A neural network based UHE neutrino reconstruction method for the Askaryan Radio Array (ARA)

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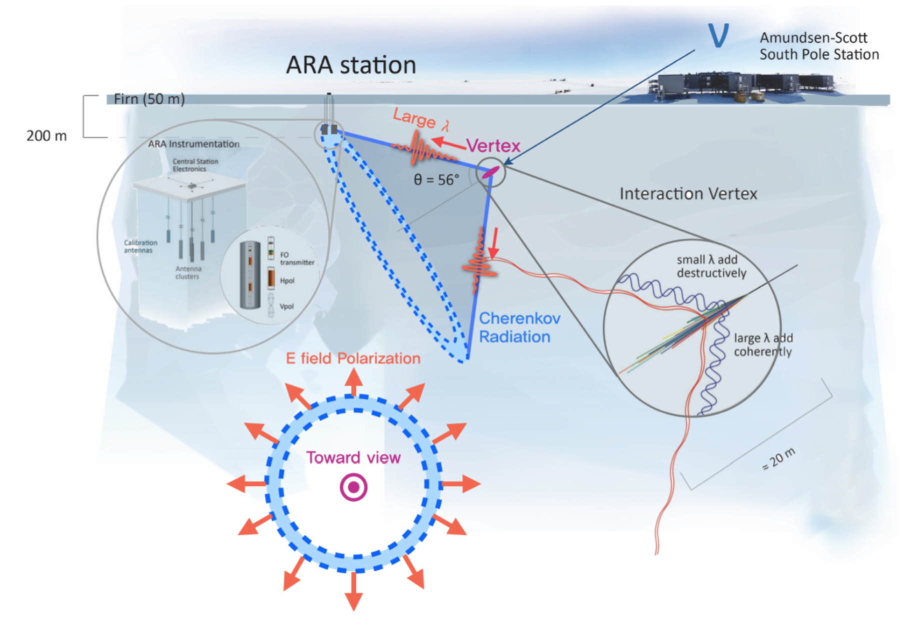
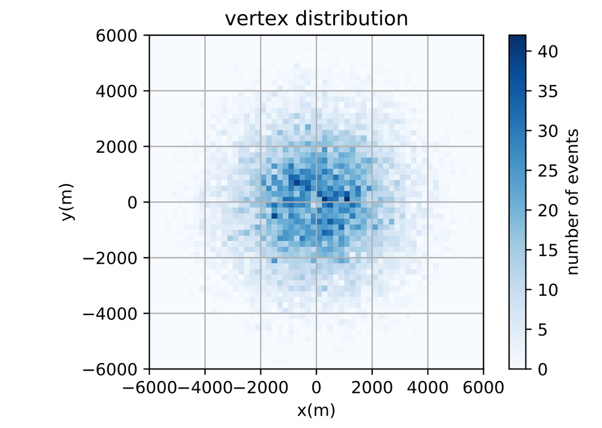
INTRODUCTION

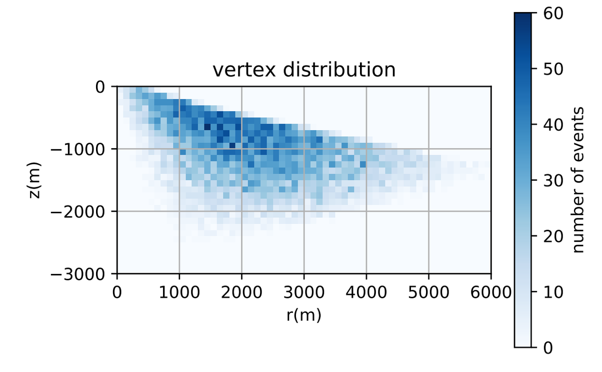


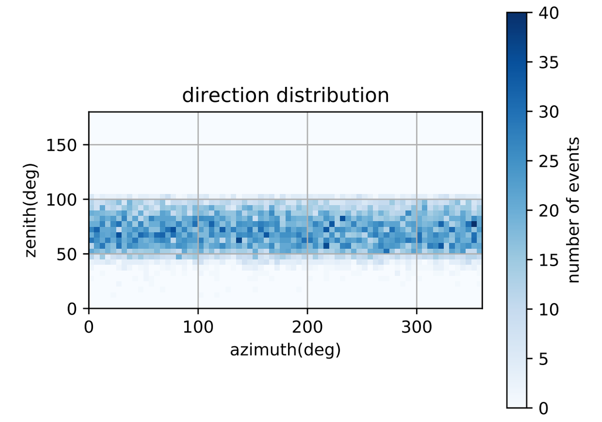
Neutrino radio detection by an ARA station.

- A multi-task convolutional neural network is developed to reconstruct both neutrino vertex and direction.
- The Askaryan Radio Array (ARA) is an UHE neutrino detector. An ARA station has 4 strings each with 4 measurement antennas. Details of the station configuration and performance can be found in [1] [2].
- When a neutrino interacts in ice, a cascade of electrons and positrons is created. This relativistic "spark" generates a radio frequency pulse via the Askaryan effect [3], which can be detected by the ARA station.
- Relative timing is important for vertex reconstruction, and relative amplitudes are important for neutrino direction reconstruction.
- The data set is generated with a Monte Carlo simulation tool for UHE neutrino experiments, NuRadioMC [4] [5]. A2 configuration is used in simulation.

DATA

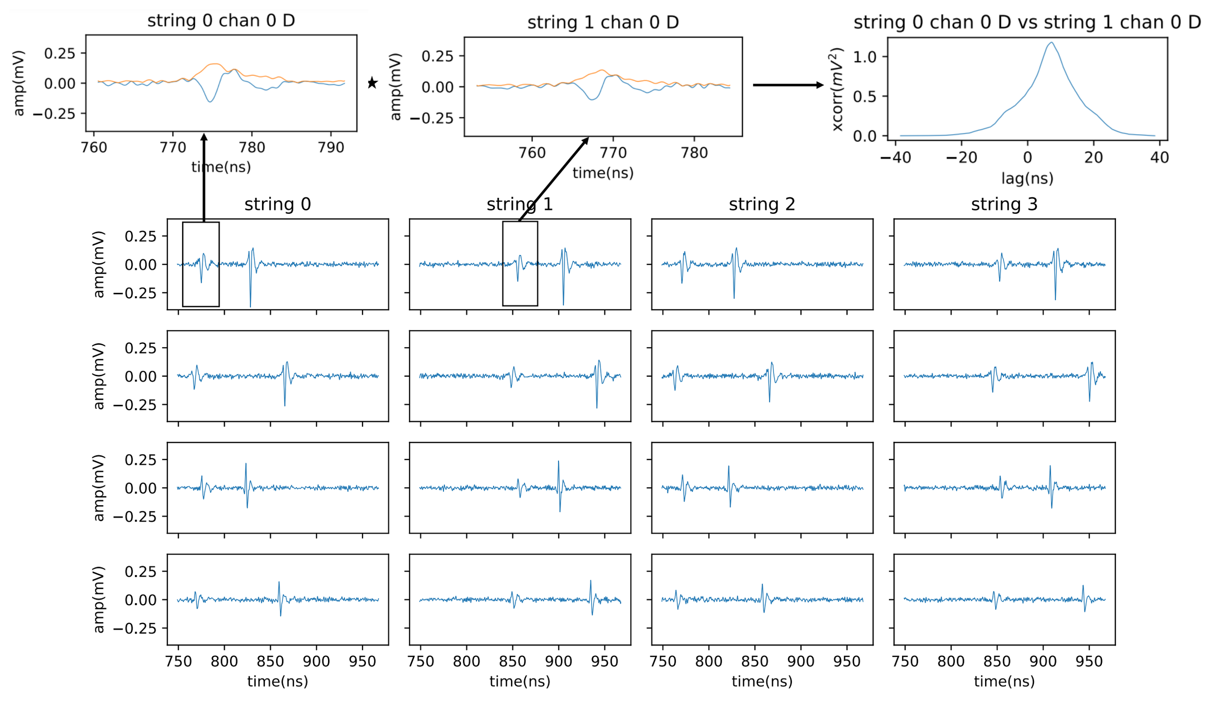






Triggered events from a simulation of ARA station 02 by NuRadioMC. The events are at $10^{18.5}$ eV.

- Simulations are produced run by run by throwing 100k events with a energy spectrum starting from $10^{16.5}$ eV to 10^{20} eV with a step of $10^{0.5}$.
- Triggered events are symmetrically distributed in azimuth and within a certain distance due to ice attenuation.
- There is a shadow line above which no event can illuminate the detector due to ice refraction.
- Only those neutrinos coming in a specific zenith range can trigger the station due to Earth absorption and the Cherenkov angle restriction [3].

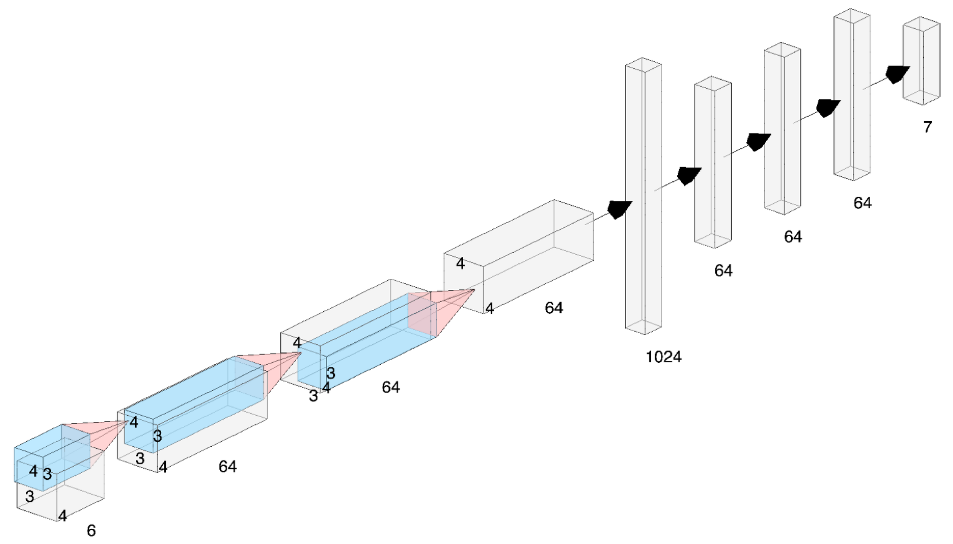


Waveforms from a $10^{18.5}$ eV neutrino event at 1768 m from the detector.

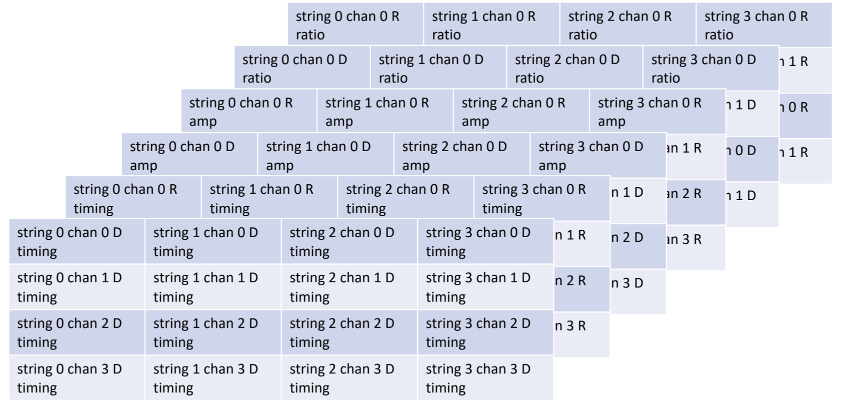
- Each antenna records either 0 or 2 pulses [6]. In the case of 2 pulses, the first is called the direct pulse (D) and the second the refracted/reflected pulse (R).
- A 31.25 ns window around each pulse is taken according to true simulation information at this stage, and a corresponding Hilbert envelope is calculated.
- An integral of the envelope within each window multiplied by the +/- sign of the simulated polarized electric field is supplied as a feature to improve reconstruction of the neutrino direction.
- The incoming time from all the pulses are calculated relative to channel 0 D pulse by cross correlation with the channel 0 D waveform.
- With a full data set of about 274k events in 320 runs, those events with missing signals in any of the channels are excluded. After cleaning, more than 243k events remain.
- The cleaned data set is then split into 90%, 5%, 5% for training, validation and test.

METHOD

- The architecture of the network is inspired by the work in IceCube [7].
- The first part consists of convolutional layers with 3×3 kernels to learn hidden characteristics and handle the high dimensional nature of the input features.
- The second half includes only dense layers after flattening the 3d intermediate output from the first part.
- The input layer is a (4, 4, 6) matrix combining timing, amplitude and ratio of amplitudes from HPol and VPol antenna pairs to reflect the detector configuration.
- The output is a vector of length 7 to predict both neutrino vertex and neutrino direction.



A diagram of the optimized network architecture.

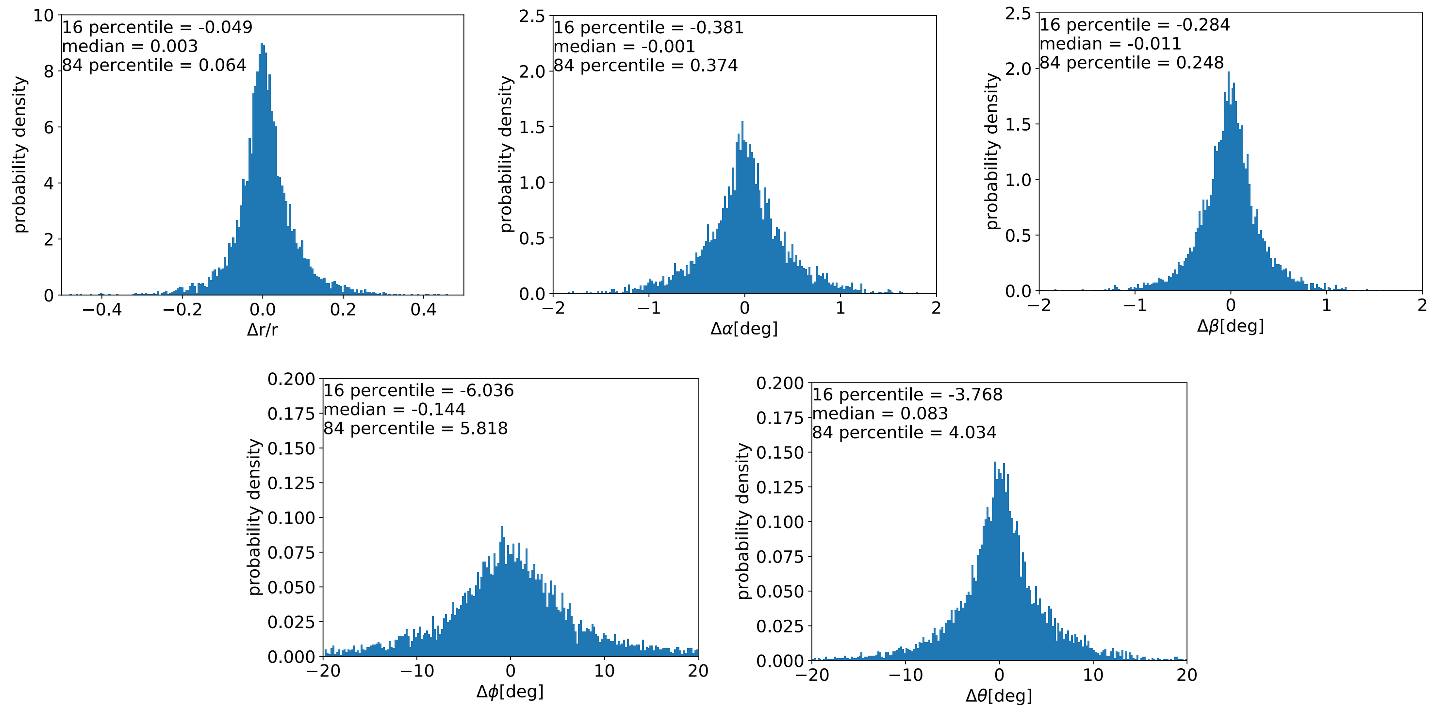


The input feature structure.

Label	Explanation	Loss
r	Horizontal distance from the station center to a vertex	MSPE
$\sin\alpha, \cos\alpha$	Azimuth angle from the station center to a vertex	MSE
β	Zenith angle from the station center to a vertex	MSE
$\sin\phi, \cos\phi$	Azimuth angle pointing back to where a neutrino comes from	MSE
θ	Zenith angle pointing back to where a neutrino comes from	MSE

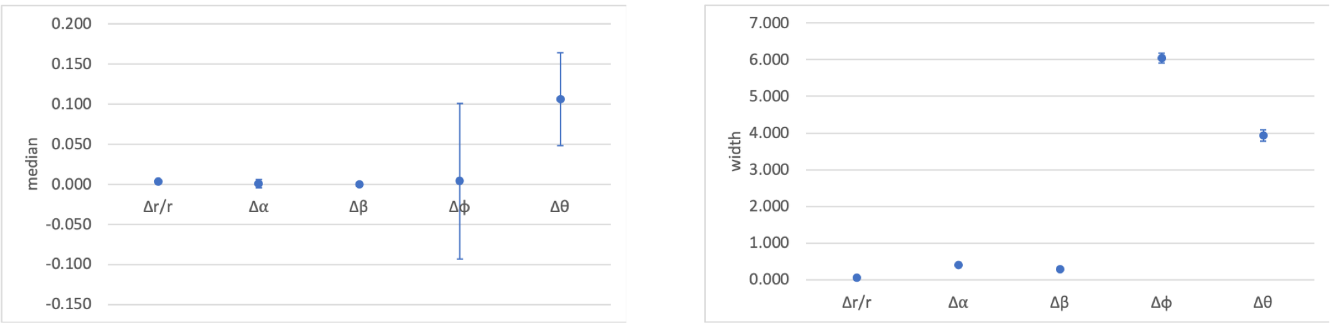
A description of outputs.

RESULTS



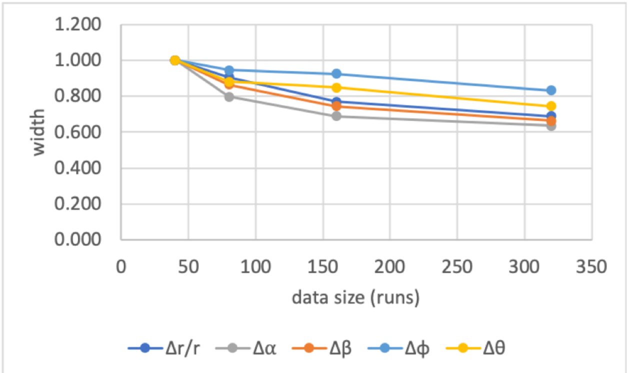
The error distribution.

- After training a neural network, its performance is estimated by applying it to the 5% test data set.
- The width of an error distribution σ is calculated as half of the difference between the 84 percentile and the 16 percentile to measure the reconstruction accuracy of the middle 68% events. The median of the error distribution m is the 50 percentile.
- All the distributions are centered around zero, suggesting there is no systematic offset.
- The use of true information for timing seed and polarity requires further investigation.
- The wider error distributions of neutrino direction reconstruction may be due to lack of frequency information.



Median m and width σ from 10 fold cross validation.

- 10 fold cross validation is applied to test model generalization.
- All medians' being around 0 shows there's no systematic.
- Short error bars suggest the the model is stable in terms of training and testing on different data sets.



Width σ from a set of models trained with 40, 80, 160, 320 runs.

- A set of network models is trained with 40, 80, 160 and 320 runs to study the relationship between data size and performance.
- The results in are normalized according to the performance of the model with 40 runs.
- Having more data can potentially lower σ.

- A grid search is applied in a limited hyper-parameter space of number of nodes, number of layers and batch size to optimize the network.
- The network architecture and all the results shown above are based on the optimized neural network.

SUMMARY AND OUTLOOK

- The multi-task convolutional neural network can give a stable and precise reconstruction result for both neutrino vertex and neutrino direction.
- Extracting timing and amplitude features from waveforms can be done by another neural network.
- Adding frequency features should be investigated.
- The model can be generalized to other station configurations to study reconstruction, e.g. IceCube-Gen2 [8].
- The model should be applied to real data set for test.

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