

Methods for muon energy loss reconstruction in IceCube

David Boersma



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Muon energy (loss)

- Low energy ($E_\mu < \mathcal{O}(10 \text{ TeV})$): track contained in detector volume
 - Track length \rightarrow energy (not in this talk)
- Minimum ionizing $E_\mu < \mathcal{O}(10 \text{ TeV})$
- Linear energy loss for $E_\mu > \mathcal{O}(10 \text{ TeV})$
- Stochastics

Assume track geometry fit independent from energy reconstruction

Depth dependent ice properties:

- absorption length $\lambda_a(z)$
- effective scattering length $\lambda_e(z)$

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Depth dependent ice properties:

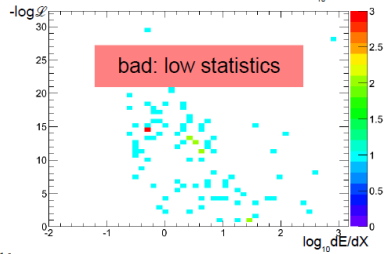
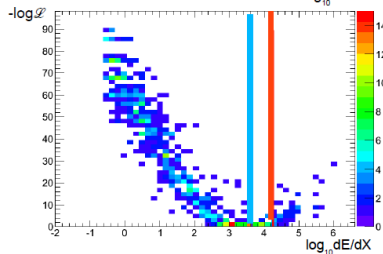
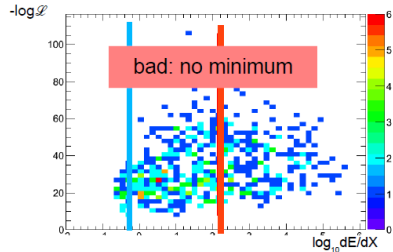
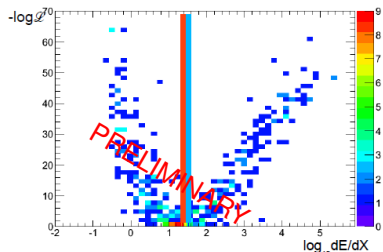
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Top-Down: Comparing to database of MC events

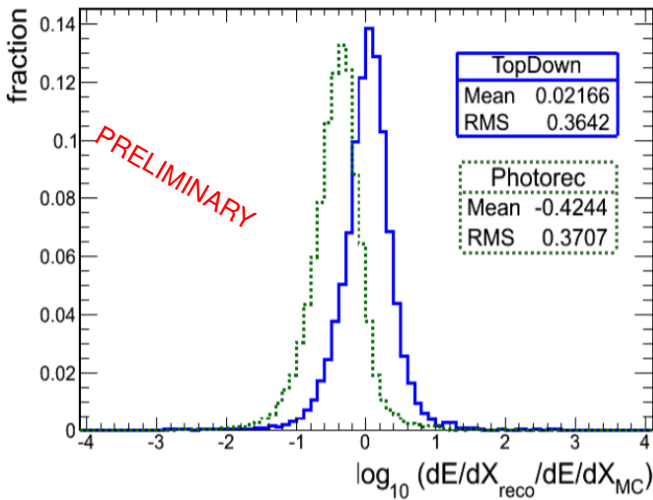
- Create a large database of MC events
- For each given event, select "similar" events from MCDB, using simple criteria
 - E.g. similar COG, similar track fit direction
- Quantify "similarity" using a (product of) likelihood(s), based on e.g.:
 - N_{ch} (Poissonian)
 - hit time distribution (KS)
 - distribution hit distance to track (KS)
- Reconstructed energy is the "true" energy of the most likely MC event

Authors: Jan-Patrick Hülß(2008) and Matthias Schunck (2009-2011)

Top-Down: Likelihood



Top-Down: preliminary test result



Poissonian Ansatz

Given:

- a muon track $m = (x_m, y_m, z_m, \theta_m, \phi_m, E_m, \dots)$
- a DOM $k = (x_k, y_k, z_k, \dots)$
- assumptions about energy loss and light yield
- a light propagation model

Define:

μ_{km} = *expected* number of photoelectrons from muon m at DOM k

q_k = *measured* number of photoelectrons at DOM k

$$\mathcal{L}_{km} = \frac{\mu_{km}^{q_k} e^{-\mu_{km}}}{q_k!}$$

$$L_{km} = -\log(\mathcal{L}_{km}) = \mu_{km} - q_k \log(\mu_{km}) + \log(q_k!)$$

$$L_m = \sum_k \{\mu_{km} - q_k \log(\mu_{km}) + \log(q_k!)\}$$

Assuming a fixed track and uniform light emission / energy loss scaling parameter η :

$$\mu_{km} = \eta \mu_{km, \text{geo}}$$

Trivial fit:

$$\eta = \frac{\sum_k q_k}{\sum_k \mu_{km, \text{geo}}}$$

Analytic (μ_e , μ_{eX}): Photons per track length

Average optical parameters between track and DOM:

$$\frac{1}{\lambda_{a,e}} = \frac{1}{|\mathbf{r}_i - \mathbf{r}_f|} \int_{\mathbf{r}_i}^{\mathbf{r}_f} \frac{1}{\lambda_{a,e}(\mathbf{r})} |\mathbf{dr}|.$$

Close by (no scattering):

$$\mu_{km} = I_0 A \cdot \frac{1}{2\pi \sin \theta_c d} \exp(-d/\lambda_a \sin \theta_c).$$

Far away (diffuse):

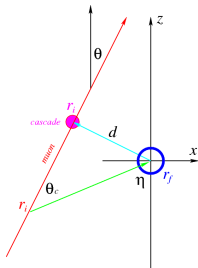
$$\mu_{km} = I_0 A \cdot \frac{3\zeta}{2\pi\lambda_e} \sqrt{\frac{\pi\lambda_p}{2d}} e^{-d/\lambda_p}$$

$$\lambda_p = \sqrt{\lambda_a\lambda_e/3} \quad \zeta = e^{-\lambda_e\lambda_a}$$

Stitched together:

$$\mu_{km} = I_0 A \cdot \frac{1}{2\pi \sin \theta_c} \exp(-d/\lambda_p) \frac{1}{\sqrt{\lambda_\mu d \tanh \sqrt{d/\lambda_\mu}}},$$

$$\left(\sqrt{\lambda_\mu} = \frac{\lambda_e}{3\zeta \sin \theta_c} \sqrt{\frac{2}{\pi\lambda_p}} \right)$$



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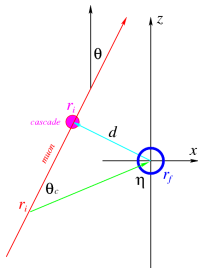
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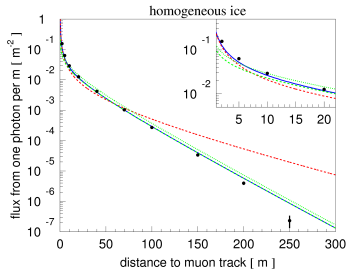
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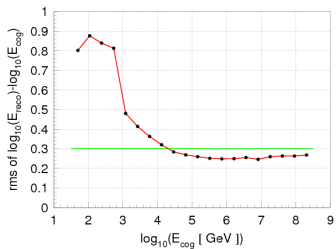
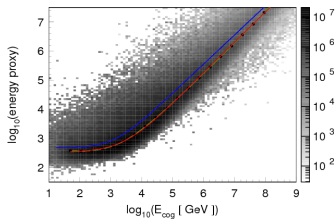
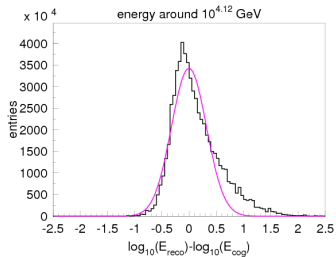
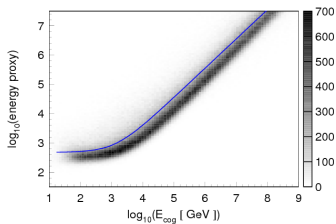
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Analytic (μ_e , μ_{eX}): Photons per track length



Photonics, photorec

4-dimensional photonics table of expected light yield and arrival time distributions, based on a ray tracing simulations with a realistic ice model:

- zenith angle
- distance to DOM
- depth of the DOM
- azimuth angle (around track)
- (length)

Table generated for muons with **constant** dE/dx (“light saber model”).

“PhotorecEnergyEstimator” uses this table to determine μ_{mk} .

Pro: taking layered ice structure properly into account (no averaging)

Contra(1): spoiling it with coarse binning (table needs to fit in RAM)

Contra(2): light saber model ignores stochastics

Authors: Sean Grullon, Gary Hill, David Boersma (2007-2008)

Truncated Energy reconstruction

Attempt to improve photorec resolution by removing outliers → less sensitive to stochastics. Two variations:

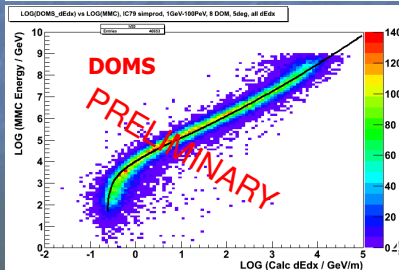
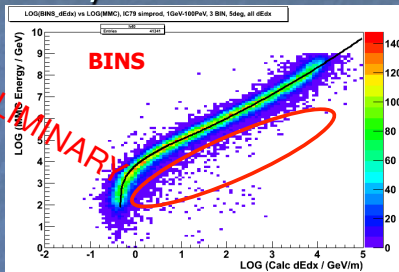
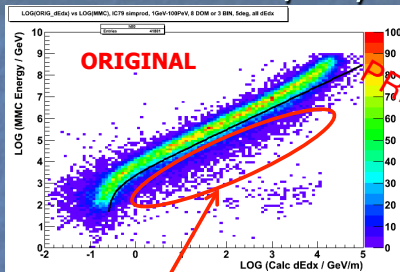
- BINS method
 - “Bin” the detector by defining planes perpendicular to the track
 - Use only DOMs within 10-80m from the track
 - Determine dE/dx for each “bin” separately
 - Remove bins with top 40% of dE/dx values
 - (Keep at least 3 bins)
 - Recompute dE/dx with DOMs from remaining bins
- DOMS method
 - Use only DOMs with 60m from the track
 - Determine dE/dx for each DOM individually
 - Remove DOMs with top 50% of dE/dx values
 - (Keep at least 8 DOMs)
 - Recompute dE/dx with remaining DOMs
 -

Author: Sandy Miarecki (2011)



IceCube

Plot dE/dx vs. MMC energy 5° zen/azi, 8 DOM, 3 BIN



High-energy tail from stochastics skews dE/dx and pulls the best fit curve off the densest part of the Original Photorec curve, which worsens the energy resolution; reduced in Truncated

Millipede: using splines and NNLS

Idea:

- 1 a spline fit to the photonics table (for *cascades*), using spline coefficients obtained from a fit to a very finely binned photonics table.
- 2 segment the track in short segments (e.g. 15m) and reconstruct the dE/dx for each segment individually

To find the energy loss in each of n segments, causing charges N_k in m DOMs, solve this (NNLS):

$$\begin{pmatrix} B_1(x_1) & B_2(x_1) & \cdots & B_n(x_1) \\ B_1(x_2) & B_2(x_2) & \cdots & B_n(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ B_1(x_m) & B_2(x_m) & \cdots & B_n(x_m) \end{pmatrix} \begin{pmatrix} E_1 \\ E_2 \\ \vdots \\ E_m \end{pmatrix} = \begin{pmatrix} N_1 \\ N_2 \\ \vdots \\ N_m \end{pmatrix}$$

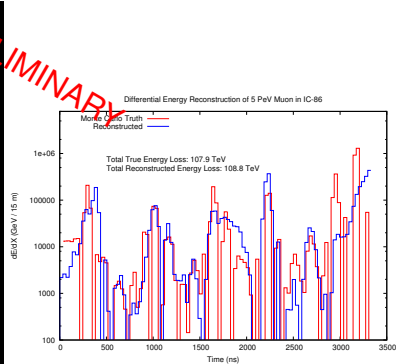
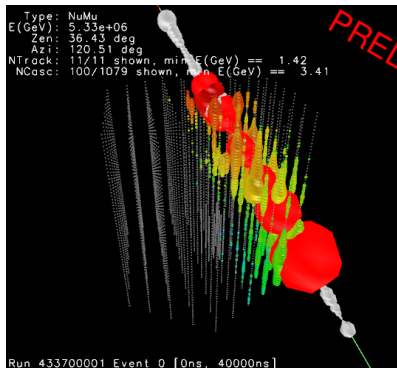
$B_i(x_j)$: predicted photon distribution at x_j from a shower with reference energy loss at segment i

E_j : energy loss at each segment/shower

N_j : measured photon counts

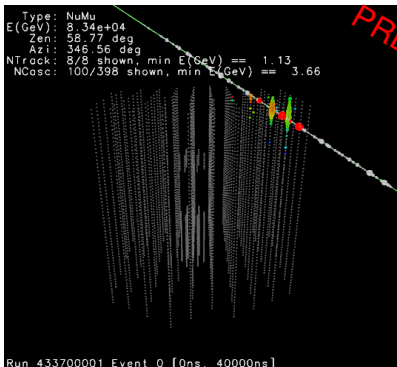
Author: Nathan Whitehorn (2011)

High Energy Performance

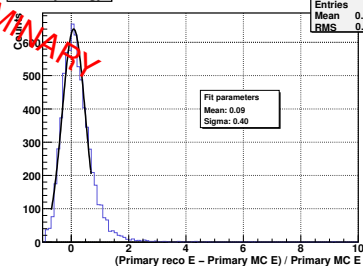


$\approx 1\%$ energy deposition resolution at 1 PeV, cascade position resolution \approx a few meters

Low Energy Performance



Primary energy



J. P. Yañez, DESY

≈ 50% energy deposition resolution at 20 GeV, track length to
 ≈ 10 meters

Conclusions

We have quite a number of interesting energy loss reconstructions in IceCube:

- photorec: old
- truncated photorec: current
- mue/muex: current
- millipede: future
- top-down: interesting concept

Skipped: data-derived dE/dx reconstruction (DDDDR) by Patrick Berghaus.