Applications of the Topological Track Reconstruction to low energy events

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together with

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Universität Hamburg
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Topological Reconstruction
In unsegmented large-volume liquid scintillator detectors

Outline

1. Motivation
2. Topological Track Reconstruction
3. Particle discrimination (Machine Learning)
4. Direction reconstruction (Machine Learning)
5. Outlook
6. Summary

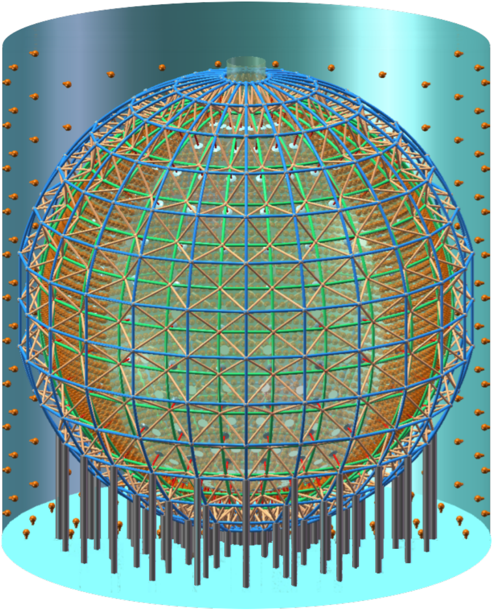
Motivation: Topological Track Reconstruction

Recapitulation

- Talk by **M. Meyer: "Track Reconstruction and Characterization in Liquid Scintillator Detectors at High Energies"**
- Large liquid scintillator detectors have high dead time due to cosmic muons and resulting cosmogenic isotopes.
- **T**opological **T**rack **R**econstruction (TTR) developed for reconstructing high energy muons ($\sim \mathrm{GeV}$).
- Determine volume containing the muon track by investigating dE/dx.
- Reduce vetoed volume and increase active volume.
- Current focus lies on the **J**iangmen **U**nderground **N**eutrino **O**bservatory (JUNO).
- Other Experiments:
  1. LENA
  2. Borexino
  3. SNO+
- See also: arXiv:1803.08802

JUNO

- 20 kton liquid scintillator in acrylic sphere
- ∼18.000 20 inch PMTs; ∼25.000 3 inch PMTs for optical coverage of 77 %
- Plastic scintillator on top and water Cherenkov detector as Muon veto
- Main Goals: Determination of the mass hierarchy, improvement of the precision on oscillation parameters and measurement of solar neutrinos



Motivation: low energy events

Low energy events

- Positrons, electrons and gammas; energies of a few MeV
- Treated as point-like events in contrary to the track-like GeV muons.

What can we gain with low energy events?

Applications

- Localisation of e^+, e^- and γ events
- Direction reconstruction using Cherenkov photons for background rejection (without TTR)
- **Most important: e^+/e^- and γ/e^- discrimination**
  $\Rightarrow$ great use for background suppression and study

Motivation: e^+/e^- discrimination

Mass hierarchy

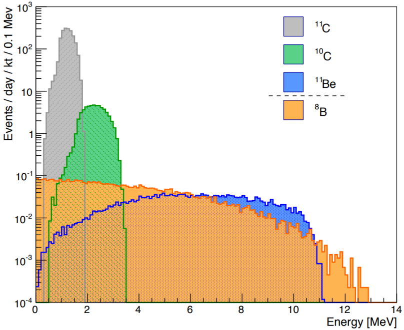
- Signal: inverse beta decay from reactor neutrinos:
  $\overline{\nu_e} + p \rightarrow \mathbf{e}^+ + \mathbf{n}$
- Background: Muon induced cosmogenic isotopes $^8\mathrm{He}$, $^9\mathrm{Li}$
  $^8\mathrm{He} \rightarrow {}^8\mathrm{Li} + \mathbf{e}^- + \ldots \quad {}^8\mathrm{Li} \rightarrow X + \mathbf{n} + \ldots$
  $^9\mathrm{Li} \rightarrow {}^9\mathrm{Be} + \mathbf{e}^- + \ldots \quad {}^9\mathrm{Be} \rightarrow X + \mathbf{n} + \ldots$

Solar sector

- Signal: elastic scattering of solar neutrinos off electrons
  $\nu_e + e^- \rightarrow \nu_e + \mathbf{e}^-$
- Background: β^+ decay from $^{11}\mathrm{C}$, $^{10}\mathrm{C}$
  $^{10}\mathrm{C} \rightarrow {}^{10}\mathrm{B} + \mathbf{e}^+ + \boldsymbol{\gamma} + \ldots$
  $^{11}\mathrm{C} \rightarrow {}^{11}\mathrm{B} + \mathbf{e}^+ + \ldots$

Motivation: γ/e^- discrimination

- Natural radioactivity from all kinds of materials in and around the detector
- Examples: rock, water buffer, steel, etc.
- $\Rightarrow$ Gamma emission in the fiducial volume.
- With γ/e^- discrimination one can
  - Study and characterise the gamma background.
  - Reduce the gamma background in the solar sector.

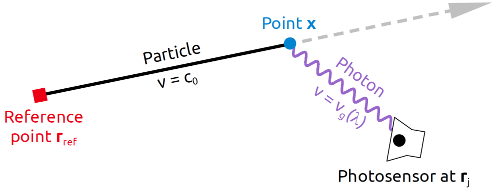


[Neutrino Physics with JUNO; DOI: 10.1088/0954-3899/43/3/030401]

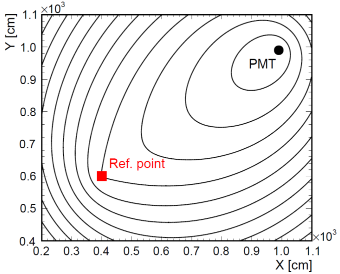
General concept of the TTR

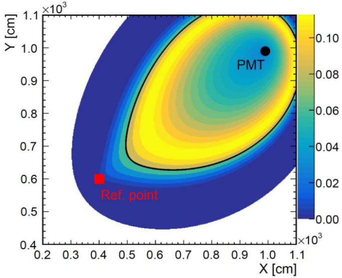
- Known reference point in time t_{ref} and space $\mathbf{r}_{\text{ref}}$
- Assume straight particle path with velocity c_0.
- Calculate possible locations $\mathbf{x}$ of the particle at time $t(\mathbf{x})$.

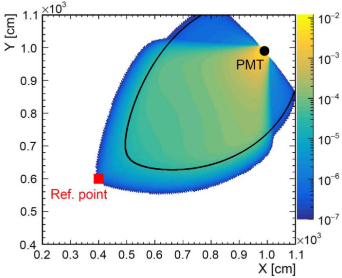
$$t(\mathbf{x}) = t_{\text{ref}} \pm \underbrace{\frac{|\mathbf{x} - \mathbf{r}_{\text{ref}}|}{c_0}}_{\text{particle}} + \underbrace{\frac{|\mathbf{r}_j - \mathbf{x}|}{v_g(\epsilon)}}_{\text{photon}}$$



Probability density functions



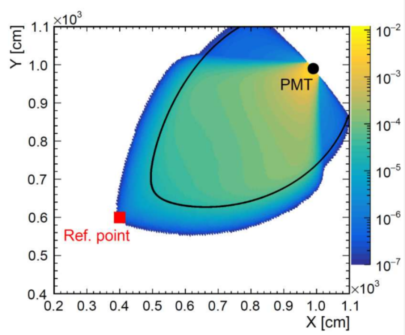


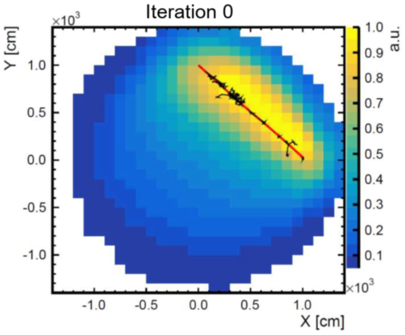


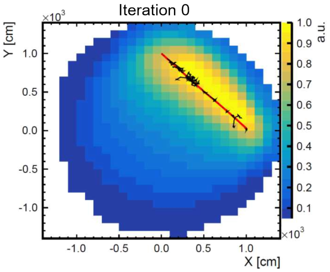
- Development of **p**robability **d**ensity **f**unctions (**p.d.f.**s) when taking more effects into account.
  1. Isochrones coming from the inversion of $t(x)$.
  2. Time uncertainty of scintillation light and response of photosensor
  3. Detection and propagation effects like angular acceptance and attenuation

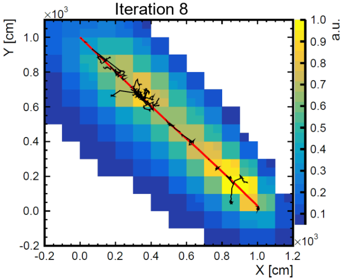
Reconstruction method I

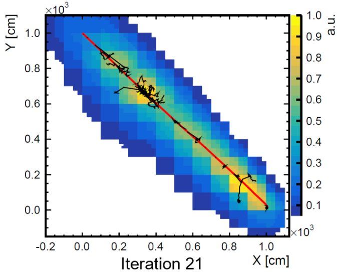
- Create a p.d.f. for every hit and each PMT.
- Superimpose the p.d.f.s for every bin in the detector.
- Gain a probability mask for the whole detector showing the most-likely origin of the light.











- Treat iteration 0 as truth; discard all bins below threshold.
- Reconstruct again in the area of interest based on the previous iteration.
- Refine the binning in later iteration steps for more detailed result.

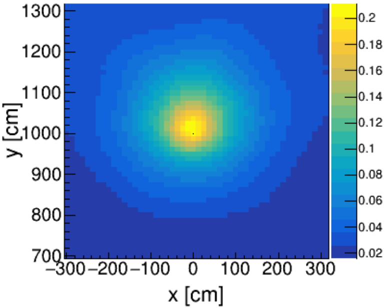
Low energy events

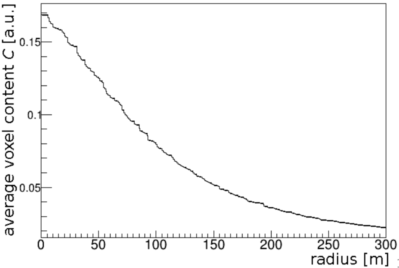
- **Range in liquid scintillator**
  - for e^+/e^- :$\sim$ cm
  - for γ :$\sim$ 50 cm
- Resolution $> 10\,\mathrm{cm}$
- Cloud-like structure
- **Annihilation gammas**
  $\Rightarrow$ lower contrast for e^+ events; energy deposition for e^- events is more point-like

Discrimination:

- Determine maximum voxel $V_{\max}$
- Plot **average voxel content** C over radius R around $V_{\max}$
- Build **derivative** D (25 cm average)

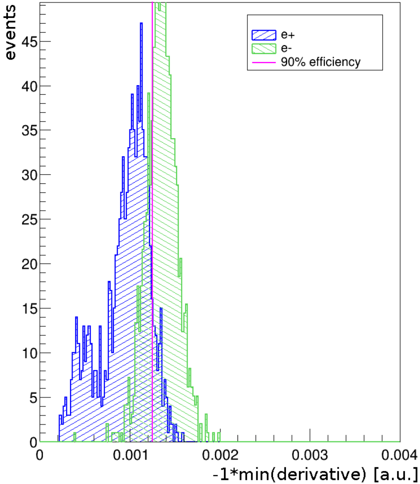
$\rightarrow$ expect $C(R)$ to decrease faster for electrons than for positrons





e^+/e^- discrimination cut

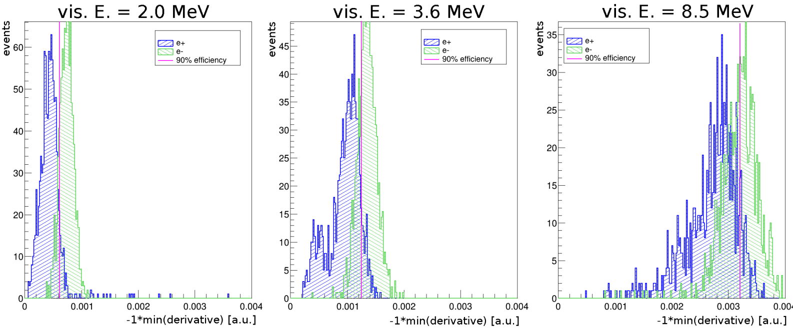
Discrimination parameter:
Minimum of derivative of $C(R)$



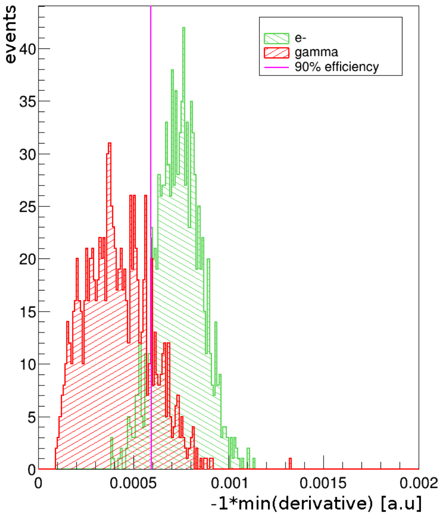
- Simulation of each 1000 positron and electron events (offline)
- kinetic energy: $E_{e^+} = 2.6\,\mathrm{MeV}$, $E_{e^-} = E_{e^+} + 2 \cdot 511\,\mathrm{keV}$
- Position: $(0, 10, 0)\,\mathrm{m}$ from JUNO center
- Direction: random
- TTS (FWHM) 20 inch PMTs: $3\,\mathrm{ns}$ for $28\,\%$, $12\,\mathrm{ns}$ for $72\,\%$
- Vertex reconstruction + TTR
- Determination of derivative
- Result: Overlapping, but distinguishable distribution
  $\Rightarrow$ **Perform a separating cut**

Results with different energies

- Lower energies yield better results.
- Above 8.5 MeV the discrimination potential vanishes.
- The gammas from the annihilation are lost in the energy deposition of the positron-ionisation at higher energies.



γ/e^- discrimination



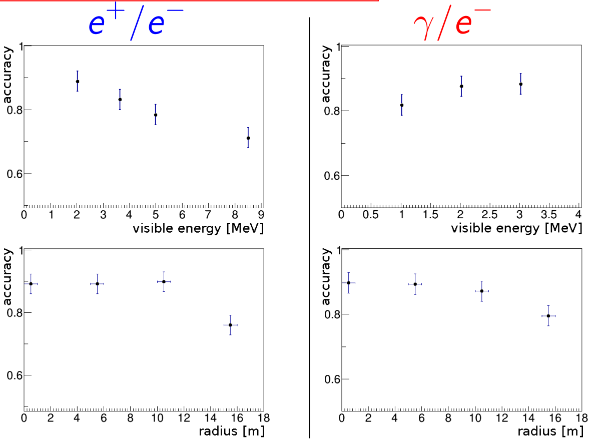
- Simulation of each 1000 gamma and electron events (offline)
- Kinetic energy: $2\,\mathrm{MeV}$
- Position: $(0, 10, 0)\,\mathrm{m}$ from JUNO center
- Direction: random
- TTS (FWHM) 20 inch PMTs:
  $3\,\mathrm{ns}$ for $28\,\%$,
  $12\,\mathrm{ns}$ for $72\,\%$
- Vertex reconstruction + TTR
- Determination of derivative
- Result: Similar to the result of the e^+/e^- discrimination; again a cut can be done with sufficient efficiency

Performance

$$\boxed{\text{accuracy} = \frac{\text{number of true predictions}}{\text{total number of events}}}$$

Different energies (radius: $10\,\mathrm{m}$)

Different position (vis. e.: $2\,\mathrm{MeV}$)



- Stable discrimination throughout detector volume
- At detector edge used discrimination parameter needs adjustment (limit to a certain area)

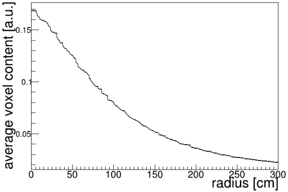
Use Machine Learning for e^+/e^- discrimination

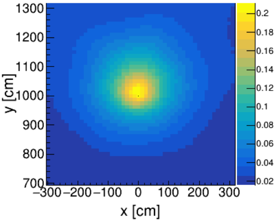
Convolutional **N**eural **N**etwork (CNN) often used for image classification.

Usage of **TensorFlow** as **M**achine **L**earning (**ML**) framework

Testing the potential of three different inputs:

1. 1D radial event profile ⇒ **1D-CNN**
   - Similar to the previous method
   - Fast performance
2. 3D TTR result ⇒ **3D-CNN**
   - Unbiased network
   - Net can consider asymmetric features
   - More computing time
3. "Gradient field" ⇒ **3 channel 3D-CNN**
   - Like method 2, but giving the net a parameter already proven as useful





CNN structure

1D

- Input size: [300]
- **Conv1D** (100 filters, size: [5])
- Activation (ReLu)
- **MaxPooling1D** (size: [3])
- **Conv1D** (10 filters, size: [3])
- Activation (ReLu)
- **Conv1D** (5 filters, size: [2])
- Activation (ReLu)
- **MaxPooling1D** (size: [3])
- Flattening
- **Dense** (100 neurons)
- Activation (ReLu)
- Batch normalisation
- **Dense** (2 neurons)
- Activation (Softmax)

3D (3 channel)

- Input size: [17x17x17 (x3)]
- **Conv3D** (100 filters, size: [3x3x3]
- Activation (ReLu)
- **Conv3D** (8 filters, size: [2x2x2])
- Activation (ReLu)
- Flattening
- **Dense** (200 neurons)
- Activation (ReLu)
- Batch normalisation
- **Dense** (2 neurons)
- Activation (Softmax)

e^+/e^- discrimination results with ML

1D

- **10^4** events
- Visible energy: $2\,\mathrm{MeV}$
- Position: $(0, 10, 0)\,\mathrm{m}$
- Running time: $17\,\mathrm{min}$
- **Accuracy:** 0.93

3D

- **10^3** events
- Visible energy: $2\,\mathrm{MeV}$
- Position: $(0, 10, 0)\,\mathrm{m}$
- Running time: $115\,\mathrm{min}$
- **Accuracy:** 0.90

3D (3 channel)

- **10^3** events
- Visible energy: $2\,\mathrm{MeV}$
- Position: $(0, 10, 0)\,\mathrm{m}$
- Running time: $150\,\mathrm{min}$
- **Accuracy:** 0.90

Depending on cut, the derivative method achieves

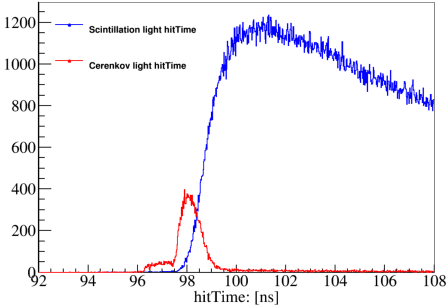
Accuracy:
$\sim$ 0.90

$\Rightarrow$ **Results are very similar for both methods.**

Direction reconstruction

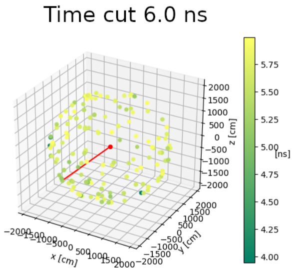
- In JUNO $\sim 3\,\%$ of the emitted light is Cherenkov light.
- This opens an opportunity for a direction reconstruction.
- Motivation: background suppression for neutrinos of sources with known location, especially solar neutrinos

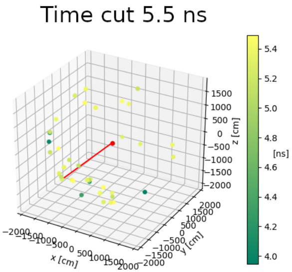
- **No usage of the TTR**
- Training sample: 100,000 electron events ($3\,\mathrm{MeV}$) at the center of JUNO (using detector simulation)
- Validation and evaluation: 10,400 events for every $1\,\mathrm{Mev}$ step between 1 and $8\,\mathrm{MeV}$
- Time of flight correction
- Time cut $5.5\,\mathrm{ns}$ after time of flight correction
- Usage of known vertex position



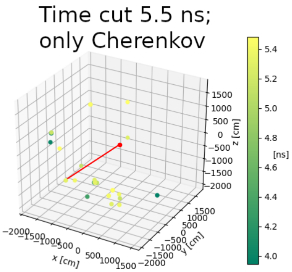
[Determination of Supernovae Direction with Reconstructed Positron Information; DOI: 10.22323/1.244.0067]

Hit distribution



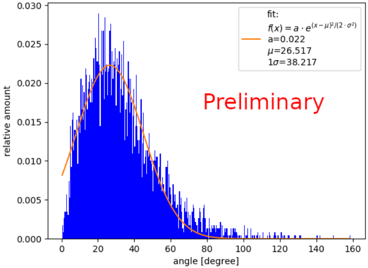


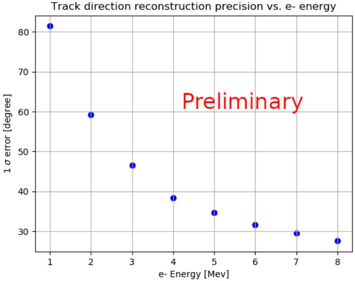
- Not using a CNN because
  - Edge effects if trying to parameterize the 3D sphere to 2D cartesian coordinates
  - 3D CNN would contain lots of entries with a zero $\Rightarrow$ massive amount of memory and running time



Results

- Network PointNet (see arXiv:1612.00593); Framework: **TensorFlow**
- Data represented as PointCloud (PMT positions, hit times)
- Implementation based on **Dynamic Graph** CNN with modifications:
    - No rotation and moving of input
    - Reduce output to three values
    - Add quadratic normalisation to output
    - Cosine function as loss function
    - Use Convolution, MaxPooling and Dense layer instead of ReduceMax and fully connected layer



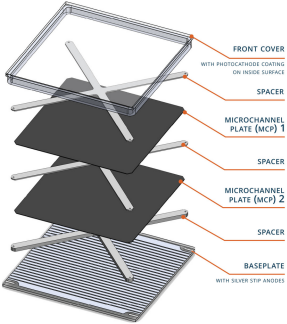


Outlook: Water based liquid scintillator

- Applying TTR to water Cherenkov detectors has started:
  - **A**ccelerator **N**eutrino **N**eutron **I**nteraction **E**xperiment (**ANNIE**) at Fermilab, one of the first experiments to use **L**arge-**A**rea **P**icosecond **P**hoto**D**etectors (**LAPPDs**) + PMTs
    - Reconstruction works with the ANNIE simulation data.
  - LAPPDs have a time resolution of $\sim 0.1\,\mathrm{ns}$ and a spatial resolution of $\sim 1\,\mathrm{mm}$
  - Idealised detector completely covered with LAPPDs
    - Simple Geant4 simulation as proof of principle

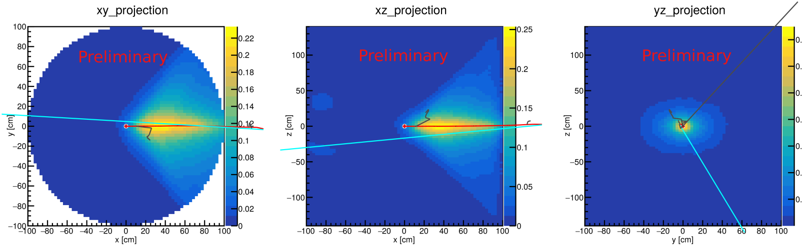
- First step on the way to reconstruct in **W**ater **b**ased **L**iquid **S**cintillator (**WbLS**).
- Ultimate goal: separate Cherenkov and scintillation light
- Possible application to **Theia** (see arXiv:1409.5864), proposed multi-purpose experiment using WbLS and LAPPDs

[Incom]



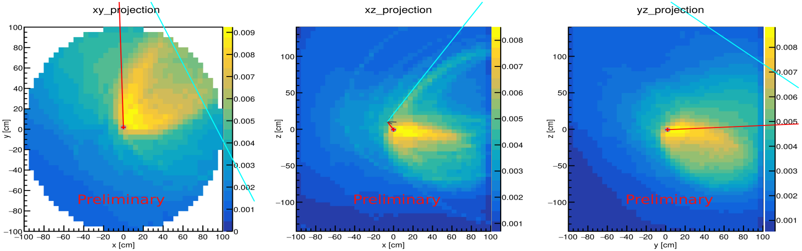
Results ideal detector

- Small detector: Cylinder with $1.2\,\mathrm{m}$ radius and $3\,\mathrm{m}$ height
- Currently treat every hit as LAPPD pixel with time resolution of $0.1\,\mathrm{ns}$.
- $500\,\mathrm{MeV}$ Muon from center in $(1, 0, 0)$ direction
- Results look like expected; a clear distinguishable track around the MC truth is visible.



Results ANNIE

- ANNIE detector: $1.38\,\mathrm{m}$ radius, $3.71\,\mathrm{m}$ height
- Used test setup with 145 PMTs (5 different types with time resolution of about $2\,\mathrm{ns}$ and 24 LAPPDs (only 5 in the real experiment)
- $5\,\mathrm{GeV}$ Muon from center in $(0,1,0)$ direction
- Results prove: different photodetectors with a big variation in time resolution are difficult to handle.
- Less optical coverage reduces the ability to pin down the track.



Summary

Discrimination

- Applying the TTR to low energy events gives discrimination options.
- Both e^+/e^- and γ/e^- discrimination yield good results with conventional cut (90 % accuracy for low energies)
- ML methods for e^+/e^- discrimination gives comparable values.

Direction reconstruction

- A direction reconstruction using only ML (without TTR) shows first results.

WbLS and LAPPDs

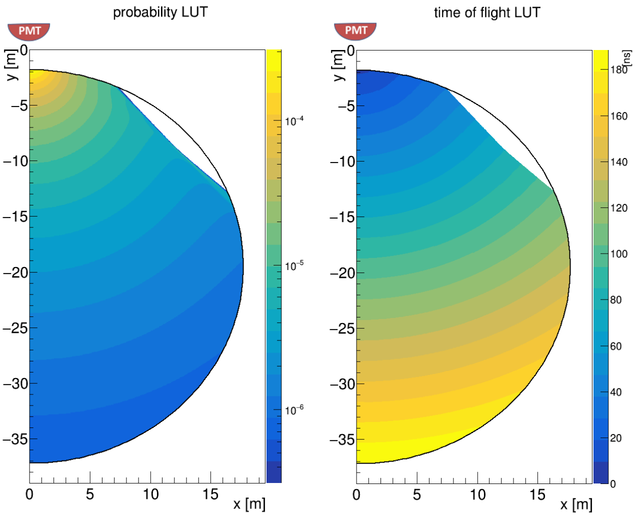
- Ongoing studies in water Cherenkov detectors for future WbLS applications with first results

Thank you for your attention!

Backup

LUTs

- Precalculate **L**ook **U**p **T**ables (LUTs) to reduce computing time.
- Photon run time and hit probability (also light scattering) can be stored in LUTs.



Network structure

- Edge Feature
- Transform
- Edge Feature
- Main Net

Transform Net

Name	Type	Output-Shape
tconv1	Conv2D	(None, 300, 8, 64)
tconv2	Conv2D	(None, 300, 8, 128)
reduce_max	Reduce_max	(None, 300, 1, 128)
tconv3	Conv2D	(None, 300, 1, 1024)
tmaxpool	Max_Pool2D	(None, 1, 1, 1024)
tfc1	Fully_connected	(None, 512)
tfc2	Fully_connected	(None, 256)
transform_XYZ/weights	MatMul	(None, 16)
transform_XYZ/biases	BiasAdd	(None, 16)

Main Net

Name	**Type**	**Output-Shape**
dgcnn1	Conv2D	(None, 300, 8, 16)
pool1	Max_Pool2D	(None, 149, 4, 16)
dgcnn2	Conv2D	(None, 149, 4, 16)
pool2	Max_Pool2D	(None, 74, 2, 16)
dgcnn3	Conv2D	(None, 74, 2, 16)
pool3	Max_Pool2D	(None, 37, 1, 16)
dp1	Dropout(0.5)	(None, 37, 1, 16)
flatten1	Flatten	(None, 592)
local1	Dense	(None, 320)
local2	Dense	(None, 160)
local3	Dense	(None, 80)
dp2	Dropout(0.5)	(None, 80)
prediction/dense	Dense	(None, 3)
prediction/l2_normalize	L2 normalisation	(None, 3)