Optimal Signal Selection for a Highly Segmented Detector

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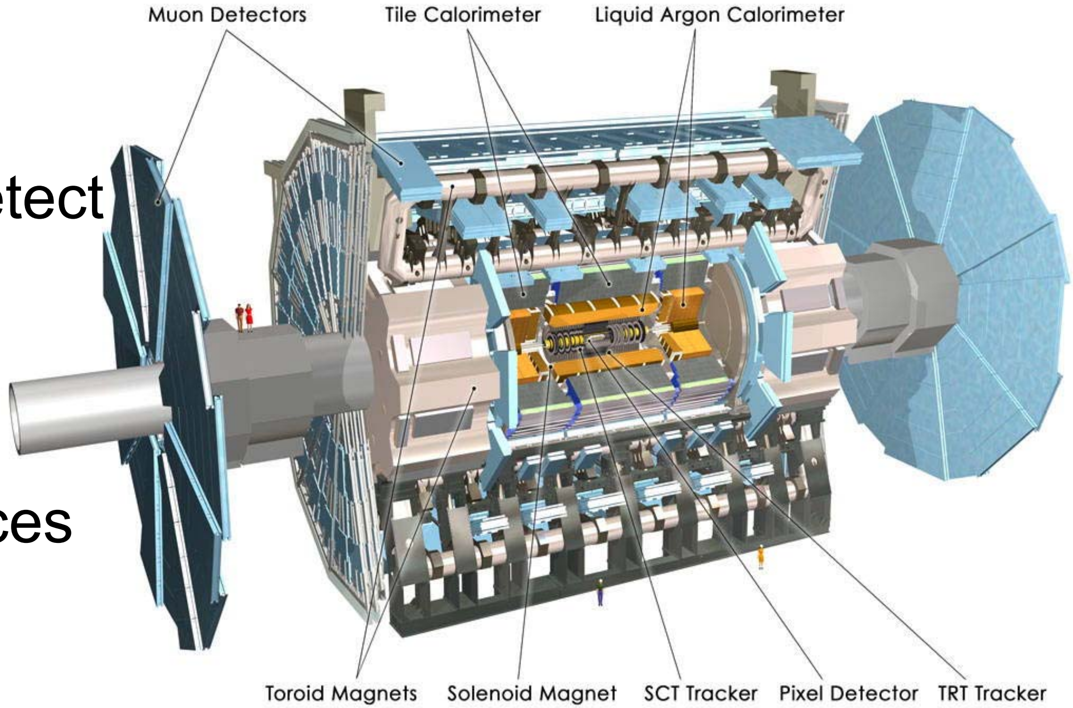
On behalf of the ATLAS Tile Calorimeter Group

Summary

- Introduction
- Motivation and goal
- The Tilecal detector in the ATLAS LHC experiment at LHC
- Proposed methods for the Tilecal signal detection
- Results
- Conclusions

Introduction – The ATLAS detector

- General purpose detector for the LHC
- Wide range of physics
- Different subsystems to detect and measure particles produced at the collisions
- 42 m length, 11 m radius
- Treating background sources and detector noise is a challenge
- Trigger output frequency *O*(~100 Hz)



Motivation and goal

Motivation:

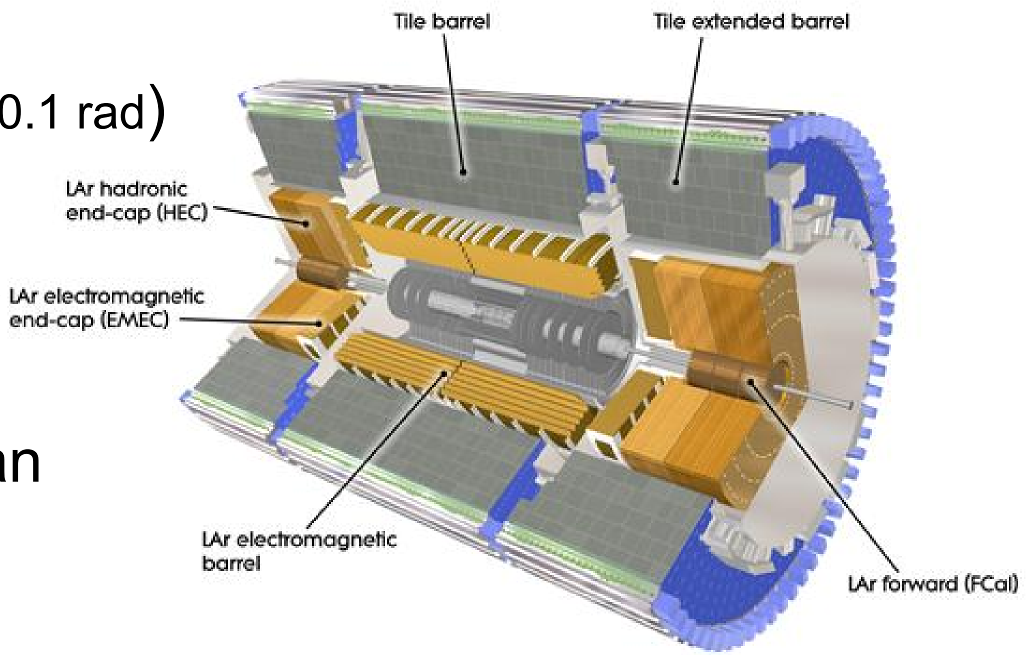
- Distinguish signal from particle with low energy deposition in the calorimeter from noise and LHC collision backgrounds
- Cells with useful but low energy from particles risk to be discarded during the particle reconstruction

Goal:

- To detect low signal to noise ratio (SNR) signals for the ATLAS Barrel Hadronic Calorimeter (Tilecal)

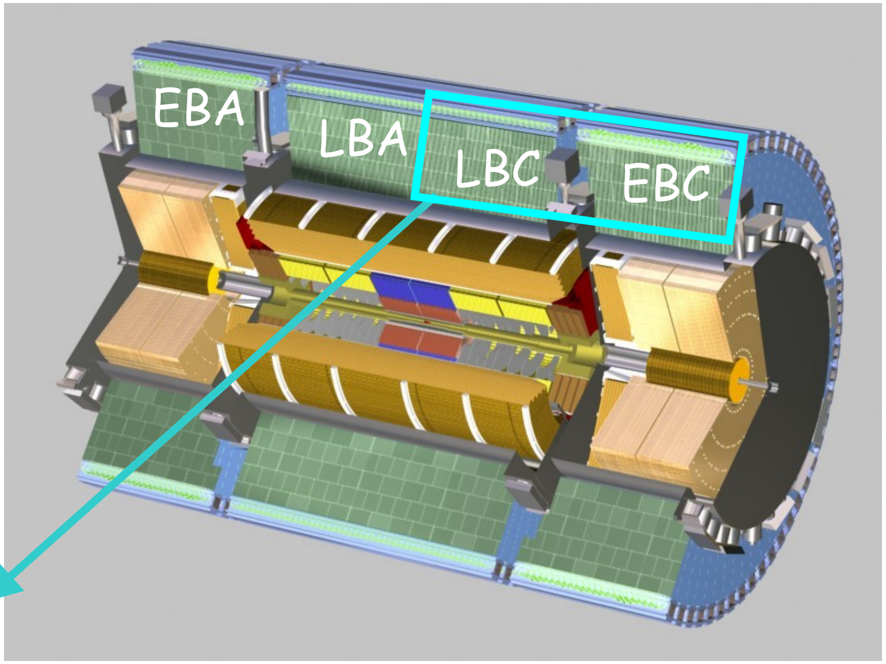
The Tilecal Detector

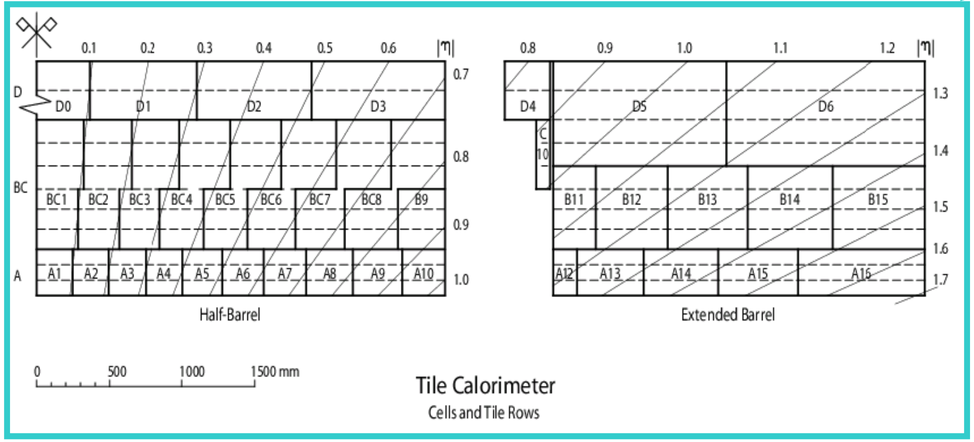
- Sampling calorimeter: steel (absorber) and scintilating tiles (active material)
- One long barrel (divided for readout in two parts) and two extended barrels
- 64 modules each part ($\Delta\phi$ = 0.1 rad)
- 10.000 channels (signals)
- Each signal: 7 dig. samples with 25 ns period
- Energy estimated through an optimal filtering algorithm



The Tilecal Detector

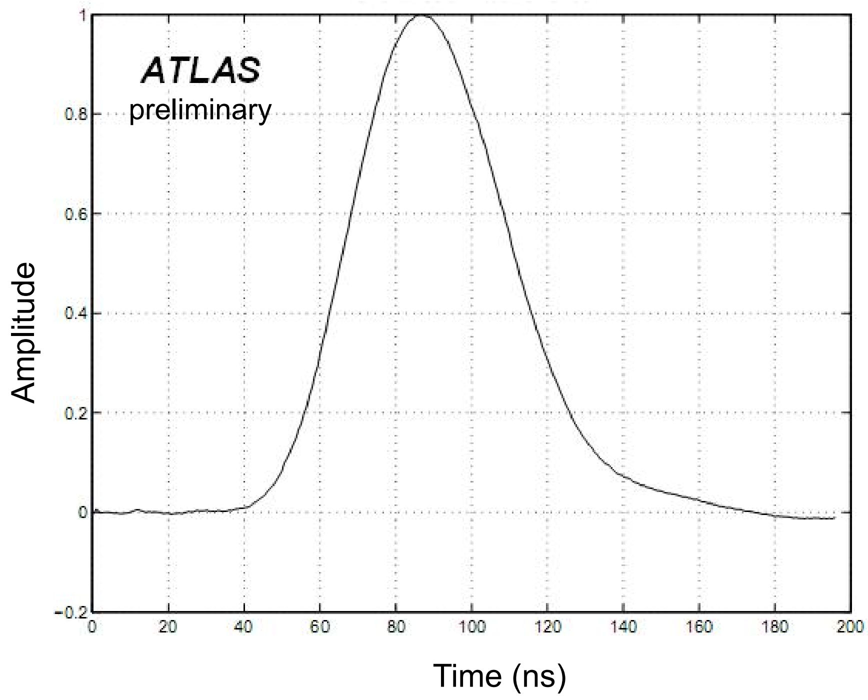
- Three longitudinal layers
- Highly segmented: $\Delta\eta \times \Delta\phi$ = 0.1x0.1 (0.2x0.1 in the last layer)
- Two PMT per cell for readout redudancy



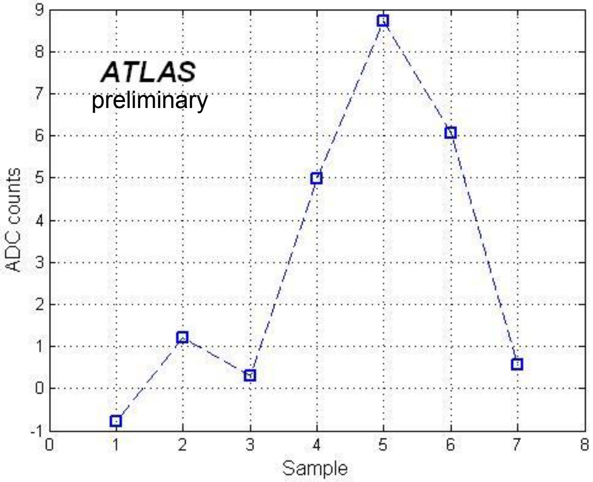


The Tilecal Detector

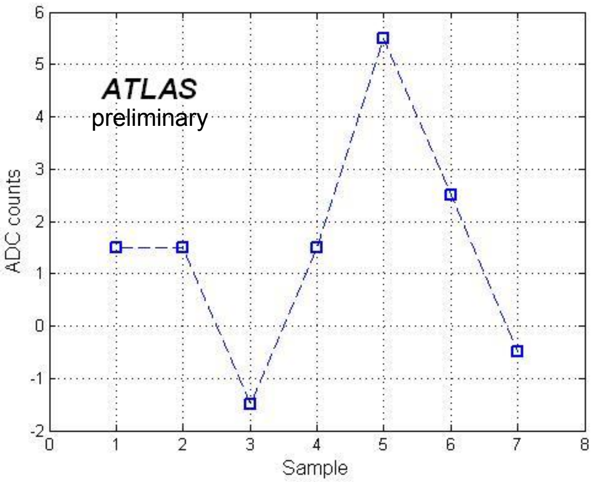
- Typical Tilecal signals



Simulated low energy event signal (muon)



Simulated noise signal



Proposed Methods – Maximum Likelihood Detection

- Based on hypothesis test

$$H_0 : r[k] = n[k]$$
$$H_1 : r[k] = s[k] \cdot n[k]$$

- Decision rule:

$$\frac{f_{R|H_1}(r \mid H_1)}{f_{R|H_0}(r \mid H_0)} \underset{H_0}{\overset{H_1}{\lessgtr}} \lambda$$

Maximum Likelihood Detection – PDF Estimation

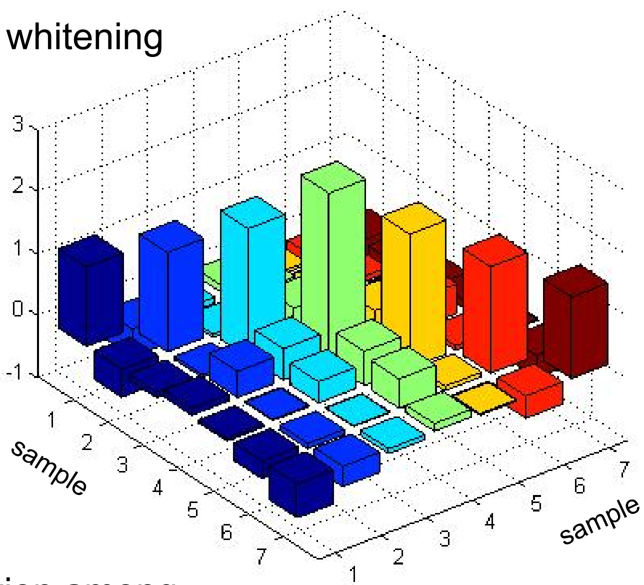
- Based on sample distributions of the digitized Tilecal signal
- Product of individual probability distributions (independence)

$$\frac{\prod_{i=1}^{7} p(l_i \mid H_1)}{\prod_{i=1}^{7} p(l_i \mid H_0)} \underset{H_0}{\overset{H_1}{\lessgtr}} \lambda$$

Maximum Likelihood Detection – Noise Whitening

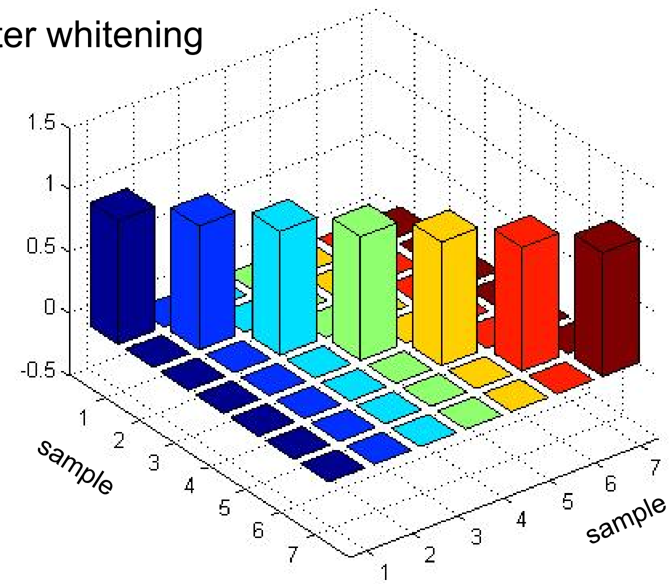
- Additive noise should be white.
- Aim: to uncorrelate noise samples

Before whitening



Correlation among neighbor noise samples

After whitening



Noise samples uncorrelated

Maximum Likelihood Detection – Principal Component Analysis (PCA)

- Aim: to uncorrelate signal (H_1) samples

Assumptions:

- Sample distributions are Gaussians
- Noise is Gaussian and white (so that PCA applied on H_1 does not correlate samples of H_0)

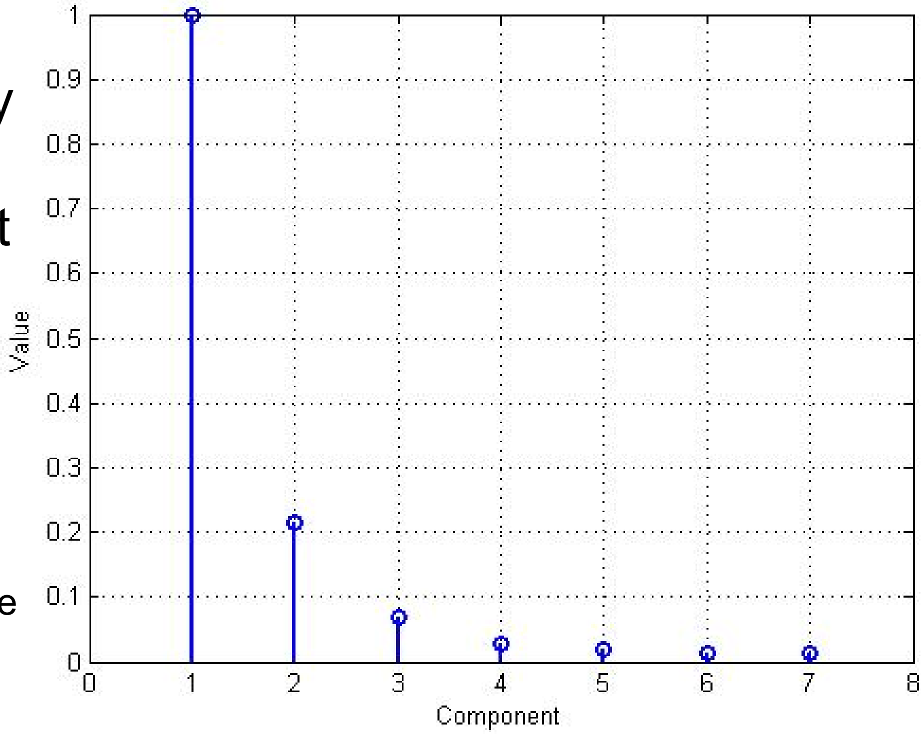
Steps:

- Apply the whitening filter to the incoming signals
- Develop the PCA transformation using signal data (development set)

Maximum Likelihood Detection – Principal Component Analysis (PCA)

• It results in dimensional reduction (samples are highly correlated)

• Signal can be represented by only two components (uncorrelated variables) without losing significant information



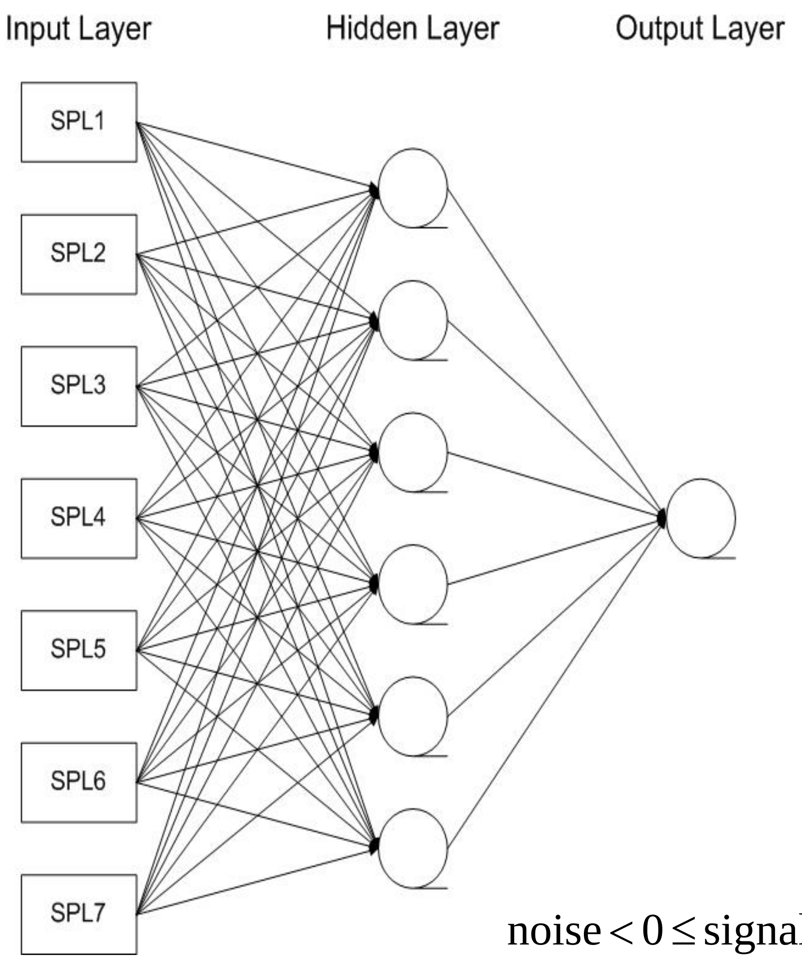
Eigenvalues of the covariance matrix for the signal dataset

Maximum Likelihood Detector – Independent Component Analysis (ICA)

- In reality signals are not Gaussian.
- Aim: to maximize the statistical independence (based on maximizing the nongaussianity of the components)
- The algorithm used was the FastICA
- Takes into account the 7 samples of a signal pulse

Neural Network

- Aim: Design a neural network to identify the input signal
- All 7 samples feed the input nodes
- A single hidden layer with 6 neurons
- Hyperbolic tangent as neuron activation function
- The single output neuron decides beetwen noise or signal

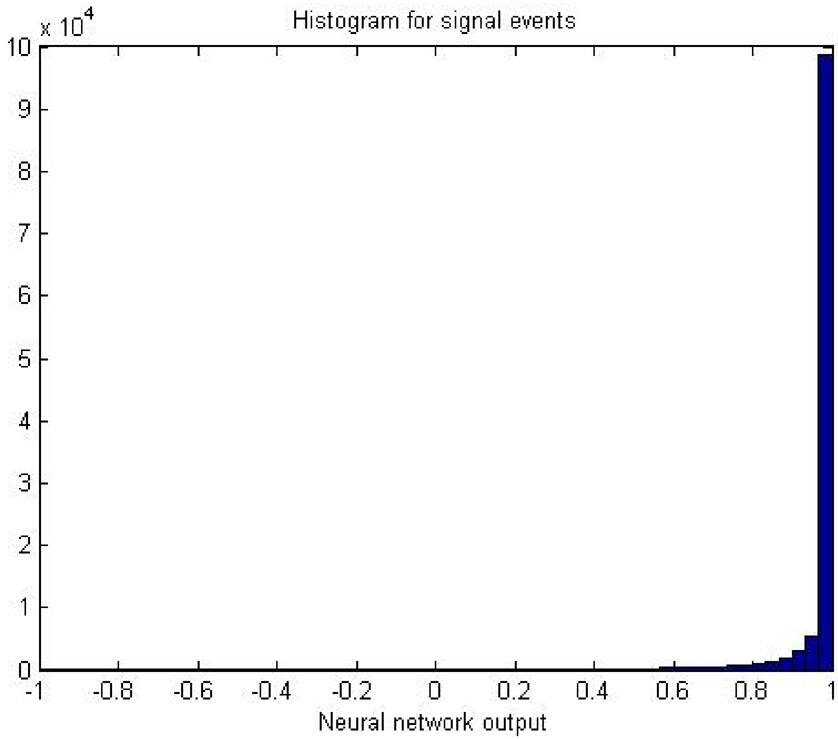


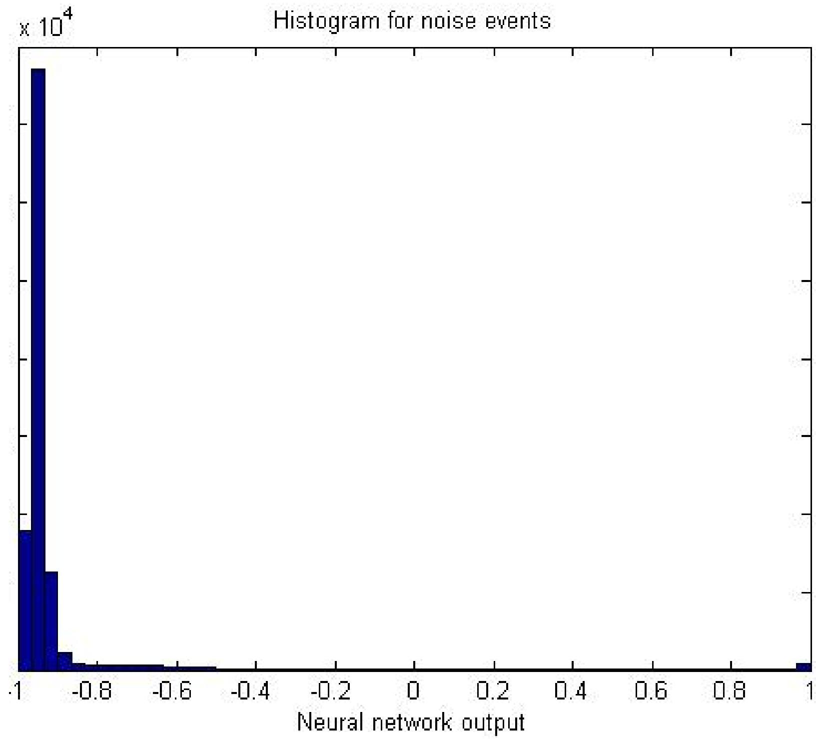
$\text{noise} < 0 \leq \text{signal}$

Results

- The database comprises 240,000 low SNR simulated muon signals and 240,000 noise signals taken from specific Tilecal noise acquisitions
- Noise signals obtained from specific Tilecal noise acquisitions while event signals taken from MC simulations
- For PCA and ICA, half of each data set was used for PDF estimation as well as for training the neural network
- The other half was used for performance evaluation

Results – Neural Network



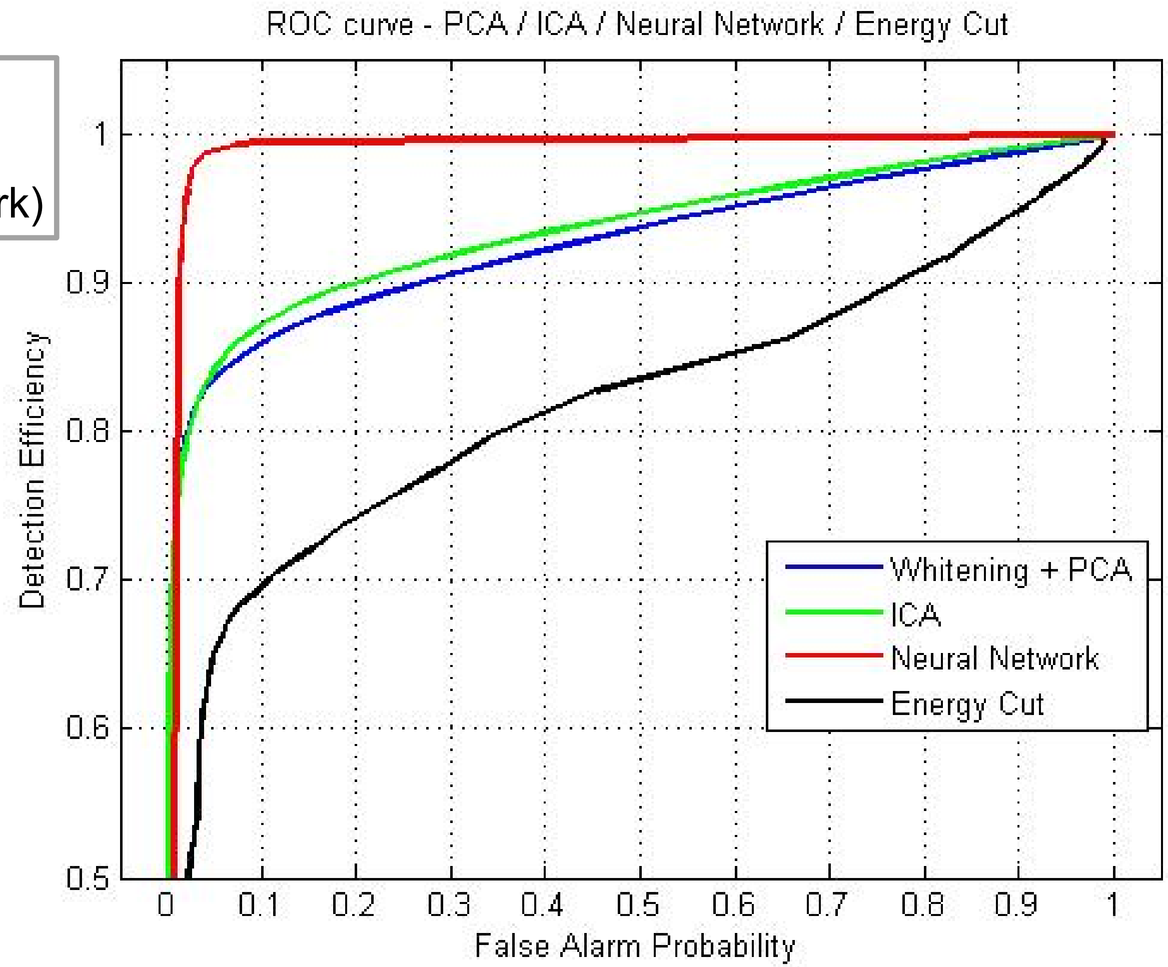


Detection performance: 97,5258 %, if threshold = 0

Results

For 10% of false alarm

- 69% detection (Energy cut)
- 98% detection (Neural nework)



Conclusions

- Different approaches for signal detection in low SNR conditions were presented
- All proposed methods have higher detection efficiency with respect to applying a simple energy threshold
- Neural network showed the best performance
- All methods can be implemented in the offline software for the calorimeter signal identification and reconstruction.