A neural network based algorithm for MRPC time reconstruction

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Motivation

• The 3rd generation of Time of Flight (ToF) system is aimed to have even better time resolution —— 20ps. Multi-gap resistive plate chamber (MRPC) is designed to have thinner gaps and the signal is read out with high speed waveform sampling electronics instead of ToT technique.
• A comprehensive study of improving the time resolution with the entire signal waveform is in need.
• We study a new algorithm to reconstruct the MRPC time with the waveform based on the Artificial Neural Network (NN) and deep learning.

Simulation framework

• The simulation is based on Geant4 and ROOT package

Creating a event
Simulating the primary energy deposition with PAI model
Charge Digitization
Original current signal
Electronics
Waveform

4 GeV mu- (cosmic)
30 MeV e- (HZDR beam)

Photo Absorption Ionization (PAI) model is more accurate for thin absorbers *

Avalanche gain

\[ N(t) = e^{\alpha x} \]

\[ I(t) = \frac{E}{V_{in}} N(t) e^{-\alpha x} \]

\[ f(t) = A(e^{-\alpha x} - e^{-\beta x}) \]

MRPC a: 5 × 0.25 mm
MRPC b: 32 × 0.104 mm

The neural network structure and time resolution

• A fully-connected neural network is used in this study.
• Take 2 hidden layers as an example:

\[ F_i(x) = h \left( \sum_j \omega_{ij} g \left( \sum_k \omega_{jk} \left( \sum_l \omega_{kl} x_l + \chi_i^0 \right) + \chi_i^0 \right) + \chi_i^2 \right) \]

• g(x) and h(x) are activation functions: sigmoid \[ g(x) = \frac{1}{1 + e^{-2x}} \]

Input layer dim: 1
Hidden layer 1 dim: k
Hidden layer 2 dim: j
Output layer dim: i

Signal
peak time

• Network: 5–6 hidden layers, about 10 nodes in every layer
• Input: 8–9 points along the leading edge
• Output: peak time - particle arriving time

Before the waveform start

Result of experiment data — MRPC b

• Test system: 2 MRPC b:

\[ \sigma(\Delta t) = \sigma(t_{\text{est}1} - t_{\text{est}2}) = \sqrt{\sigma^2(t_{\text{true}1} - t_{\text{true}2}) + \sigma^2(t_{\text{est}1} - t_{\text{est}2})} = \sqrt{2\sigma^2_{\text{MRPC}}} \]

\[ = \sigma(t_{\text{true}1} - t_{\text{true}2} - t_{\text{est}1} + t_{\text{est}2}) = \sigma(t_{\text{est}1} + t_{\text{est}2}) \]

\[ = \frac{t_{\text{est}1} + t_{\text{est}2}}{2} \]

\[ \sigma_{\text{MRPC}} = \frac{\sigma(\Delta t)}{\sqrt{2}} \]

• SCA+ADC waveform sampling
• Train with simulation data, test with experiment data
• Plot

\[ T_{\text{Time}} = \frac{t_{\text{est}1} + t_{\text{est}2} - t_{\text{est}1} - t_{\text{est}2}}{2} \]

• The time resolution can reach 20 ps

Result of Simulation data — MRPC a

• Result of MRPC a, train with simulation data, test with simulation data

\[ \sigma_{\text{MRPC}} = \sigma(\text{estimated time} - \text{truth time}) \]

• Both the two algorithms provide a stable result with respect to the uncertainty of the particle arriving time.
• Neural network improves the time resolution of MRPC by 20 ps or more through the voltage scan.

\sigma(\Delta t) = \sigma(t_{\text{res1}} - t_{\text{res2}}) = \sqrt{\sigma^2(t_{\text{resi1}}) + \sigma^2(t_{\text{resi2}})} = \sqrt{2\sigma^2_{\text{MRPC}}}

\sigma(\Delta t) = \sigma(t_{\text{res1}} - t_{\text{res2}}) = \sqrt{\sigma^2(t_{\text{resi1}}) + \sigma^2(t_{\text{resi2}})} = \sqrt{2\sigma^2_{\text{MRPC}}}

= \sigma\left(\frac{t_{\text{est1l}} + t_{\text{est1r}}}{2} - \frac{t_{\text{est2l}} + t_{\text{est2r}}}{2}\right)

\sigma_{\text{MRPC}} = \frac{\sigma(\Delta t)}{\sqrt{2}}

\text{Time} = \frac{t_{\text{est1l}} + t_{\text{est1r}}}{2} - \frac{t_{\text{est2l}} + t_{\text{est2r}}}{2}