Muon Track Reconstruction and Data Selection Techniques in AMANDA

- Introduction
- Likelihood Methods
- Initial track and Minimization
- Performance
- Transient Waveform Recording
- Critique and Outlook

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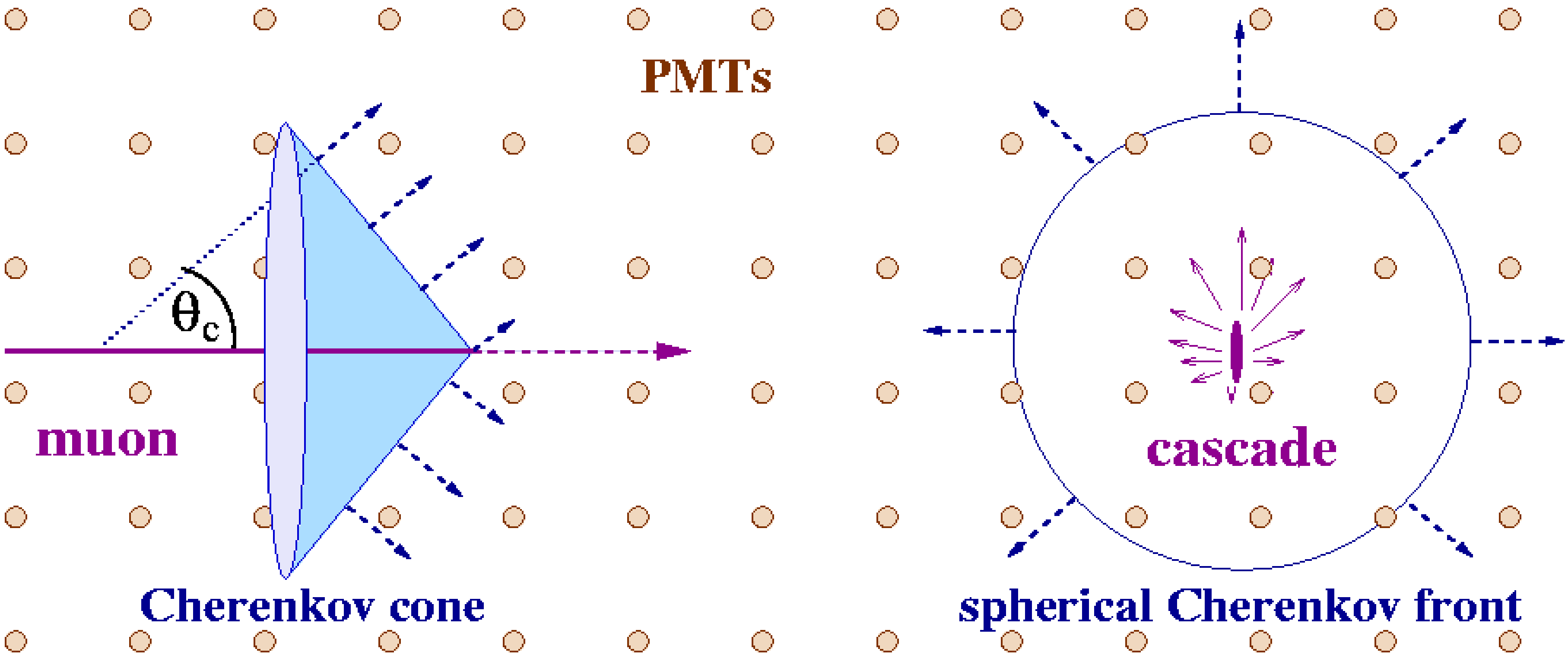
VLVnT Workshop
Amsterdam, October 2003

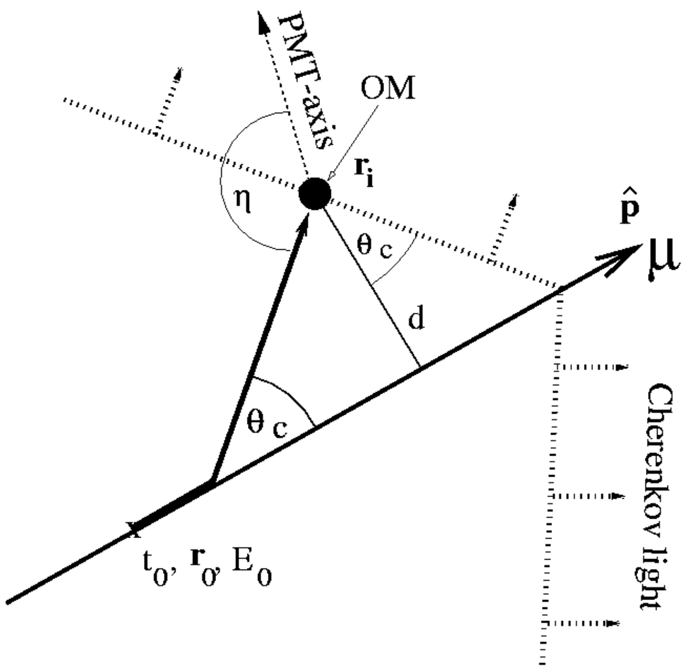
Detection Modes

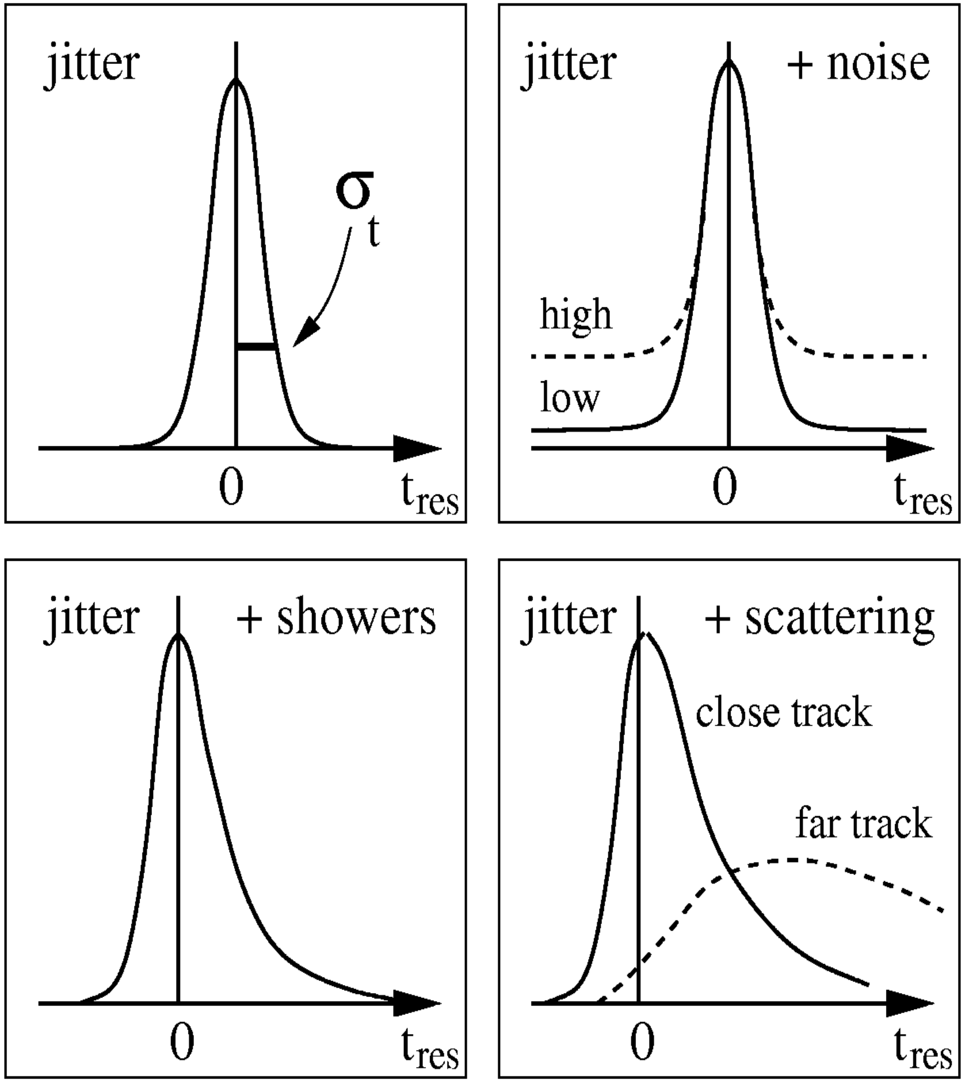
Track-like

Cascade-like



Arrival Time





$$t_{\text{geo}} = t_0 + \frac{\hat{\mathbf{p}} \cdot (\mathbf{r_i} - \mathbf{r_0}) + d \tan \theta_c}{c_{\text{vac}}}$$

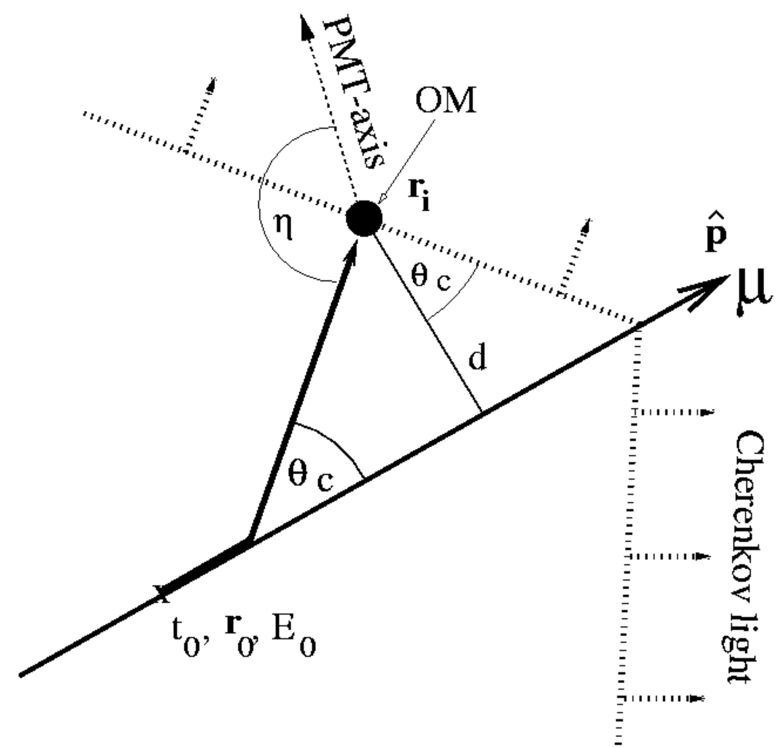
Likelihood Description

Maximize:

L (Event $\equiv$ {t_1, A_1, ..., t_n, A_n } | Track $\equiv$ { $\mathbf{r}_0$, t_0, $\mathbf{p}$, E })

Single Photo-Electron Time Likelihood (SPE)

$$\mathcal{L}_{\text{time}} = \prod_{i=1}^{N_{\text{hits}}} p_1(t_{\text{res},i} | \mathbf{a} = d_i, \eta_i, \ldots)$$



Multi Photon Likelihood (1st photon)

AMANDA

AMANDA

Multi Photo-Electron Likelihood
(MPE)

$$p_N^1(t_{\text{res}}) = N \cdot p_1(t_{\text{res}}) \cdot \left(\int_{t_{\text{res}}}^{\infty} p_1(t)dt\right)^{(N-1)} = N \cdot p_1(t_{\text{tres}}) \cdot (1 - P_1(t_{\text{res}}))^{(N-1)}$$

Poisson Saturated Amplitude Likelihood
(PSA)

$$p_\mu^1(t_{\text{res}}) = \frac{1}{N} \sum_{i=1}^{\infty} \frac{\mu^i e^{-\mu}}{i!} \cdot p_i^1(t_{\text{res}}) = \frac{\mu}{1 - e^{-\mu}} \cdot p_1(t_{\text{res}}) \cdot e^{-\mu P_1(t_{\text{res}})}$$

If several photons arrive, the earliest arrives earlier than predicted by the SPE likelihood

Likelihood Extensions

P_{hit}-P_{nohit} Likelihood

$$\mathcal{L}_{\mathrm{hit}} = \prod_{i=1}^{N_{\mathrm{ch}}} P^{\mathrm{hit},\mathrm{i}} \cdot \prod_{i=N_{\mathrm{ch}}+1}^{N_{\mathrm{OM}}} P^{\mathrm{no-hit},\mathrm{i}},$$

essentially evaluates mean visual range

Combination of Time and Phit Likelihood

$$\mathcal{L}_{\mathrm{MPE}\oplus\mathrm{P}^{\mathrm{hit}}\mathrm{P}^{\mathrm{no-hit}}} = \mathcal{L}_{\mathrm{MPE}} \cdot \left(\mathcal{L}_{\mathrm{hit}}\right)^{w}$$

Currently best performance

Likelihood of Waveforms

Likelihood of a waveform with N photons (resolved)

$$\mathcal{L} = N! \cdot \prod_{i=1..N} p_1(t_i)$$

Likelihood of a waveform with N pulses of npe_i photons (unresolved)

$$\mathcal{L} = N! \cdot \prod_{i=1..N} npe_i \cdot p_1(t_i) \cdot (P_1(t+\Delta)-P_1(t_i))^{npe_i-1}$$

Zenith weighted reconstruction

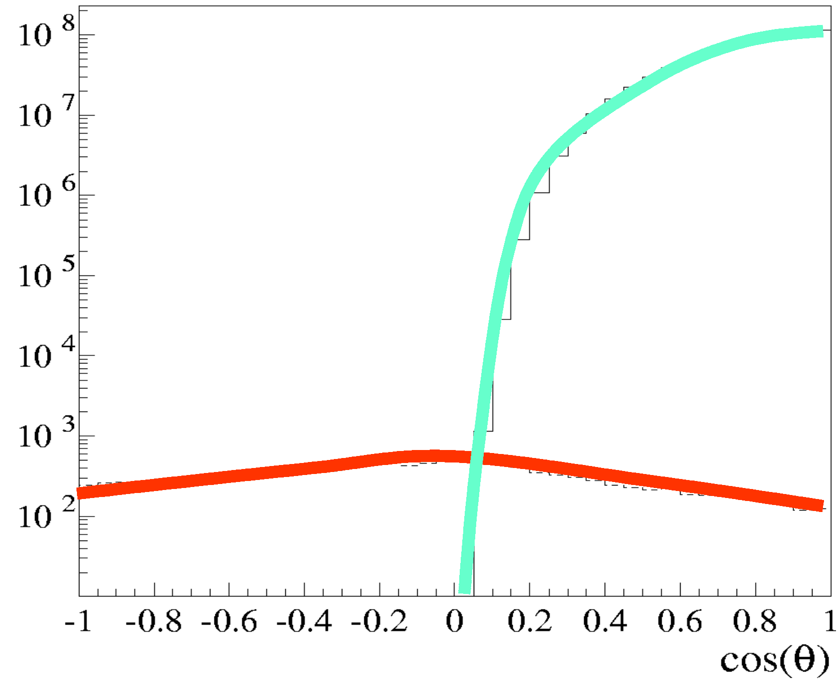
Maximize:

$$\mathcal{L}(\text{Track} \mid \text{Event}) = \frac{\mathcal{L}(\text{Event} \mid \text{Track}) * \mathcal{L}(\text{Track})}{\mathcal{L}(\text{Event})}$$

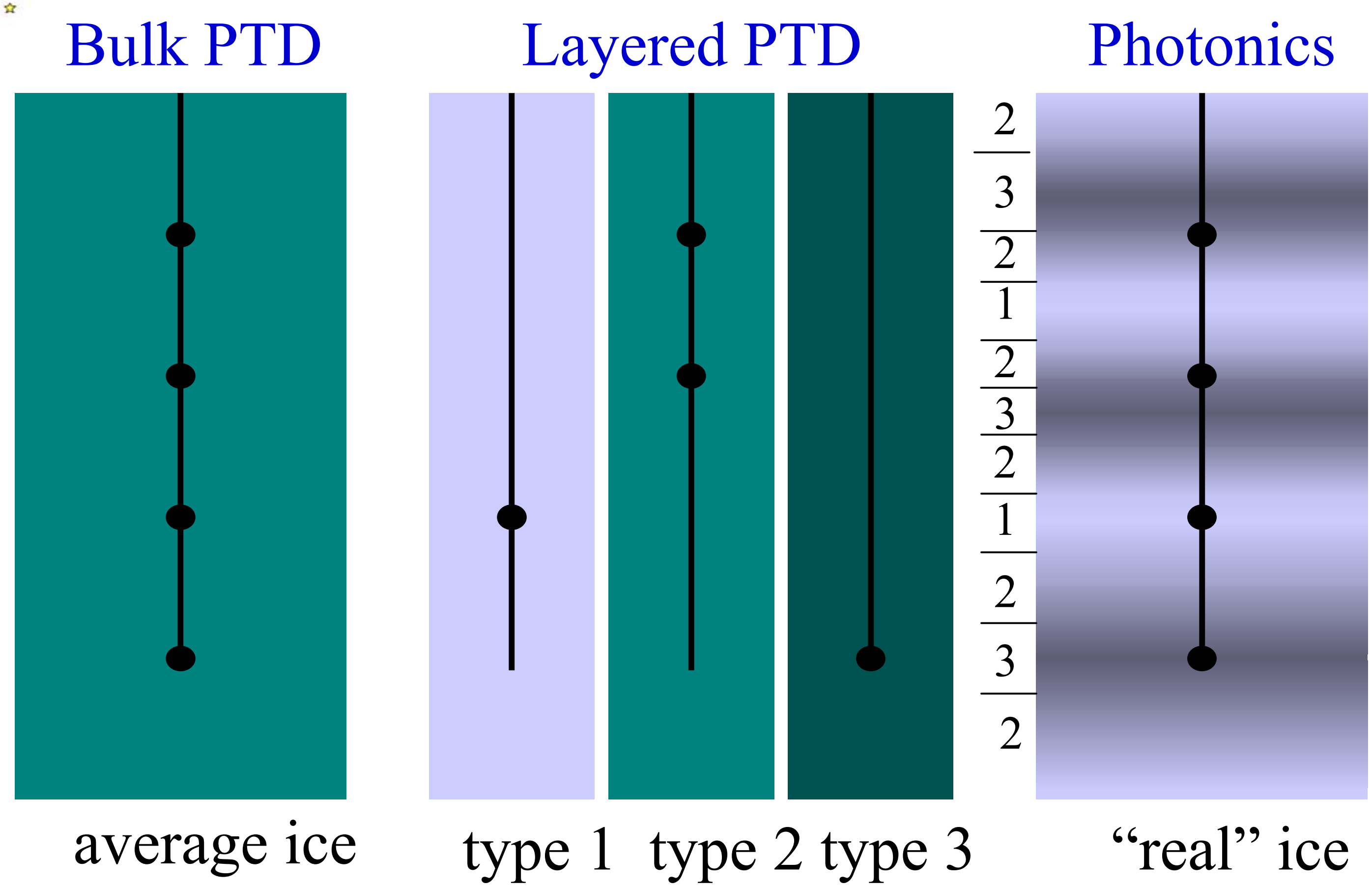
Motivated by Baye's Theorem

Zenith weighted Reconstruction:
$L(\text{Track}) = \Phi(\theta)$

Convergence in one hemisphere
$L(\text{Track}) = \Theta(\pm(\theta - 90))$



Ice modeling



3d-Simulation of photons emitted from track-segments and cascades:
Arrival probability and time at the receiver

Likelihood Implementation

- Direct reconstruction using PTD tables
  -> extension layered Ptd and Photonics
- Simplified analytical parameterization with a Gamma distribution (Pandel function)

$$p(t_{\mathrm{res}}) \equiv \frac{1}{N(d)} \frac{\tau^{-(d/\lambda)} \cdot t_{\mathrm{res}}^{(d/\lambda-1)}}{\Gamma(d/\lambda)} \cdot e^{-\left(t_{\mathrm{res}} \cdot \left(\frac{1}{\tau} + \frac{c_{\mathrm{medium}}}{\lambda_a}\right) + \frac{d}{\lambda_a}\right)}$$

$$N(d) = e^{-d/\lambda_a} \cdot \left(1 + \frac{\tau \cdot c_{\mathrm{medium}}}{\lambda_a}\right)^{-d/\lambda} ,$$

Very few parameters describe the full phase space:

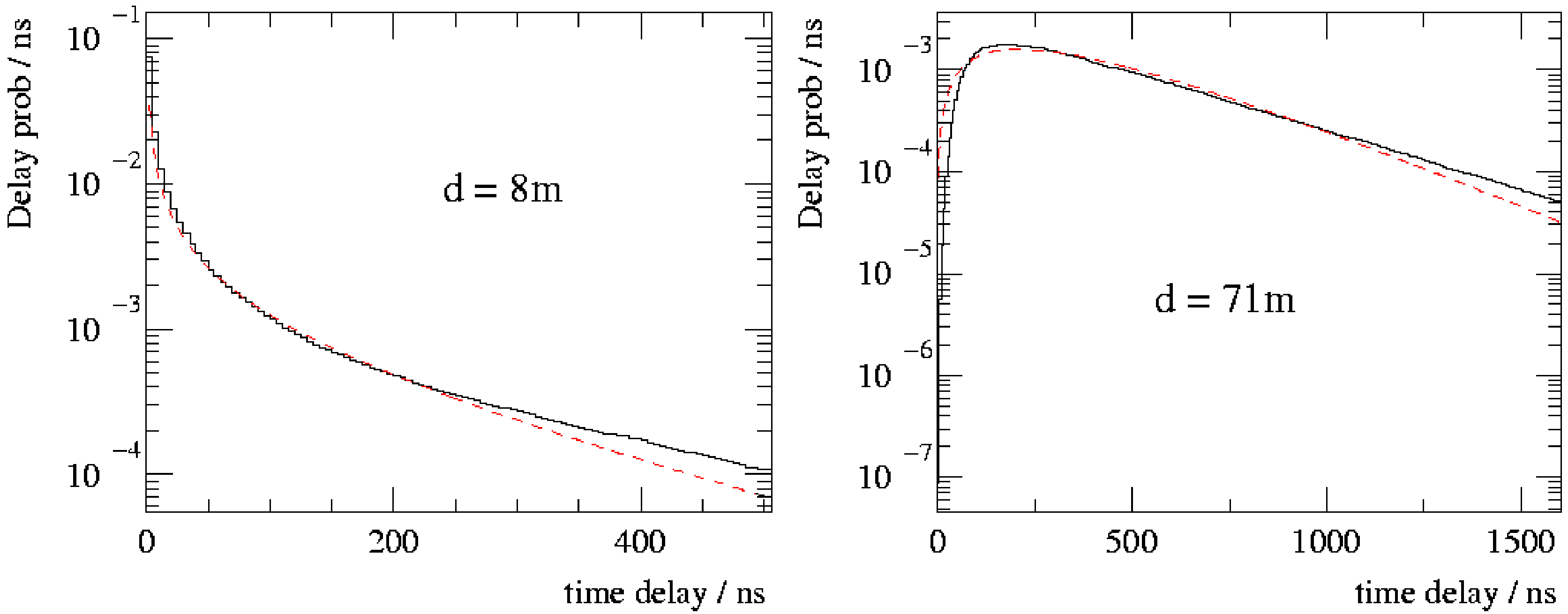
$$\begin{aligned} \tau &= 557\,\mathrm{ns} & d_{\mathrm{eff}} &= a_0 + a_1 \cdot d \\ \lambda &= 33.3\,\mathrm{m} & a_1 &= 0.84 \\ \lambda_a &= 98\,\mathrm{m} & a_0 &= 3.1\,\mathrm{m} - 3.9\,\mathrm{m} \cdot \cos(\eta) + 4.6\,\mathrm{m} \cdot \cos^2(\eta) \end{aligned}$$

Fast calculation, integrable (->MPE ...)

Limited accuracy, need to convolute with a Gaussian (PMT jitter)

Only Bulk ice (status 1998) implemented. Upgrade is underway!

Parameterization



Ptd bulk ice (1998)

Pandel parameterization

Initial Track: LineFit

Assume all hits are points on a line, which is moving with velocity v through the detector

$$\mathbf{r}_i \approx \mathbf{r} + \mathbf{v} \cdot t_i$$

Constructing:

$$\chi^2 \equiv \sum_{i=1}^{N_{\text{hit}}} (\mathbf{r}_i - \mathbf{r} - \mathbf{v} \cdot t_i)^2$$

$d\chi^2 / d\mathbf{r} = 0$ and $d\chi^2 / d\mathbf{v} = 0$ gives the analytic solution:

$$\mathbf{r} = \langle \mathbf{r}_i \rangle - \mathbf{v} \cdot \langle t_i \rangle \qquad \mathbf{v} = \frac{\langle \mathbf{r}_i \cdot t_i \rangle - \langle \mathbf{r}_i \rangle \cdot \langle t_i \rangle}{\langle t_i^2 \rangle - \langle t_i \rangle^2}$$

V.Stenger, J.Jacobsen, A.Roberts (?)

Initial Track: Direct Walk

Four step fast pattern recognition algorithm:

1.) Select track-elements (TE) by finding distant OMs (d>50m) for which:

$$|\Delta t| < d/c_{vac} + 30\text{ns}, \qquad \text{(causality)}$$

2.) Select associated hits (AH) for each TE with reasonable relative times:

$$-30\text{ns} < t_{res} < 300\text{ns}, \qquad d < 25\text{m ns}^{1/4} / (t_{res}+30\text{ns})^{1/4}$$

3.) Select track candidates (TC):

More than 10 AH and lever arm (RMS of AH points) > 20m

4.) Cluster search: Select cluster with most TC

$$\psi < 15° , Q_{TC} > 0.7\, Q_{max} \text{ with } Q_{TC} = \min(N_{AH},\ 0.3\text{m}^{-1} \cdot \sigma_L + 7)$$

Algorithm is fast, efficient and has a good angular resolution.

Capable to identify muon bundles

reconstruction	atm. μ	atm. ν
direct walk	1.5%	93%
line-fit	4.8%	85%

(P.Steffen, 2001)

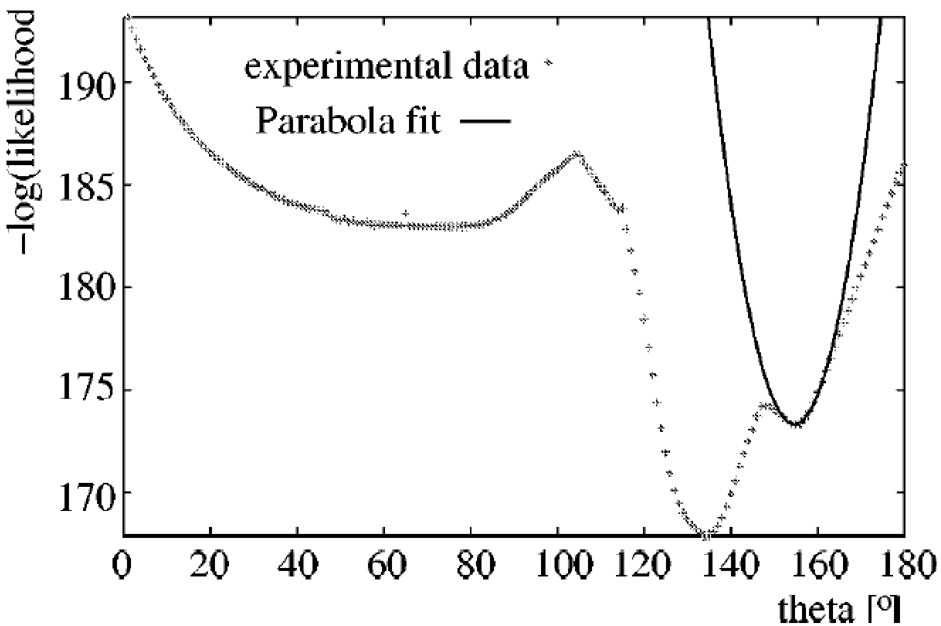
Minimization

Minimization of -log(L)

- Powell's (NR)
- Minuit (Mini)
- Simplex
- Simulated annealing (NR)
- TMinuit

Problems:

- Local Minima
- Vertical coordinates
  (ambiguity in azimuth)



Manipulate initial track to improve convergence:

- Shift r_0 close to COG
- Transform t_0: Evaluate all arrival times
  and avoid negative times

-> Iterative Reconstruction

Iterative Minimization

Ability to find global minimum depends on initial track but 5 free parameter (ϑ, φ , $\mathbf{r}_0$) -> no systematic scan of the full parameter space

Iterate: Reconstruct the event N - times.
Use the track result of previous iteration and randomize ϑ and φ
Use reasonable values for $\mathbf{r}_0$ (shift to COG, t_0 shift)

Store each found minimum and use finally the best result

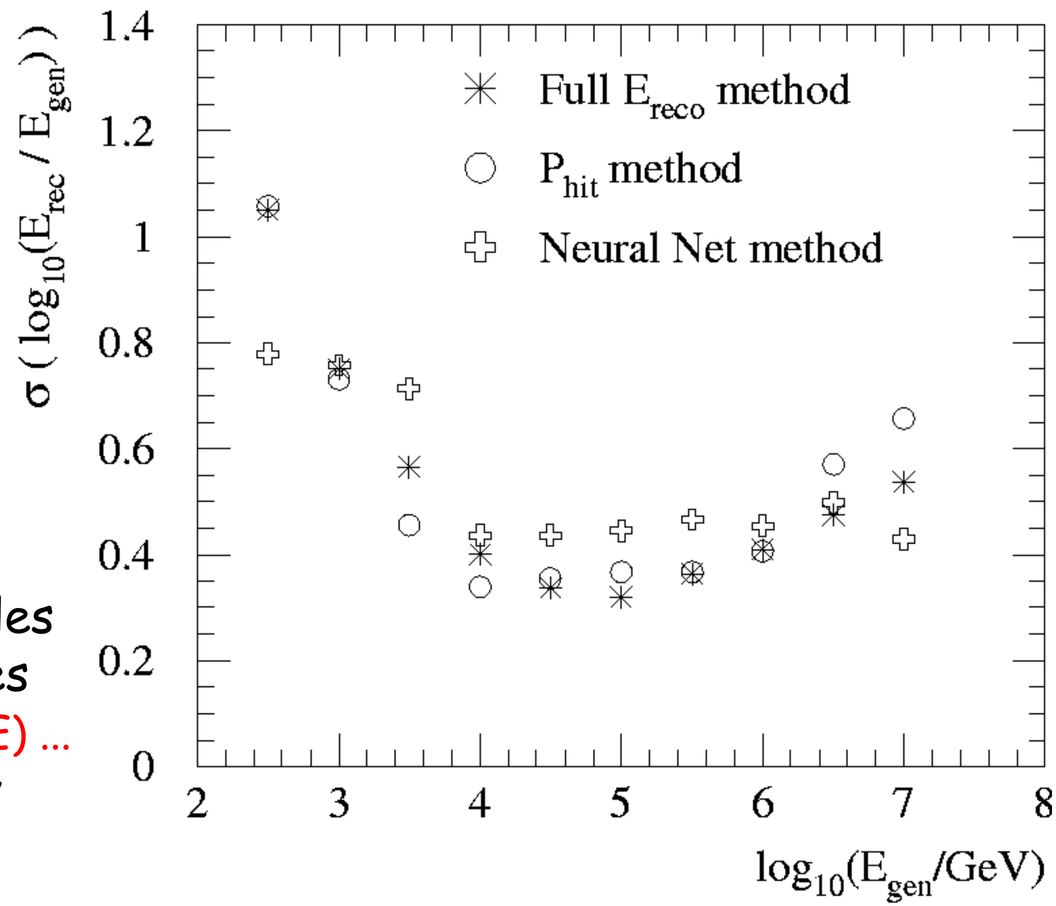
Already about 10 to 20 iterations are sufficient to find the global minimum.

CPU time is proportional N but ok for filtered data

Energy Reconstruction

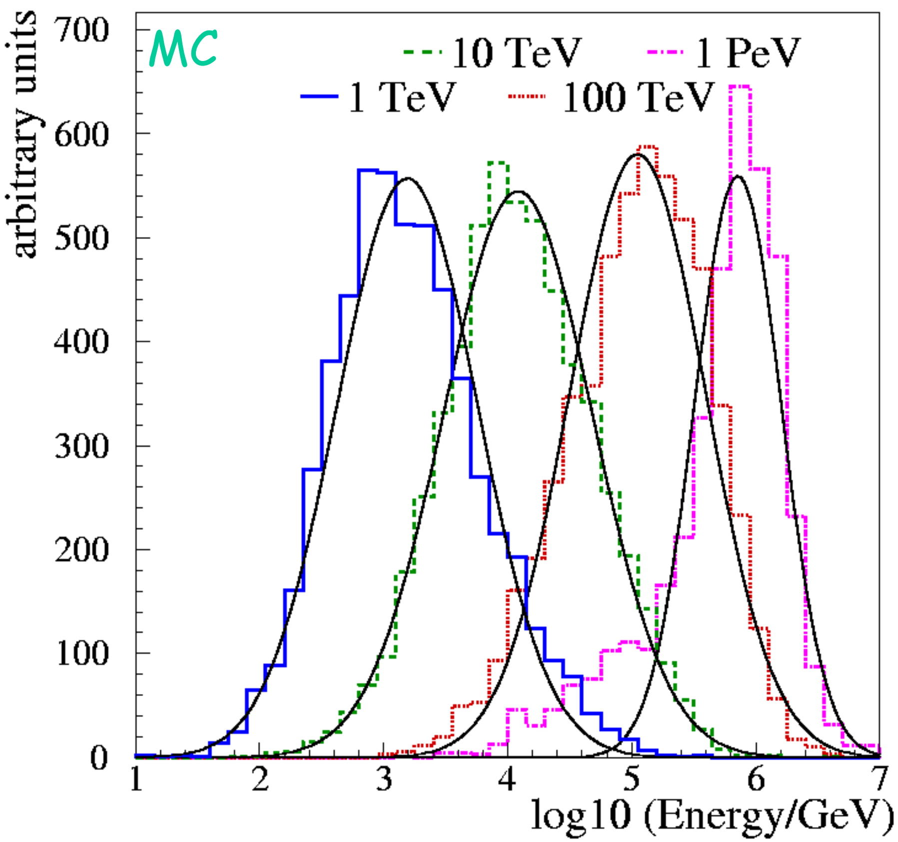
3 (+1) Strategies:

- Fit mean visual range with P_{hit}-P_{nohit} Likelihood
- Amplitude Likelihood
  - Complicated, needs detailed Ice Model
  - Fluctuations, Dynamic range
- Neural Network
  - use energy correlated variables
  - presently only simple variables Nch, Nhits, <ADC>, <LE>, RMS(LE) ...
  - Use reconstruction geometry information in future
- Cut on Nch (-> diffuse limit)

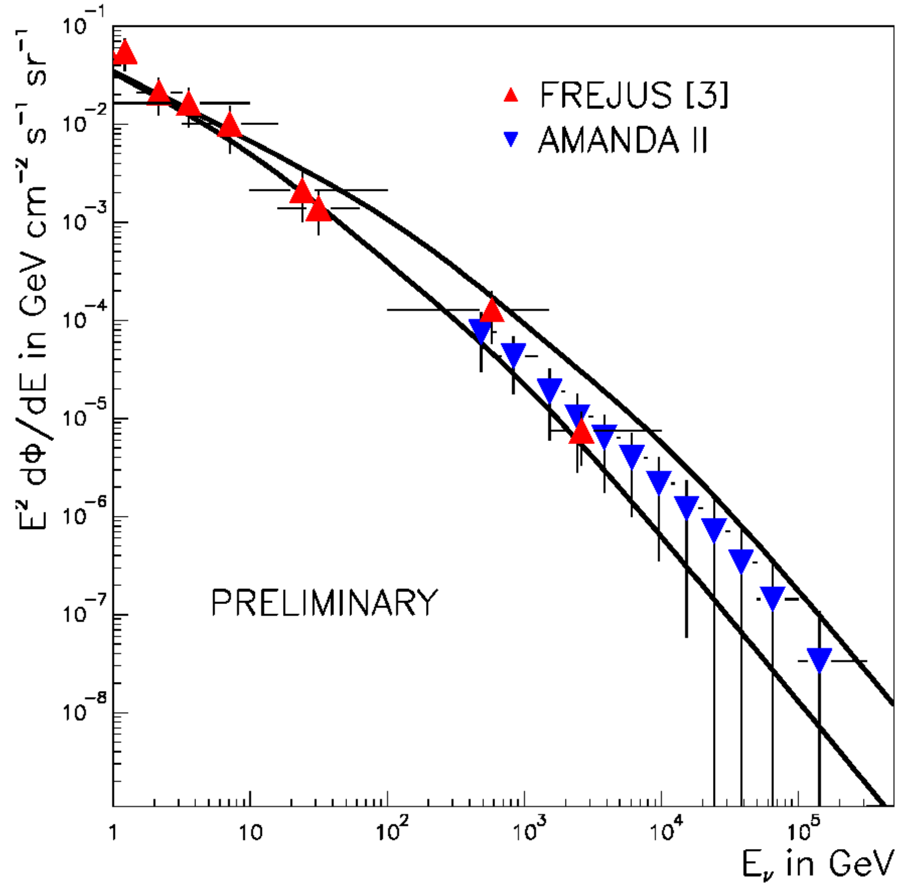


Neural Network result

MC Test network with mono-energetic muons



Result after unfolding the energy spectrum of measured neutrinos (2000 point-source sample)



Background rejection

Background classes:

- Horizontal muons
- Muon bundles
- Secondary cascades (brems)
- Stopping muons
- Scattering ice layers
- Corner clippers
- Synchronous muons
- Instrumental effects
  (X-talk, noisy channels)

Important selection cuts:

$l = -\log(L)/N_{free}$ Likelihood parameter

l_{track} / $l_{cascade}$

l_{up} / l_{down}

N_{direct} : Number of unscatterd hits

L_{direct} : Track length (*Lever arm*)

S : Smoothness = MAX(Sj)

$$S_j \equiv \frac{j-1}{N-1} - \frac{l_j}{l_N}$$

$$S_j^{P^{\mathrm{hit}}} \equiv \frac{\sum_{i=1}^{j} \Lambda_i}{\sum_{i=1}^{N_{\mathrm{OM}}} \Lambda_i} - \frac{\sum_{i=1}^{j} P^{\mathrm{hit,i}}}{\sum_{i=1}^{N_{\mathrm{OM}}} P^{\mathrm{hit,i}}}$$

... many more

Typically these cuts quantify information which was not evaluated in the reconstruction itself

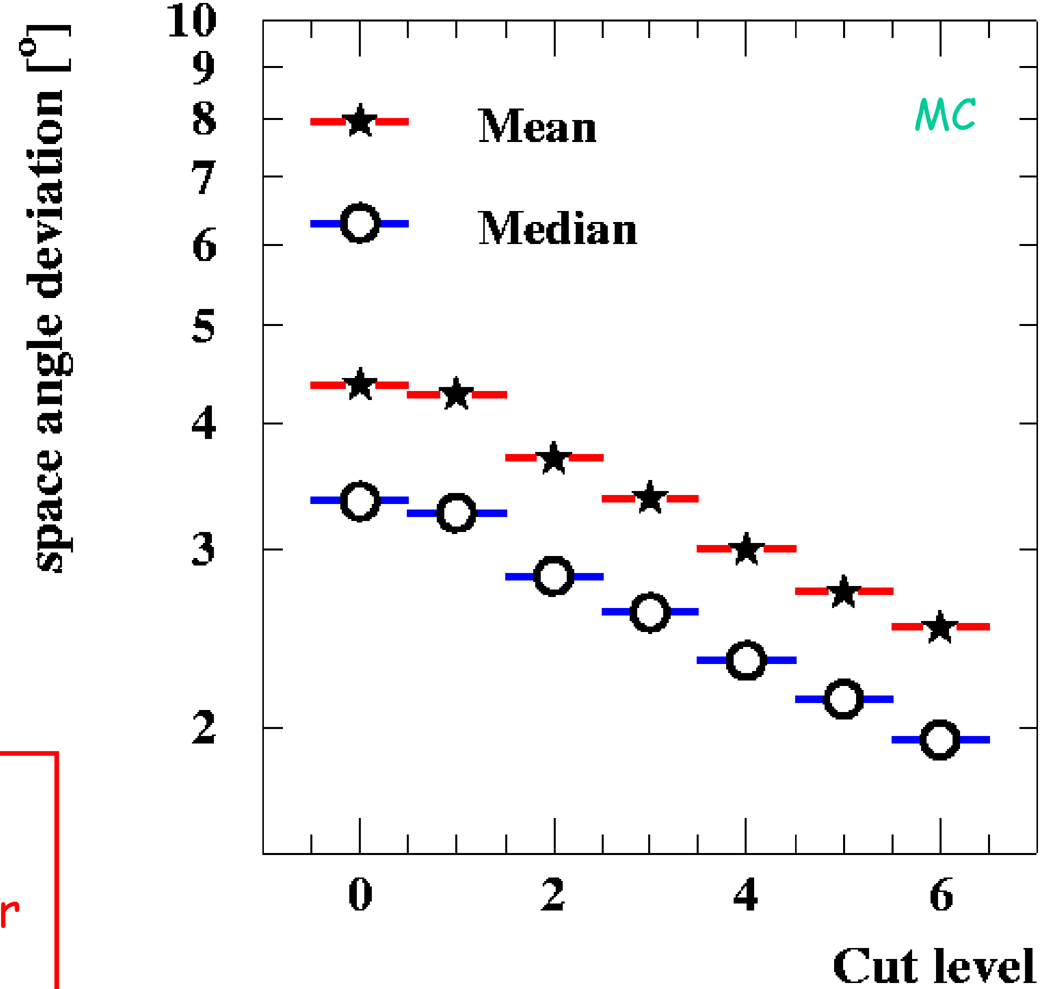
Performance: Dependence on Selection

Strawman analysis for the demonstration of the typical AMANDA-II performance:

Cuts: N_{ch}, N_{dir}, L_{dir}, l_{SPE}, ψ (DW, SPE, MPE)

Cut level:
Each cut set to 95% passing efficiency for atm. neutrinos relative to the previous level

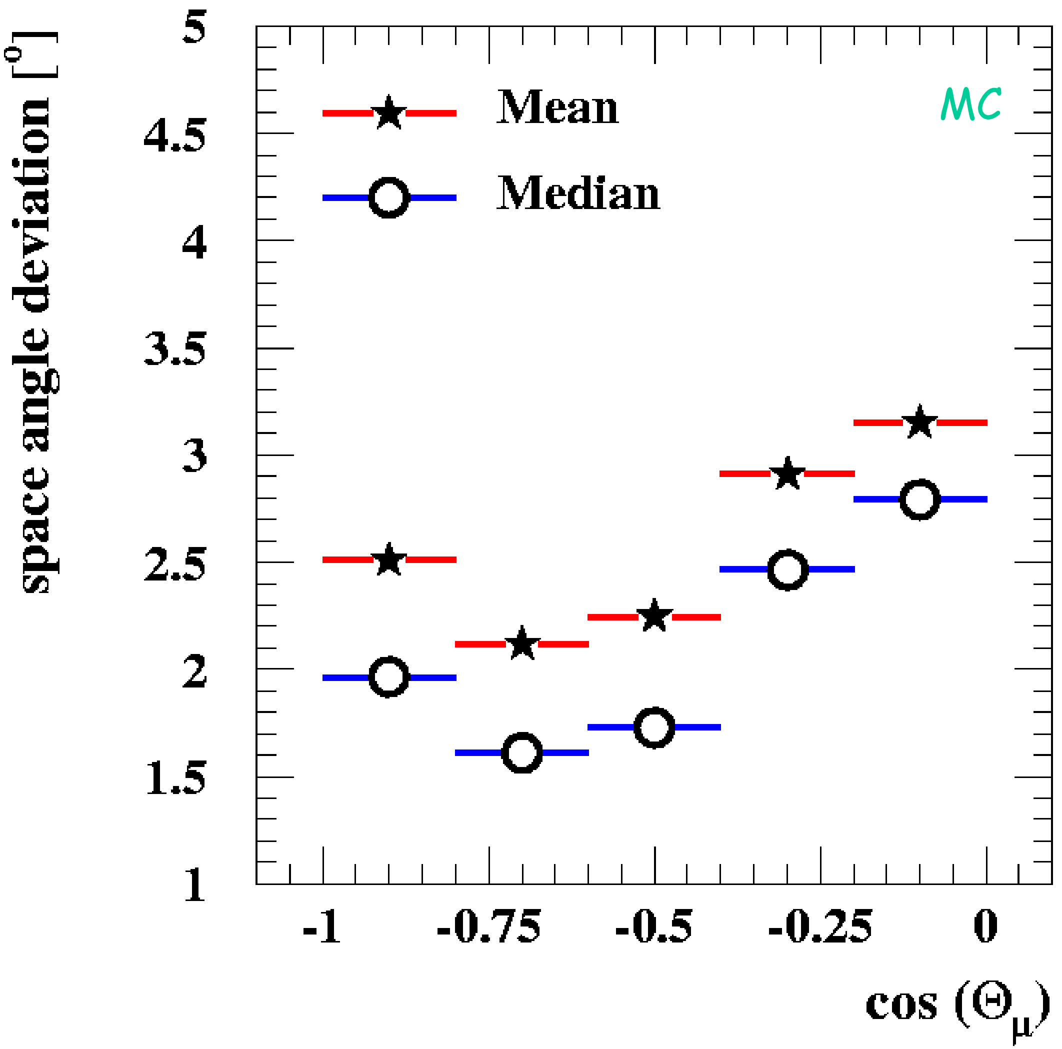
- Angular resolution strongly depends on the selection
- AMANDA-II achieves an angular resolution of typically 2°



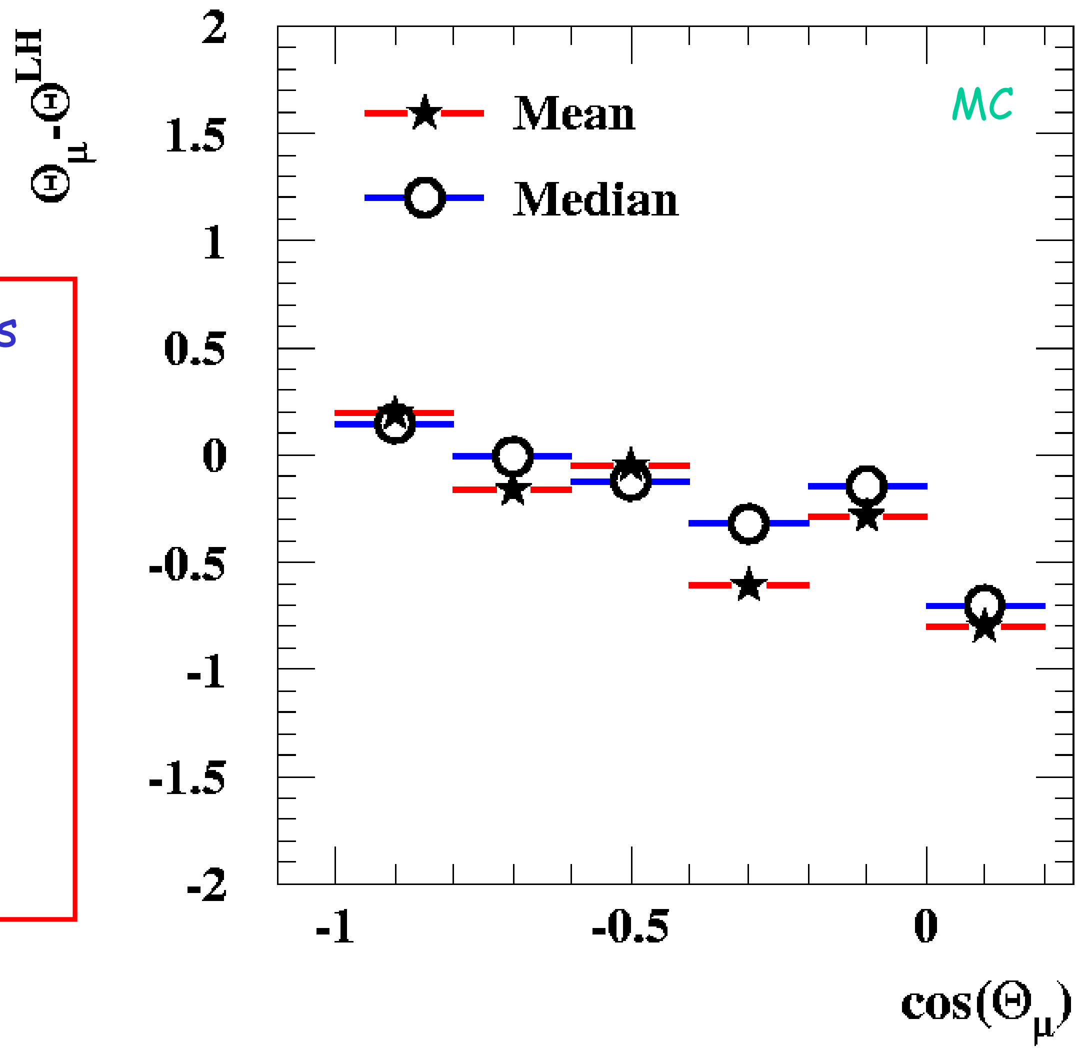
=> Use "Cut level 6" sample in the following

Zenith Dependence

Zenith angle dependence due to geometry of the AMANDA-II detector



Zenith Shift



Small zenith shift (± 0.5°) as function of the zenith angle due to geometry of the AMANDA-II detector

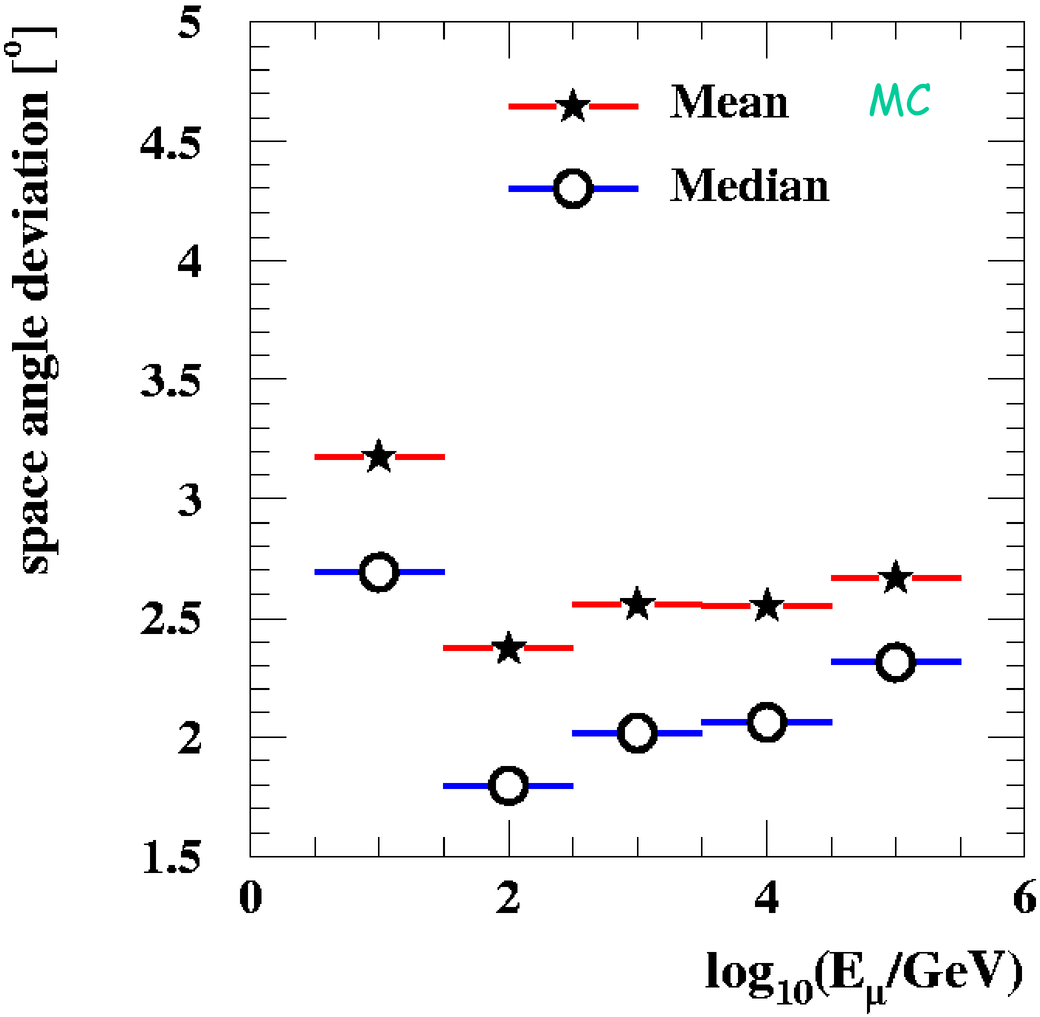
- Verified by SPASE coincident events
- Can be corrected for (Not corrected here)

Energy Dependence

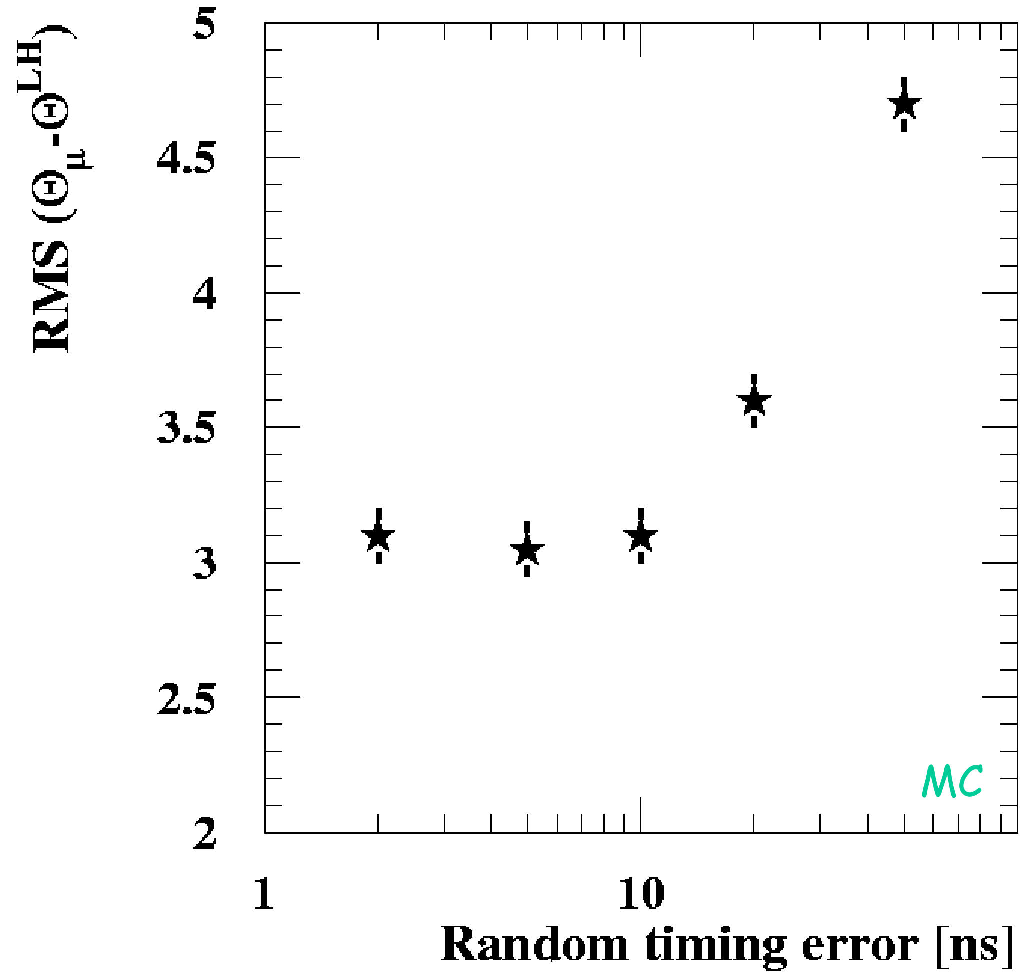
Angular resolution is degrading at higher energies because of a wrong fit model:

- SPE fit
- infinite minimum ionizing track
  (but secondary cascades dominate the light output)

-> improved likelihood model
-> pattern recognition
   (in wave-forms)



Calibration Uncertainties



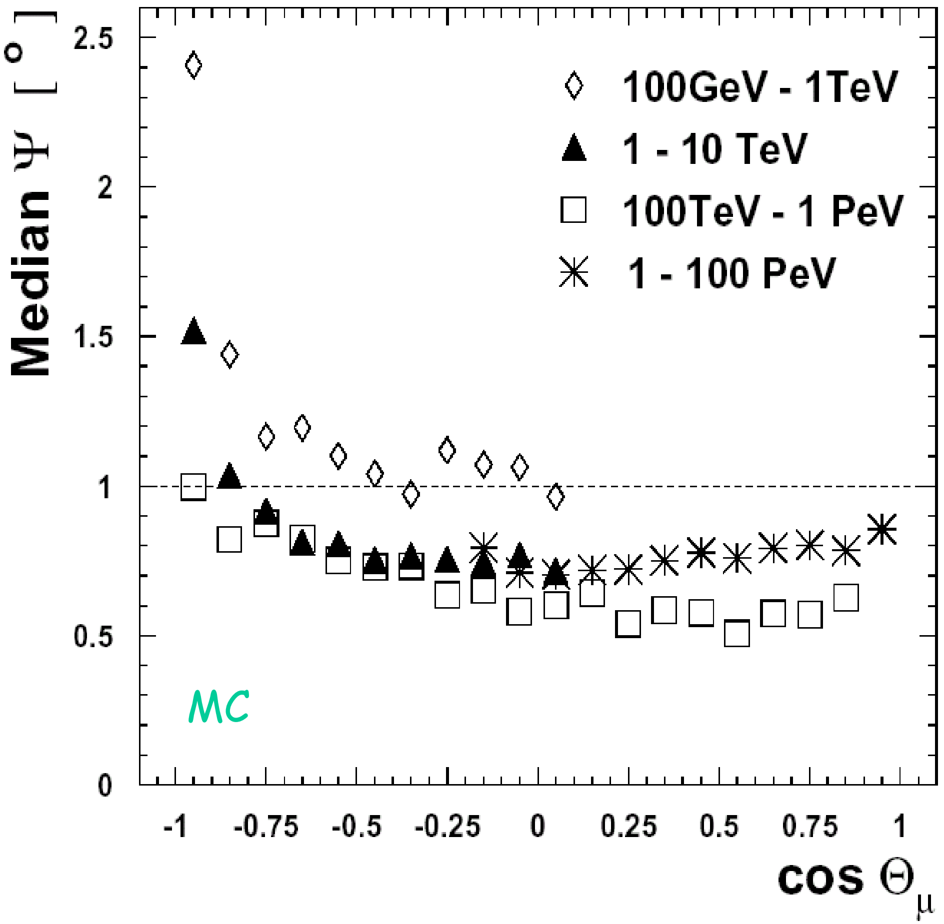
The reconstruction is insensitive to calibration uncertainties, which are of the order of 5-7 ns

IceCube

Current performance estimates of IceCube are <u>only</u> based on the standard AMANDA reconstruction

Still a lot of things improve
- $\Delta\psi \sim 0.6° - 0.8°$ (E>1TeV)
- no degradation at high energies
- good performance at horizon

We expect a strong improvement, after establishing advanced capabilities of the IceCube Digital OMs



Critique of the current reconstruction

Reconstruction in AMANDA is still (!) not final. So far the collaboration concentrated on:
Finding a method that works and producing first physics results.
(so, its actually bad and that's why we can expect strong improvements in the future)

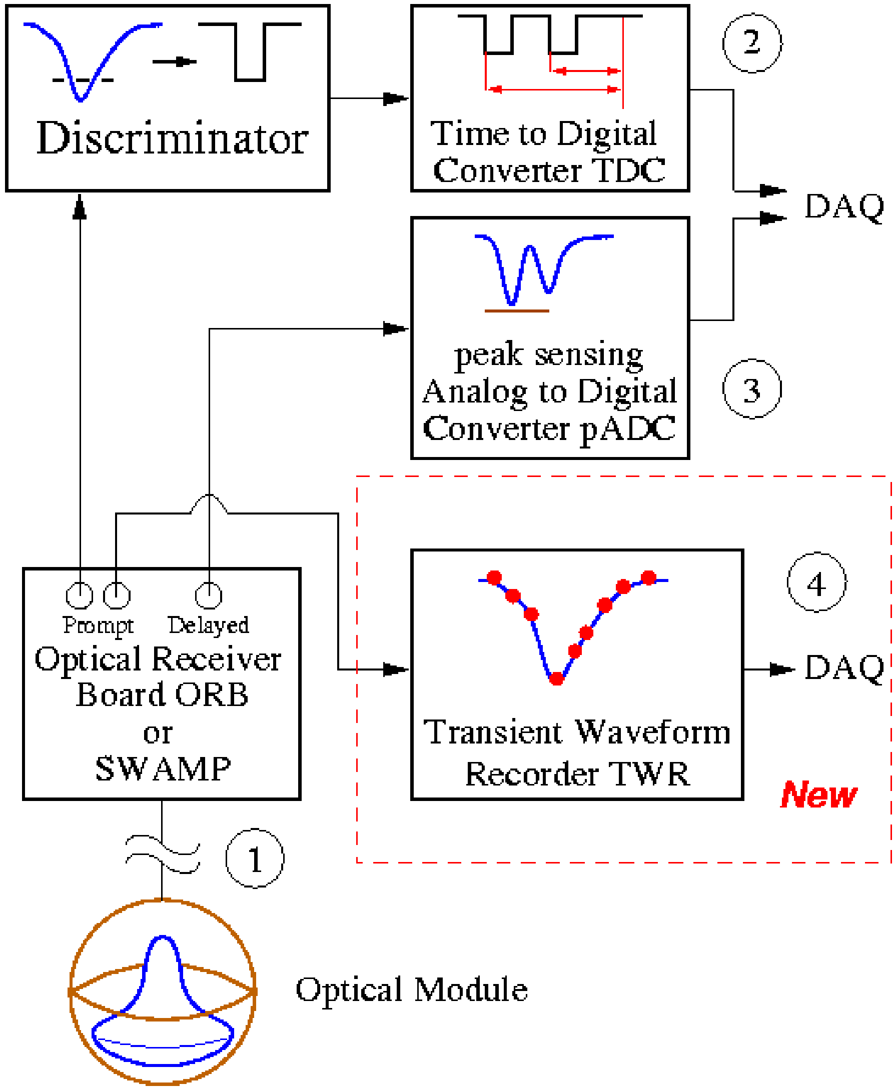
<u>The current Likelihood Model:</u> The assumption of a single minimum ionizing track is an underlying problem when trying to improve the current performance.

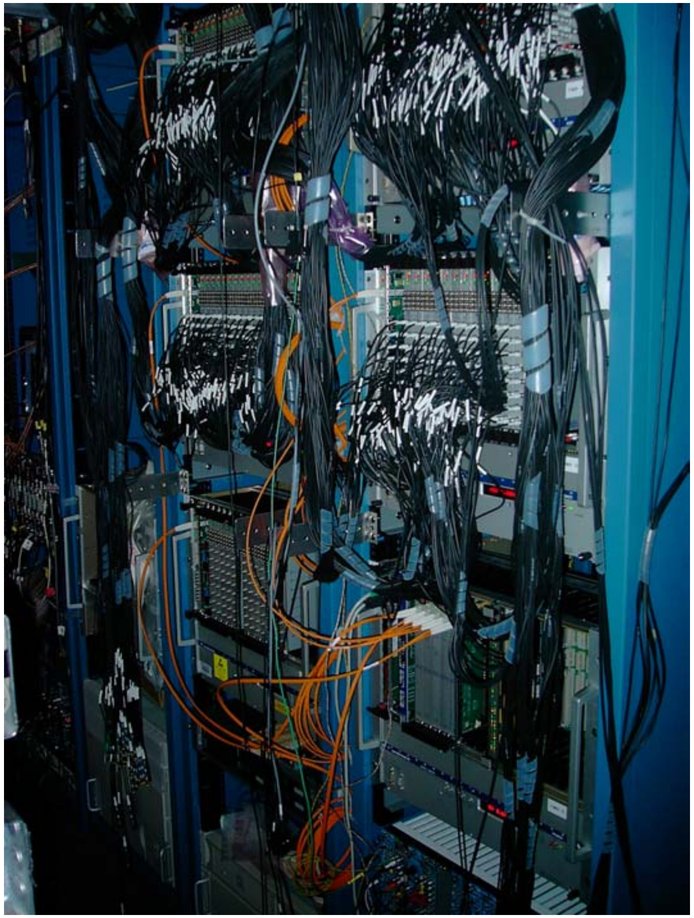
<u>The current Parameterization:</u>
- The optical model is completely outdated (Old values and no vertical ice properties)
- The Pandel parameterization is not very accurate.
  -> Reconstruction directly from tables and better functions are in work

<u>The current Likelihood function:</u> The current SPE or MPE reconstruction do not use the full information (or are even wrong). With help of TWR the full wave-forms can be evaluated.

-> Work underway on all 3 fields

Transient Waveform Recording (TWR)

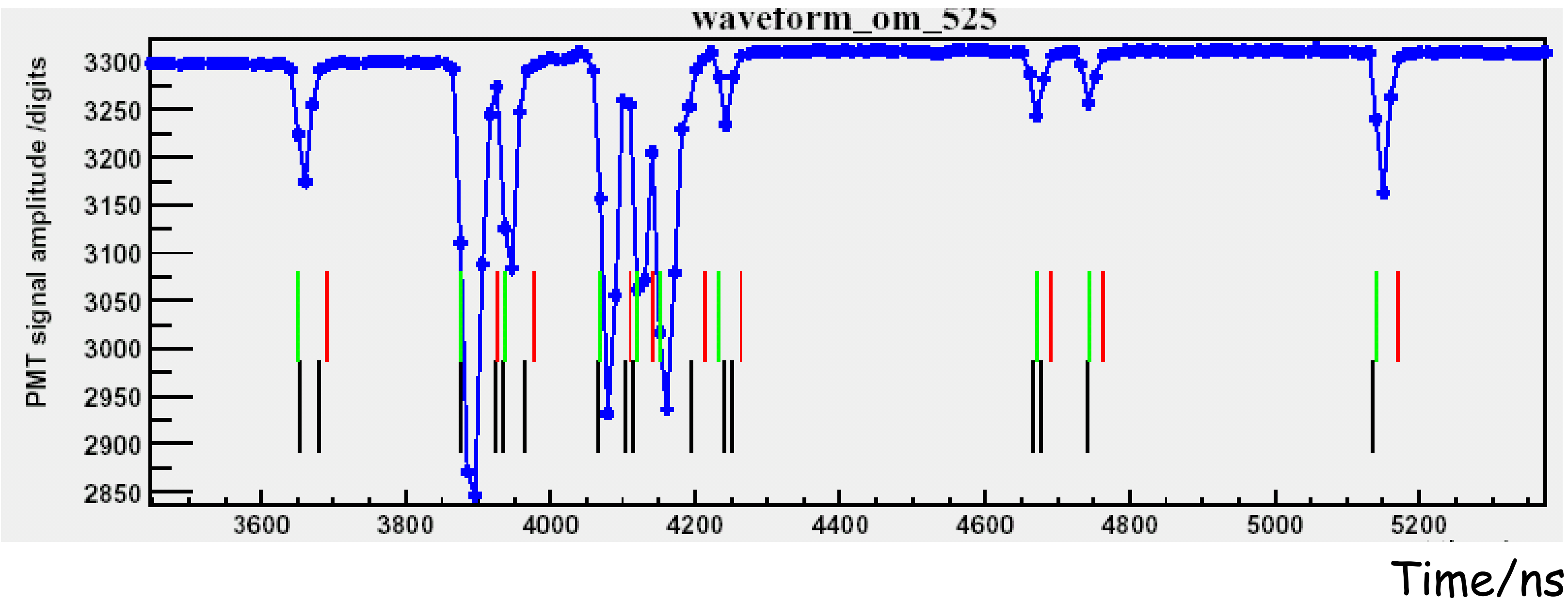




100 MHz FADC, 12 bit, (Struck)

Installed ~580 channels 2002/03

Complex waveforms

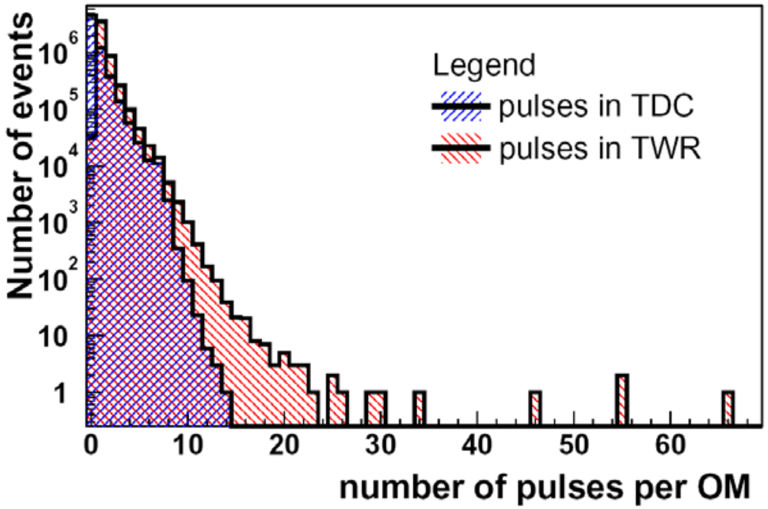


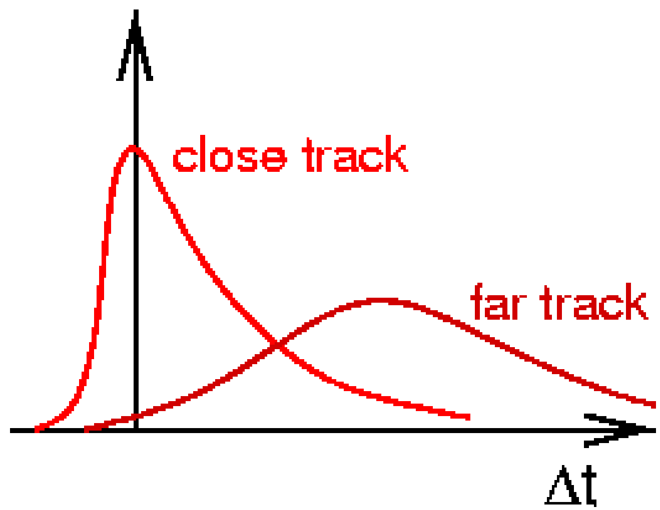
Very complex structures of multi-photon hits not measured by the old DAQ

Need for pattern recognition and appropriate likelihood models -> in work

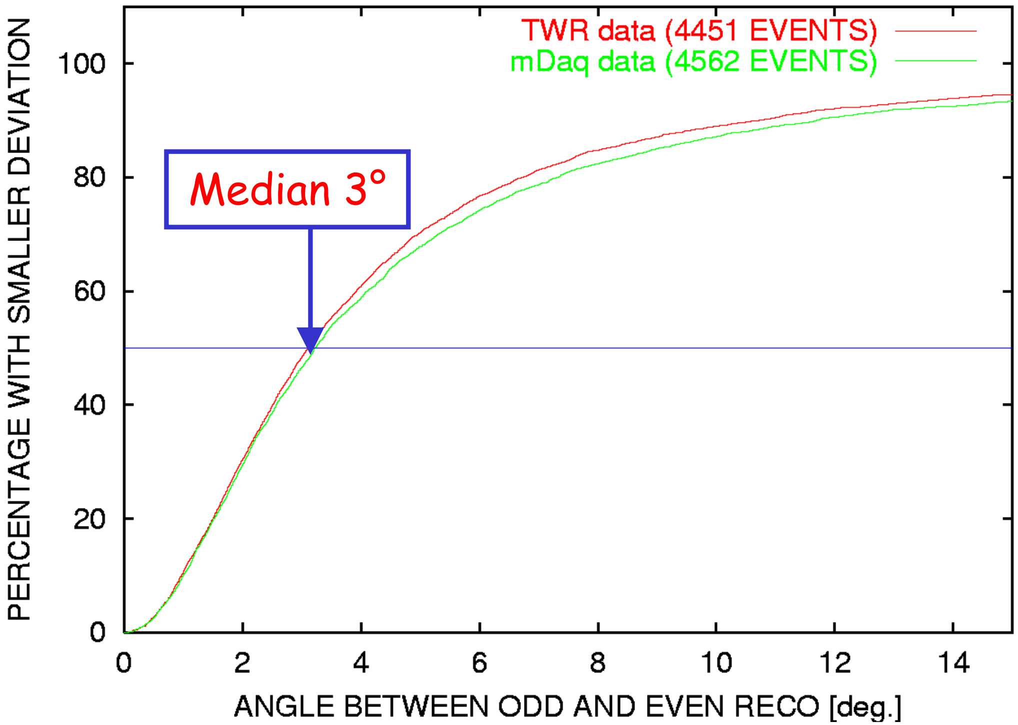
Advantages from TWR

- Dead-time: 10-20 % -> 0%
- No limitation on the number of Hits
  (max 8 for the TDC)
- Larger dynamic range
- Measurement of the amplitude of each pulse
  and photon counting
- In ice each sensor is a full muon detector
  For very high energy events individual PMTs sample hundreds of photons.
  The arrival time distribution strongly depends on the distance.
  Measurement of d and E -> in each sensor
  (2 parameter fit)





Initial TWR Results



Cumulative distribution
Percentage of events reconstructed better than xx degrees

TWR DAQ already slightly better than the old DAQ. No new methods used yet.

- Simulation of old DAQ in TWR data leads to identical results (not shown)
- How to test new methods: Experimental test
  - Sort hits by time and split in 2 independent samples (odd - even)
  - Angular difference is a measure of the angular resolution (but worse than the full sample)

Summary

Present Reconstruction has been proven to be sufficient to produce good initial physics results:

- Background rejection up to 10^{-8}
- High efficiency up to the horizon (-> point source analysis)
- Angular resolution: ~0.8° (IceCube), ~2° (AMANDA-II)

Large room for improvements:

- Optical model: Depth dependence, Parameters
- Likelihood model: SPE, MPE, pulse trains ...
- Physics model: Hadr. Vertex, brems cascades, Bundles, Starting/Stopping μ,
- Pattern recognition, iterative methods

Transient Waveform Recording:

- Pattern recognition, each PMT is a detector
- Accurate photon timing, MPE Likelihood, Amplitude likelihood
- No Dead-time
- Larger dynamic range, improved reconstruction at large energies