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Astronomy ESFRI & Research Infrastructure Cluster

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Feasibility of Neural Networks in image reconstruction techniques.

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Abstract

This report is about a feasibility study on using deep neural networks (DNN) to speed up solar image reconstruction. The study successfully showed that to fully exploit the capabilities of DNNs, the methods should not only generate reconstructed images but should generate coefficients of a modular expansion of the wavefront, i.e., containing a physical component rather than a blind guess.

I. COPYRIGHT NOTICE

II. DELIVERY SLIP

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IV. APPLICATON AREA

This document is a formal deliverable for the GA of the project, applicable to all members of the ASTERICS project, beneficiaries and third parties, as well as its collaborating projects.

V. TERMINOLOGY

ASTERICS	Astronomy ESFRI & Research Infrastructure Cluster
BBI	Broad Band Imager
CTA	Cherenkov Telescope Array
DADI	Data Access, Discovery and Interoperability (ASTERICS WP4)
DNN	Deep Neural Network
ELT	Extremely Large Telescope
ESFRI	European Strategic Forum for Research Infrastructures
EST	European Solar Telescope
GAN	Generative Adversarial Network
IVOA	International Virtual Observatory
KIS	Leibniz-Institut fuer Sonnenphysik, previously known as Kiepenheuer Institut für Sonnenphysik
KM3NeT	Cubic Kilometre Neutrino Telescope
MFBD	multi frame blind deconvolution
OBELICS	Observatory E-environments LInked by common ChallengeS (ASTERICS WP3)
PSF	point spread function
SKA	Square Kilometre Array

A complete project glossary is provided at the following page:
http://www.asterics2020.eu/glossary/

VI. PROJECT SUMMARY

ASTERICS (Astronomy ESFRI & Research Infrastructure Cluster) aims to address the cross-cutting synergies and common challenges shared by the various Astronomy ESFRI facilities (SKA, CTA, KM3NeT & ELT). It brings together for the first time, the astronomy, astrophysics and particle astrophysics communities, in addition to other related research infrastructures. The major objectives of ASTERICS are to support and accelerate the implementation of the ESFRI telescopes, to enhance their performance beyond the current state-of-the-art, and to see them interoperate as an integrated, multi-wavelength and multi-messenger facility. An important focal point is the management, processing and scientific exploitation of the huge datasets the ESFRI facilities will generate. ASTERICS will seek solutions to these problems outside of the traditional channels by directly engaging and collaborating with industry and specialised SMEs. The various ESFRI pathfinders and precursors will present the perfect proving ground for new methodologies and prototype systems. In addition, ASTERICS will enable astronomers from across the member states to have broad access to the reduced data products of the ESFRI telescopes via a seamless interface to the Virtual Observatory framework. This will massively increase the scientific impact of the telescopes, and greatly encourage use (and re-use) of the data in new and novel ways, typically not foreseen in the original proposals. By demonstrating cross-facility synchronicity, and by harmonising various policy aspects, ASTERICS will realise a distributed and interoperable approach that ushers in a new multi-messenger era for astronomy. Through an active dissemination programme, including direct engagement with all relevant stakeholders, and via the development of citizen scientist mass participation experiments, ASTERICS has the ambition to be a flagship for the scientific, industrial and societal impact ESFRI projects can deliver.

VII. EXECUTIVE SUMMARY

Image reconstruction is a big computational effort and new methods need to be devised as data volumes will grow with the upcoming of the European Solar Telescope (EST) ESFRI. Triggered by the extended use of machine learning in Astronomy and Astroparticle Physics, we pursued the development of image reconstruction for ground-based solar data using deep neural networks (DNNs). This report describes the feasibility study on using neural networks to speed up solar image reconstruction. The study successfully showed that to fully exploit the capabilities of DNNs, the methods should not only generate reconstructed images but should generate coefficients of a modular expansion of the wavefront, i.e., containing a physical component rather than a blind guess. These coefficients can then be fed into a MFBD metric for evaluation, leading to a pioneering approach in this field.

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1. Introduction

Astronomical observations from ground in high resolution are limited by the turbulent motion of Earth’s atmosphere. The fluctuations of the refractive index of air induced by temperature gradients heavily influence image quality. Differences in the refractive index change the phase of the incoming wavefront which leads to errors. This effect is called seeing and is affecting all ground based telescopes. Especially, solar telescopes which observe during daylight, when temperature gradients are strongest. Adaptive optics remove a large part of the wavefront error, but sophisticated image reconstruction is essential to restore diffraction limited information. These image reconstruction methods use the assumption that the object, the Sun, stays static during acquisition of several short exposures affected by seeing. By averaging over multiple realisations of the atmosphere, the missing information can be restored up to the diffraction limited resolution of the telescope. Image reconstruction is a big computational effort and new methods need to be devised as data volumes will grow with the upcoming of the European Solar Telescope (EST) ESFRI.

The participation in the 2nd OBELICS/ASTERICS Workshop (Barcelona, Oct 16-19, 2017) became most enlightening when learning about the extended use of machine learning in Astronomy and Astroparticle Physics. The use of AI in ground-based solar physics was back then close to inexistent. Discussions there inspired us to pursue the development of image reconstruction for ground-based solar data using deep neural networks, as they offer solutions that could enhance and speed up the process, thus, providing added value to the existing data that, within the activities we have carried out in WP4-DADI, were planned to become available to the broad Astrophysical community following the IVOA standards.

The integration in ASTERICS of activities on ground-based solar (EST ESFRI) within the EOSC spirit has been indeed a pioneering endeavour since, until then, the broad Astrophysical community and the ground-based Solar community where somehow disconnected although part of the same scientific family.

2. Plan

We made a feasibility study on using neural networks to speed up solar image reconstruction. This is a follow-up study on the results of Asensio Ramos 2018 (arXiv:1806.07150) using speckle reconstructed data instead of multi frame blind deconvolution (MFBD). In contrast to the promising results reported in the previous study, a similar reconstruction quality could not be achieved. An explanation could be that neural networks and blind deconvolution methods share similarities in their algorithm by minimising a loss function or metric. This is not true for speckle interferometric methods, which instead try to reconstruct the Fourier phase spectrum by bispectral averaging. Rather than following up on the study done by Asensio Ramos, we further investigated the feasibility by using neural networks for guessing wavefront parameters inside a new multi frame blind deconvolution framework. In this case the coefficients of a modular expansion of the wavefront, using Zernike or Karhunen-Loéve functions, is estimated by neural networks. This will also eliminate one drawback of neural networks: the physical meaning of the estimated solution, which in our case will still be justified in the sense of Fourier optics and atmospheric statistics.

3. Content

To develop a new neural network for image reconstruction, a new infrastructure was needed. This included the acquisition of a NVIDIA Tesla P100 GPU server for high performance computation. The server was connected to the existing institute’s infrastructure and necessary software was installed. Development of the neural network was done with the Python package Pytorch (https://pytorch.org).

4. Analysis

The first part of the feasibility study was done by comparing the existing neural network devised by Asensio Ramos et al. (2018) on MOMFBD (van Noort et al. 2005) and KISIP (Wöger et al. 2008) restored datasets. Therefore, the code basis had to be modified to be compatible to already available datasets from the Broad Band Imager (BBI). The modification included the option to retrain the network on a multitude of available datasets in different wavelengths obtained during observations in 2017.

Secondly, new neural networks were devised, which worked on simulated point spread functions (PSF). The wavefronts of these PSFs were simulated by randomizing coefficients of a modal expansion following Kolmogorov turbulence statistics. By letting the neural networks guess the coefficients of the modal expansion it was hoped they could device a model which could solve the inverse problem.

5. Deviations from the plan

A deviation from the plan was taken as it was found that the used neural networks could not generalise on guessing of coefficients. It was also found that the neural network of Asensio Ramos et al. (2018) would not generalise on some of the selected datasets. The deviation included further study on possible networks and new metrics.

6. Results

The result of the analysis was that current methods to reconstruct solar data with neural networks such as Asensio Ramos et al. (2018) can be used as quick look or context data. Unfortunately, they provide no further information about the imaging process or atmospheric parameters such as Fried's parameter or the wavefront in the form of coefficients of a modal expansion.

7. Next steps

Next steps would be to define a new neural network that includes the MFBD metric in a Generative Adversarial Network (GAN). These networks have shown great results in the form of image (re-)construction.

8. Conclusion

To fully exploit the capabilities of DNN's, the methods should generate coefficients of a modular expansion of the wavefront. These coefficients can then be fed into a MFBD metric for evaluation. This can include a second network that evaluates the coefficients with a best guess of the object provided by the network. By using this additional layer, one can not only extract physical information about the Earth's atmosphere in the form of the wavefront, but one can additionally generalise the network without losing valuable parameters.