

The z-Vertex Trigger for Belle II

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Outline

Introduction

Motivation

Signal Flow

Multi Layer Perceptron - MLP

Theory

Setup

Preprocessing

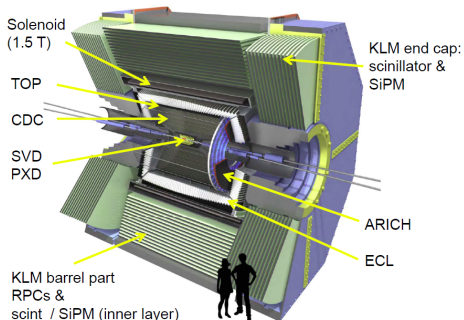
Least Square fit - LS

Results

MLP and LS results

Neuro Team

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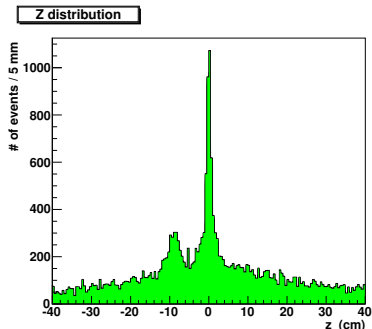
Introduction

Goals

- ▶ build a z-vertex track trigger
- ▶ achieve high precision
(spatial resolution $\Delta z \approx 2$ cm)
- ▶ get a fast decision ($< 1 \mu\text{s}$)

Method

- ▶ Input:
 - ▶ CDC Track Segment data
[IDs & clock cycle (2 ns timing)]
- ▶ Algorithms:
 1. Bayes Classifier / Hough Transformation
(pattern recognition)
 2. LS - Least Square fit
(linear estimation)
 3. MLP - Multi Layer Perceptron
(nonlinear correction)



Offline z distribution in the Belle Experiment^a.

a) T. Abe et al., *Belle II Technical Design Report*, KEK-REPORT-2010-1, arXiv:1011.0352v1 [physics.ins-det] (2010).

Main approach

Pattern recognition - Bayes Classifier / Hough Transform

sectorize Input in the track parameters $(p_T, \varphi, \vartheta)$

$$P(\text{Sector}|\text{Hits}) = P(\text{Hits}|\text{Sector}) \cdot \frac{P(\text{Sector})}{P(\text{Hits})} \quad (1)$$

Fitter - Least Squares

$$\vec{n} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \vec{y} \quad (2)$$

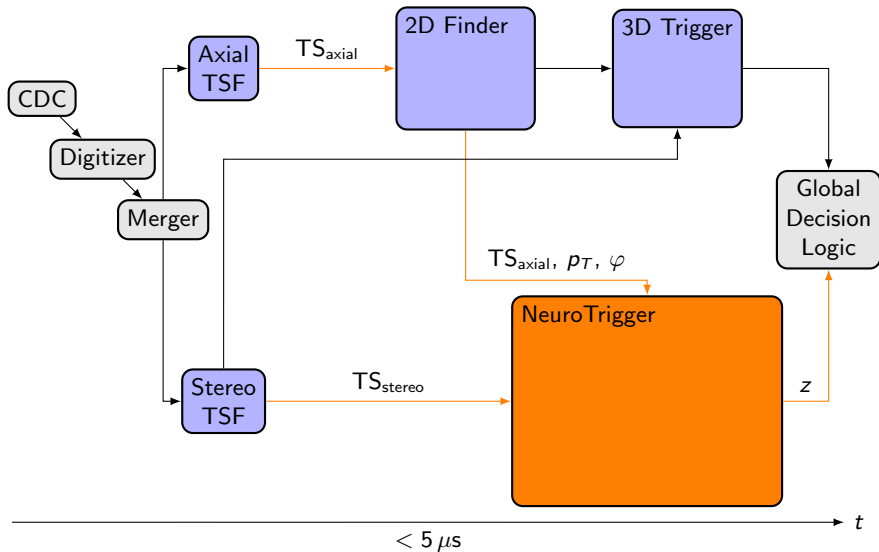
\mathbf{X} and \vec{y} contain the hits, \vec{n} defines a track parameter sector

Neural Network - MLP

$$z(\text{Hits}, p_T, \varphi, \vartheta) = NN(f(\text{Hits}, p_T, \varphi, \vartheta)) \quad (3)$$

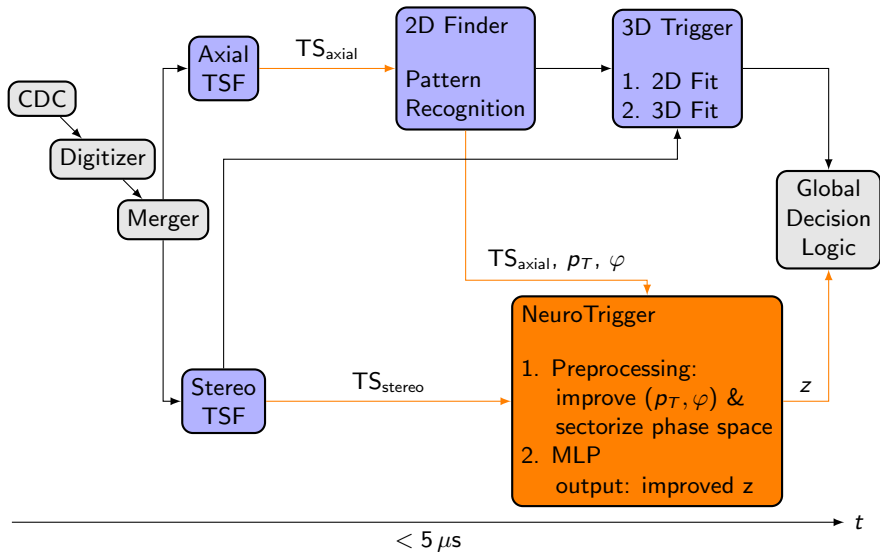
- ▶ output float value interpreted as scaled z-position
- ▶ NN input transformation (function f) requires preprocessing

Signal flow in the CDC Trigger



→ The neural network trigger will be implemented on a Virtex 7 FPGA

Signal flow in the CDC Trigger



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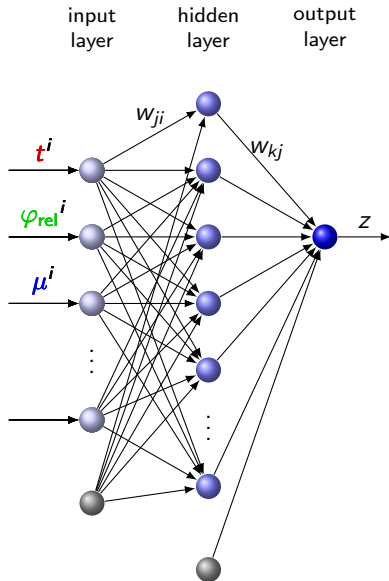
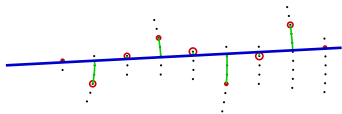
MLP - Multi Layer Perceptron

Properties

- ▶ supervised machine learning
- ▶ function approximation
- ▶ short deterministic runtime
- ▶ one neuron:
$$y = \tanh\left(\sum_{i=1} w_i \cdot x_i + w_0\right)$$

Input

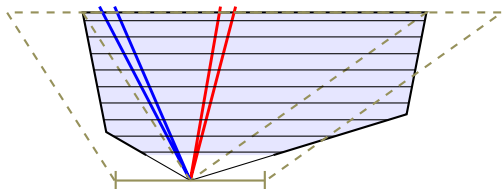
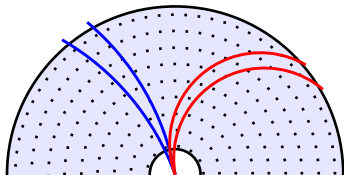
3 nodes per SL (t , φ_{rel} , μ)
with t : drift time, φ_{rel} : relative
wire position, μ : 2D arc length



MLP - Setup

Sectorization

- ▶ the track parameter space is sectorized in $(p_T, \varphi, \vartheta)$
- ▶ for each sector an expert MLP is trained
- ▶ asymmetry in ϑ , and p_T can be taken into account
- ▶ preprocessing selects the proper MLP



Two different sectors in (p_T, φ) (left) and in ϑ (right).

“Expert” MLP - Capabilities

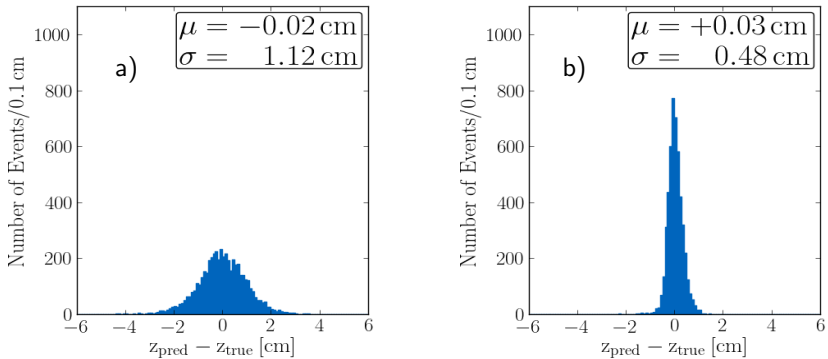


Figure: z-vertex prediction with an “expert” MLP for a small sector in two p_T regions with $\phi \in [0, 360]^\circ$, $\theta \in [56, 62]^\circ$ and $z \in [-10, 10]$ cm.

a) $p_T \in [0.3, 0.317]$ GeV. b) $p_T \in [3.5, 9.625]$ GeV.

! high accuracy on the z-vertex within a small sector

Preprocessing

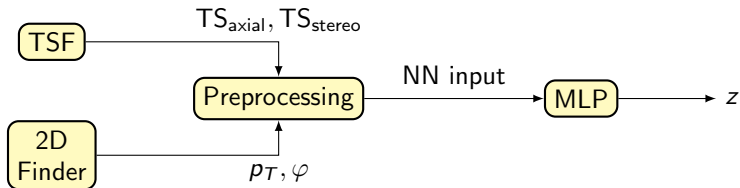


Figure: Information flow in the NeuroTrigger

Tasks

1. match Track Segments to tracks
2. improve (p_T, φ) estimate (2D fit)
→ Least Squares fit including drift times
3. provide 3D estimate (ϑ, z)
4. prepare Neural Net Input (& choose sector)

Preprocessing - Least Square fit

solve the linear equation $\vec{y} = \mathbf{X} \cdot \vec{n}$ by: $\vec{n} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \vec{y}$

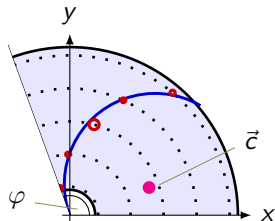
2D fit

circle fit; center at \vec{c} ; track from origin.

$\rho_T, \varphi \leftarrow c_x, c_y$

x_i, y_i : cartesian coordinates of axial hits in the (r, φ) plane.

$$(x_i^2 + y_i^2) = 2c_x \cdot x_i + 2c_y \cdot y_i$$

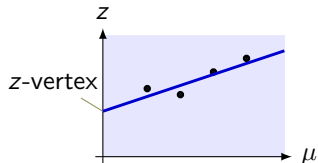


3D fit

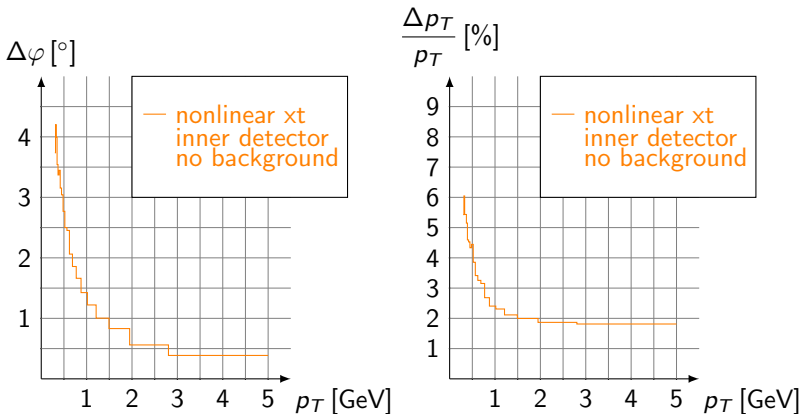
line fit in the (μ, z) plane.

μ_i, z_i : stereo hits transformed by 2D fit result.

$$z_i = \cot(\vartheta) \cdot \mu_i + z_0$$

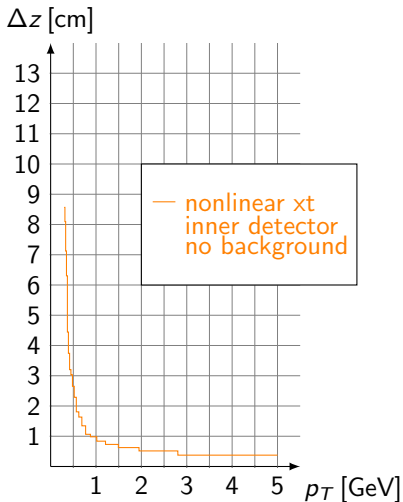
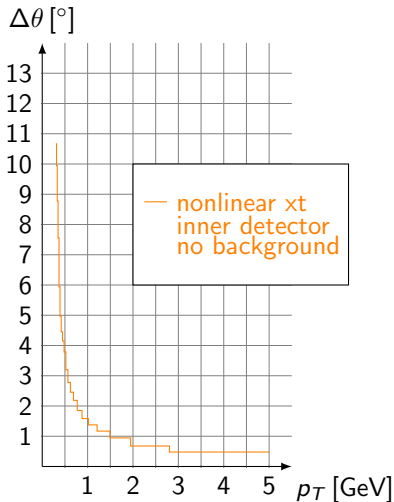


Results - 2D LS Fit (φ, p_T) 90% RMS



$p_T \in [0.3, 5] \text{ GeV}$	$\varphi \in [0, 90]^\circ$	$\vartheta \in [35, 123]^\circ$	$z \in [-50, 50] \text{ cm}$
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Results - 3D LS Fit (ϑ, z) 90% RMS

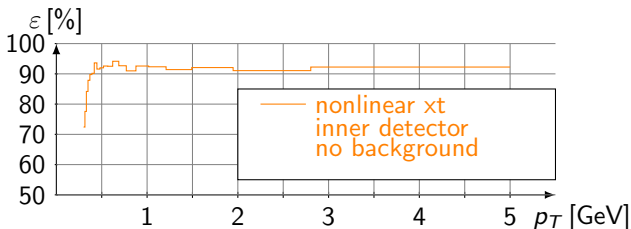


$p_T \in [0.3, 5] \text{ GeV}$	$\varphi \in [0, 90]^\circ$	$\vartheta \in [35, 123]^\circ$	$z \in [-50, 50] \text{ cm}$
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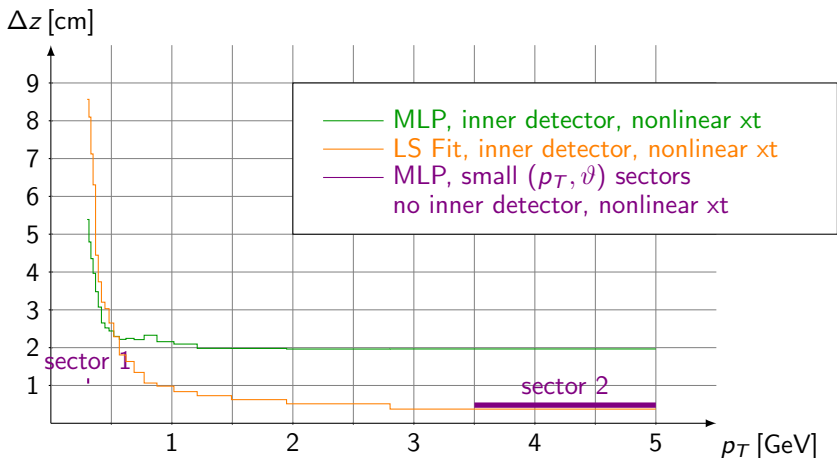
LS Fitter efficiency

Cuts lead to efficiency decrease

- ▶ min 3 axial hits in different layers
- ▶ max 10 axial hits total
- ▶ min 2 stereo hits in different layers
- ▶ max 8 stereo hits total
- ▶ min 5 hits total



z-90% RMS with LS fit and MLP



$p_T \in [0.3, 5] \text{ GeV}$	$\varphi \in [0, 90]^\circ$	$\vartheta \in [35, 123]^\circ$	$z \in [-50, 50] \text{ cm}$
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Conclusion

MLP

- ▶ MLP requires preprocessing
- ▶ MLP can improve z-RMS in low p_T region
- ▶ Sectorization improves MLP prediction

Preprocessing

- ▶ LS fit useful for preprocessing
- ▶ LS fit achieves good z-RMS for high p_T tracks

Outlook

- ▶ MLP optimization for low p_T tracks
- ▶ further preprocessing studies
- ▶ hardware implementation on Virtex 7 FPGA