaptive optics systems at small angular separations will be highly impacted by the lag time of the correction, which can be anywhere from 1-5 milliseconds; the natural solution is to apply a predictive correction to catch up with the system delay. Predictive control provides exemplary results in simulation (on the order of 5-10x improvement in RMS error compared with a standard integral controller), but shows only modest improvement on-sky (less than 2x in RMS error). This performance limitation is likely impacted by elements of pseudo open loop (POL) reconstruction, which requires assumptions about the response of the deformable mirror and accuracy of the wavefront measurements that are difficult to verify in practice. In this work, we explore a closed-loop method for data-driven prediction using a reformulated empirical orthogonal functions (EOF). We examine the performance of the open and closed-loop methods in simulation on perfect systems and systems with poor understanding of the DM response.

Adaptive Optics Systems Run in Closed-Loop

Open loop systems make for good linear prediction problems, but closed-loop systems are built into the way telescope systems run on-sky.

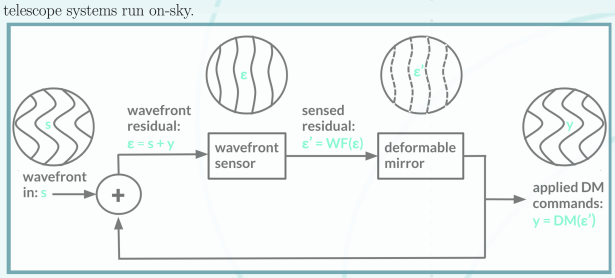

Figure 1: Closed-loop block diagram with a two-step delay. A wavefront comes into the system, s, and is immediately added to a deformable mirror (DM) command (from a previous iteration), y, at the sum junction. The wavefront sensor sees the corrected wavefront $\epsilon = y + s$, and passes on a discretized signal (along with whatever error is added by an imperfect wavefront sensor, ϵ'.) Finally, the DM uses some logic to convert this signal into the command y for the next iteration. In this diagram, each arrow denotes a step that takes a single time interval, making for a full two steps between s into the system and y applied.

Empirical Orthogonal Functions Served Two Ways

Empirical Orthogonal Functions (EOF) builds a predictive filter to estimate the future state of the wavefront. Using history vectors full of previous wavefront states, we estimate linear trends induced by wind layers and other reoccurring dynamics. $\mathbf{D}$ and $\mathbf{P}$ contain history vectors ($\mathbf{h}$ for open loop and $\boldsymbol{\phi}$ for closed-loop) with previous states of the wavefront and the future state of the wavefront (i.e., truth condition), respectively. We use a least squares inversion to find the predictive filter $\mathbf{F}$ with regularization constant α.

$$min||\mathbf{D}^T\mathbf{F}^T - \mathbf{P}^T||^2 \tag{1}$$

$$\mathbf{F} = ((\mathbf{D}^T)^\dagger \mathbf{P}^T)^T \tag{2}$$

$$\mathbf{F} = \mathbf{P}\mathbf{D}^T(\mathbf{D}\mathbf{D}^T + \alpha\mathbf{I})^{-1} \tag{3}$$

$$\text{prediction} = \mathbf{F}\mathbf{h} \text{ or } \mathbf{F}\boldsymbol{\phi} \tag{4}$$

For the open loop implementation (Guyon, 2017), our history vector contains only psuedo open loop (POL) wavefronts. However, this closed-loop update (based on Dessenne, 1998) builds a history vector, $\boldsymbol{\phi}$, with both DM commands and wavefront sensor residuals. Given $w(t)$, our pseudo open loop reconstruction the two history vectors take the form:

$$\mathbf{h}(t) = \begin{bmatrix} w(t) \\ w(t-1) \\ ... \\ w(t-n+1) \end{bmatrix}, \boldsymbol{\phi}(n) = \begin{bmatrix} y(n-1) \\ y(n-2) \\ ... \\ y(n-p) \\ \epsilon(n-2) \\ \epsilon(n-3) \\ ... \\ \epsilon(n-p-1) \end{bmatrix} \tag{5}$$

This new history vector encodes the same information, but allows a predictive filter to find coefficients for the wavefront sensor measurements and deformable mirror commands individually (as well as allows more robust consideration of time delays propagating through the system).

How to Train Your Empirical Orthogonal Functions

$\mathbf{P}$, the truth condition, must be the full distortion of the wavefront (i.e., open loop turbulence) at a given iteration. The original work from Dessenne estimated the open loop wavefront from the rejection transfer function of the system, essentially a higher fidelity pseudo open loop reconstruction than that of Guyon, 2017. For these simulations, we gave the system perfect knowledge, using the full scale of turbulence from simulation. This acts as a laboratory to test the perfect performance of a closed-loop implementation, and future work will explore more realistic $\mathbf{P}$ generation.

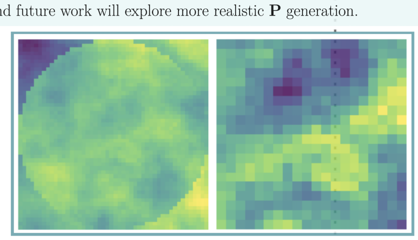

Figure 2: Left: Piston, tip, and tilt subtracted simulated phase screens from an 8 meter telescope with a single wind layer. Right: A square cutout in the middle of the pupil used as the training data for these simulations.

Current State of the Art in Predictive Control

Despite a variety of predictive control simulations and lab demonstrations, to date, only open loop EOF has been demonstrated on-sky for a high contrast imaging instrument. However, on-sky demonstrations do not match the performance expectations from high-fidelity simulations.

- EOF on Keck: **contrast gain of 2-3** (van Kooten, 2022)
- EOF on Subaru: **improvement in coronagraphic PSF** (Guyon, 2018)
- LQG on SPHERE, and GPI for low-order modes: **4-10 factor of improvement in tip/tilt jitter** (Poyneer, 2016; Petit, 2011)
- LQG on CANARY demonstrator for WHT: **~10% Strehl improvement in H/K band** (Sivo, 2014)

run on sky

- EOF on SPHERE telemetry: **~5x factor of improvement phase variance** (van Kooten, 2020)
- Neural networks on Gemini/ALTAIR telemetry: **2-5x factor of improvement in tip/tilt jitter** (Hafeez, 2022)
- Reinforcement Learning on 40 meter simulation: **~3% Strehl improvement** (Nousiainen, 2022)
- EOF and LQG on Keck telemetry: **~2x factor of improvement RMS error** (Fowler, 2022)

strictly simulation

Preliminary Result: Simulated Single-Layer Atmosphere

In our initial implementation, we find an improvement in root mean square (RMS) error of ~ 2.5 over a standard integrator from closed-loop EOF when applied to a simulated atmosphere with a single 7 m/s wind layer with an r_0 of 20 cm, under-performing compared to the standard psuedo open loop.

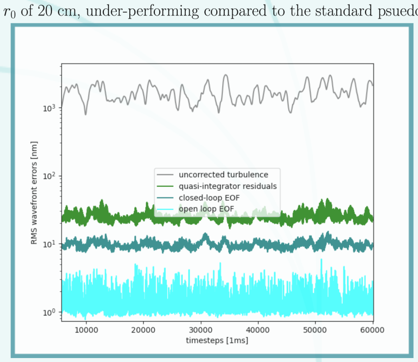

Figure 3: Full uncorrected turbulence RMS median: 1534.21 nm, quasi-integrator: 24.30 nm, closed-loop predictor: 9.49 nm, open loop predictor: 1.03 nm.

Preliminary Result: Introducing Model Errors

The performance of closed-loop EOF is less sensitive to errors in the system model. Here, while the closed-loop performance drops when a DM model issue is introduced, the closed-loop predictor still outperforms a typical integrator. However, introducing the same issue into a open loop EOF increases the residual error by more than an order of magnitude.

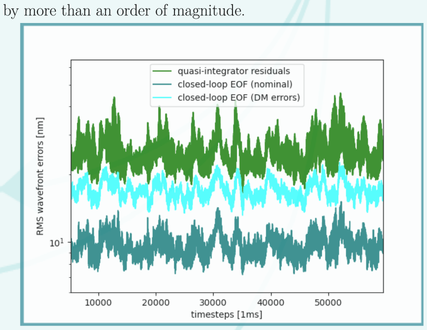

Figure 4: Closed-loop EOF correction goes from a median of 9.49 to 16.66 nm when a DM model error is introduce; the open loop EOF error increases by an order of magnitude.

Conclusions and Future Work

Our preliminary results find that closed-loop EOF shows performance gains over a typical integral controller and is more robust to system errors, though its current state cannot outperform the open loop implementation in the absence of system errors. Next steps include:

- further optimization of the closed-loop predictive control filter parameters
- examining the evolution of filter coefficients to see if they correctly learn errors in the DM commands or wavefront sensor reconstruction
- computational benchmarking (with the added history information introduced by closed-loop)
- further consideration of the optimal future vector $\mathbf{P}$ or multi-stage training schemes

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References

- Guyon, 2017, Adaptive Optics Predictive Control with Empirical Orthogonal Functions (EOFs)
- Dessenne, 1998, Optimization of a predictive controller for closed-loop adaptive optics