A neural network based algorithm for MRPC position reconstruction

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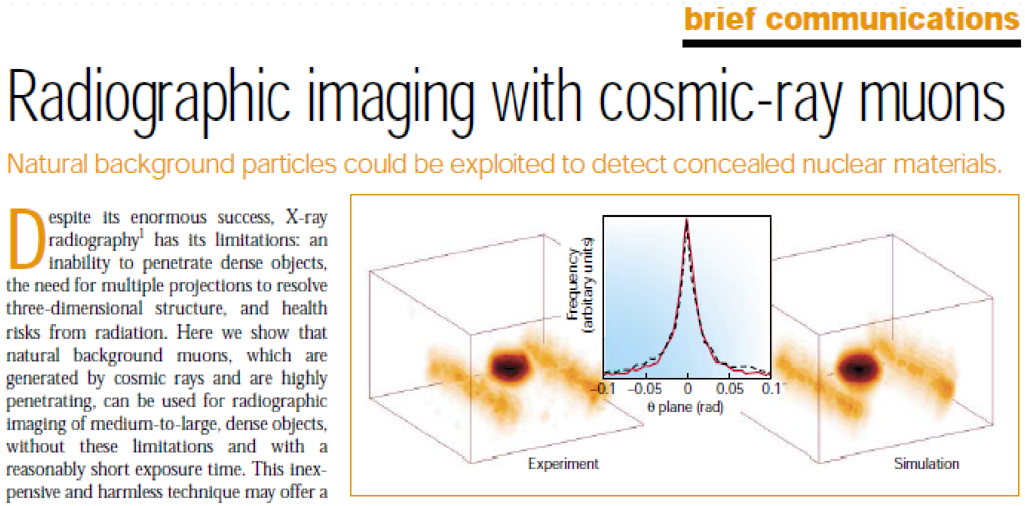
Outline

- Introduction
- MRPC simulation using Geant4
- Neural network based reconstruction algorithm
- X-ray Experiment
- Conclusion

Introduction



brief communications

Radiographic imaging with cosmic-ray muons

Natural background particles could be exploited to detect concealed nuclear materials.

Despite its enormous success, X-ray radiography[1] has its limitations: an inability to penetrate dense objects, the need for multiple projections to resolve three-dimensional structure, and health risks from radiation. Here we show that natural background muons, which are generated by cosmic rays and are highly penetrating, can be used for radiographic imaging of medium-to-large, dense objects, without these limitations and with a reasonably short exposure time. This inexpensive and harmless technique may offer a

Nature, 2003, 422(6929): 277.

✓ No artificial radiation

The flux is about 1/$\boldsymbol{cm^2 \cdot min}$

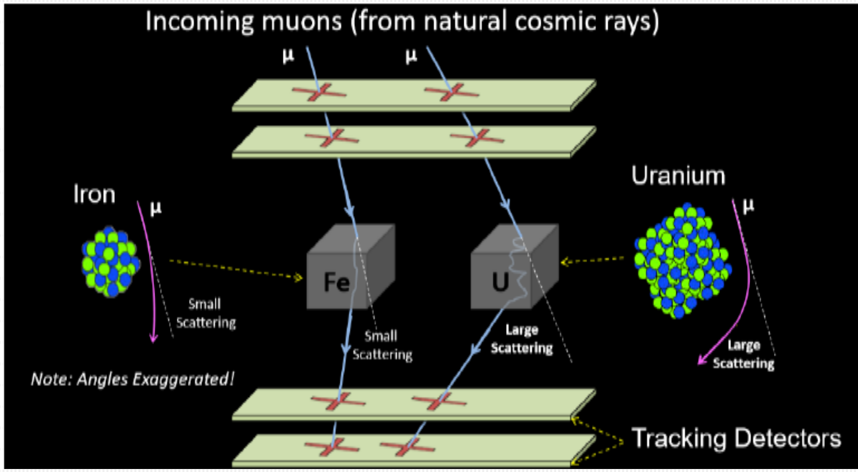
✓ No radiation damage

Only electromagnetic effect, no nuclear effect

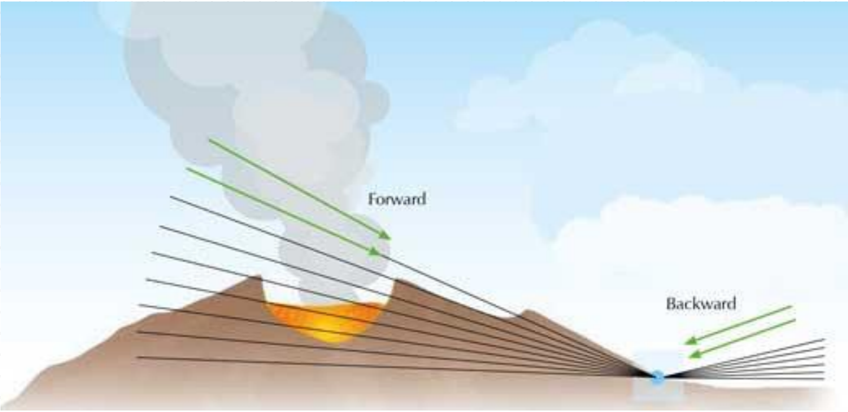
✓ Strong penetration

Energy distribution in the distribution of 0.1-1000GeV, the average energy of 3-4GeV

Muon Tomography



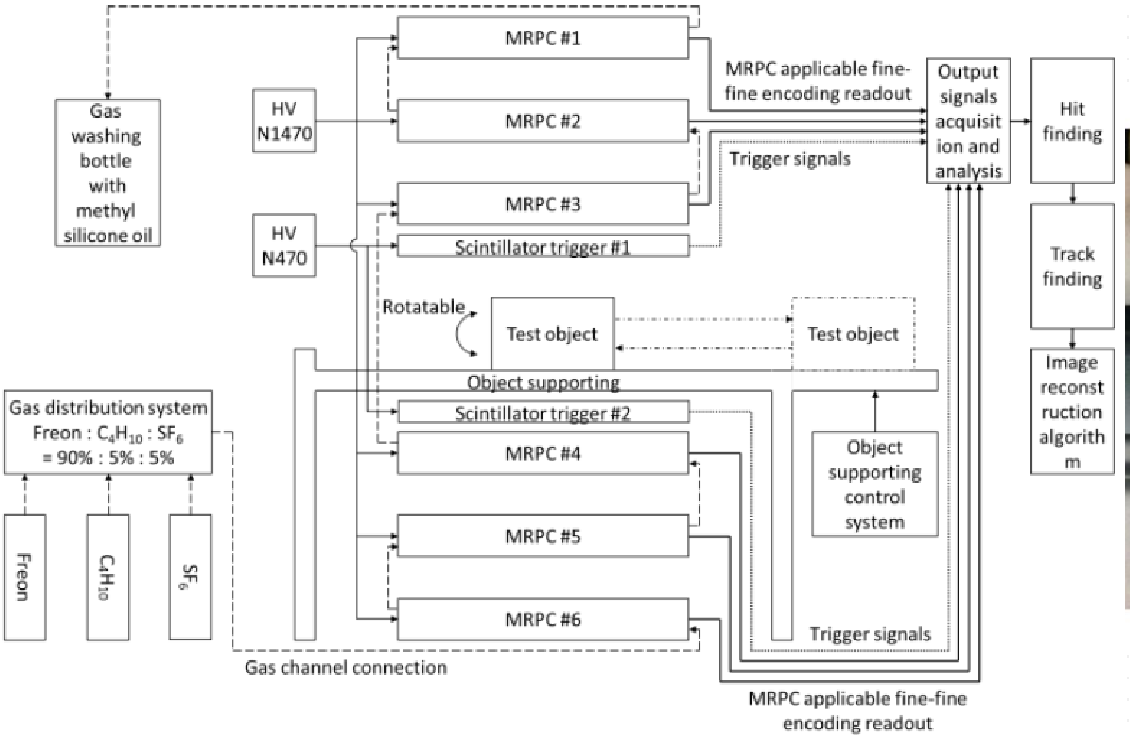
muon multiple scattering imaging

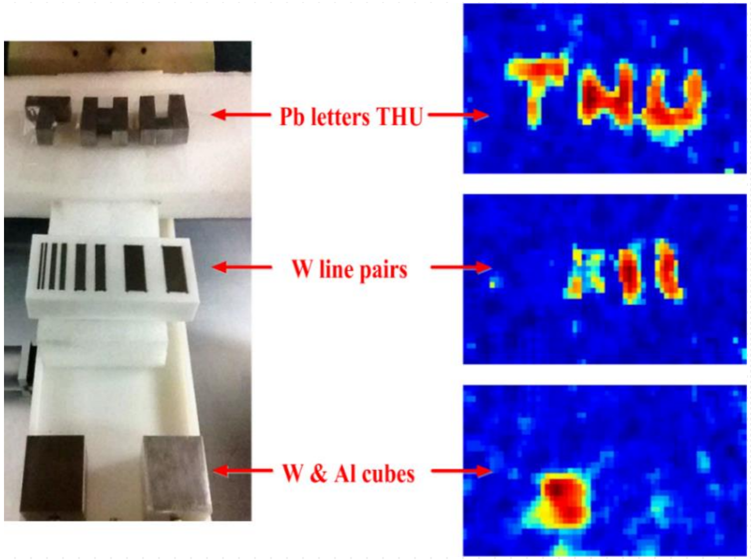


muon absorption imaging

Introduction

The "TUMUTY" (Tsinghua University Muon Tomography)





- ◆ 6 groups of detectors, can realize the 2D readout.
- ✓ 2 cm lead gets imaging result "THU".
- ✓ the 10 mm line pairs can be distinguished.
- ✓ the tungsten cube can be identified while the aluminum cube is invisible due to its small density.

Introduction

How to improve the MRPC detectors and the system?

1. MRPC Geometry:

   Smaller strip pitch (2.54 mm)

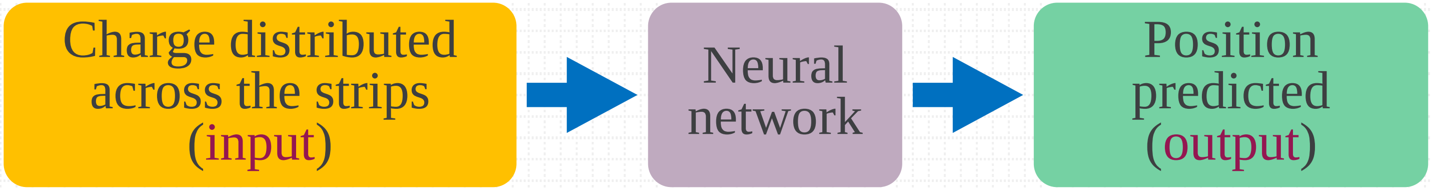
2. Electronics and read out system:

   Higher signal-to-noise ratio

3. Position reconstruction algorithms:

   Center of gravity method

   New algorithm ---- neural network!



Charge distributed across the strips (input)

Neural network

Position predicted (output)

Simulation data used for training, experiment data for testing

MRPC simulation

Design a MRPC

↓

Shoot a particle

↓

Simulate the primary energy deposition with PAI model

↓

Digitize the charge of the avalanche

↓

Original current signal

↓

Electronics

☐ MRPC structure

- ✓ Materials
- ✓ Gap/glass thickness, stack/gap number
- ✓ Gas: **90% $C_2H_2F_4$ + 5% i-C_4H_{10} + 5% SF_6**

☐ Particle source

- ✓ perpendicular to the MRPC

☐ **PAI** model is used to simulating the primary energy deposition*, rather than **Emstardard**

***W. Allison. Ann. Rev. Nucl. Part. Sci. 30 (1980) 253.**
2018 JINST 13 P09007.

MRPC simulation

Design a MRPC

↓

Shoot a particle

↓

Simulate the primary energy deposition with PAI model

↓

Digitize the charge of the avalanche

↓

Original current signal

↓

Electronics

☐ Primary energy loss

- ✓ Ionize electron-ion pairs
- ✓ W = 30 eV

☐ Avalanche multiplication — **Townsend effect**

α: Townsend coefficient

β: Attachment coefficient (by **Magboltz)**

☐ Electrons drifting in the electric field: induce a signal on the read out strips

☐ **[*]Ramo theory:**

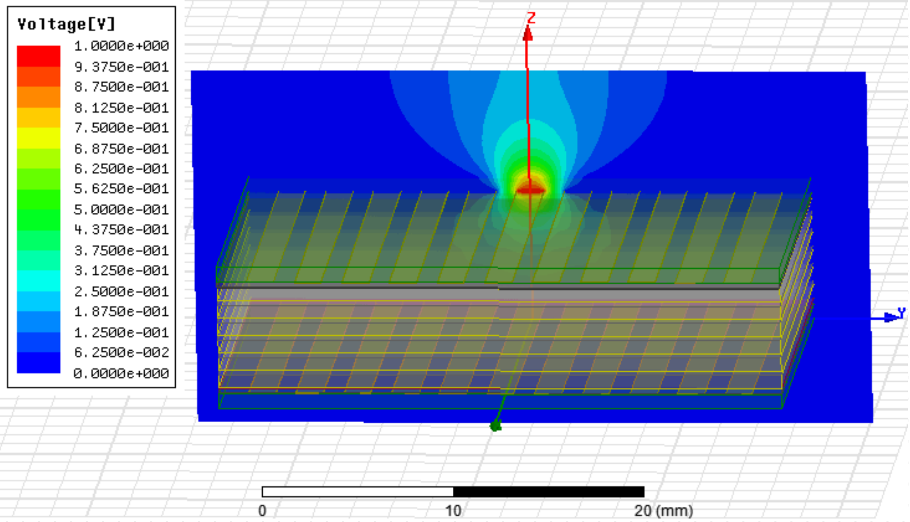
$$i(t) = \frac{E_W \cdot v}{V_W} e_0 N(t)$$

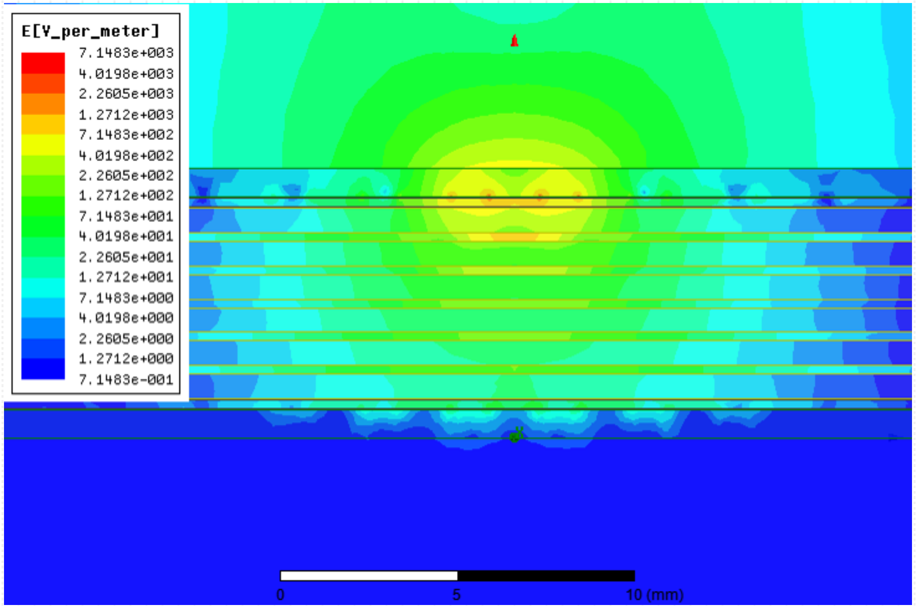
[*]S. Ramo, Currents induced by electron motion, Proc. IRE 27 (1939) 584.

MRPC simulation

☐Weighting field

- ✓ E_W is the weighting field which is the electric field when setting the potential of the read out electrode to be V_W and others 0.





MRPC simulation

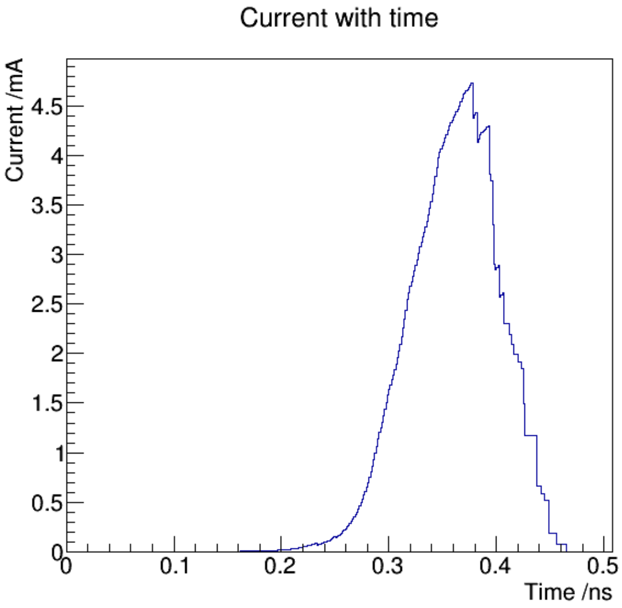
- Space charge effect: $\sim 10^7$ electrons

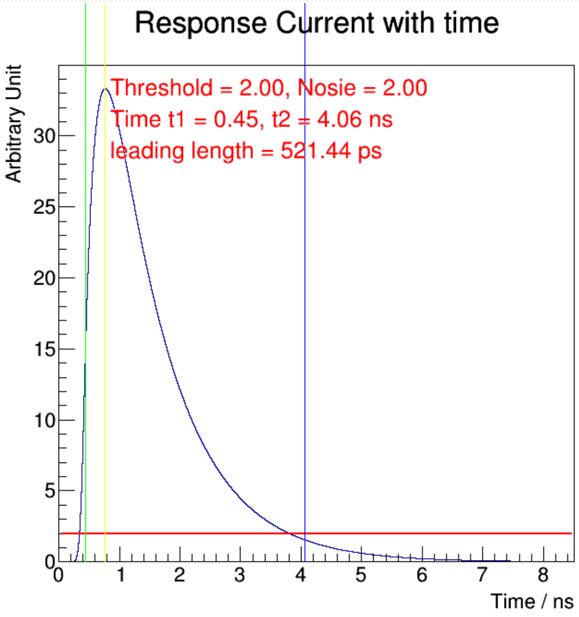
Werner Riegler, Christian Lippmann. Nucl. Instrum. Meth. A 500 (2003) 144.

- Include the Front-end electronics response by convolving the original current with a simplified FEE response function:

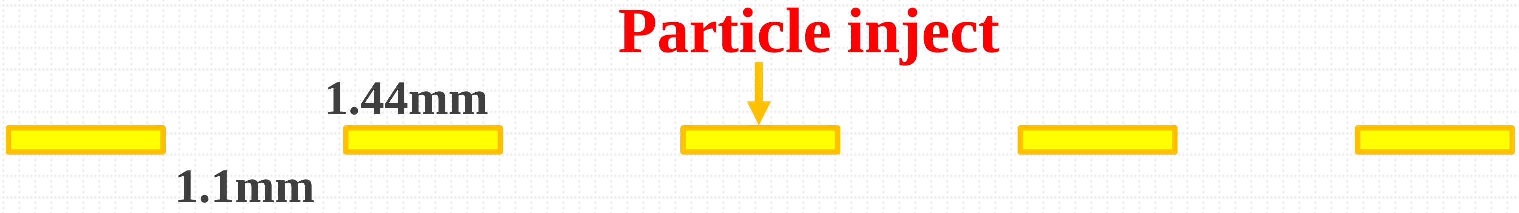
$$f(t) = A\left(e^{-t/\tau_1} - e^{-t/\tau_2}\right)$$

- Noise: by adding a random number sampled from Gauss(0, σ) to every time bin





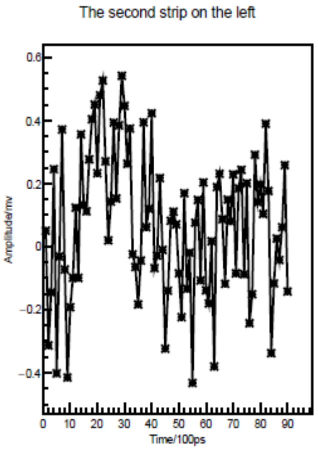
MRPC simulation



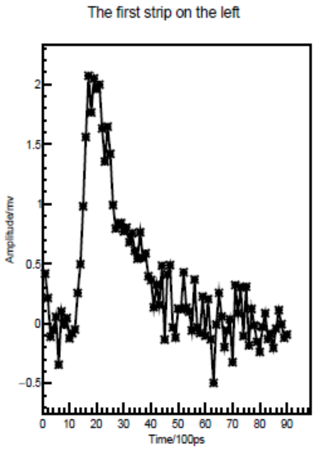
Particle inject

1.44mm

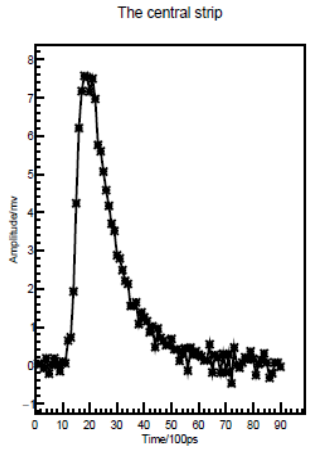
1.1mm



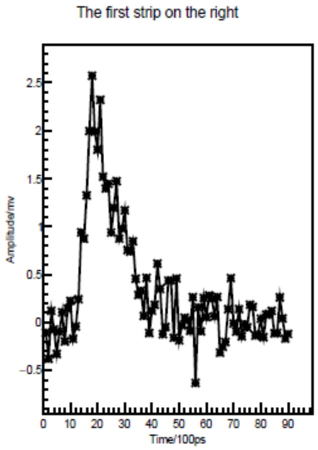
The second strip on the left



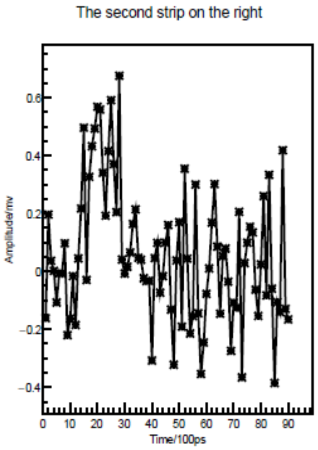
The first strip on the left



The central strip



The first strip on the right



The second strip on the right

- **Induced signals** generated by the energy deposition of **all sensitive areas**
- **Induced signals** on each readout electrode
- **Information** about time, charge, cluster size……
- **Position resolution**

Neural network

Center of gravity (COG) algorithm

- ✓ Extremely widespread in scientific and practical applications.
- ✓ But introduces a systematic error (discretization error) due to its origin in the discretization of the signal collection.
- ✓ The COG of $\varphi(x)$:

$$x_g = \int_{-\infty}^{+\infty} x\varphi(x)dx$$

$$x_g = \sum\nolimits_n \alpha_n(\varepsilon)n\tau \Big/ \sum\nolimits_n \alpha_n(\varepsilon)$$

(ε the impact point)

$$x_g(\varepsilon) = x_g - \varepsilon$$

$$+\frac{\tau}{\pi}\sum_{k=1}^{\infty}\frac{(-1)^k}{k}\sin(2\pi k\varepsilon/\tau)\Phi(2\pi k/\tau)$$

→ The systematic error

Machine learning algorithms

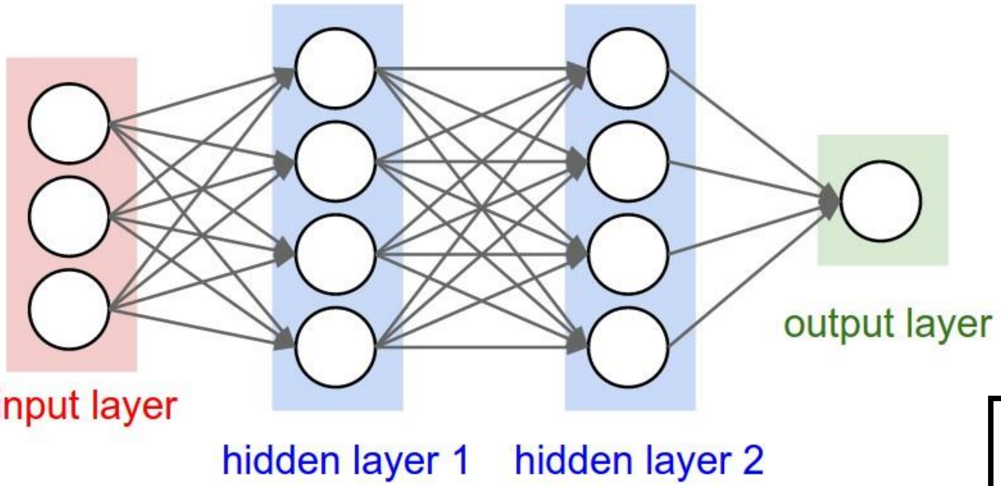
- ✓ Acquire knowledge from the data through feature extraction and representation learning
- ✓ **Deep neural networks** are one of the most important machine learning algorithms
- ✓ Solve problems with significant nonlinearities
- ✓ Widely used in high energy physics

Gregorio Landi. Nucl. Instrum. Meth. A 485 (2002) 698.

Neural network

Fully connected neural network(DNN)

$$\underset{\text{Output}}{\underline{F_i(\vec{x})}} = h(\sum_j(\omega^2_{ij} g(...g(\sum_k(\omega^1_{jk} g(\sum_l(\omega^0_{kl} \underset{\text{Input}}{\underline{x_l}} + \chi^0_k)... + \chi^1_j) + \chi^2_i)$$



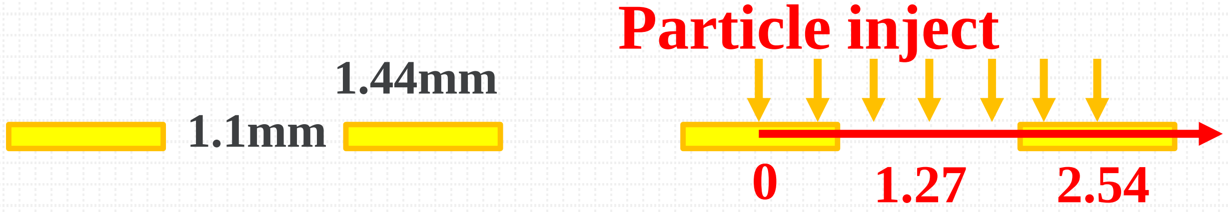
- Activation function: g and h —tanh
- Weights: $\omega^{0,1...}$, $\chi^{0,1...}$
- "Dropout": avoid overfitting

The incident position of the particle

The charge distributed across several strips

- Tensorflow & GPU: GTX 1080 Ti
- **8 layers**: ~ 90 mins for training

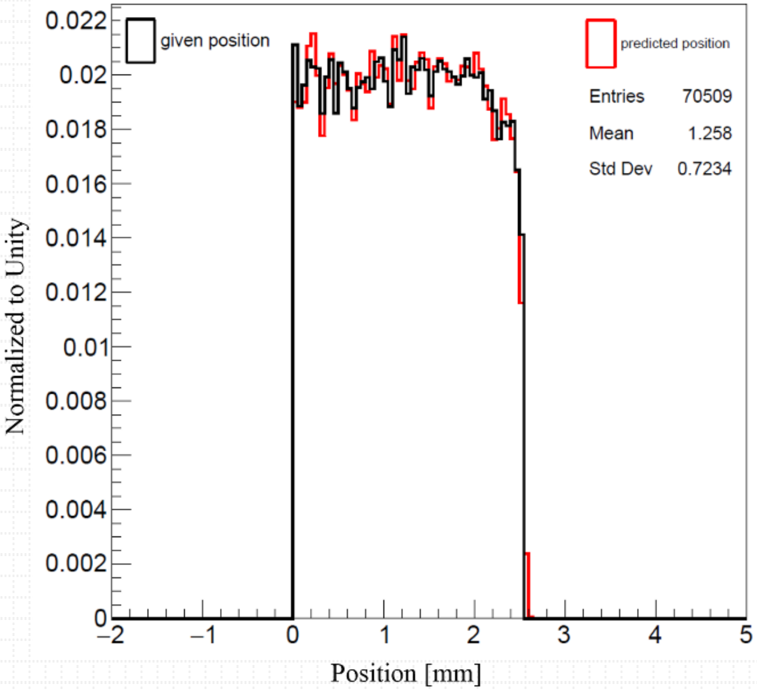
Neural network

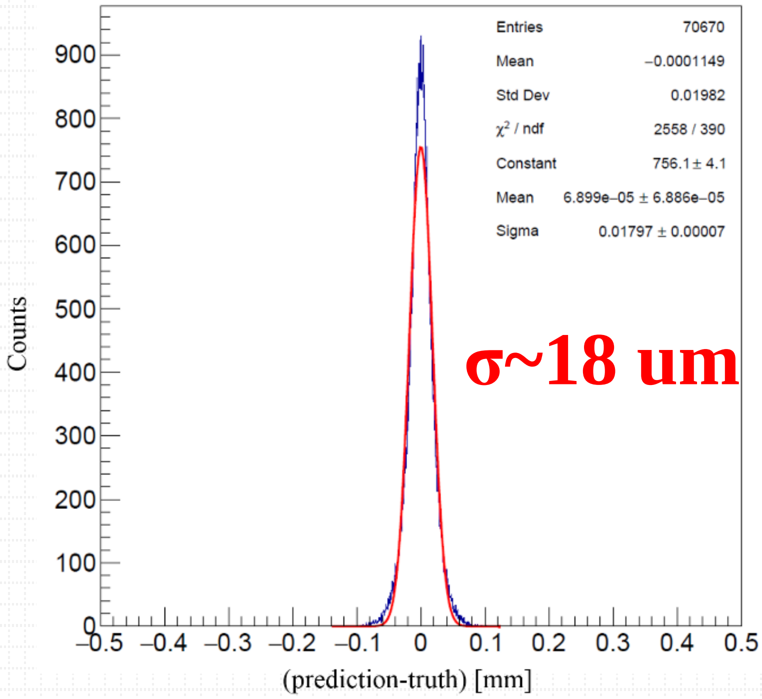


Training data: one strip pitch, 70000 simulation events

Evaluating data: position scan (0~1.27mm), 3000 simulation events/each

Testing data: X-ray experiment data

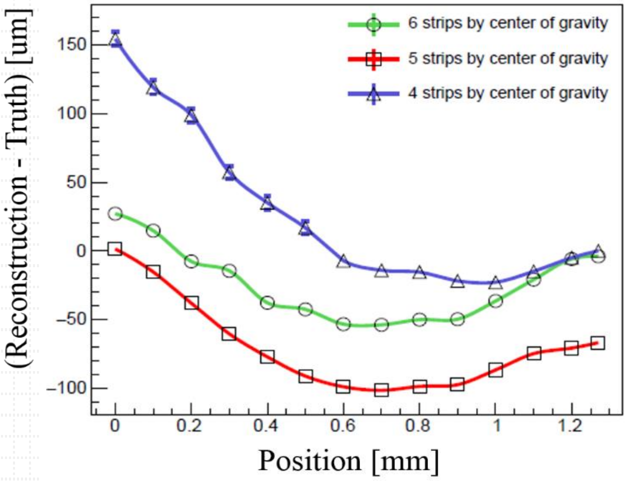


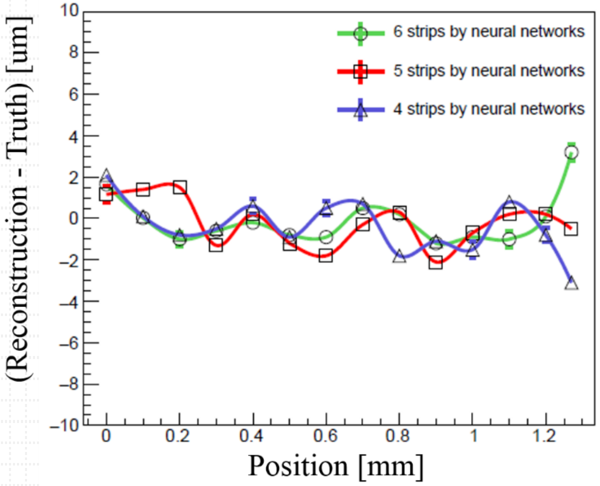


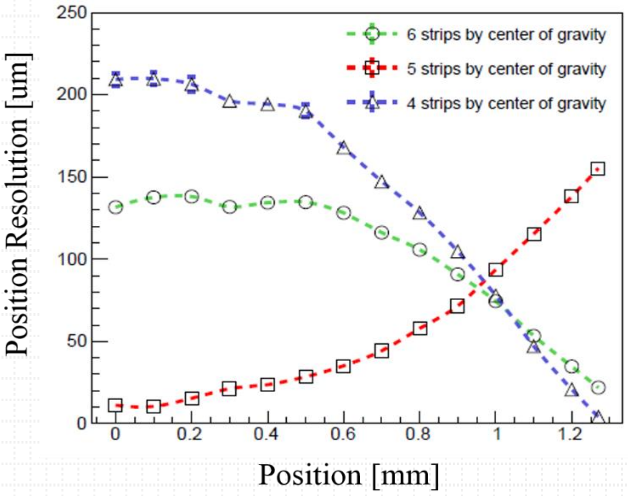
σ~18 um

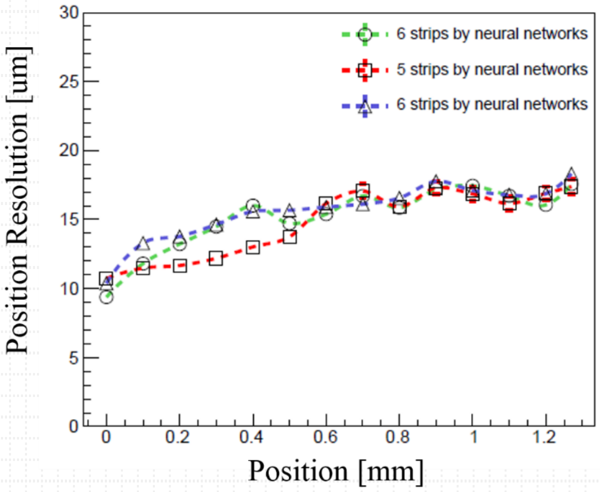
Neural network

Center of gravity (COG) VS Neural network

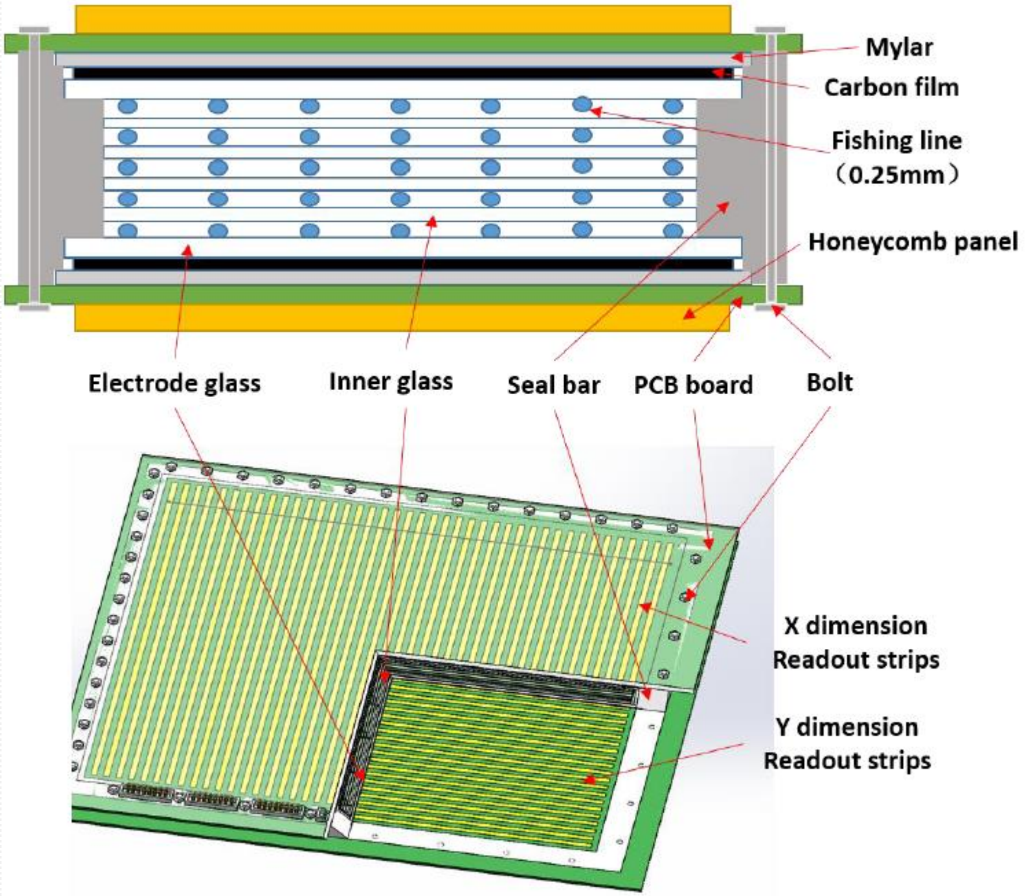






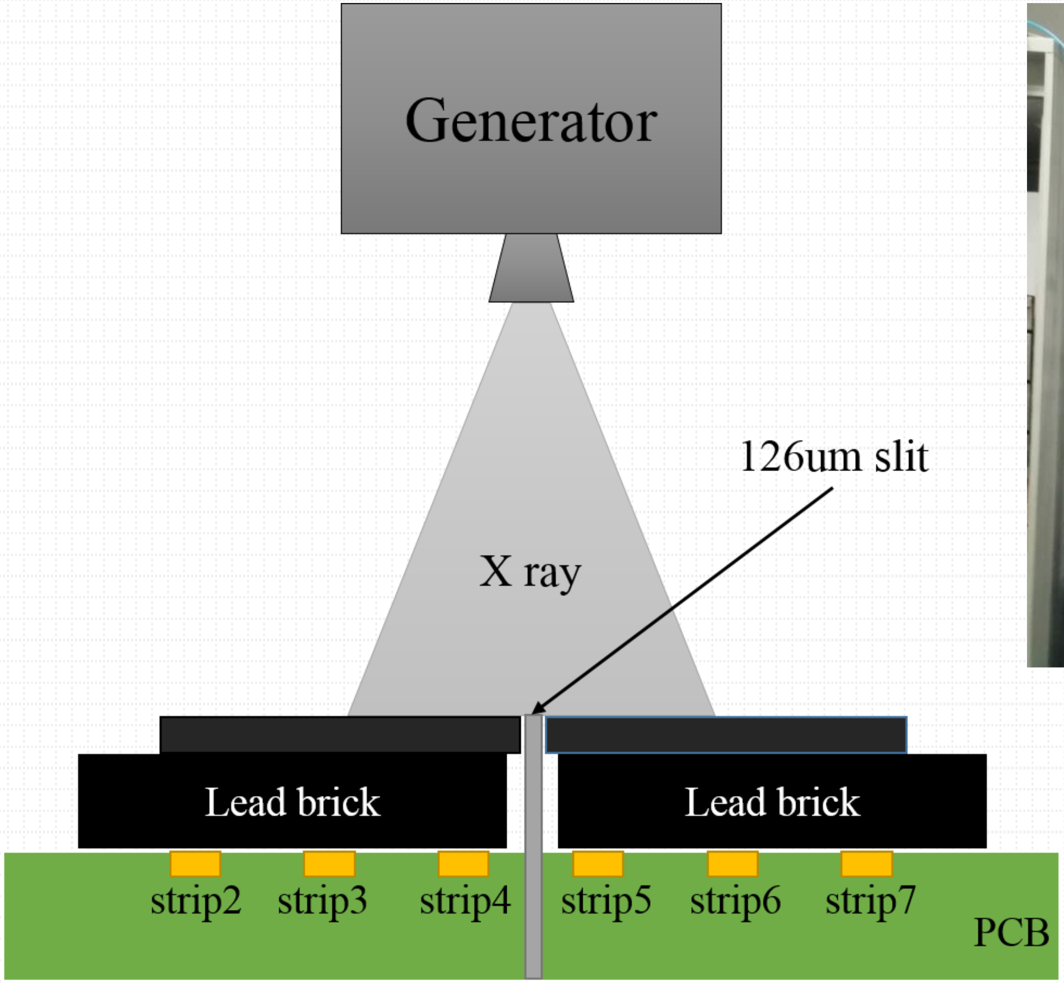


X-ray Experiment



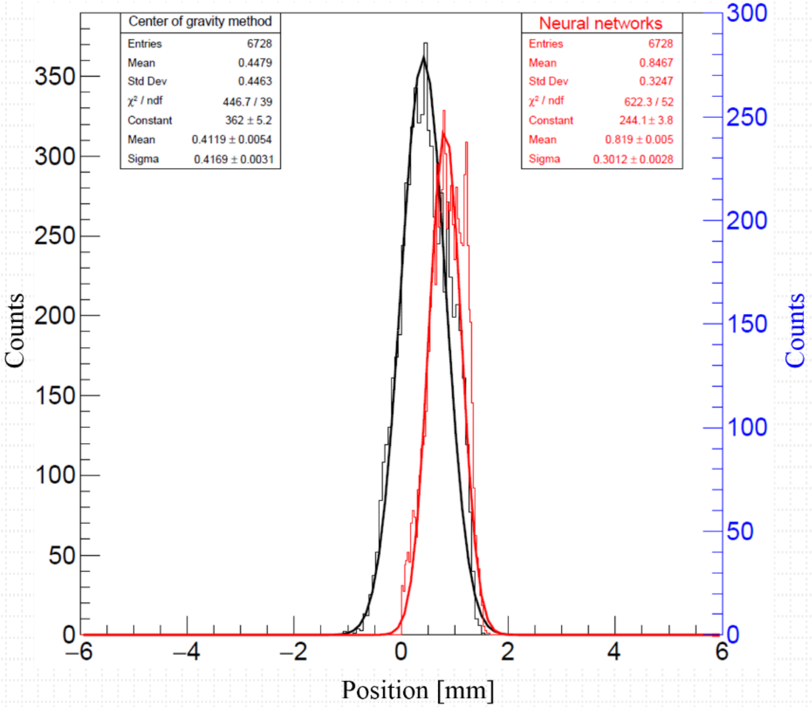
Dimensions	Value
Inner glass size	420*420mm^2
Outer glass size	470*470mm^2
Glass thickness	0.7mm
Gas gap thickness	0.25mm
Number of gas gaps	5
PCB size	500*500mm^2
Sensitive area	420*420mm^2

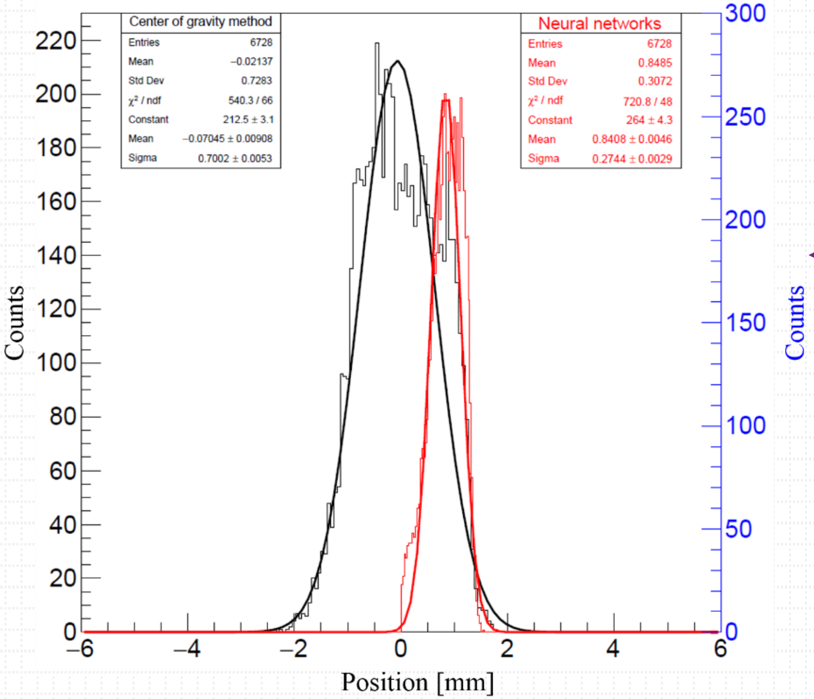
X-ray Experiment



Digitizer module (DT5742)
to record the signals

X-ray Experiment





	Center of gravity method		Neural network	
The number of strips used to reconstruct the position	Mean/mm	Sigma/um	Mean/mm	Sigma/um
4	0.412	416.9	0.819	301.2
5	-0.222	670.2	0.838	286.5
6	-0.07	700.2	0.841	274.4

Conclusion

- Detailed simulation of MRPC detectors based on Geant4 has been introduced.
  - ✓ **Signal, charge, position, time, cluster size……**
- A neural network based algorithm has been developed to reconstruct the position of MRPC detectors.
  - ✓ **No systematic error**
  - ✓ **Position resolution much improved**
- It is really hopeful for the implementation of neural networks in analyzing the position detected by MRPC.

Q & A

Thank you for your attention!