IceCube High-Energy Neutrino Cascade Alerts

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1 Motivation

The IceCube neutrino observatory [1] has proven the existence of an astrophysical neutrino flux with the observation of isotropically distributed high-energy neutrinos [2, 3, 4]. More recently, IceCube has found evidence for the first likely astrophysical neutrino source, the blazar TXS 0506+056 [5, 6]. This was made possible thanks to the realtime alerts of IceCube high-energy tracks sent to the community which allowed rapid followup of the blazar in the electromagnetic bands.

First IceCube realtime alerts have been high-energy tracks [7] as they offer a good angular resolution and a fast event reconstruction. However, the high-energy cascade reconstruction has recently been improved by the use of a neural network allowing a reconstruction near realtime with an improved resolution. The event selection is also improved by the use of a second neural network allowing a high signalness.

A first neural network is used for the event classification [8], selecting cascade events contained inside of the detector. It allows to better reject tracks, therefore reducing the amount of atmospheric muons and neutrinos. This selection applied on the high-energy starting event sample leads to a very high astrophysical purity, larger than 85%.

The second neural network is used for the event reconstruction [9], allowing to reconstruct the direction and energy of an event with an estimation of the uncertainty on these parameters. This neural network reconstruction takes a few seconds to run instead of about a day for the previous reconstruction [10], allowing to reconstruct cascades in realtime. This results in 50% of the events having an angular resolution better than 7°, including systematics.

2 Event selection

For this alert stream, cascade events of the High Energy Starting Events (HESE) sample are considered. The HESE sample is made of high-energy events whose interaction vertex is well contained in the instrumented volume in order to use the external part of the detector as a veto to reject atmospheric muons. From this sample we select cascade events using a deep neural network (DNN) classifier.

This classifier takes a four-dimensional input grid with three dimensions of space, one optical module corresponding to one pixel of the grid, and the fourth dimension being the features dimension as detailed in [8]. 15 features are used:

- Total charge and charge after 10 ns, 50 ns, 100 ns [PE]

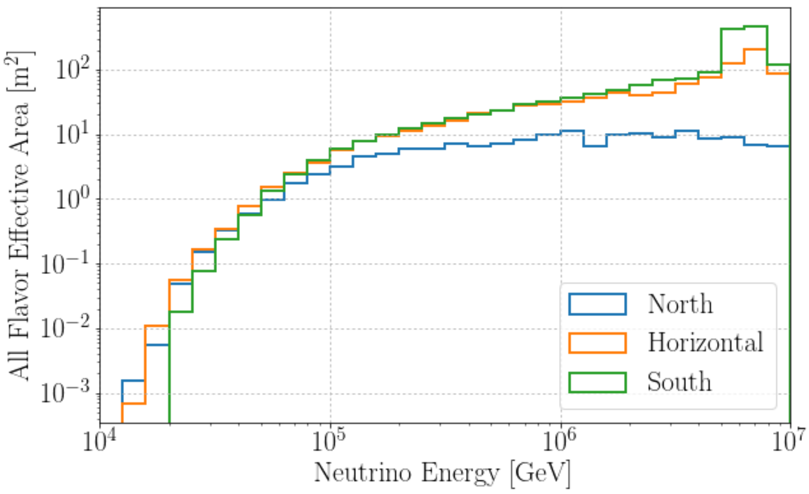

Figure 1 – All flavour neutrino effective area as function of the neutrino energy in three bands of cos(zenith) corresponding to [-1,-$\frac{1}{3}$], [-$\frac{1}{3}$,$\frac{1}{3}$] and [$\frac{1}{3}$,1].

- Time of the first hit, time spread, standard deviation of time [ns]
- Time after which 1%, 3%, 5%, 11%, 15%, 20%, 50%, 80% of the charge has been collected [ns]

This event selection rejects muons and most of the atmospheric neutrinos, leading to a total of 7.9 evts/yr with 86% of them having an astrophysical origin as can be seen in Table 1. Applying this selection on 7 years of data from 2011 to 2017 resulted on an average of 8.1±1.0 evts/yr matching the Monte Carlo simulation predictions. The neutrino effective areas for this selection is shown on Figure 1 for three different bins of zenith.

The event selection does not include a cut on the angular resolution as different follow-up observatories require different resolutions. However, given the angular uncertainty estimator, observers will be able to select those events that best fit their instrument capabilities.

3 Event reconstruction

Up to now the cascade event reconstruction relied on a search for best match of re-simulated events, taking nearly a day to run. In this work, a recently developed deep neural network reconstruction is used offering an improved angular resolution and taking only seconds to run. A previous version of this DNN reconstruction has already been used and described in [9] on medium energy cascade events, leading to increased sensitivity to diffuse or point source signals. The DNN will be described in more details in a dedicated publication, only the essentials will be summarized here.

Similarly to the DNN classifier, the input of the DNN reconstruction consists of a three-dimensional grid approximating the detector, each node of the grid representing an optical module, as well as two other grids for the lower and upper parts of DeepCore. These grids have a forth dimension containing the time and charge information for each optical module. More precisely, it contains 9 features:

- the relative arrival time of the first pulse, the time elapsed until 20%, 50% and 100% of the total charge is collected

Table 1 – Number of astrophysical and atmospheric events per year passing the selection cut and their proportion in the sample. The total is given for the Monte Carlo sample and 7 years of data from 2011 to 2017.

		Number of events/year	Proportion
Astrophysical	Cascades	6.7	85%
	Tracks	0.1	1%
	Total	6.8	86%
Atmospheric	Neutrinos	1.1	14%
	Muons	0.0	0.0%
Total Monte Carlo		7.9	100%
Data		8.1±1.0	

- the charge collected during the 100 ns and 500 ns after the first pulse as well as the total charge
- the charge-weighted mean and standard deviation of relative pulse arrival time.

The DNN outputs not only the direction and energy of the incoming neutrino but also the uncertainty on these parameters. In order to account for systematic uncertainties, the training is done on a mix of the baseline Monte Carlo simulation and all systematic datasets.

Figure 2 shows the opening angle between the reconstructed and the Monte Carlo directions in function of the 1σ angular error estimated by the DNN, the 50%, 68% and 90% quantiles are shown. Figure 3 is a projection of Figure 2 along the X axis. Including systematics, 50% of events have an angular error lower than 7° and 68% lower than 9°.

On Figure 2 and 3 the circularized error is used, however the DNN allows us to compute more sophisticated error contours which can be asymmetrical but are nevertheless usually elliptical as can be seen on Figure 4.

4 Description of event contents

The GCN Notice will contain several information about the event, allowing follow-up observers to select the events they are interested in.

- Time and date in Universal Time to 0.01 second precision.
- Stream number, which is 26 for the IceCube cascade stream.
- The IceCube Run number and event number - used as a unique ID within the IceCube collaboration.
- Direction (Right Ascension and Declination) in several epochs (J2000, current and 1950) with 50% and 90% containment angular error radii, corresponding to a circularized error.

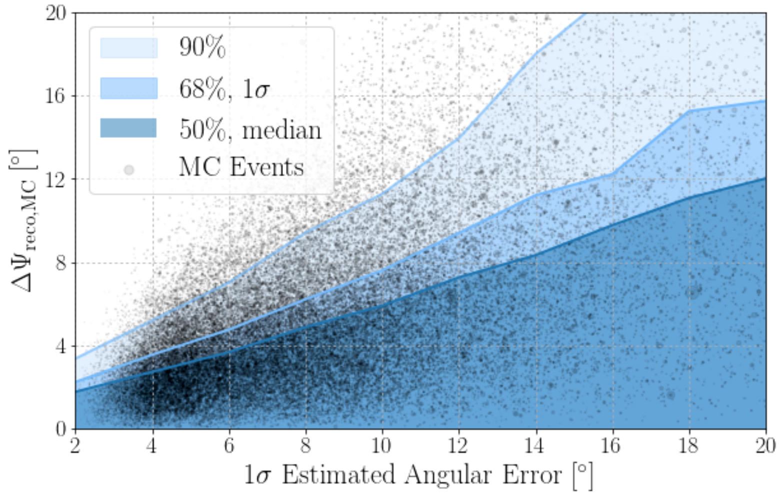

Figure 2 – Opening angle $\Delta\Psi$ between the reconstructed and Monte Carlo directions in function of the circularized 1σ (68%) error estimated by the deep neural network reconstruction. The 1σ estimated error is larger than the 68% quantile of the opening angle because systematic uncertainties are not included in the opening angle while they are in the estimated angular error.

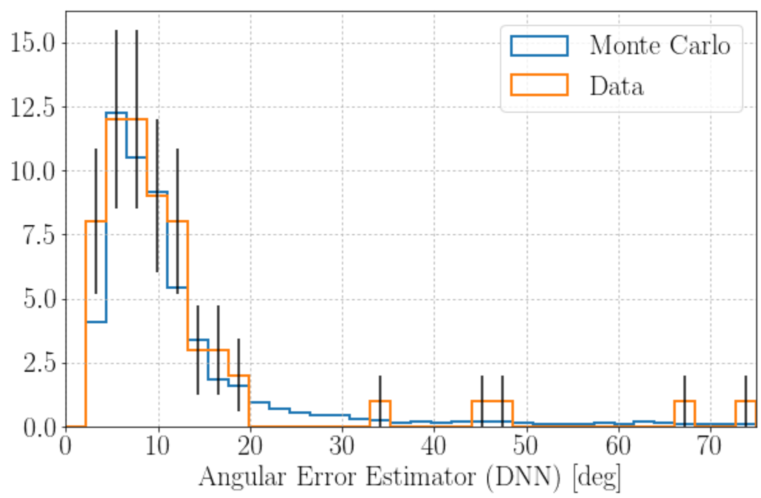

Figure 3 – Circularized 1σ (68%) error estimated by the deep neural network reconstruction for baseline Monte Carlo simulation and Data.

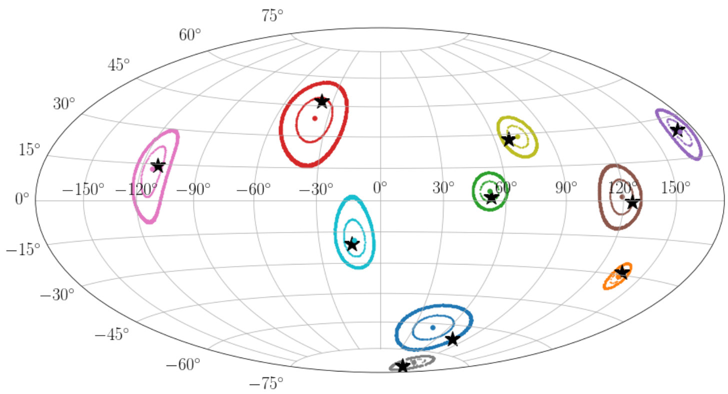

Figure 4 – Contours of the 50% and 90% containment regions of ten Monte Carlo events, each event in a different color. The best fit directions are represented by dots and the true directions by black stars.

- URL of the FITS file containing the probability density of the neutrino source direction and URL of the PNG image illustrating the content of the FITS file, Figure 5 is an example of such PNG file. More details on the FITS files and how to read them are given in section 4.1.
- Signalness - probability that an event with that reconstructed energy or higher is an astrophysical event accounting for three bins of zenith. The signalness is shown in Figure 6. There are uncertainties on the signalness, therefore in order to be conservative it will be capped at 0.90, the alert message will remain "0.9" if it is higher.
- False Alarm Rate (FAR) - rate of background events per year expected to have that reconstructed energy or higher. The false alarm rate is shown in Figure 7. In order to be conservative only the false alarm rate larger than 0.311 per year will be given, this corresponds to a signalness of 90%, the alert message will contain the information "0.311 [yr^-1]" for lower values.
- Energy of the incoming neutrino reconstructed by the deep neural network reconstruction.

As can be seen in Figures 6 and 7, events from the southern sky have a larger signalness as atmospheric neutrinos can be rejected. Indeed, cosmic ray air showers produce both atmospheric neutrinos and muons, therefore neutrinos arriving at the same time as muons can be rejected to be of likely atmospheric origin. Additionally, the number of astrophysical cascades is lower in the northern sky as the Earth is not transparent to high-energy events. For these reasons the signalness is split into three curves corresponding to three bins in zenith as can be seen in Figure 6. Statistically, the events with the highest energy and signalness will also have a better angular resolution.

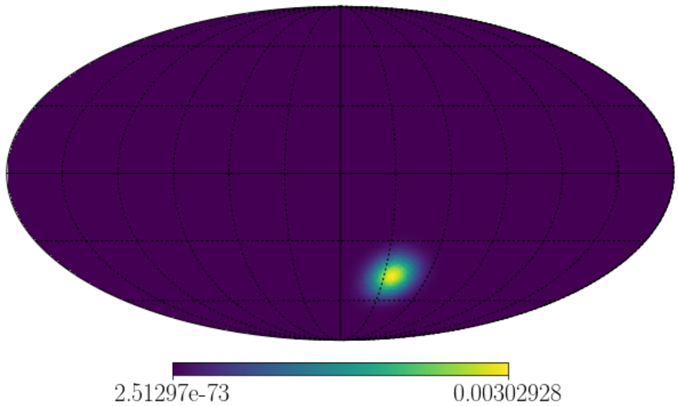

Figure 5 – Image of the content of a typical FITS file containing the probability density of the neutrino source direction. Each pixel contains the probability that the source lies in that pixel.

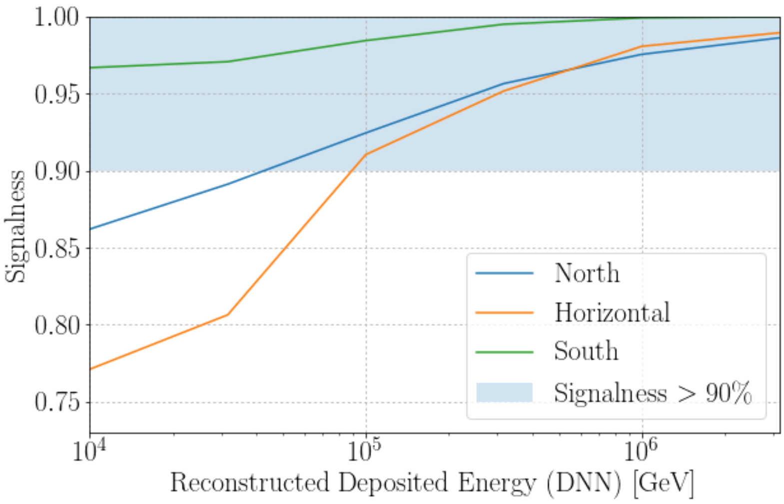

Figure 6 – Signalness in function of the reconstructed energy for events coming from three bands of cos(zenith) corresponding to [-1,-$\frac{1}{3}$], [-$\frac{1}{3}$,$\frac{1}{3}$] and [$\frac{1}{3}$,1]. The alert will not give values higher than 90%.

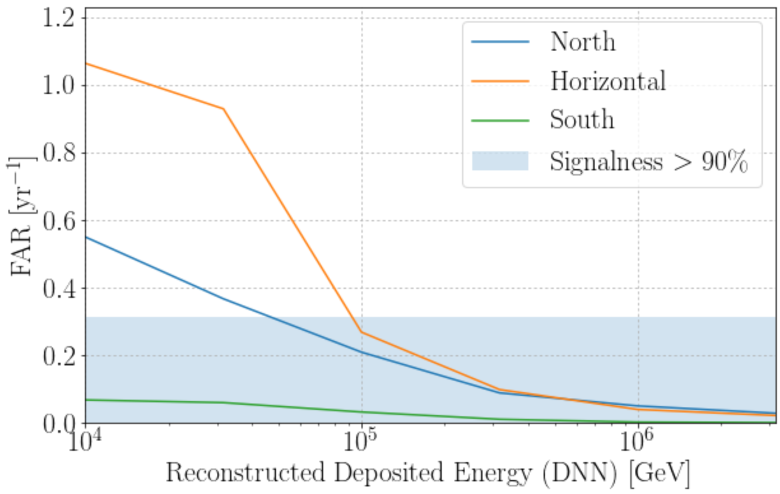

Figure 7 – False alarm rate in function of the reconstructed energy for events coming from in three bands of cos(zenith) corresponding to [-1,-$\frac{1}{3}$], [-$\frac{1}{3}$,$\frac{1}{3}$] and [$\frac{1}{3}$,1]. The alert will not give values lower than 0.311.

4.1 FITS files

The header of the FITS files contains the summary information for each event, including:

- RUNID, EVENTID: Unique identifiers from the IceCube data acquisition system.
- SENDER: "IceCube Collaboration".
- START: YYYY-MM-DD HH:MM:SS.SSSS representing the event time in UTC.
- EVENTMJD: decimal representation of the event time in MJD.
- I3TYPE: "hese-cascade". Internal event stream that identified the event.
- RA/DEC (CIRC_ERR90, CIRC_ERR50): Best fit direction with circularized error at 90% and 50% confidence levels. [deg].
- ENERGY: Most probable neutrino energy that would create an event with the observed light deposition levels, assuming an astrophysical neutrino spectrum following a power law of $E^{-2.87}$. [TeV]
- FAR: Rate of background events expected similar in nature to the observed event. [1/yr]
- SIGNAL: Signalness of this neutrino candidate. Probability this is an astrophysical signal relative to backgrounds.
- Neural Net classification scores:
  - CASCADE_SCR: DNN classifier score for a contained cascade event topology.
  - SKIMMING_SCR: DNN classifier score for a poorly contained detector-edge skimming topology.
  - START_SCR: DNN classifier score for a starting track topology.
  - STOP_SCR: DNN classifier score for a stopping track topology.
  - THRGOING_SCR: DNN classifier score for a through-going track topology.

The FITS files also contain a skymap with each pixel containing the probability that the source falls in this pixel. Here is an example code to read the skymap and get the 50% contours:

```
import healpy as hp
import numpy as np
import matplotlib.pyplot as plt
import math

## Show skymap
def draw_skymap(skymap):
    hp.mollview(skymap, title="", cbar=True, notext=True, hold=False)
    hp.graticule()
    plt.text(2.0, 0., r"$0^\circ$", ha="left", va="center")
    plt.text(1.9,0.45, r"$30^\circ$", ha="left", va="center")
    plt.text(1.4,0.8, r"$60^\circ$", ha="left", va="center")
    plt.text(1.9,-0.45, r"$-30^\circ$", ha="left", va="center")
    plt.text(1.4,-0.8, r"$-60^\circ$", ha="left", va="center")
    plt.text(2.0, -0.15, r"$180^\circ$", ha="center", va="center")
    plt.text(1.333, -0.15, r"$240^\circ$", ha="center", va="center")
    plt.text(.666, -0.15, r"$300^\circ$", ha="center", va="center")
    plt.text(0.0, -0.15, r"$0^\circ$", ha="center", va="center")
    plt.text(-.666, -0.15, r"$60^\circ$", ha="center", va="center")
    plt.text(-1.333, -0.15, r"$120^\circ$", ha="center", va="center")
    plt.text(-2.0, -0.15, r"$180^\circ$", ha="center", va="center")
    plt.draw()

## Read file
skymap, header = hp.read_map(
                    './stuff_58967_run00134021.evt000057320089.fits',
                    h=True, verbose=False)
draw_skymap(skymap)

## Get 50% contour
quantile = 0.50 # to get 50% contour
header = dict(header)
NSIDE = header['NSIDE']
argsort = np.argsort(-skymap)
cum_skymap = np.cumsum(sorted(skymap,reverse=True))
cont_ind = argsort[cum_skymap < quantile]
contour = np.array(
            [1. if pix in cont_ind else 0. for pix in range(len(skymap))])
draw_skymap(contour)

## Get ra, dec of the max pixel
max_pix = np.argmax(skymap)
dec, ra = hp.pix2ang(nside=NSIDE, ipix=[max_pix])
dec = math.pi/2. - dec
```

5 Example alert messages

An example cascade alert GCN Notice is shown below:

```
TITLE:            GCN/AMON NOTICE
NOTICE_DATE:      Fri 31 Jul 20 17:12:52 UT
NOTICE_TYPE:      ICECUBE Cascade
EVENT_NAME:       IceCubeCascade-200701b
STREAM:           26
RUN_NUM:          134244
EVENT_NUM:        34406854
SRC_RA:           220.0434d {+14h 40m 10s} (J2000),
                  220.2371d {+14h 40m 57s} (current),
                  219.5707d {+14h 38m 17s} (1950)
SRC_DEC:          +43.1731d {+43d 10' 23"} (J2000),
                  +43.0859d {+43d 05' 09"} (current),
                  +43.3870d {+43d 23' 13"} (1950)
SRC_ERROR:        44.06 [deg radius, stat+systematic, 90% containment]
SRC_ERROR50:      24.17 [deg radius, stat+systematic, 50% containment]
DISCOVERY_DATE:   19031 TJD;   183 DOY;   20/07/01 (yy/mm/dd)
DISCOVERY_TIME:   69893 SOD {19:24:53.44} UT
REVISION:         0
ENERGY:           10.99 [TeV]
SIGNALNESS:       8.7016e-01 [dn]
FAR:              0.4021 [yr^-1]
SUN_POSTN:        131.38d {+08h 45m 31s}  +18.02d {+18d 01' 06"}
SUN_DIST:          76.99 [deg]   Sun_angle= -5.9 [hr] (East of Sun)
MOON_POSTN:       273.18d {+18h 12m 43s}  -23.86d {-23d 51' 49"}
MOON_DIST:         82.75 [deg]
GAL_COORDS:        76.15, 62.79 [deg] galactic lon,lat of the event
ECL_COORDS:       195.83, 54.53 [deg] ecliptic lon,lat of the event
SKYMAP_FITS_URL:  https://roc.icecube.wisc.edu/public/hese_cascades/hese_590
 ↪  31_run00134244.evt000034406854.fits
SKYMAP_PNG_URL:   https://roc.icecube.wisc.edu/public/hese_cascades/hese_590
 ↪  31_run00134244.evt000034406854.png
COMMENTS:         IceCube Cascade event.
COMMENTS:         The position error is the combined statistical and the
 ↪  systematic.
```

References

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[9] M. G. Aartsen et al. “Search for Sources of Astrophysical Neutrinos Using Seven Years of IceCube Cascade Events”. In: *ApJ* 886.1 (Nov. 2019), p. 12. DOI: 10.3847/1538-4357/ab4ae2. arXiv: 1907.06714 (cit. on pp. 1, 2).

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