Event reconstruction using pattern spectra and convolutional neural networks for the Cherenkov Telescope Array

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ABSTRACT

The Cherenkov Telescope Array (CTA) is the future observatory for ground-based imaging atmospheric Cherenkov telescopes. Each telescope will provide a snapshot of gamma-ray induced particle showers by capturing the induced Cherenkov emission at ground level. The simulation of such events provides camera images that can be used as training data for convolutional neural networks (CNNs) to differentiate signals from background events and to determine the energy of the initial gamma-ray events. Pattern spectra are commonly used tools for image classification and provide the distributions of the sizes and shapes of features comprising an image. The application of pattern spectra on a CNN allows the selection of relevant combinations of features within an image. In this work, we generate pattern spectra from simulated gamma-ray images to train a CNN for signal-background separation and find that the pattern spectra-based analysis is computationally less expensive but not competitive with the purely CTA images not captured by the pattern spectra.

1 - Introduction

The interaction of a gamma ray with the Earth atmosphere induces a particle shower, which produces a flash of Cherenkov light. The Cherenkov Telescope Array (CTA) will be able to capture the Cherenkov emission at ground level, which provides information about the energy of the initial gamma ray. Pattern spectra [1] are commonly used tools for image classification, which provide the distributions of the shapes and sizes of various objects comprising an image Requiring significantly (Fig. less computational power other compared to algorithms, they can be used for signalbackground separation and to reconstruct the energy of the initial gamma ray [2].

2 - Analysis

The pattern spectra are generated from the CTA images by calculating the size (area A) and shape (I/A^2) with the moment of inertia /) of each feature (Fig. 2). Separately, the CTA images or the pattern spectra are used as an input for a convolutional neural network (CNN), which is trained and tested for signal-background separation and energy reconstruction. The CNN is trained ten times for energy reconstruction to obtain a mean energy resolution and its uncertainty.

3 - Results

The CTA images-based analysis outperforms the pattern spectrabased analysis in both the signal-background separation (Fig. 3) and the energy reconstruction (Fig. 4).





(a) 2D image



(b) Peak components







Fig 1: Visual representation of the pattern spectra algorithm (adapted from [1, 3]).

Fig 2.: Top: CTA image with detected features (in red/orange). Bottom: pattern spectrum with the pixel (in red) corresponding to the detected features.

30000 20000 10000

During training, the CNN based on pattern spectra needs a factor 3.1 less random access memory (RAM) and is a factor 2.6 faster compered to the CNN based on the CTA images (Tab. 1).

4 – Discussion

The pattern spectra-based analysis is computationally less expensive but not competitive with the CTA images-based analysis. Thus, we conclude that the CNN must rely on additional features in the CTA images not captured by the pattern spectra.



Fig. 4: Reconstructed energy E_{rec} as a function of true energy E_{true} obtained with CTA images (left) and pattern spectra (middle). Energy resolution comparison (right). The data points represent the mean value and the shadowed regions one standard deviation.



Tab. 1: Computational performance of the CNNs based on (a) CTA images and (b) pattern spectra during training for energy reconstruction

	CTA images	Pattern spectra	ratio
Max. RAM	~100 GB	~32 GB	3.1
Time	~29 ks	~11 ks	2.6

BIBLIOGRAPHY

[1] Urbach et al., 2007. DOI:10.1109/TPAMI.2007.28 [2] Aschersleben et al., 2021, DOI:10.22323/1.395.0697 [3] Teeninga et al., 2016. DOI: 10.1515/mathm-2016-0006

ACKNOWLEDGEMENTS

We gratefully acknowledge financial support from the agencies and organizations listed here: www.cta-observatory.org/consortium_acknowledgm ents

We would like to thank the Center for Information Technology of the University of Groningen for their support and for providing access to the Peregrine high performance computing cluster.