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Reconstruction of stereoscopic CTA events using deep learning with CTLearn

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The Cherenkov Telescope Array (CTA), conceived as an array of tens of imaging atmospheric Cherenkov telescopes (IACTs), is an international project for a next-generation ground-based gamma-ray observatory, aiming to improve on the sensitivity of current-generation instruments a factor of five to ten and provide energy coverage from 20 GeV to more than 300 TeV. Arrays of IACTs probe the very-high-energy gamma-ray sky. Their working principle consists of the simultaneous observation of air showers initiated by the interaction of very-high-energy gamma rays and cosmic rays with the atmosphere. Cherenkov photons induced by a given shower are focused onto the camera plane of the telescopes in the array, producing a multi-stereoscopic record of the event. This image contains the longitudinal development of the air shower, together with its spatial, temporal, and calorimetric information. The properties of the originating very-high-energy particle (type, energy, and incoming direction) can be inferred from those images by reconstructing the full event using machine learning techniques. In this contribution, we present a purely deep-learning driven, full-event reconstruction of simulated, stereoscopic IACT events using CTLearn. CTLearn is a package that includes modules for loading and manipulating IACT data and for running deep learning models, using pixel-wise camera data as input.
1. Introduction

The Cherenkov Telescope Array (CTA) [1] is the next-generation ground-based gamma-ray observatory, aiming to improve on the sensitivity of current-generation instruments by a factor of five to ten and provide an energy coverage from 20 GeV to more than 300 TeV. CTA will consist of two arrays of tens of imaging atmospheric Cherenkov telescopes (IACTs) to be built in the Northern Hemisphere (La Palma, Canary Island, Spain) and in the Southern Hemisphere (near Cerro Paranal, Chile). Arrays of IACTs observe simultaneously the Cherenkov light induced by the showers of particles produced when very-high-energy (VHE; above 20 GeV) gamma rays or charged cosmic rays enter the atmosphere. Those Cherenkov photons are collected by the optical systems and focused onto cameras, producing a stereoscopic record of the event. The IACT images contain the longitudinal development of the air shower, together with its spatial, temporal, and calorimetric information.

The gamma-ray and cosmic-ray initiated showers can be distinguished from their morphological differences, translated into their IACT stereoscopic images. This distinction, dubbed particle or event classification, is crucial for IACTs since cosmic-ray events are their main background. The original approach to classify IACT events from their images was to extract handcrafted features, like the commonly used Hillas parameters [2], and perform parameter-wise selection over the multidimensional space of those parameters. As a result of the improvement in available computational resources and algorithms over the past few decades, this original approach evolved into more sophisticated strategies where supervised learning algorithms like Random Forests [3] or Boosted Decision Trees [4–6] are trained on those handcrafted features, substantially improving the performance of the particle classification and, consequently, the sensitivity of the instruments. In addition, IACT data analysis methods also need to infer further properties of the gamma-ray events, namely, the energy and the incoming direction of the originating particles. This so-called full-event reconstruction could also be performed with deep convolutional neural networks (DCNs), a particular class of deep learning algorithms, which are currently the most successful machine learning methods for computer vision, excelling at image classification and regression among other tasks [7]. Rather than crafting the features by hand, these types of algorithms are capable of learning the feature extraction by themselves (representation learning). Therefore, DCNs can access all the information contained in the images, not only those condensed in handcrafted features extracted from those images.

Previous works have demonstrated the potential application of these algorithms for IACT event reconstruction [8–13]. DCN-based monoscopic telescope performance and the application of DCNs on observational data from the first Large-Sized Telescope (LST-1 prototype) of CTA North is discussed in these proceedings elsewhere [14, 15]. As a natural continuation of this line of work, this contribution focuses on full-event reconstruction of MC-simulated stereoscopic events.

2. CTA analysis workflow with deep learning

The CTA analysis workflow consists of several software blocks. The MC simulations and later the observational data are reduced with the stage1-tool of ctapipe\(^1\) [16, 17], a prototype

\(^1\)https://github.com/cta-observatory/ctapipe
low-level data processing pipeline for CTA, and the resulting calibrated images, as well as their image parameters, are stored in the official CTA Data Level 1 (DL1) format. Data loading and pre-processing, specially designed for deep learning purposes, are managed using an associated external package, DL1-Data-Handler\textsuperscript{2} \cite{DL1-Data-Handler}. It supports event-wise data reading using generators to handle big datasets. The training of the deep learning models and their inference, the actual full-event reconstruction, are performed with CTLearn\textsuperscript{3} \cite{CTLearn}. The high-level products like instrument response functions (IRFs) and sensitivity curves are obtained using pyirf\textsuperscript{4} \cite{pyirf}, a prototype for the generation of IRFs and sensitivities for CTA. The CTA analysis workflow with conventional methods can be found in these proceedings in Ref. \cite{CTAAnalysis}.

**Full-event reconstruction with CTLearn** The high-level, open-source CTLearn package provides a framework for training deep learning models for IACT full-event reconstruction using TensorFlow. This work focuses on the thin ResNet (TRN) model \cite{TRN} (see Fig. 1, left model), a deep DCN-based architecture for monoscopic full-event reconstruction with residual connections (meaning that the original input is added to the output at each stage, demonstrated to improve performance) \cite{ResNet}. A dual (squeeze-and-excitation) attention mechanism \cite{SqueezeAndExcitation} is deployed in each of the residual blocks. Either particle classification or regression (energy or arrival direction reconstruction) is performed with a selectable fully-connected head (FCH), a traditional multi-layer perceptron neural network (MLP), after the deep backbone, consisting of several stacked residual blocks.

![Diagram depicting the main layers of the TRN (left) and the TRN-RNN model (right).](https://arxiv.org/abs/2101.07626)

\textsuperscript{2}https://github.com/cta-observatory/dl1-data-handler
\textsuperscript{3}https://github.com/ctlearn-project/ctlearn
\textsuperscript{4}https://github.com/cta-observatory/pyirf
The stereoscopic full-event reconstruction is performed with the TRN-RNN model (see Fig. 1, right model), which consists of multiple thin ResNet blocks connected via a recurrent neural network (RNN) [7]. In particular, the RNN - implemented in CTLearn - is a dynamic long short-term memory network (LSTM) [7], which adjusts its size according to the number of triggered telescopes for each event. The images of triggered telescopes are sorted a priori by the total amount of integrated charge in the camera. To train this large architecture, and to overcome computing limitations, transfer learning [7] is utilized: the DCN backbone of the TRN model is trained beforehand, its parameters are set to be untrainable weights and transferred into the TRN-RNN model.

3. Dataset

The analysis is carried out with the CTA South (zenith angle of 20°, North pointing) reference dataset, processed with ctapipe [5]. A detailed description of the simulation production, together with the telescope layout and performance study of CTA can be found elsewhere in Ref. [26]. For the deep learning training process of the particle classification, diffuse gamma-ray and proton-initiated events, simulated within a cone of 10° radius (covering the whole field of view of the instrument) are considered, in a balanced way so both populations contribute equally to the statistics of the datasets. 80% of the data are used for training (from which 5% are reserved for validation of the learning process) and 20% for testing. The regression models (energy or arrival direction reconstruction) are trained with the whole training set of diffuse gamma rays. The performance of the deep learning models is evaluated on simulated protons (∼7e9), electrons (∼2e9) and point-source gamma rays (∼2e9) with 0.4° offset with respect to the telescope pointing.

Array layout The array layout M5C5, consists of 13 medium-size telescopes (MSTs) and 40 small-size telescopes (SSTs), and four additional large-size telescopes (LSTs) are considered in this work. The M6C5 array layout with 14 MSTs, 40 SSTs and no LSTs is depicted in lower left panel of Fig. 1 in Ref. [26]. For the monoscopic full-event reconstruction, all images from the corresponding telescope type, regardless of the particular telescope, are included at training stage. However, the single telescope performances are evaluated with one particular telescope per telescope type.

Data selection (quality cuts) In order to compare to the conventional IACT analysis methods, two different data selection cuts are performed. The TRN model are trained and tested with a modest cut, adapted from Ref. [14], where faint images (Hillas intensity less than 50 photoelectrons) and images close to the camera edge (leakage2 parameter more than 0.2) are discarded. For the stereoscopic reconstruction, faint and truncated images are kept, but a multiplicity cut of four or more triggered telescopes is applied.

4. Results

The TRN and TRN-RNN models successfully learn to perform monoscopic and stereoscopic full-event reconstruction, respectively, for all sizes of CTA telescopes. The standard IACT IRFs and

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5 The first stage of the analysis was performed on the EGI (www.egi.eu).
6 Please note that DCNs are fed with all the information contained in the event images and therefore no default quality cuts have to be applied.
sensitivities are depicted in Fig. 2 and 3. The angular resolution is defined as the angle containing 68% of the reconstructed gamma-ray events relative to the simulated point source gamma-ray direction. This is calculated in each logarithmic energy bin. The energy resolution in each energy bin is calculated with 68% of containment of \((E_{\text{reco}} - E_{\text{true}})/E_{\text{true}}\). The effective collection area, which is proportional to the gamma-ray efficiency of detection, is computed as a function of the simulated energy. Only events entering the calculation of the sensitivity curve are considered for the effective collection area and the resolution curves. The differential sensitivity calculation requires a minimal significance of more than 5 \(\sigma\), at least ten detected gamma rays and a minimal excess over background ratio of 0.05 for a observation of 50 hours. For IACTs, the receiver operating characteristic (ROC) curve visualizes the diagnostic ability of the gamma/hadron separation as its gammaness threshold is varied. The area under the ROC curve (AUC) is a measurement of the quality of the background rejection.

4.1 Single-telescope event reconstruction (TRN model)

The TRN model is trained on \(\sim 200k\) batches of 64 images for each telescope type, validating periodically. As expected (see Fig. 2), the LST is the most sensitive telescope type at the lowest energies; the sensitivity of an MST is best where this telescope type will be responsible for the full-array sensitivity; the SST is providing competitive sensitivity at multi-TeV energies. In the mono telescope analysis, SSTs are competitive with MSTs only at the highest energies. The LST, MST, and SST provide excellent energy resolutions of \(\sim 13\%, 9\%\), and \(10\%\) at their best, angular resolutions of \(\sim 0.12^\circ\), \(0.13^\circ\) and \(0.1^\circ\) at their best, and an AUC of 0.89, 0.944, and 0.959, in their entire energy ranges, respectively.

Figure 2: The single telescope IRFs and sensitivities, as defined in Sec. 4, obtained with the TRN model for the LST (blue), MST (green), and SST (orange).
4.2 Reconstruction of stereoscopic events (TRN-RNN model)

As discussed in Sec. 2, the backbone of the TRN model is transferred into the TRN-RNN model. Therefore, only \( \sim 100k \) batches of 16 images for each telescope type are needed to train the RNN and the FCH blocks of the model. The learning is also validated periodically. The particle classification, performed by the TRN-RNN model (see Fig. 3), works well, with an AUC score of 0.98, 0.994, and 0.996 for the subarrays of 4 LSTs-LSTCam, 13 MSTs-NectarCam, and 40 SSTs-CHEC, respectively. The three subarrays reach promising top values for the the energy resolution of \( \sim 10\% \), 7\%, and 6\% for LSTs, MSTs and SSTs, respectively. The IRFs produced with our models are cut off above 80 TeV, likely because they fail the requirement of 10 gamma rays in each energy bin. This should be solved once all telescope types would be combined in the reconstruction.

The TRN-RNN model performs poorly on the reconstruction of the arrival direction. The angular resolution for the highest energies differs from the conventional analysis significantly, which translates to the sensitivity curves, causing a deficit of performance especially at energies above 10 TeV. Achieving just a small improvement for the angular resolution by adding more telescopes concludes that this version of the TRN-RNN model needs further adjustments to be fully capable of learning stereoscopic features relevant for the arrival direction reconstruction. Including further information like the telescope position may help the network to better reconstruct the arrival direction. Future studies are planned to improve the angular resolution with DCN-based models especially in stereo mode. A fair comparison to the conventional analysis with the Eventdisplay software package (see black curves in Fig. 3) is not feasible at this stage of the development, because no LSTs are considered in the conventional analysis, and it is not limited to a per-telescope-type analysis [27].

Figure 3: The multi telescopes IRFs and sensitivities, as defined in Sec. 4, obtained with the TRN-RNN model for 4 LSTs (blue), 13 MSTs (green), and 40 SSTs (orange). The black curves depict the IRFs and sensitivities obtained with the conventional analysis of the array layout M6C5 with 14 MSTs, 40 SSTs, and no LSTs taken from Ref. [26].
5. Conclusion and Outlook

This contribution shows for the first time that DCN-based full-event reconstruction works for all sizes of CTA telescopes, in both single-telescope and stereo modes. The performance of the TRN and the TRN-RNN models for the particle classification and the energy estimation is promising. Tackling the arrival direction reconstruction task via DCNs requires additional modifications and improvements to the existing stereoscopic deep learning models to suit the requirements of CTA.

Future developments of CTLearn will include the combination of different telescope types to evaluate the full-array performance of CTA North and South with deep learning models. The results of each telescope type are obtained with the same set of non-optimized hyperparameters. Hyperparameter optimization will be explored in future. Multitask learning experiments (see Ref. [15]), where one single model performs the IACT specific tasks (particle classification, energy and arrival direction estimation), as well as the application of DCNs model on observational data, are also planned. Further validation of DCN-based full-event reconstruction under various circumstances (i.e. off-axis performance, divergent pointing, different zenith angles and night sky backgrounds, etc.) is very important and will be considered in future works.

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