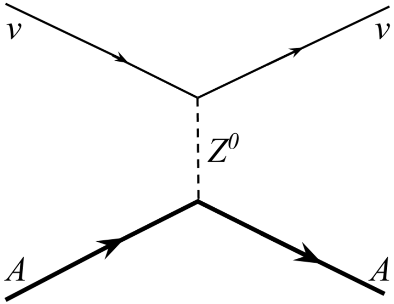
Point-like event discrimination in RED-100

Razuvaeva O.E.
or.firefox@gmail.com
on behalf of RED collaboration

Moscow
ICPPA 2020

Coherent Elastic Neutrino-Nucleus Scattering



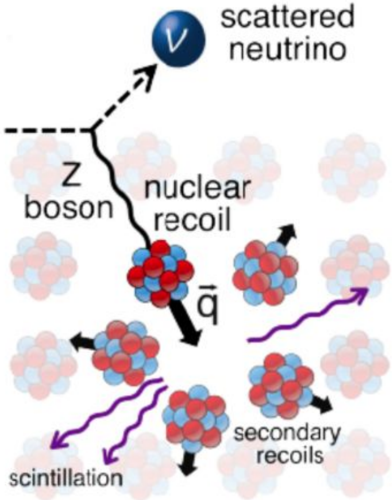
Coherent Elastic Neutrino-Nucleus Scattering (CEνNS) is predicted by Standard Model but it has not been observed experimentally for a long time due to extremely low energy of the recoil nucleus. Only in 2017 it was discovered by COHERENT collaboration

$$\frac{d\sigma}{d\Omega} = \frac{G^2}{4\pi^2}k^2(1+\cos\theta)\frac{(N-(1-4\sin^2\theta_W)Z)^2}{4}F^2(Q^2) \propto N^2$$

Motivation of experiments:

— fundamental physics (Coherent scattering significantly affects supernova dynamics)

— practical goals (monitoring of nuclear reactors)

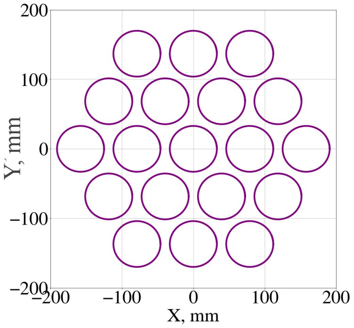


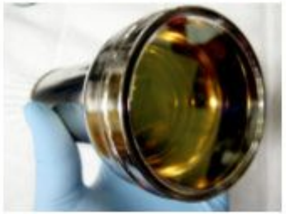
D.Z. Freedman, Phys. Rev. D 9 (1974) 1389

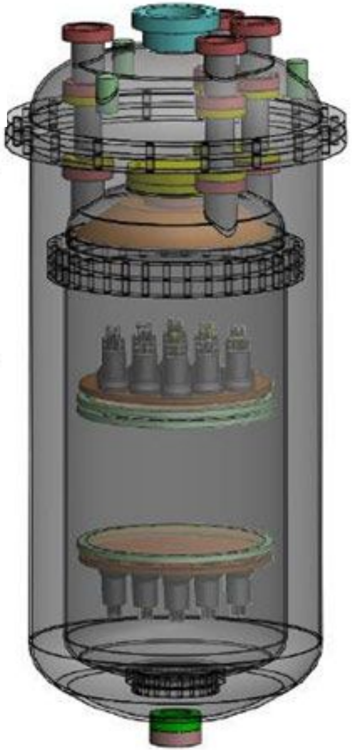
D.Akimov, J. Albert, P. An et.al., Science. — 2017.

Kopeliovich V B, Frankfurt L L JETP Lett. 19 145 (1974); Pis'ma Zh. Eksp. Teor. Fiz. 19 236 (1974)

RED-100







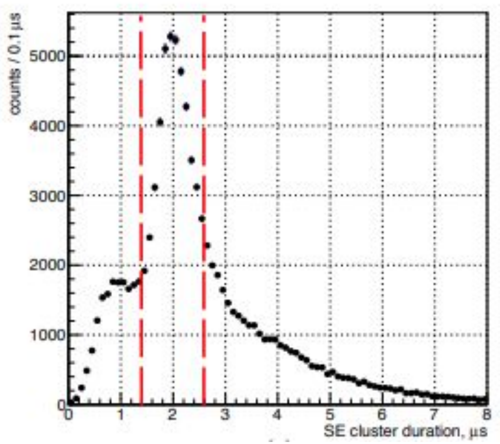
RED-100 is a two-phase emission detector for study of CEνNS with reactor electron antineutrinos off xenon atomic nuclei.

The active volume is viewed by two arrays of nineteen 3”-diameter PMTs assembled in two planes on top and bottom.

The RED-100 is moving to Kalinin NPP.

The RED-100 two-phase emission detector / D. Y. Akimov [et al.] // Instruments and Experimental Techniques. — 2017. — Mar. — Vol. 60, no. 2. — P. 175–181. — ISSN 1608-3180.

Background conditions



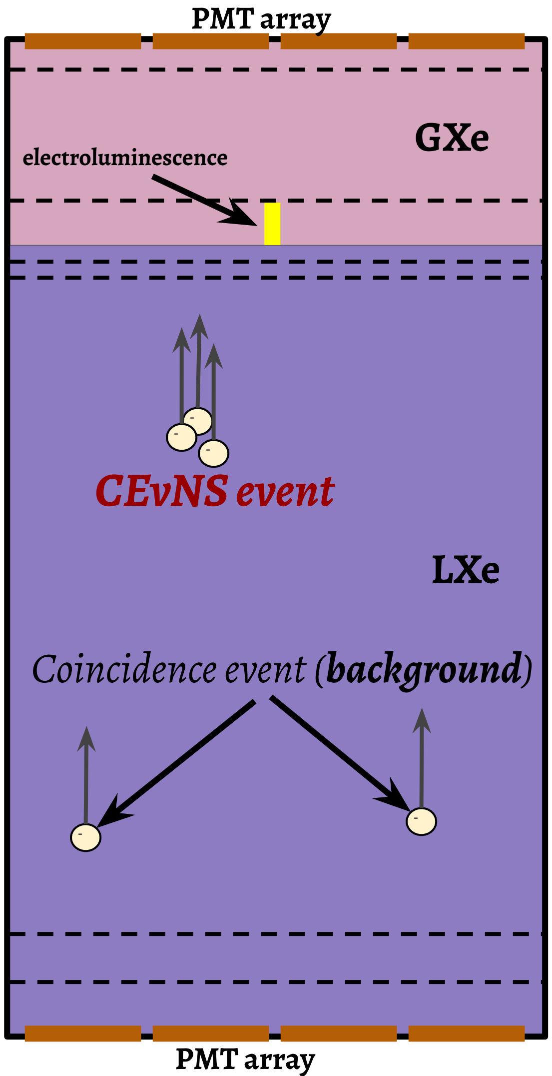
Distribution of durations of the SPE clusters. Selected for the analysis clusters having duration from 1.4 to 2.6 µs (marked by red vertical lines).

The RED-100 is working at shallow depth, unlike other similar detectors (LUX, Xenon1T)

A significant background from spontaneous emission of single electron events (SE) is expected which is related to high radioactivity level. Hence effective cut is a need.

Background event — coincidence of two or more spontaneous SE events (sometimes 2SE or 3SE).

CEvNS event — several electrons, coming from one point.



Simulation

The optical simulation of RED-100 is done via ANTS-2 software.

Number of photons in electroluminescence from single electron was estimated with NEST code (v.2.0.1)

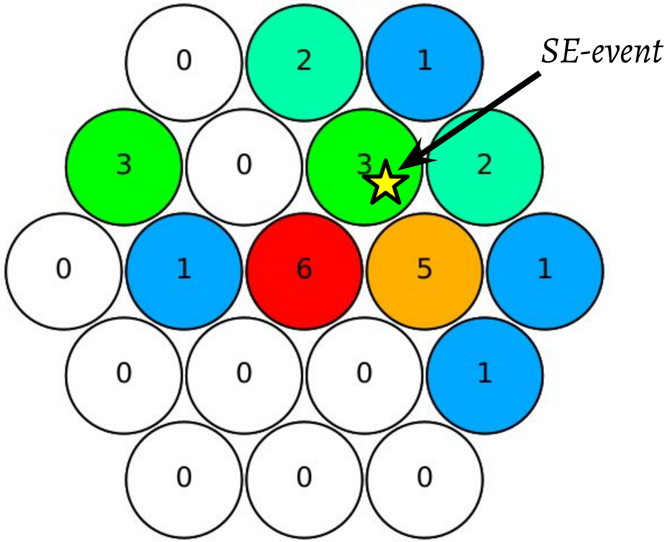
(Kozlova Ekaterina, Noble Element Simulation Technique: current status and future plans, ICPPA 2020, Facilities and advanced technologies)

The simulated event is a set of numbers of photons detected by each PMT in top array.

Simulated events: 1SE, 2SE, ..., 6SE

Background events: 1+1, 1+1+1, 2+1, 2+2, 1+3... (sum≤6) in different points uniformly scattered on the XY plane.

CEvNS events: 2,3,4,5 or 6 SE in one point



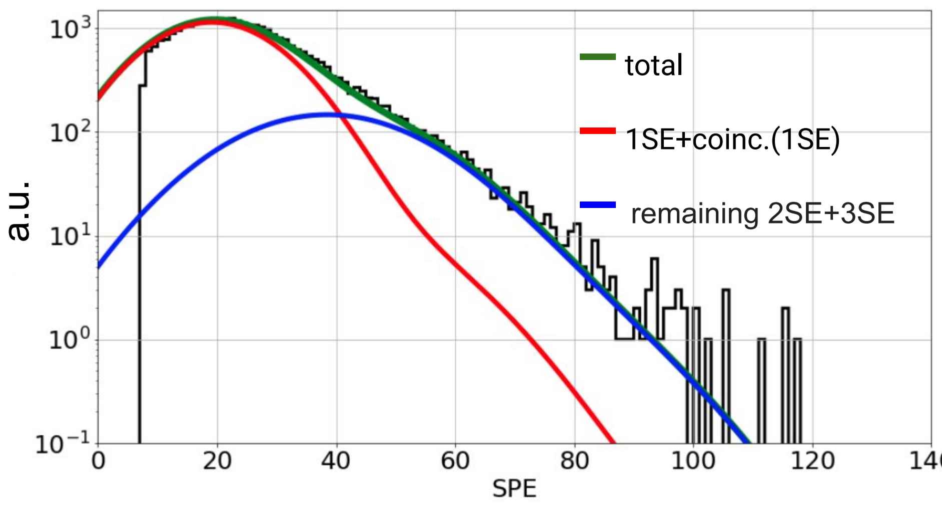
Example of simulated event (1SE)
The circles indicate the positions of the PMTs in the top array. Numbers in circles correspond to the numbers of photons detected by each PMT.

(ANTS2 package: Simulation and experimental data processing for Anger camera type detectors / A. Morozov [et al.] // JINST. — 2016.)

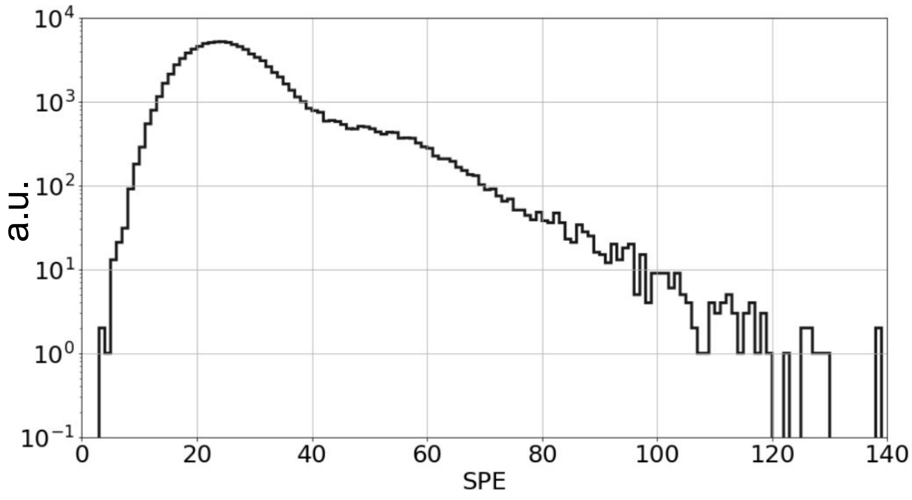
Background model

The green line — fit of the spectrum by three gaussians (1SE, 2SE, 3SE).
The red line — sum of fit by one gaussian (first peak) and two gaussians made from poisson distribution (the probability of 1+1 and 1+1+1 overlapping in 500ns).
The blue line is the difference between green and red. It gives the probability of 2SE and 3SE background events.

Simulated spectrum was made from coincidence events using this values.

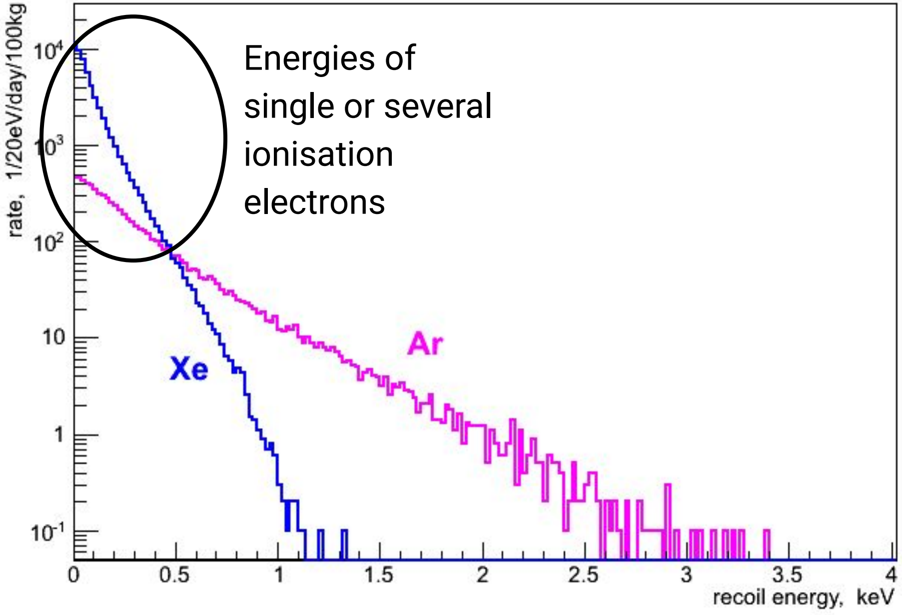


Experimental spectrum (from the MEPhI lab, without shielding)



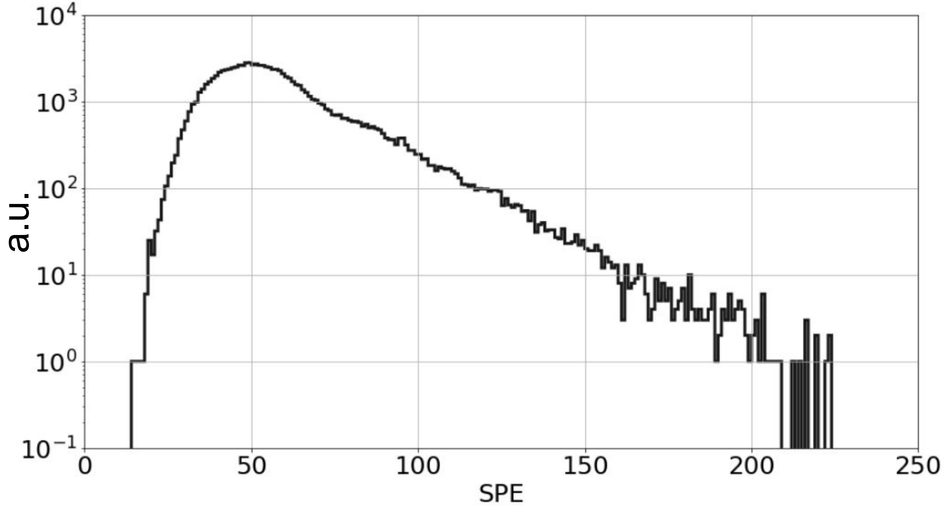
Simulated spectrum

CEνNS model



Nuclear recoil energy

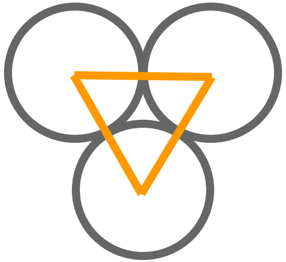
Using antineutrino energy spectrum for VVER-1000 core and average fuel composition.



Simulated spectrum (≥2SE)

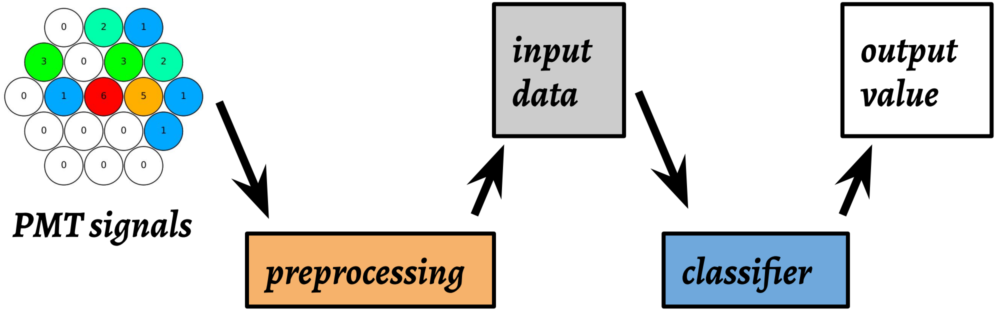
Point-like event discrimination

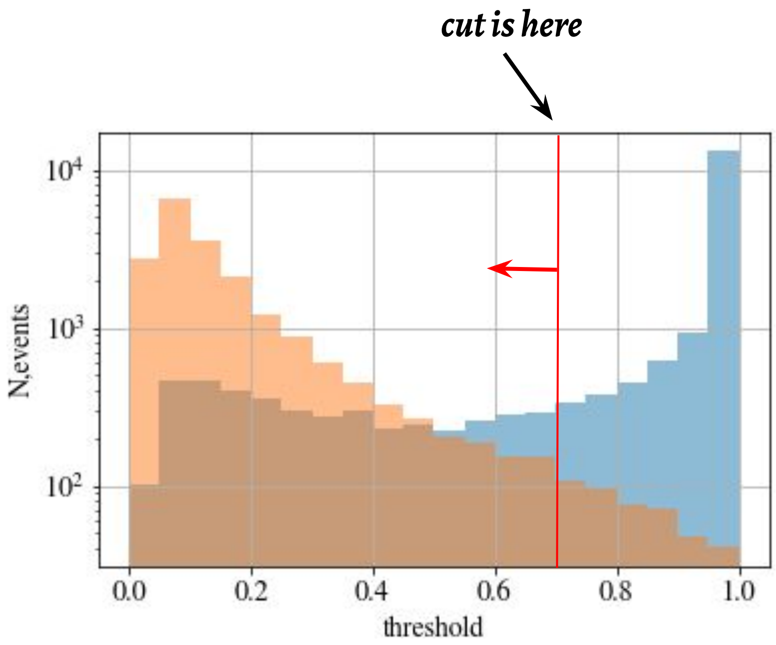
Using event classification based on total signals in PMTs. Tried several ML approaches (linear models, decision trees etc.), selected AdaBoost



Triangle cluster of three PMTs

Input signals are distribution of fraction of a signal in PMTs and three-PMT clusters, both sorted by signal size.

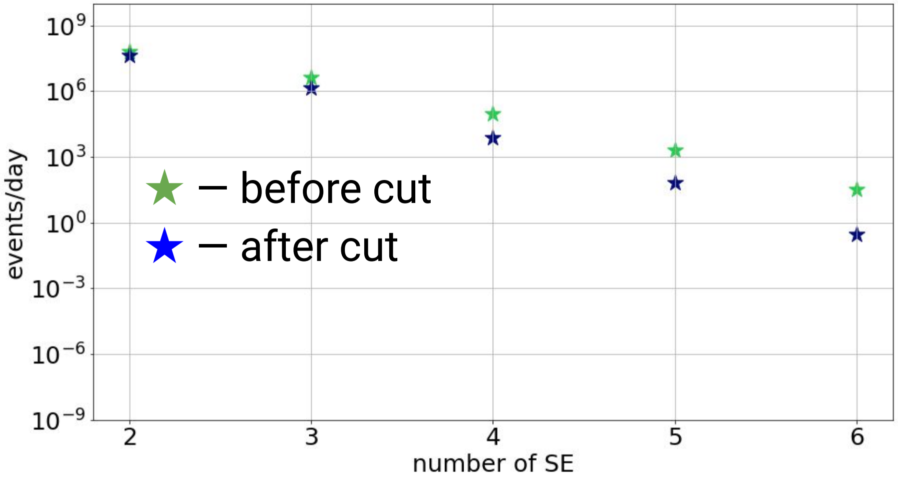




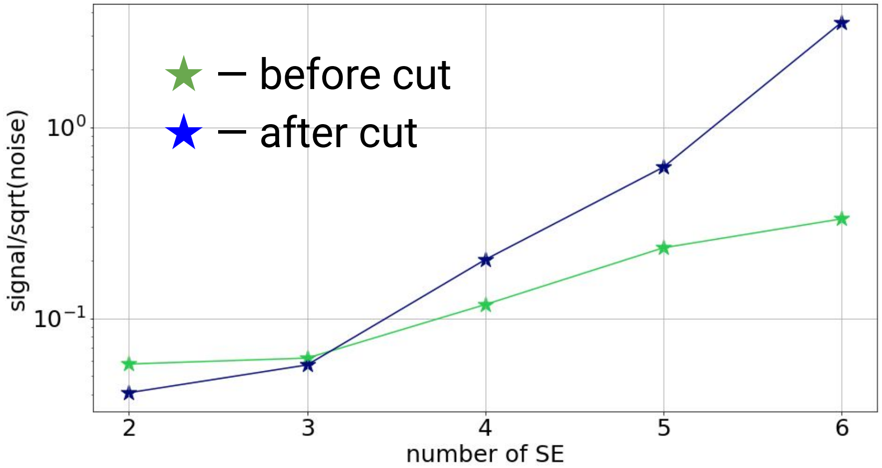
The output value of the classifier.
Orange spectrum corresponds to CEvNS events, while blue is background.

Discriminator results

on the simulated data



Background reduction (1 day)

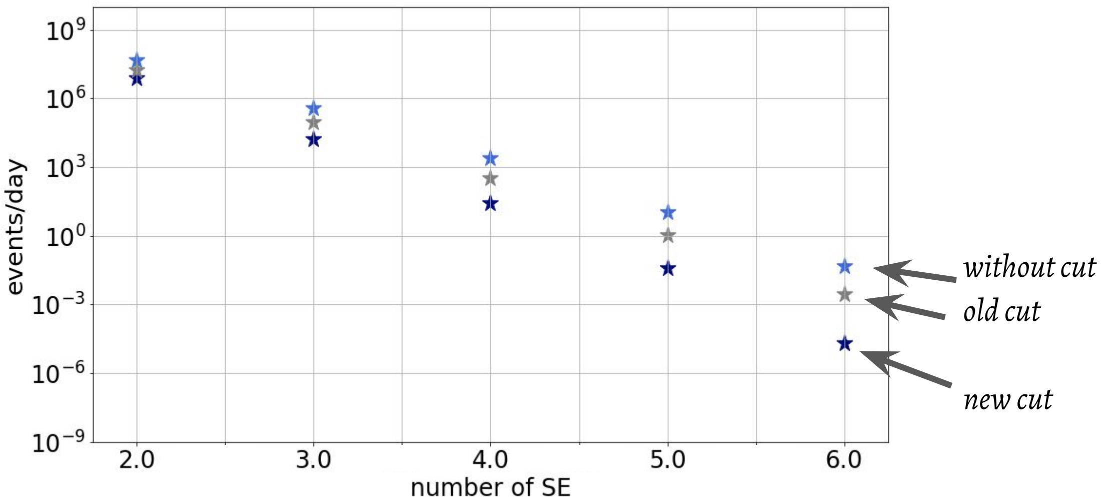


Signal/$\sqrt{\text{Background}}$, (1 day)

Discriminator results

comparison with old cut

(Dmitry Rudik, Status of the RED-100 experiment, ICPPA 2020)



Results of background reduction (only 1, 1+1, 1+1+1…), events from test run.
Classifier trained on simulation, tested on real data.

Number of SE	No cut	Old cut	ML cut
2	465	283	290.3
3	129	78	79.4
4	35.5	21.7	22
5	10.6	6.4	6.9
6	1.9	1.2	1.6

Signal reduction

First ground-level laboratory test of the two-phase xenon emission detector RED-100, Akimov D. et.al., JINST 2020

Conclusion

1. An optical model for the RED-100 was developed
2. Signal and background models were designed
3. A new discriminator based on ML algorithm was created
4. It shows better results than previous approach
5. The study continues

Thank you for your attention!

Backup

Training

Train sample consists of:
all types of background events except events containing only 2 or 3 SE, because CEνNS events can contain only 2 or 3 SE too.
This is the reason why we can't make effective discrimination for <4SE events.
The chosen threshold is 0.7

Efficiency of discrimination for different types of background

1_ : 0.516
1_1 : 0.112
1_1_1 : 0.026
1_1_1_1 : 0.006
1_1_1_1_1 : 0.001
2_ : 0.556
3_ : 0.551
2_2 : 0.088
2_1 : 0.116
2_2_1 : 0.024
2_1_1 : 0.021
2_1_1_1 : 0.004
3_2 : 0.096
3_1 : 0.139
3_1_1 : 0.036
2_2_2 : 0.0167
3_3 : 0.081
3_1_1_1 : 0.005
2_2_1_1 : 0.004
2_1_1_1_1 : 0.001
3_2_1 : 0.024
1_1_1_1_1_1 : 0.001

AdaBoost

AdaBoost refers to a particular method of training a boosted classifier. A boost classifier is a classifier in the form

$$F_T(x) = \sum_{t=1}^{T} f_t(x)$$

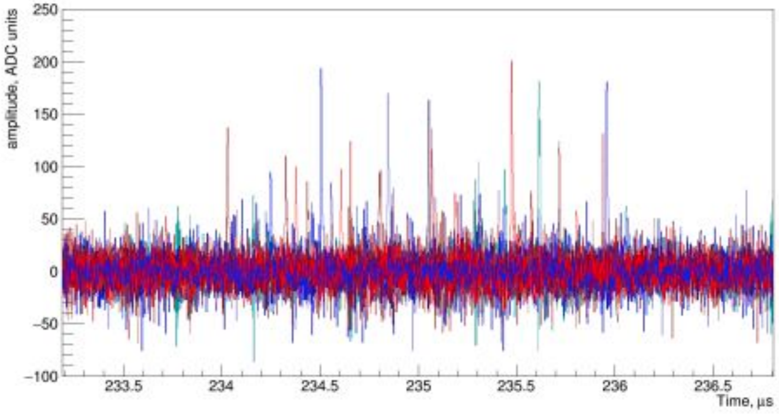
where each f_t is a weak learner that takes an object x as input and returns a value indicating the class of the object. Each weak learner produces an output hypothesis, $h(x_i)$, for each sample in the training set. At each iteration t, a weak learner is selected and assigned a coefficient α_t such that the sum training error E_t of the resulting t-stage boost classifier is minimized.

$$E_t = \sum_i E[F_{t-1}(x_i) + \alpha_t h(x_i)]$$

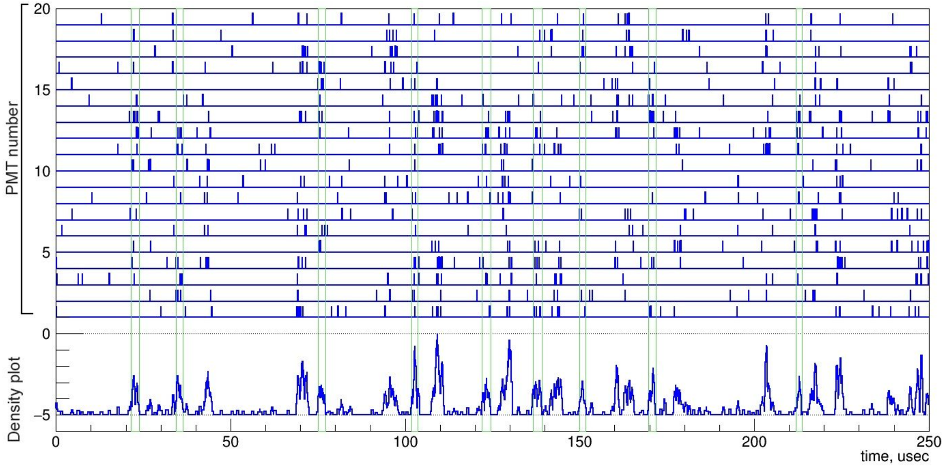
Here $F_{t-1}(x)$ is the boosted classifier that has been built up to the previous stage of training, $E(F)$ is some error function and $f_t(x)=\alpha_t h(x)$ is the weak learner that is being considered for addition to the final classifier.

At each iteration of the training process, a weight $w_{i,t}$ is assigned to each sample in the training set equal to the current error $E(F_{t-1}(x_i))$ on that sample. These weights can be used to inform the training of the weak learner, for instance, decision trees can be grown that favor splitting sets of samples with high weights.

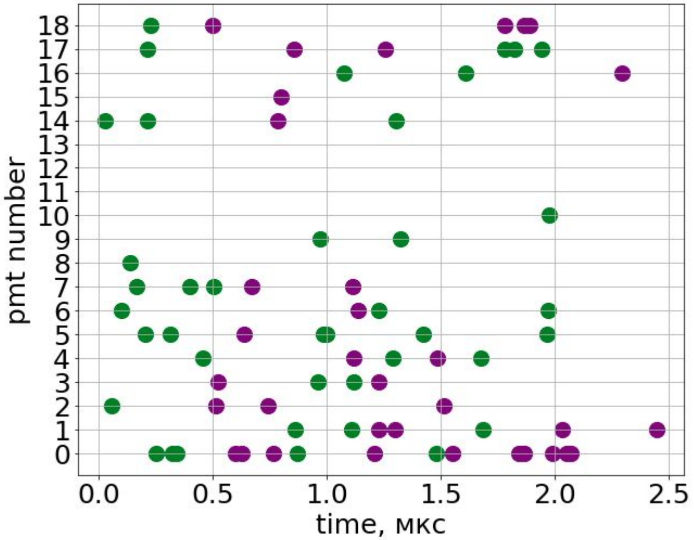
Experimental waveforms



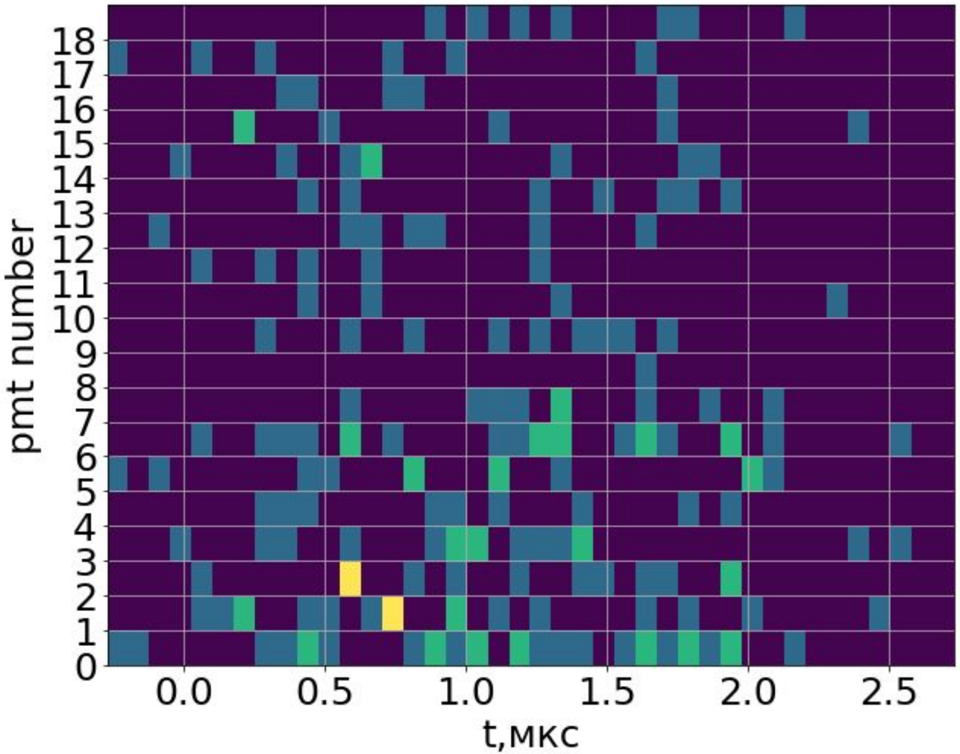
Example of SE signal (between 234 and 236 µs). The waveforms corresponding to different PMTs are overlaid



More detailed simulation



The example of simulation 2SE background event



The example of simulation 6SE CEνNS event