Deep neural networks for non-modulated Pyramid Wavefront Sensors

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The pyramid wavefront sensor (PyWFS) [1] is one of the best contenders to use on adaptive optics (AO) for extremely large telescope thanks to its performance, resolution and high sensitivity compared with other wavefront sensors. However, the PyWFS a limited linearity. To overcome this problem, the PSF is modulated around the pyramid apex using a Tip-Tilt mirror (TTM), where the modulation radius is defined by the non-dimensional value $M = \lambda/d$, where λ is the wavelength and d is the diameter of the PSF. This solution increases the linearity response but decreases the sensitivity of PyWFS. Also, this kind of solution generates experimental aberrations by the increased optical complexity. Since linear estimation techniques fail to properly model and solve the inherent non-linearities of the PyWFS, in this work we use Deep Learning techniques to train a variety of artificial neural networks (NN) to study their ability to improve the linearity response and hopefully keep the sensitivity when using a non-modulated pyramid. For this task, we compared the classical pyramidal reconstruction with four multiclass image neural networks. To compare the performance, we simulate various scenarios of strong and weak turbulence using the OOMAO toolbox on Matlab. We trained and tested three convolutional neural networks: the WFNet [3], the well-know Xception and the state-of-art convolutional neural network so-called ConvNext [4]; plus, the state-of-art of transformer neural network, the so-called Global context Visual Transformer GcViT [5]. Our results demonstrate that neural networks can the linearity and sensitivity of the PyWFS. Also, we proved that for weak turbulence cases the NN is more efficient than the classical method. For strong turbulence we note that the NN error quickly decays near to 5 cm of r_0 using a telescope of 1.5 meters of diameter, whereas under this value, the classical method error is 3 times larger than the NN method. Figure 1 shows the reconstruction predictions and residuals when using 209 Zernike's, where we can easily observe the improved performance delivered by the NNs over the classical linear estimation method for the PyWFS. We are currently working on experimentally validating these results on the PULPOS optical bench.

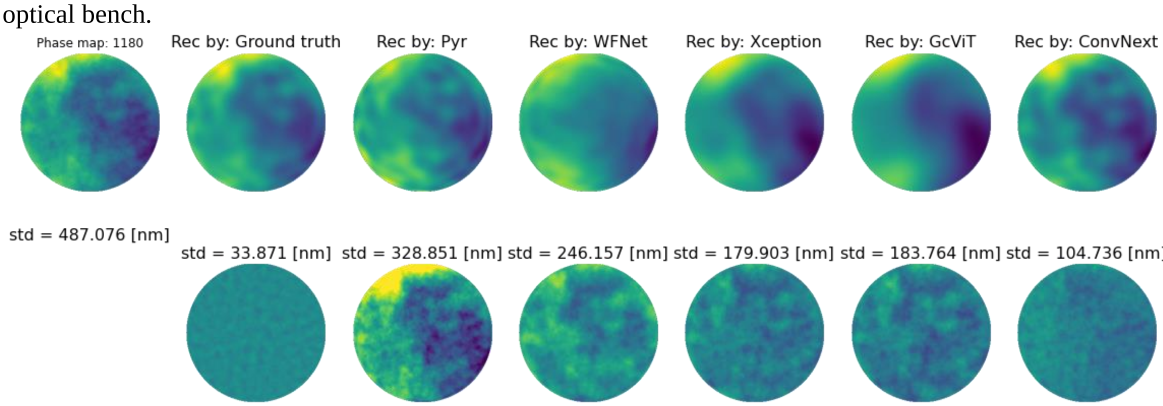

Fig.1: Sample of phasemap reconstruction from the Ground-truth values and the estimations.

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