Analyzing Stereoscopic Cherenkov Telescope Images from TAIGA Array Using Convolutional Neural Networks

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An extensive air shower caused by a high-energy particle (cosmic or gamma ray) interacting with upper atmosphere can be detected by several methods including imaging atmospheric Cherenkov telescopes (IACTs). In Russian TAIGA (Tunka Advanced Instrument for cosmic ray physics and Gamma-ray Astronomy) experiment the number of installed and commissioned IACTs has been increased from one to two in 2020, and the third telescope was installed in 2020 [1].


The TAIGA IACT located in Tunka valley, Russia

In our previous work [2, 3] we investigated the application of deep learning to the problems of identification of the original particle type and estimation of the energy of the gamma rays based on an image from a single TAIGA IACT. We demonstrated that convolutional neural networks can produce better results for cosmic ray background suppression and energy estimation than a traditional approach based on Hillas parameters [4].

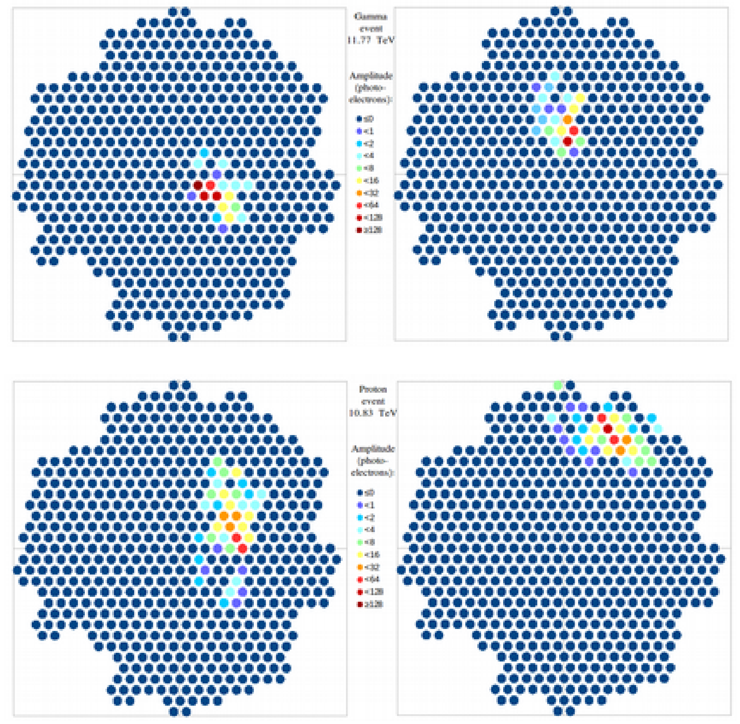
Here we present the results of applying the same approach to the problems of identification of the original particle type and estimation of the energy of the gamma rays in stereoscopic mode with two telescopes. Images for two TAIGA IACTs were generated by Monte Carlo simulation program CORSIKA [5].

Particle identification

We used convolutional neural networks to identify gamma events and background proton events. We prepared a dataset S1 of 3400 gamma events and 9306 proton events recorded by two IACTs at a varying distance between 300 and 350 m. Each convolutional network was trained 10 times on a randomly chosen subset of 10165 (80%) events, the results were evaluated on the remaining events. As a measure of background suppression we used a selection quality factor Q

$$Q = \frac{\Gamma_{true}/\Gamma}{\sqrt{\Gamma_{false}/H}}$$

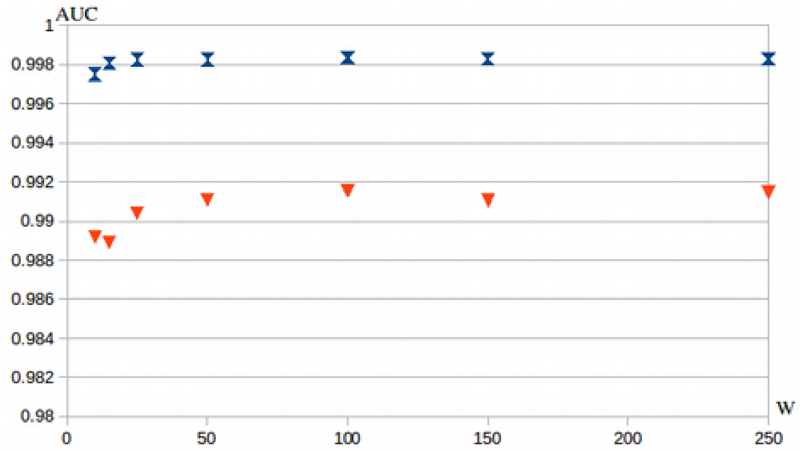
where Γ and H are the total number of gamma events and hadron events, respectively, Γ_{true} and Γ_{false} are the number of events correctly and incorrectly identified as gamma events.



Architecture of the neural networks:

Conv2D 5x5, W
AvgPool 2x2
Conv2D 5x5, W
AvgPool 2x2
Conv2D 3x3, W
AvgPool 2x2
Flatten 3x3xW → 9W
Fully connected layer, 3W
Fully connected layer, W
Output layer, 2

For the neural networks with the parameter W = 10, 15, 25, 50, 100, 150, 250 trained and evaluated on images from the first telescope only the Q factor is between 6.3 and 7.1, and for the same networks trained on images from both telescopes the Q factor is between 13.0 and 17.0. Adding the second image reduces the number of misidentified background events by a factor of 4-5. We also compared the average area under the receiver operating characteristic curve (ROC AUC) for these networks. For the networks trained on monoscopic images the average AUC was between 0.9889 and 0.9916, and for the networks trained on stereoscopic images it was between 0.9975 and 0.9983.



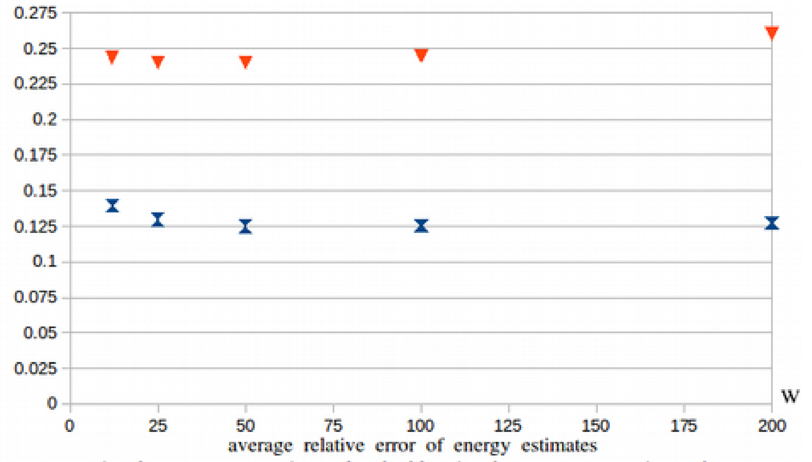
Gamma ray detection ROC AUC
triangles — monoscopic mode, double triangles — stereoscopic mode

Gamma ray energy estimation

For training and evaluating convolutional neural networks estimating the energy of gamma rays we used a dataset S2 of 18359 gamma events recorded by two IACTs at a distance 324 m. The energy of the gamma rays was between 1 and 50 TeV. Each convolutional network was trained 10 times on a randomly chosen 80% subset of the dataset.

An example of neural network architecture for energy estimation (W = 12, 25, 50, 100, 200 were used):

Conv2D 5x5, ⌊W/4⌋
AvgPool 2x2
Conv2D 5x5, ⌊W/2⌋
AvgPool 2x2
Conv2D 3x3, ⌊W/2⌋
AvgPool 2x2
Flatten 3x3x⌊W/2⌋ → 9⌊W/2⌋
Fully connected layer, W
Fully connected layer, W
Fully connected layer, W
Output layer, 1



average relative error of energy estimates
triangles — monoscopic mode, double triangles — stereoscopic mode

We compared several methods of preprocessing the input data and combining the input images (12 possible combinations) for 8 neural network architectures but found that they have statistically significant but very small effect on neural network performance, each method accounting for 0.1%-0.2% difference in average relative error. For the best combination of these methods and the neural network, the average relative error was 24.0% in monoscopic mode with only the image from the first telescope used, and 12.5% in telescopic mode.

We also estimated the energy of gamma events from the S1 dataset (energy between 1 and 45 TeV) using three different neural networks. The best results for average relative error were 20.8% in monoscopic mode and 15.5% in stereoscopic mode.
In all cases the neural networks were trained on 80% of the dataset and tested on the remaining 20%, and the results were averaged between 10 iterations.

Conclusion

We applied convolutional neural networks to the problems of particle type identification and gamma ray energy estimation based on IACT images in stereoscopic mode. We found that adding an image from a second telescope as input to the same neural network can increase the cosmic ray background suppression by a factor of 4-5, and decrease the average relative error of the energy estimates by a factor of 1.3-2.

References:

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