Updates on 1 GeV beam π^+ -Ar inclusive cross section measurement

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Previous energy slicing result

• Last time, we validated the energy slicing method using fake data.

https://indico.fnal.gov/event/53325/contributions/235193/attachments/152412/197326/pionXS_DRA_220223.pdf

$$\sigma = \frac{M_{\rm Ar}}{\rho N_A \Delta E} \frac{dE}{dx} (E) \ln\left(\frac{N_{\rm inc}(E)}{N_{\rm inc}(E) - N_{\rm int}}\right)$$



Yinrui Liu I π^+ -Ar inclusive cross-section measurement





Direct measurements

Validating by fake data

- Reco: measured fake data (after selections, background) constraints, unfolding)
- True: truth info of fake data





Contents

- some problems we encountered in mock-data test.
- In this talk, I will just show the results (some more details will be given in back-ups)
 - The latest implementation of energy slicing method
 - Ignore incomplete slices
 - Removing APA3 cut
 - Mock-data tests using the latest implementation

• We update the implementation of energy slicing method, partly motivated by



Ignore incomplete slices

• Interaction sliceID: floor $\left(\frac{1000 - E_{int}}{\Delta E}\right)$

- SliceID = $0 \leftrightarrow E_{int} \in [950, 1000)$

. . .

- SliceID = $19 \leftrightarrow E_{int} \in [0, 50)$
- Initial sliceID: ceil $\left(\frac{1000 E_{\text{front-face}}}{\Lambda E}\right)$
 - SliceID = $0 \leftrightarrow E_{\rm ff} \ge 1000$
 - SliceID = 1 $\leftrightarrow E_{\rm ff} \in [950, 1000)$



Consider $\Delta E = 50$ (MeV)



More details are given in back-up 29





Removing APA3 cut

- APA3 cut (reco_beam_calo_endZ < 220) is to cut tracks which extend into the second TPC (since it is likely to be distorted at the boundary of two TPCs), and it can also mitigate muon backgrounds.
 - It removes ~3.5% events, which are majorly long tracks.
- However, this cut can bring bias since the vetoed are all non-interaction events in the high energy slices, which means these vetoed events should have been counted in the incident histogram, and not in the interaction histogram.
 - Thus, with APA3 cut, we are likely to overestimate the cross-section in the high energy slices.



Removing APA3 cut



- Now we don't cut those long tracks, instead, we ignore slices in the second TPC.
 - To do this, we define end sliceID
 - If endZ < 220 cm
 - End sliceID = interaction sliceID floor $\left(\frac{1000 E_{int}}{\Lambda F}\right)$ The energy at Z == 220 cm If endZ >= 220 cm • End sliceID = floor $\left(\frac{1000 - E_{220}}{\Delta E}\right) - 1$

The slice at 220 cm is incomplete, so we ignore it.

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Since end sliceID differs from interaction sliceID, now we have $N_{\text{inc}}(i) = \sum_{j=i}^{N} N_{\text{end}}(j) - \sum_{j=i+1}^{N} N_{\text{ini}}(j)$

 Reco: measured fake data (after selections, background constraints, unfolding)
 True: truth info of fake data





Mock-data test

We use Geant4reweight to derive samples of reweighted cross-sections

(more details in back-up 31-32) Jacob Calcutt, et. al. https://arxiv.org/abs/2105.01744

Example: reweight XS of fake data to 1.5

curve), but the measured XS (black points) looks weird.

• We think that's because there is something wrong with unfolding.

• The XS calculated using truth info (green points) is as expected (with the red

- Reco: measured fake data (after selections, background) constraints, unfolding)
- True: truth info of fake data

Unfolding

- Unfolding accounts for the detection resolution and inefficiency.
- The response matrix R_{ij} is derived by true MC sample, and then applied to fake data.

Response matrix derived by nominal true MC

 ν_i expected observed value

 μ_i expected true value

$$\nu_{i} = \sum_{j=1}^{N} R_{ij} \mu_{j}$$

$$R_{ij} = F(\text{observed value in bin } i | \text{true value in bin}$$

$$= \frac{\int_{\text{bin } i} dx \int_{\text{bin } j} dy P(x | y) \varepsilon(y) f_{\text{true}}(y)}{\int_{\text{bin } j} dy f_{\text{true}}(y)}, \text{ calculated by}$$

$$\text{true MC sample} \quad \text{\# events in bin } j \text{ of true histogram}$$

$$f_{\text{true}}(y) \text{ is sample-dependent, which can be different for the sample}$$

Ref: Glen Cowan, Statistical Data Analysis, Chap. 11

true MC samples with different cross-sections.

Unfolding matrices derived by different true MC samples are different!

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Unfolding

- Unfolding matrices derived by different true MC samples are different!
- data sample.
- fake data), we get better agreed measured result (black points).

Which one is the best? It must be the sample which is most similar to the fake

• In the example on slide 10, if we also reweight XS of true MC to 1.5 (same as

Iterative unfolding

- - other.
- fake data, whose XS is reweighted
 - to 0.5 nominal for momentum < 600 MeV
 - to 1.5 nominal for momentum > 600 MeV
 - Let's see if the iterative method can recover these reweight factors.

• Therefore, we consider iterative unfolding when measuring XS of real data.

- In the unfolding, we start from using nominal true MC, then reweight the true MC iteratively until the true MC XS and the measured data XS are consistent with each

In the following slides, we perform a preliminary test of the iterative method on

These are the only two reweightable ranges for inelastic XS provided by Geant4reweight

Test iterative unfolding

• True MC scale=[0.5, 1.5], Chi2/Ndf = 0.398362

[P < 600 MeV, P > 600 MeV]

- XS of true MC
- Reconstructed XS of fake data (unfolded by response matrix calculated by true MC)
- • True XS of fake data

• True MC scale=[1., 1.], Chi2/Ndf = 25.3341

- XS of true MC
- Reconstructed XS of fake data (unfolded by response matrix calculated by true MC)
- \bullet • True XS of fake data

• True MC scale=[0.67, 1.22], Chi2/Ndf = 4.49229

- XS of true MC
- Reconstructed XS of fake data (unfolded by response matrix calculated by true MC)
- \bullet • True XS of fake data

• True MC scale=[0.55, 1.32], Chi2/Ndf = 1.57103

- XS of true MC
- Reconstructed XS of fake data (unfolded by response matrix calculated by true MC)
- \bullet • True XS of fake data

• True MC scale=[0.49, 1.37], Chi2/Ndf = 0.881462

- XS of true MC
- Reconstructed XS of fake data (unfolded by response matrix calculated by true MC)
- \bullet • True XS of fake data

• True MC scale=[0.45, 1.39], Chi2/Ndf = 0.730346

- XS of true MC
- Reconstructed XS of fake data (unfolded by response matrix calculated by true MC)
- \bullet • True XS of fake data

• True MC scale=[0.42, 1.39], Chi2/Ndf = 0.755139

- XS of true MC
- Reconstructed XS of fake data (unfolded by response matrix calculated by true MC)
- \bullet • True XS of fake data

Sum-up

- local best result.
 - Random jump could be helpful to find the global best result.

every 50 MeV in KE.

• The iterative method seems to work, but it's possible to converge at some

• We would like to request Geant4reweight to provide separate reweight factors

Plan

- We still seek better understanding of this "misfunction" of unfolding.
 - Suggestions are very welcome!

apply it to real data soon.

• If we can pass the test of the iterative method, we would like to proceed to

dE/dx curve of pion in LAr

• In
$$\sigma = \frac{M_{Ar}}{\rho N_A \Delta E} \frac{dE}{dx} (E) \ln \left(\frac{N_{inc}(E)}{N_{inc}(E) - N_{int}(E)} \right)$$

Bethe-Bloch formula

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), $\frac{dE}{dx}(E)$ is derived according to the

True $E_{\text{front-face}}$ and E_{int}

- For $E_{\text{front-face}}$
 - Previously, I estimate $E_{\rm ff} = E_0$
 - Now, I use $E_{\rm ff} = E_1 + 2.18 \cdot l_1$

• For E_{int}

- I use trajectory point to estimate $E_{\rm int}$ with a small correction.
- Estimate $E_{int} = E_* 2.1 \cdot l_*$

Compare instrumented beam KE and $E_{\rm front-face}$

• Using true pion sample

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Ignore incomplete slice

- Interaction sliceID: int $\left(\frac{1000 E_{int}}{\Delta E}\right)$ floor $\left(\frac{1000 E_{int}}{\Delta E}\right)$
- Initial sliceID: int $\left(0.5 + \frac{1000 E_{\text{front-face}}}{\Delta E}\right)$ ceil $\left(\frac{1000 E_{\text{front-face}}}{\Delta E}\right)$

Ignore incomplete slices can help us get rid of the ambiguity of that confusing 0.5 in initial sliceID, which may cause small bias in the first couple of slices (on the right side)

Some notes about sliceID histograms

So for sliceID $i \in [0, N-1]$ (underflow -1; overflow N),

we have
$$N_{\text{inc}}(i) = \sum_{j=i}^{N} N_{\text{end}}(j) - \sum_{j=i+1}^{N} N_{\text{ini}}(j)$$

Equivalently
$$N_{\text{inc}}(i) = \sum_{j=0}^{i} N_{\text{ini}}(j) - \sum_{j=0}^{i-1} N_{\text{end}}$$

because ideally $\sum_{i=1}^{N} N_{ini}(i) = \sum_{i=1}^{N} N_{end}(i)$, which is the total number of true signal events. i=0 i=0(This does not necessarily hold for reco histograms, because separate unfoldings on $N_{
m end}$ and N_{ini} do not guarantee the total numbers still exactly equal to each other.)

(j)

Geant4reweight

- Divide a track into several steps.
- In each step, $P_{\text{survive}} = e^{-\sigma\Delta L}$, P_{interms}

The probability that the particle surv

 The probability that the particle interacts at step f is $P_{\text{interact}} = \prod_{i=1}^{f-1} e^{-\sigma_i \Delta L_i} \cdot \left(1 - e^{-\sigma_f \Delta L_i}\right)$ l

Jacob Calcutt, et. al. https://arxiv.org/abs/2105.01744

$$e_{ract} = 1 - e^{-\sigma \Delta L}$$
.

vives after step f is
$$P_{\text{survive}} = \prod_{i}^{f} e^{-\sigma_i \Delta L_i}$$
.

$$L_{f}$$

Geant4reweight

- The probability that the particle interacts at step f is
 - $P_{\text{interact}} = \prod_{i=1}^{f-1} e^{-\sigma_i \Delta L_i} \cdot \left(1 e^{-\sigma_f \Delta L_f}\right).$
- So we can express $P_{\text{interact}} = P_{\text{interact}}(\sigma)$.
- If we scale σ to $\alpha \cdot \sigma$, then $P_{\text{interact}} = P_{\text{interact}}(\alpha \cdot \sigma)$.
- we have a sample whose cross-section is equivalently $\alpha \cdot \sigma$.

Jacob Calcutt, et. al. https://arxiv.org/abs/2105.01744

• Therefore, we assign a weight $w = \frac{P_{\text{interact}}(\alpha \cdot \sigma)}{P_{\text{interact}}(\sigma)}$ to each event, and thus

