Deployment of a 1D-CNN reduces further the BiPo background over the current PSD method.

V. Buridon[2], G.Lehaut[2], A. Vacheret[1] on behalf of SoLid collaboration
[1] *Imperial College London, London UK*
[2] *Laboratoire de Physique Corpusculaire de Caen, Caen France*

Abstract :
The BiPo-214 decay is a significant background to the antineutrino reconstruction in the SoLid detector. It has a very similar time and spatial signature as the product of the inverse beta decay (IBD). SoLid has developed a unique technique to separate scintillation signals of neutron captured on Lithium-6 from those from the Po-214 alpha. The current Pulse Shape Discrimination technique (PSD) is based on a ratio of charge integration window. Using a 1-dimensional convolutional network (CNN) to fully characterise the shape of the waveform, we demonstrated a factor of two to three improvement in the discrimination power over the current technique.

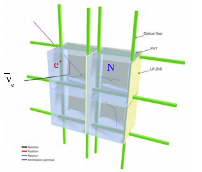
Motivations and contents

→ Two classes of Electromagnetic Signal (ES)- Nuclear Signal (NS) coincidence events (BiPo-214 events as background and IBD signal) identified.
→ Discrimination method based on waveform shape of NS from Alphas (BiPo-214 background) and Neutrons (Li-6 capture).
→ Need powerful discrimination method :
  → to distinguish these 2 classes of events even at low thresholds.
  → independent of external and instrumental conditions to stabilise cuts used for IBD analysis.
    → External conditions : Pressure, Temperature and Humidity.
    → Instrumental conditions : baseline variation on signals.

BiPo-214 @ SoLid

→ Dominating BiPo-214 background for energies lower than 3 MeV.

A)



IBD : $\bar{\nu}_e + p \rightarrow N + e^+$
n capture : $^6Li + N \rightarrow t + \alpha$
with t = 2.05 MeV and a = 2.73 MeV

B)

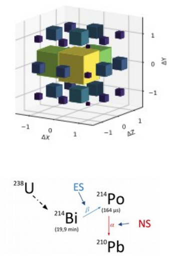


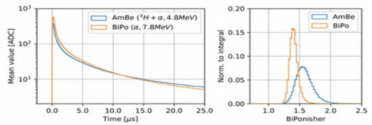
Fig 1 : ES-NS coincidence event : IBD signal (left) BiPo Background (right) [1].

Discrimination of NS : α (BiPo-214) and N (Li-6 capture) using PSD

→ Discrimination done on average waveform over active fibres, event by event.
→ Current method (classical one) exploits the difference in waveform shape between energy deposits of pure alphas and alpha+triton (from neutron Li-6 capture).

$$PSD = Q_{long}/Q_{short} \qquad (1)$$

1 sample : 25 ns, Q_{long} is computed from 3500 samples (87.5 µs) and Q_{short} is computed from 300 samples (7.5 µs).



→ *PSD named « BiPonisher »*
→ *85 % α rejection*
→ *85 % N efficiency*

Fig 2 :On left : Average waveform shape for α (BiPo) and N (Li-6 capture). This average waveform is computed from average waveforms of several events. On right : PSD distribution for Alphas (BiPo) and Neutrons (Li-6 capture).

(α/N) discrimination using 1D image recognition with Convolutional Neural Network

→ PSD method **[1]** is simple and well defined but :
  → Sensitive to the baseline variations (as all integration methods) => plays on cut stability.
  → It requires to get information on waveforms in a large time interval (3000 samples).

→ 1D-CNN method named "BiPonator", was developed by the SoLid Collaboration **[2]**.
  → Approach is based on image recognition applied on NS waveforms **[4]**.
  → It captures all the relevant local and global correlation of a waveform for discrimination
    → Amplitude, peak structure, decay, size of all PA peaks (first and secondary ones).
    → Robust against small baseline variation => It gives more stability of cut value used for IBD analysis.
    → It can be used to monitor the data quality.

1D-CNN architecture

1) Simple architecture using two 1D-convolutional following by two dense layers (Fig 3.1). This method was developed first in Python from keras and tensorflow backend [2].

2) Implementation of this method in a cpp code from a built trained keras model.
  → *to get 1D-CNN dicrimination value as parameter inside analysis ROOT® files.*
  → *to keep performances according to trained keras model.*

3) Implementation of this method in cpp to perform training in parallel.
  → *to monitor the data-quality over time.*
  → *to use in reconstruction after validation.*

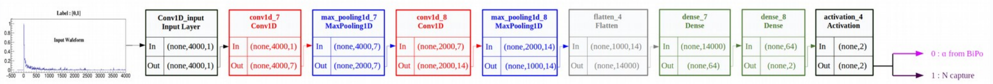


Fig 3.1 : 1D-CNN architecture using keras and tensorflow backend [2,4].

1D-CNN keras model

Keras Model Input :
  → *Average waveforms over active fibres **(Fig 3.1)**.*
  → *Real data extracted event by event.*
  → *Average waveforms normalised to their maximal amplitude.*
  → *Each average waveform covers a time range of 4000 samples **(Fig 3.2, Fig 3.3)**.*
    → *Input can have less samples (for example 1000 : **Reducing number of samples in input, right side**).*

Keras Model Training :
  → *Training is done from 20000 average waveforms.*
  → *Using 2 reference NS datasets **(Build pure α and N dataset, right side)**.*
    → *Pure Neutrons (AmBe calibration campaign).*
    → *Pure Alphas (BiPo-214 selection in Reactor off data-taking).*
    → *Further technical details on **(1D-CNN* training, right side)**.*

Keras Model Output :
  → *For each average NS waveform, one value of "BiPonator" is got between 0 and 1.*
  → *Distribution of this value **(Fig 3.2)** shows a repartition in accordance to sigmoidal shape.*
  → *Cases close to 0 are identified as Alphas and ones close to 1 as Neutrons.*

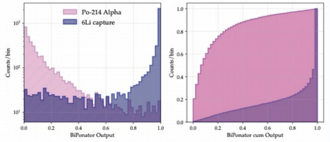


Fig 3.2 : Left : 1D-CNN output for validation samples of α/N. Right : Cumulative output values showing fraction of events.

1D-CNN keras model against PSD

Trained Keras Model Performances :
→ Superior discrimination power obtained compared to current PSD method (x2.5).
→ Powerful discrimination, despite baseline variations and large rate differences.

Saved Trained Keras Model and Applications :
  → Deployment on mixed control datasets.

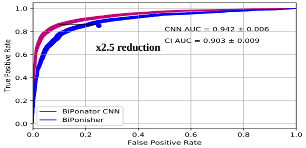
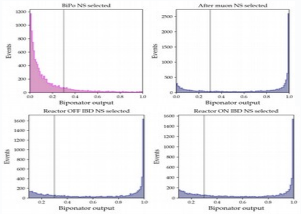


Fig 3.3 : 1D-CNN against PSD (ROC Curve)

1D-CNN keras model performance

Deployment of 1D-CNN "BiPonator" method
→ *Use previous saved keras model for control dataset **(Fig 3.3)** :*
→ ***Test on several datasets***
  → *Pure BiPo-214 dataset* → *NS after muon dataset*
  → *Reactor off IBD selection.* → *Reactor on IBD selection.*
→ *Each dataset embeds up than 30000 average waveforms to test model*
  → *between 1 and 5 days of data taking depending on datasets.*
→ *Estimation of α,N proportions.*
→ *Comparison and validation to expectation.*



Test Dataset	mix (n/alpha)	Biponihser cut	Survival fraction	expected	Biponator cut	Survival fraction	expected
Bipo alpha	5/95	1.44	0.247	0.24	0.3	0.16	0.14
After muon n	90/10	1.44	0.769	0.79	0.3	0.74	0.82
Roff data	50/50	1.44	0.555	0.55	0.3	0.53	0.51
Ron data	47/53	1.44	0.546	0.53	0.3	0.51	0.58

Fig 3.4 : Validation on selected control samples.

Data-driven α and N datasets

Pure α dataset :
→ Side-band Reactor off BiPo selection
→ BiPo-214 selection cuts (on ES-NS coincidence analysis) results in sample with > 96 % purity.
→ Independent estimation of BiPo-214 given from NS-ES difference of time distribution (Δt NS-ES) **(Fig 4)**.
  → Measurement of decay time associated to Po-214 in ^{238}U decay chain.
  → Proportion estimation by fitting distributions with 2 exponential laws.
    → First associated to N thermalisation.
    → Second associated to Half-Life of Po-214 decay.

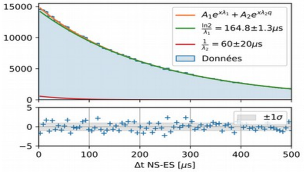


Fig 4 : Purity of BiPo-214 dataset using Δt NS-ES distribution.

Pure N dataset :
→ From regular AmBe calibration campaign.

1D-CNN Training

→ Model used Adam Optimiser.
→ Loss funtion is categorical entropy.
→ Model trained over 30 epochs with a batch size of 128 events.
→ Training time is ~1hour using CPU in a recent laptop.

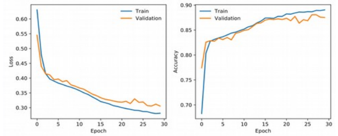


Fig 5 : 1D-CNN training.

Reducing the number of samples in input

→ No significant loss of performance even with 1/4 of the waveform is used.

Neutron Training Dataset	NSamples	Biponator AUC	Biponisher AUC
AmBe Global Stack	4000	0.947 ± 005	0.918 ± 005
AmBe Global Stack	1000	0.951 ± 006	''

Conclusion

→ Improvement in (α/N) discrimination power, compared to PSD method (factor 2.5).
→ Training on pure α and N datasets and test in control datasets => In accordance with what it is expected.
→ Possibility to save trained model for C++ implementation using class developed by MIT **[3]**.
→ Implementation into C++ code to monitor data-quality and to improve BiPo-214 background rejection.
→ Tests done with smaller number of samples in input shows stability of method and gain of time in training.

Bibliography

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Acknowledgements

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