Deep Learning Method for Determining EAS Parameters in TAIGA HiSCORE

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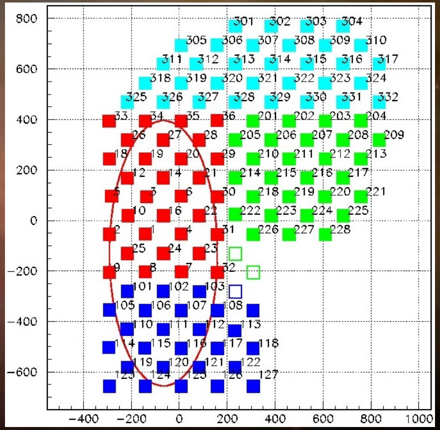
Problem

- The TAIGA-HiSCORE installation is an array of wide-angle Cherenkov detectors. It contains about 120 stations located in the Tunka Valley. The effective area of the TAIGA-HiSCORE is about 1 sq. km. The HiSCORE is designed to register cosmic particles and gamma rays with TeV energies.
- Each station records a large amount of data, including the signal arrival time and its amplitude. Primary data analysis includes the reconstruction of EAS parameters. These are the EAS axis direction, the type of primary particle, and its energy. We present the preliminary results of application of the deep learning method to reconstruct the EAS parameters registered by HiSCORE.

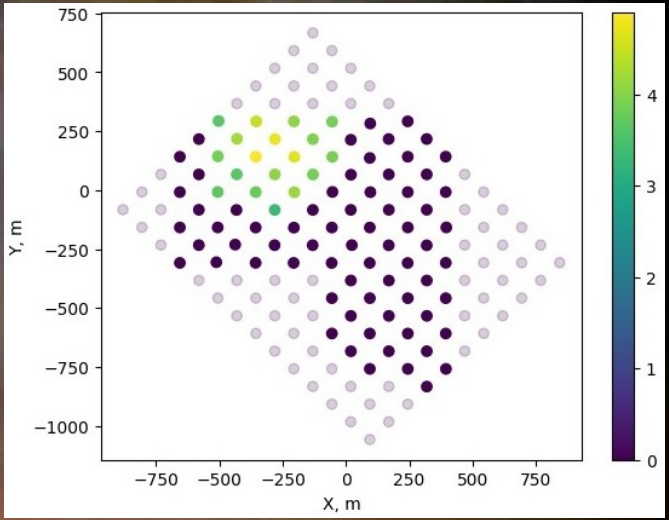


Approaches

- Using the example of determining the EAS axis direction, we will consider two approaches based on deep neural networks.
  - The first approach is based on representing a set of time stamps for signal arrival as an image and processing such data using convolutional neural networks.
  - The second approach uses fully connected deep neural networks to solve the regression problem based on time stamps.

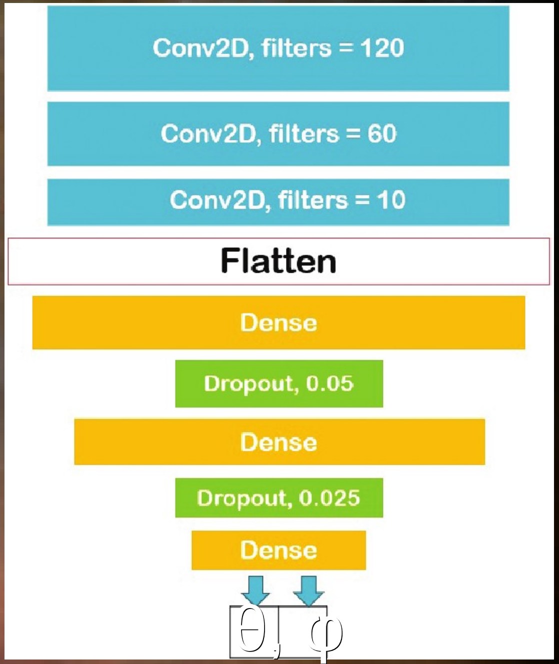
Convolutional neural network

- The HiSCORE event is presented as an image, where Cherenkov stations are considered as pixels of this image. Each pixel is assigned the values of the signal arrival time and its amplitude.
- As a labeled array for training and validating the CNN, we used the data on the EAS axis parameters provided by V. Prosin's group, obtained by the conventional method.
- To transform the grid into a Cartesian grid, we used an oblique coordinate system and added virtual stations at free points with zero values.



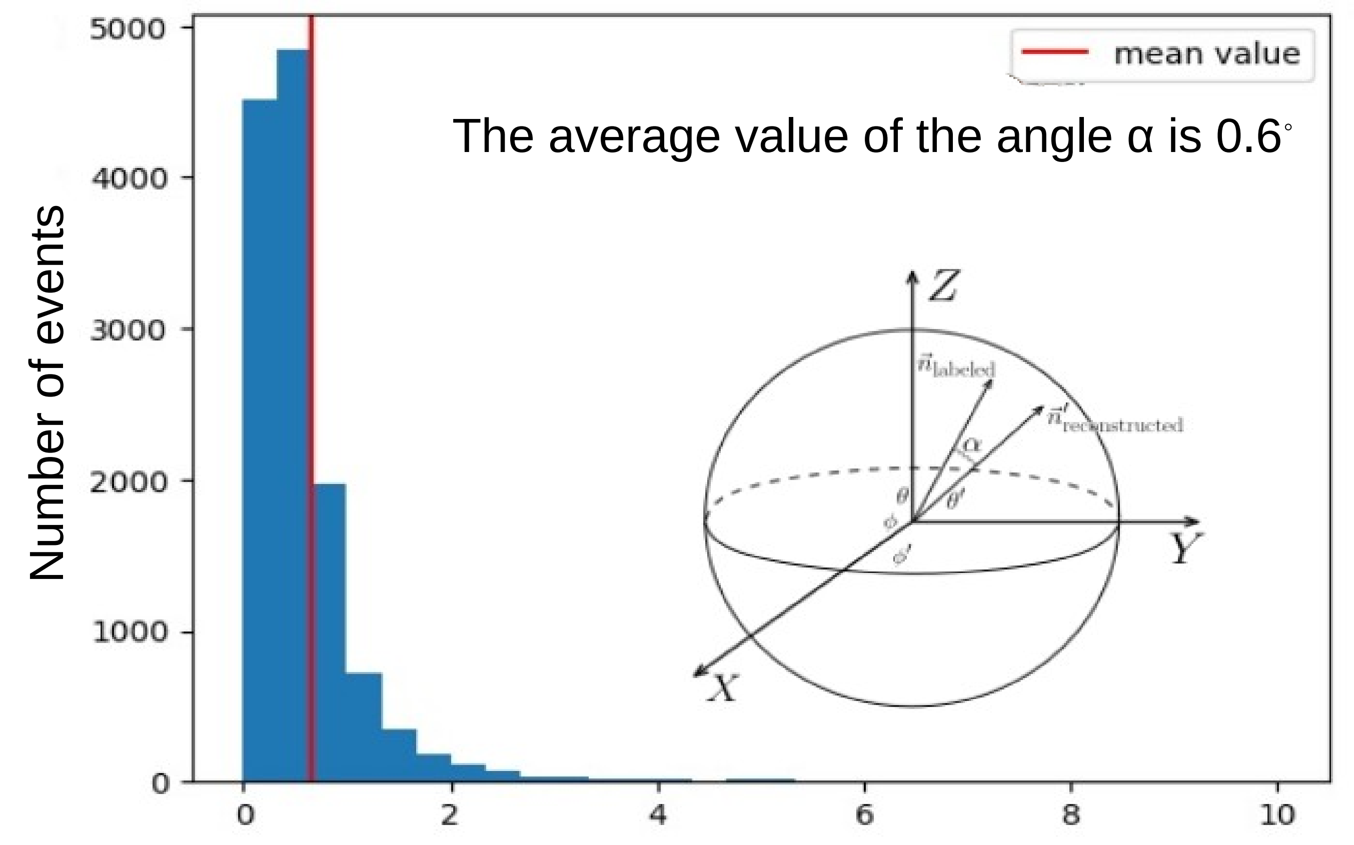
Convolutional neural network

- The data array passes through three convolutional layers with a sequential decrease in the number of filters. The number of filters in each layer is 120, 60 and 10, respectively. The convolution kernel sizes are (3,3).
- To prevent overfitting, the model uses dropout regularization. The probability of switching off a random neuron is 5% in the first fully connected layer and 2.5% in the second. To improve accuracy and avoid overfitting, the learning rate is automatically reduced when a plateau in the accuracy of neural network predictions is reached.



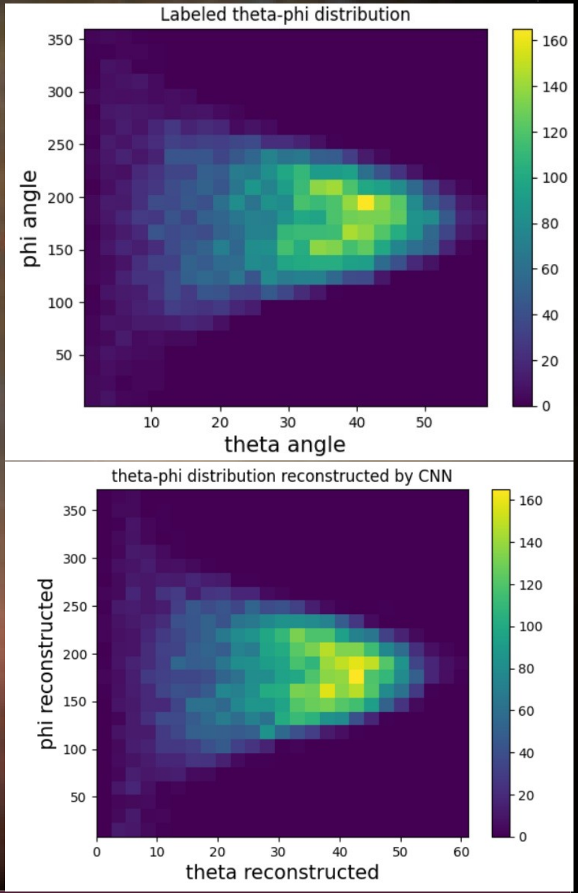
Convolutional neural network

- Deviation of the direction determined by the CNN from the direction determined by the conventional algorithm



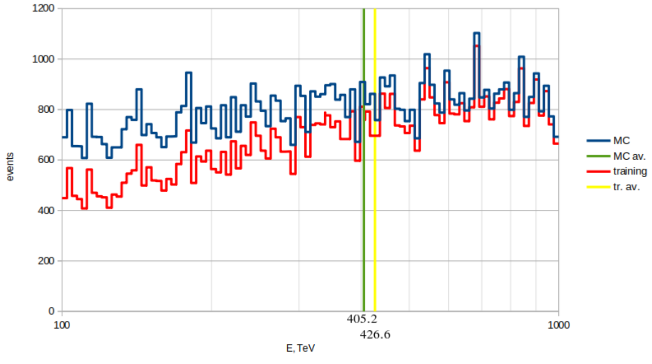
Convolutional neural network

- Distributions of TAIGA HiSCORE events by angle values φ and θ. The distribution by labeled data is shown on the top, and the distribution reconstructed is shown on the botton.
- Both histogram show similar distributions, indicating that the neural network successfully reconstructed the angle distribution. The peaks in frequency of occurrence (the brighter areas) match in location and shape in both histogram, indicating rather good accuracy of reconstruction.



Full connected neural network

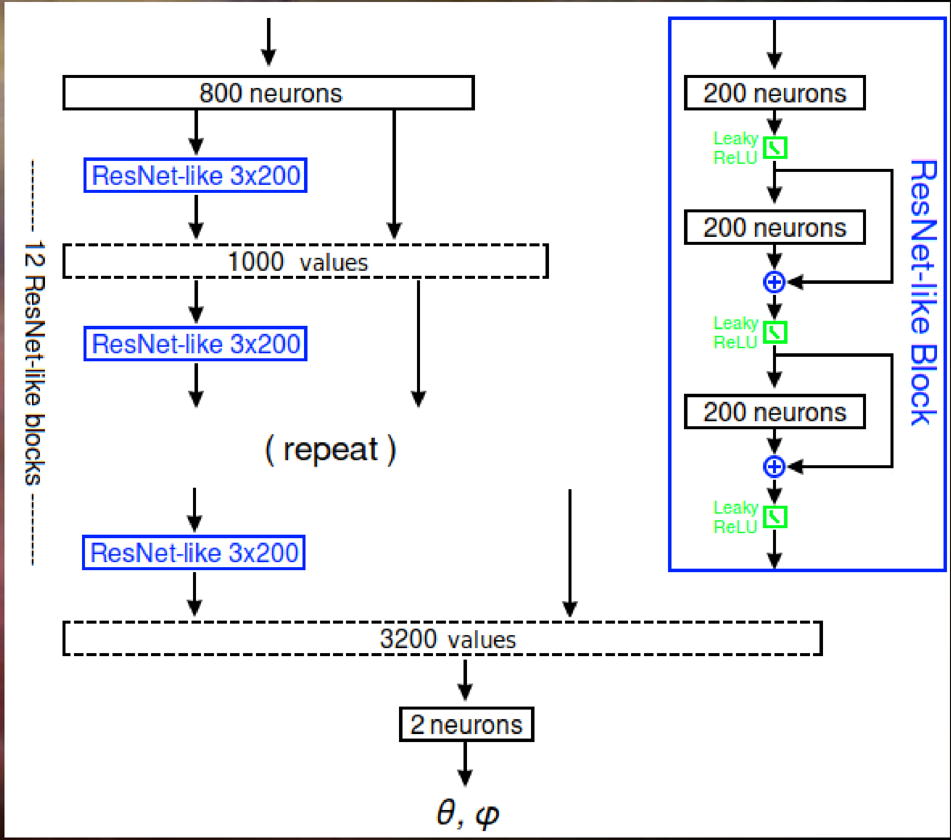
- The neural networks were trained using HiSCORE data simulated by the Monte Carlo method. We considered only gamma events. Events with less than 10 triggered stations and less than 100 photoelectrons were excluded. The zenith angles θ of the simulated EAS axes are in the range from 30° to 40°, and the azimuth angles φ are in the range from –60° to 60°.



- To determine the direction of the EAS, data from a fixed number K of HiSCORE stations are fed to the input of a fully connected neural network. The time of signal registration by the station, the signal amplitude, and the coordinates of the station are used as input data. The stations are selected randomly from among those that registered a signal above the threshold level, after which they are ordered by time. The first of the selected stations is taken as the reference point.

Full connected neural network

- We use a two-stage algorithm. At each stage we use a separate neural network. For each EAS, several estimations of the axis direction are calculated and based on them, a composite estimation of the EAS direction is calculated.
- The first neural network uses K=8 stations in the set. The fully connected neural network has 37 hidden layers. To prevent the problem of vanishing gradients, networks of the DenseNet and ResNet types are used.
- Two output values correspond to the azimuth and zenith angles θ and φ.

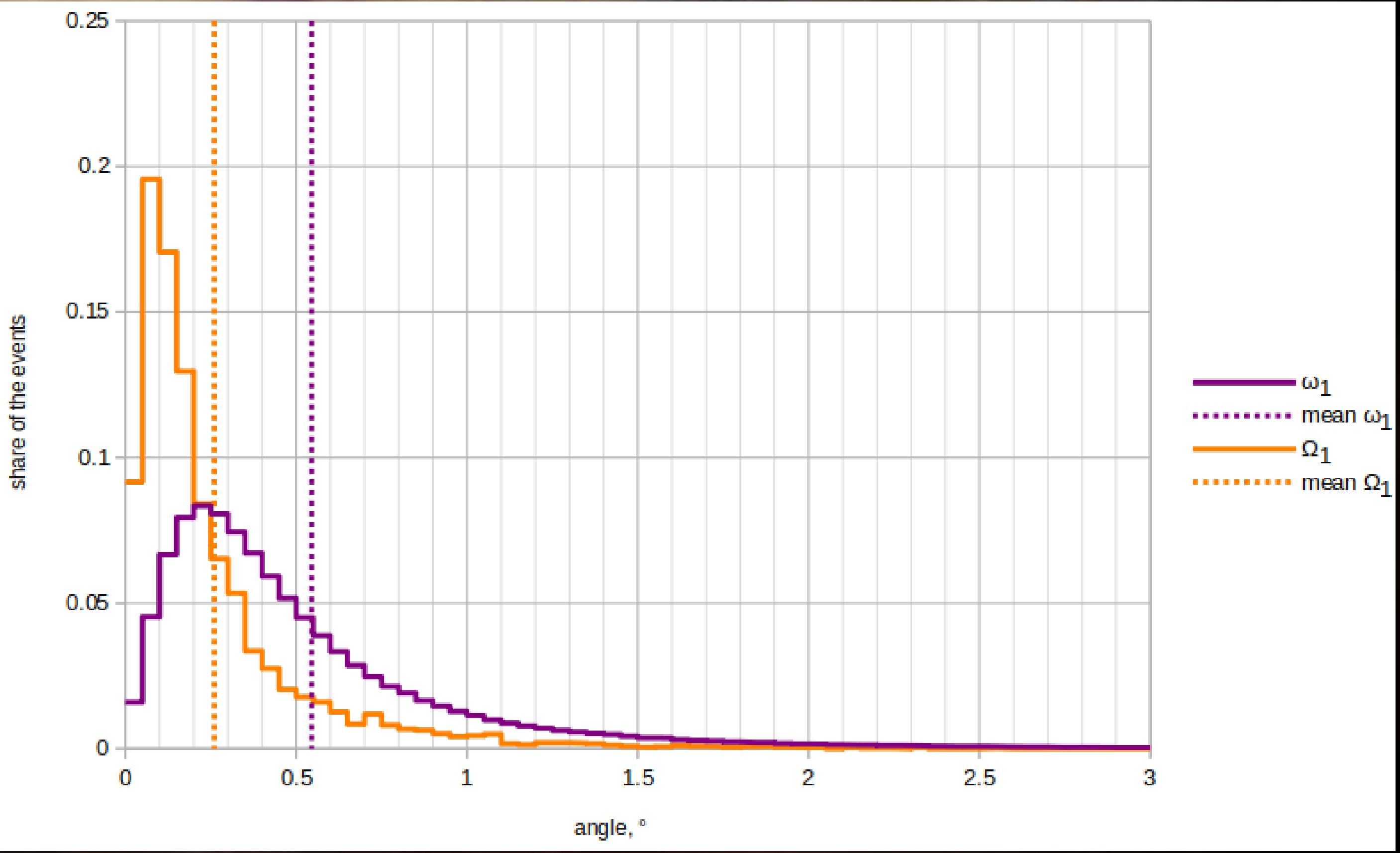


FCNN. 1st stage

- The first neural network was trained for 330 epochs on 4 million input vectors were constructed from 68256 events of the training sample.
- Sin(2ω) was used as the loss function, where ω is the angle between the direction of the EAS axis (θ_0, φ_0) and the direction determined by the network (θ, φ).
- To obtain more accurate estimates of the EAS direction, a large number of eights of stations were selected for the test sample (120 for all events with at least 11 triggered stations), separate estimates were constructed for them, and the final estimate (θ_1, φ_1) for each event was calculated as a weighted median of the estimates of θ and φ for individual eights.

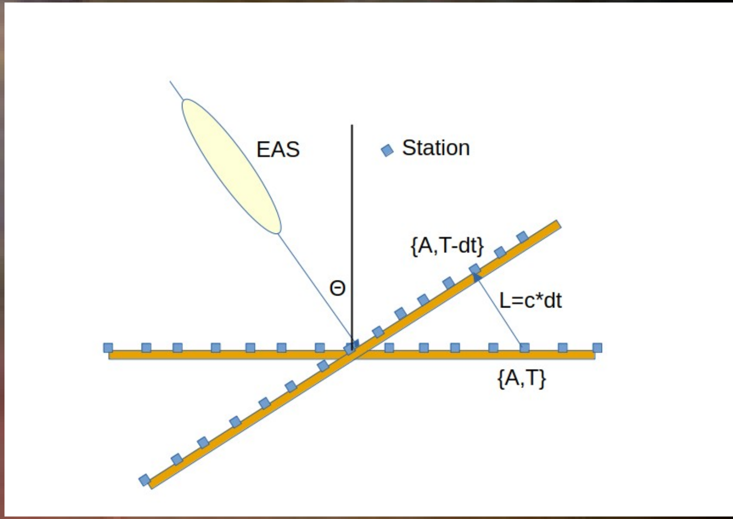
FCNN. 1st stage

- Distribution of errors ω_1 of first-stage estimates for individual eights and errors Ω_1 of composite estimates. Average values: $\langle\omega_1\rangle = 0.546°$, $\langle\Omega_1\rangle = 0.26°$.



FCNN. 2nd stage

- The obtained direction estimates can be refined. To do this, the coordinates of the stations are projected onto a plane perpendicular to the found direction of the shower axis (θ_1, φ_1), and the signal arrival time for the projected stations is recalculated. The second neural network is trained to estimate the necessary corrections to (θ_1, φ_1) based on the data from the projected stations.
- The neural network for refining estimates has an architecture similar to the first neural network, but has 46 input values (using tens of stations instead of eight), 61 hidden layers. The two output values are interpreted as corrections $\Delta\theta$ and $\Delta\varphi$ to the corresponding angles.



FCNN. 2nd stage

- For the training sample of the second network, the directions (θ_1, φ_1) of the normal vectors to the projection plane were chosen randomly, which allowed us to create a training sample of about 42.4 million tens from the same 68,256 events. The neural network was trained for 45 epochs with the loss function

$$(\Delta\theta)^2 + \sin^2\theta_1 \, (\Delta\varphi)^2.$$

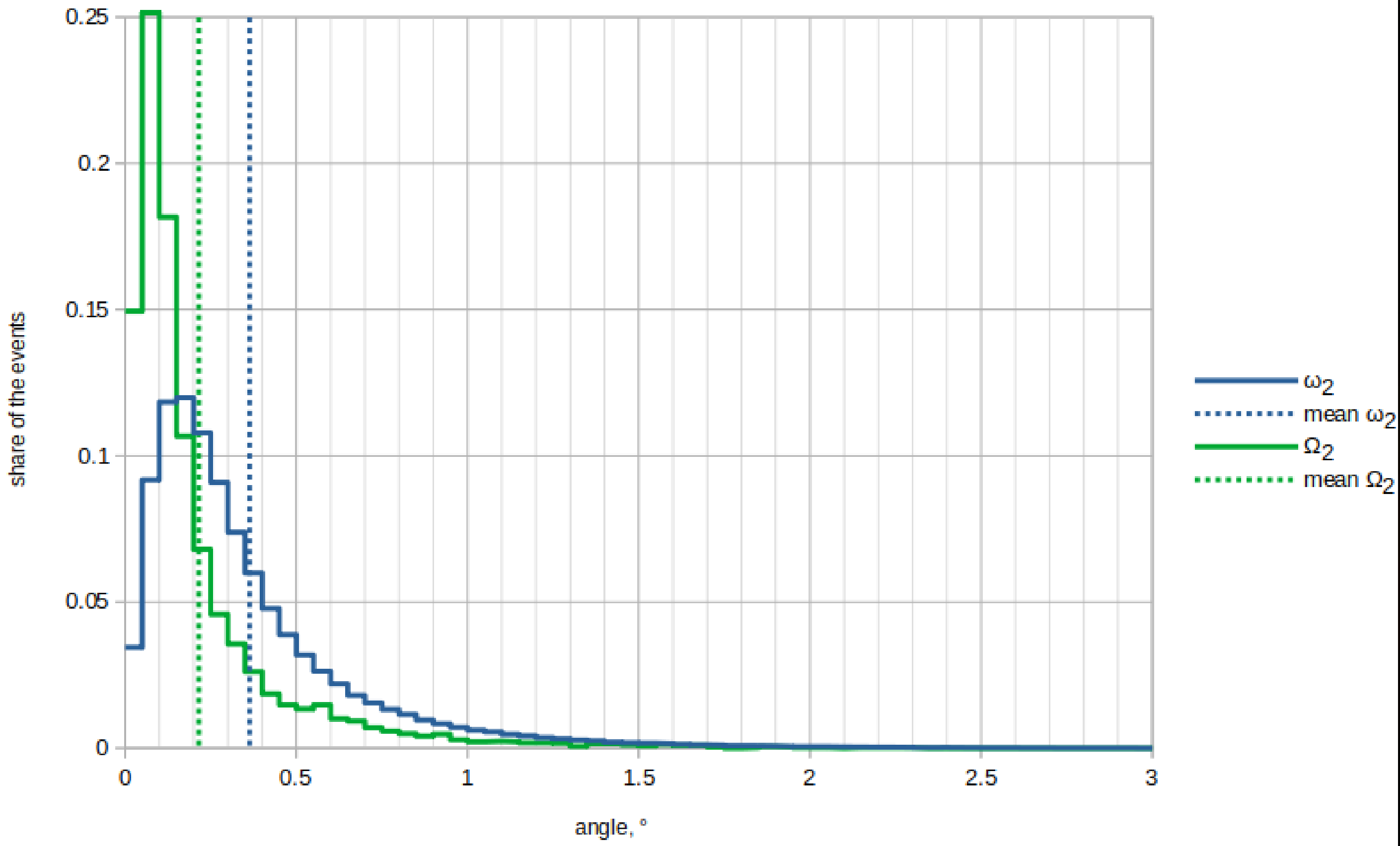
- For the events of the test sample, the directions determined by the first neural network were used as (θ_1, φ_1). For the first neural network, a large number of tens of stations were selected (100 or all possible subsets if there are fewer than 100) and the final corrections ($\Delta\theta_2$, $\Delta\varphi_2$) were calculated as weighted medians of the corrections for individual tens.

FCNN. 2nd stage

- The angles Ω_1 between the EAS axis directions (θ_0, φ_0) and the median directions (θ_1, φ_1) obtained by the first neural network have a mean value of 0.401°, a root mean square value of 0.574°, and a median of 0.265°. The angles Ω_2 between the EAS axis directions and the directions obtained by the two neural networks ($\theta_1+\Delta\theta_2$, $\varphi_1+\Delta\varphi_2$) have a mean value of 0.284°, a root mean square value of 0.437°, and a median of 0.168°.

FCNN. 2nd stage

- Distribution of errors ω_2 of the second stage corrections by individual tens and final errors Ω_2. Average values: $\langle\omega_2\rangle = 0.364°$, $\langle\Omega_2\rangle = 0.215°$.



Conclusion

- The convolutional neural network method allowed us to determine the EAS direction with an accuracy of 0.6 spherical degrees. Note that the data from the TAIGA experiment analysis group were used as the true direction, which in themselves have an error of 0.15-0.2 degrees. A further increase in the accuracy of this method is possible by optimizing the network structure, as well as by using an additional network at the second stage by analogy with the method used in the case of fully connected neural networks.
- The possibility of using fully connected neural networks to obtain direction estimates of extensive air showers from the HiSCORE ground-based wide-angle detector array is demonstrated. The obtained accuracy is comparable to the results of conventional methods. The average direction determination error is about 0.26° when using a single neural network and about 0.215° when using a two-stage algorithm with two neural networks.

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Thank you!

Any questions?