Improved Pyramid Wavefront Sensor using a Diffractive Optical Layer

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Abstract: We propose to design an optical preconditioner using an End-to-End approach to improve the linear response of the pyramid wavefront sensor (PyWFS). We added an optical diffractive layer into a relayed Fourier plane and design it using a joint optimization approach with the goal to enlarge the linearity range of the modified PyWFS linear estimation. Simulation results show a notorious improvement at different turbulence profiles, providing with the additional benefit of obtaining equivalent results to the traditional PyWFS but with lower modulation requirements, thus also improving the sensitivity of the novel proposed approach. We are currently working on the experimental demonstration in the PULPOS optical bench using the digital implementation of the PyWFS using a phase-only spatial light modulator.

1. Introduction

The pyramid wavefront sensor (PyWFS) is an optical system that allows performing modern adaptive optics [1]. The PyWFS sample the incoming wavefronts at the Fourier plane, splitting light into four beams and producing four different intensity projections of the entrance pupil onto the imaging detector. Although the PyWFS has become one of the chosen wavefront sensors (WFSs) for the next-generation of extreme large telescopes due to its high sensitivity, its linearity range is very limited. Often, a tip tilt mirror is used to modulate the PSF around the apex of the pyramid to improve linearity at the expense of sensitivity [2, 3]. With the increasing popularity of deep learning, some works have demonstrated the performance of different WFS by training a deep neuronal network (DNN) to estimate the incoming phase [4,5]. However, DNN-based WFSs suffer from training limitations and lack of generalization. An emerging area is to train diffractive elements (DE) to translate a digital layer into a physical layer used as a part of a computational imaging systems [6]. This work proposes to place an optical preconditioner in the Fourier plane to improve the linear response of the PyWFS. This optical element correspond to a designed DE which is trained in an End-to-End (E2E) scheme.

2. Proposed pipeline

The proposed E2E scheme consists of simulating all the sensing and reconstruction stages from a PyWFS, including the new DE. We first build an interaction matrix (IM) from projections of the WFS to known phases on a modal basis (Zernike or KL). Then, any aberrated measurement coefficients are estimated using the pseudo-inverse of the IM. As shown in Fig. 1, and for each iteration, the PyWFS+DE must be calibrated. Then, the loss function is computed and the error is back-propagated to the DE to update its weights via a gradient-descent approach. The DE phase maps are constrained to be in the $[-\pi, \pi]$ range.

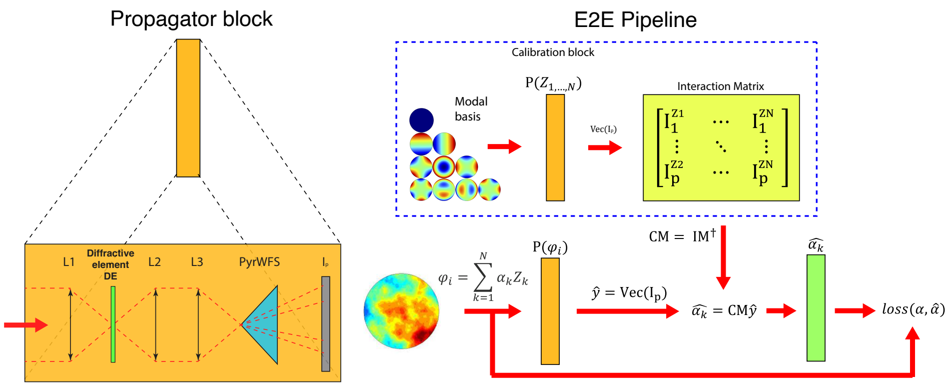

Fig. 1. Architecture for the E2E diffractive element training. It considers a calibration stage where the interaction matrix is built, which is then used to perform the inference of the data that enters the network during the training stage.

Note that in the training stage, the system must be bounded by a specific number of Zernike coefficients, however, the only element trained is the DE. Therefore, the DE can be used even if estimating a different number of coefficients after training.

3. Simulation Results

The training stage was performed by using Python 3.8 with the TensorFlow (TF) package, plus some functions of the OOMAO toolbox [7] related to the physical model. The DE was initialized from a constant phase. Fig. 2 (a) illustrates the results of the learned DE for 5000 training phases with 35 Zernike modes without considering the piston. One testing example can be seen in Fig. 2 (b), where we observe that the proposed method performs better than the traditional PyWFS using the same linear estimation procedure. Also, in Fig. 2 (c), we present a linearity analysis, observing a clear improvement in the linear response of the PyWFS when the DE is used, though the gain is diminished for higher coefficients.

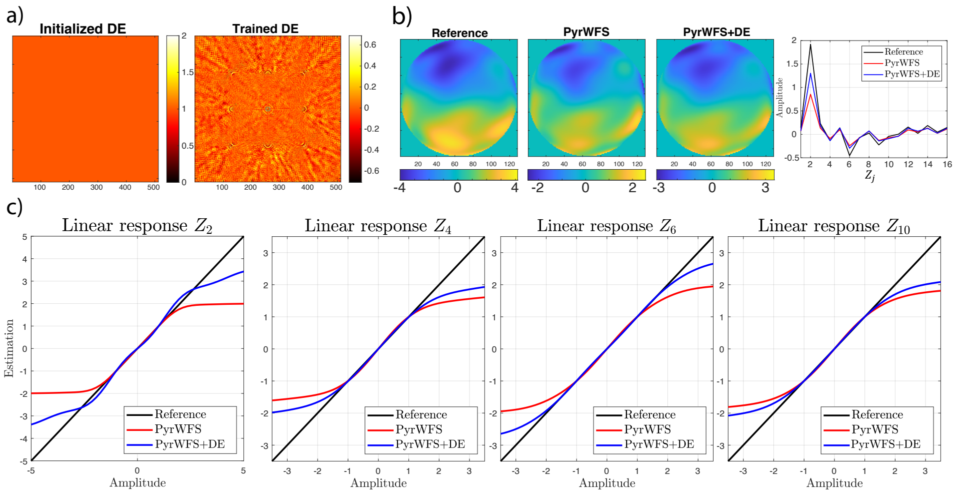

Fig. 2. (a) the DE before and after the training; (b) one example of phase estimation; (c) results of the linear response when compared to the PyWFS without DE.

4. Conclusion

In this work, we presented a design strategy for an optical preconditioner for the PyWFS. Through simulations, we demonstrated that we can design on optimal diffractive element able to improve the linearity range of the PyWFS. Further work will include an experimental demonstration in the PULPOS optical bench [8] using the digital implementation of the PyWFS using a phase-only spatial light modulator.

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