Status of the $\overline{p}p \rightarrow \overline{\Lambda}\Lambda$ Spin Observables Analysis

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on behalf of the $\overline{\text{P}}$ANDA collaboration

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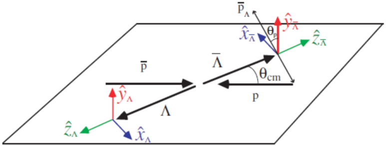
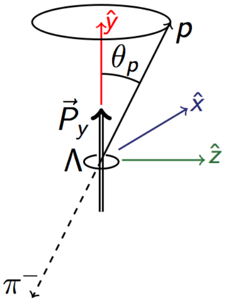
Outline

- Recap on Spin Observables
- Issues with current Kalman filter implementation
- Performance of new 4-constraint fit
- Preliminary background study
- Outlook

Spin observables in $\bar{p}p \to \overline{Y}Y$





$$\hat{z} = \frac{\vec{p}_\Lambda}{|\vec{p}_\Lambda|}, \hat{y} = \frac{\vec{p}_i \times \vec{p}_f}{|\vec{p}_i \times \vec{p}_f|}, \hat{x} = \hat{y} \times \hat{z}$$

Polarisation

Proton angular distribution:

$$I(\theta_p) \propto \frac{1}{4\pi}(1 + \alpha P_y \cos\theta_p)$$

$\overline{\alpha}, \alpha$ - decay asymmetry parameter

Spin correlation

Nucleon angular distribution:

$$I(\theta_i, \theta_j) \propto \frac{1}{16\pi^2}(1+$$

$$\overline{\alpha}\alpha \sum_{i,j} C_{ij} \cos\theta_i \cos\theta_j)$$

Reconstructing the Spin Observables

Spin observables can be extracted using Method of Moments:

$$\langle \cos\theta_y \rangle = \langle k_y \rangle = \int_{-1}^{1}\int_{-1}^{1} I(k_y, k_{\overline{y}}) \times k_y \, dk_y \, dk_{\overline{y}}$$

Polarisation and Spin Correlation is given by:

$$P_y = \frac{3}{\alpha}\langle k_y \rangle = \frac{3}{\alpha}\frac{\sum_{m=1}^{N} k_{y,m}}{N}$$

$$C_{ij} = \frac{9}{\overline{\alpha}\alpha}\langle \overline{k}_i k_j \rangle = \frac{9}{\alpha\overline{\alpha}}\frac{\sum_{m=1}^{N} \overline{k}_{i,m} k_{j,m}}{N}$$

Erik Thomé, Elisabetta Perotti, Uppsala University

Reconstructing the Spin Observables

If $\cos\theta_y$ is symmetric around 0 i.e.

$$A_y(\cos\theta_y) = A_y(-\cos\theta_y)$$

$$A_{\overline{y}}(\cos\theta_{\overline{y}}) = A_{\overline{y}}(-\cos\theta_{\overline{y}}),$$

the spin observables are obtainable without acceptance correction:

$$P = \frac{1}{\alpha}\frac{\langle k_y\rangle}{\langle k_y^2\rangle}$$

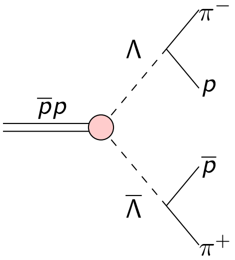
$$C_{yy} = \frac{1}{\alpha\overline{\alpha}}\frac{\langle \overline{k}_y k_y\rangle}{\langle \overline{k}_y^2\rangle\langle k_y^2\rangle}$$

$$C_{ij} = \frac{1}{\alpha\overline{\alpha}}\frac{\langle \overline{k}_i k_j\rangle - \langle \overline{k}_i\rangle\langle k_j\rangle}{\langle \overline{k}_i^2\rangle\langle k_j^2\rangle}, i,j = x,z$$

Simulation parameters

Simulations are done with feb17 release version.

- $\sim 10^6$ $\overline{p}p \to \overline{\Lambda}\Lambda$ events
- Forward-peaking distribution
- Antiproton beam $p_{\overline{p}} = 1.642$ GeV/c
- Full $\overline{\text{P}}$ANDA Detector setup
- Ideal Pattern Recognition
- Ideal Hypothesis in Kalman filter
- Ideal Particle Identification



Pull Distributions (Stretch Functions)

The pull distribution z for an observation i, also known as stretch function, is defined as

$$z_i = \frac{y_i - \eta_i}{\sqrt{\sigma^2(y_i) - \sigma^2(\eta_i)}}$$

Also used to study deviation from MC values (calling it MC pull distribution)

$$z_i = \frac{y_{MC,i} - \eta_i}{\sigma(\eta_i)}$$

- Pull distribution used to study performance of kinematic fits
- MC pull used to see performance of Kalman filter

Performance of Kinematic Fit

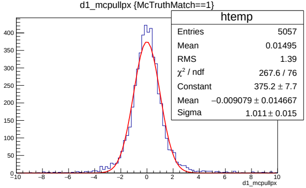
In an ideal kinematic fit:

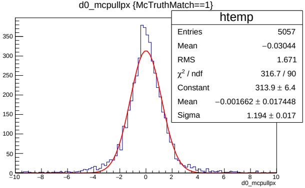
- Pull distributions should be normal distributed
- Probability distribution should be flat

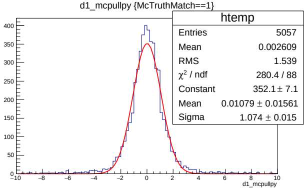
There are issues with the fit if:

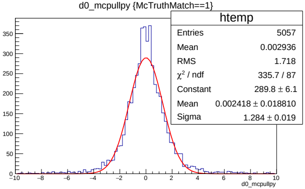
- Peaks at 0 in probability distribution $\implies$ bad events/poor convergence
- Skews towards higher (lower) values $\implies$ errors over(under)estimated
- Skews in pull distributions $\implies$ bias in measurements
- Narrower (broader) normal distributions $\implies$ errors over(under)estimated

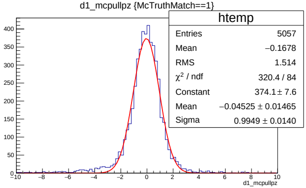
MC pull distribution (with Ideal Hypothesis)

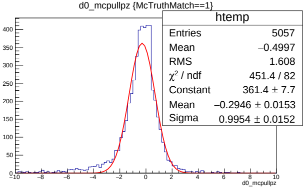




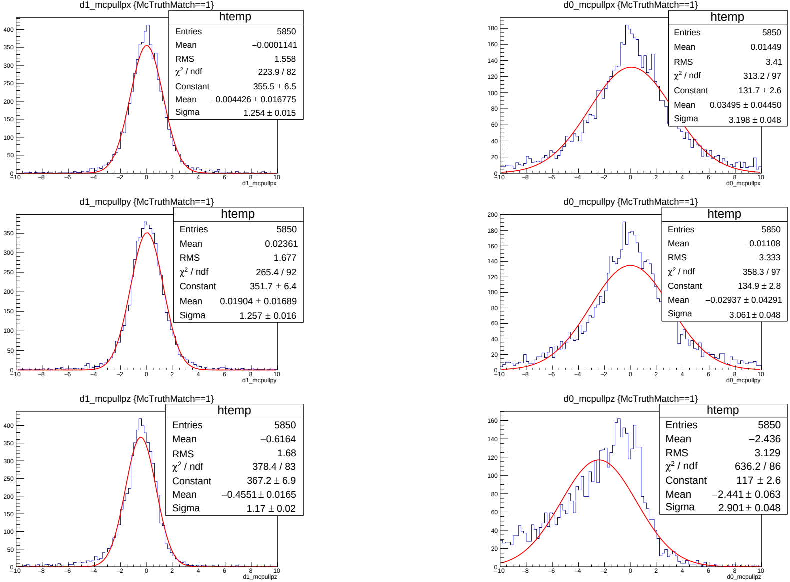








MC pull distribution, (no Ideal Hypothesis)



Kalman filter current design

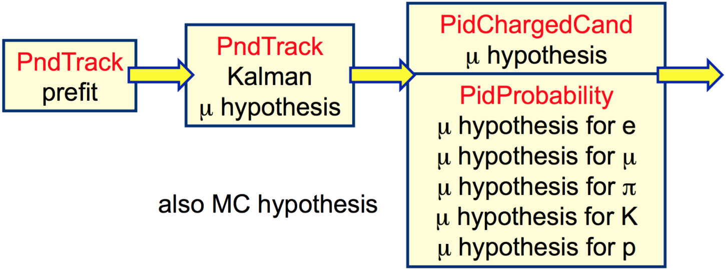


Figure from PANDA Computing Workshop 2017

Kalman filter new design?

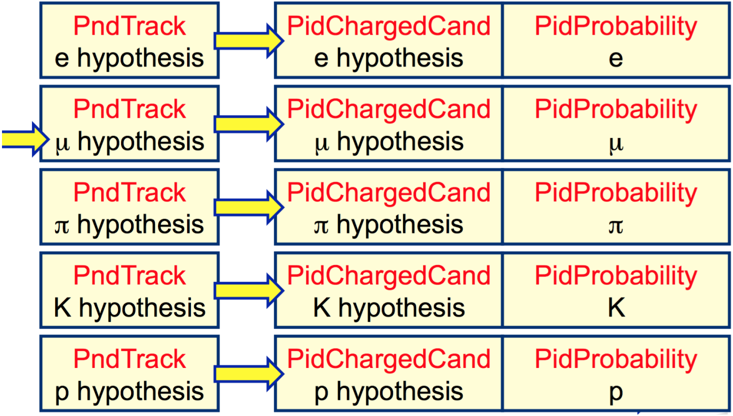
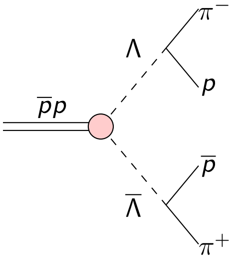


Figure from PANDA Computing Workshop 2017

Event reconstruction

Event selection:

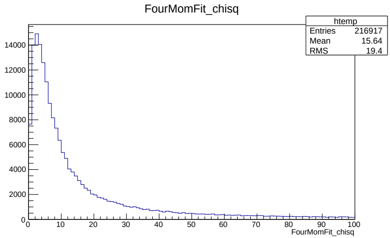
- Combine $p\pi^-$, $\overline{p}\pi^+$
- Select $|m_\Lambda - M(p\pi^-)| < 0.3$ GeV
- Vertex fit on all combinations of $p\pi^-$, $\overline{p}\pi^+$
  Reject a candidate if $P(\mathrm{Vtxfit}) < 0.01$
  Select combination with smallest χ^2
- Perform a 4 constraint fit on the $\overline{\Lambda}\Lambda$ candidates

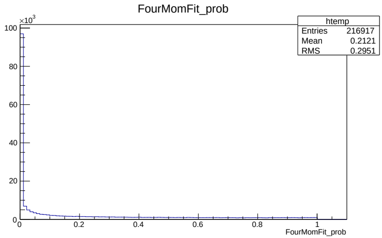


4-Constraint Fit on $\bar{p}p \rightarrow \bar{\Lambda}\Lambda$

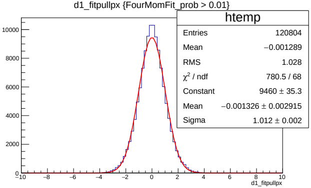
Xinying Song introduced a fix to the propagation of covariance matrices in the RhoFitter package

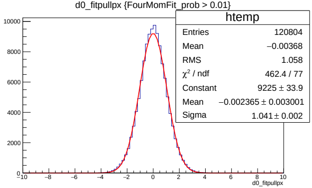
- Perform vertex fit on $p\pi$ pairs.
- Use covariance matrix of Λ and $\bar{\Lambda}$ in 4C-fit, treating $\bar{\Lambda}\Lambda$ as final state particles

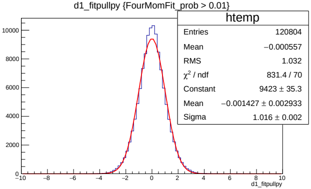


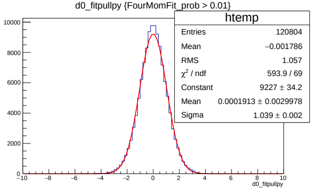


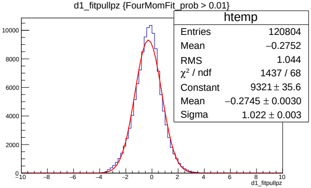
4 Constraint Fit on $\bar{p}p \rightarrow \bar{\Lambda}\Lambda$

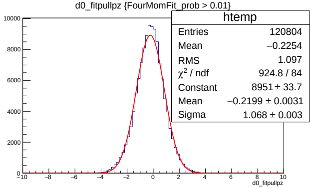




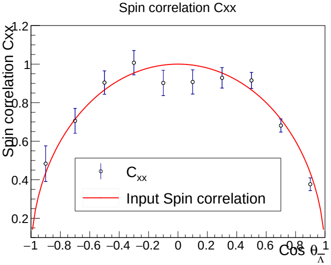


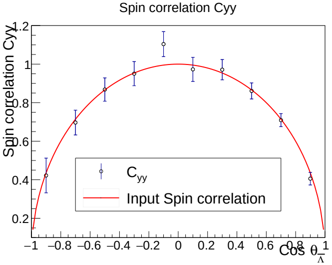






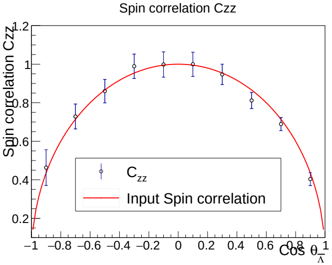
Spin Correlation C_{ii}, using 4C fit output



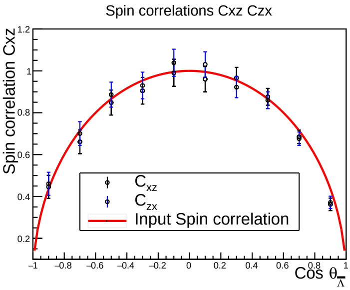


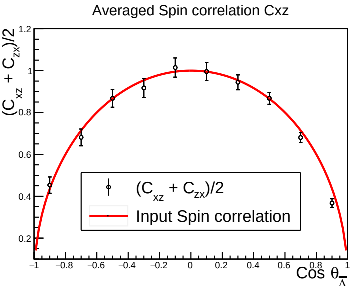
Spin correlation error given by

$$\sigma_{C_{ij}} = \frac{9}{\overline{\alpha}\alpha}\sqrt{\frac{1}{N-1}\left(\langle\overline{k_i^2}k_j^2\rangle - \langle\overline{k}_i k_j\rangle^2\right)}$$



Spin Correlation C_{ij}, using 4C fit output





- From charge conjugation argument, $C_{xz} = C_{zx}$
- Calculate the average of both measurement in each bin for smaller statistical errors

Background Samples

In addtion to DPM samples, following non resontant background channels are relevant:

- $\pi^+\pi^- p\overline{p}, \sigma = 125.317\mu\mathrm{b}$
- $\pi^+\pi^- p\overline{p} + \gamma, \sigma = 4128.983\mu\mathrm{b}$
- $\pi^+\pi^- p\overline{p} + \gamma\gamma, \sigma = 67.928\mu\mathrm{b}$

Other hyperon antihyperon pair production threshold above $p_{\overline{p}} = 1.64$ GeV/c, not relevant!

Background Samples

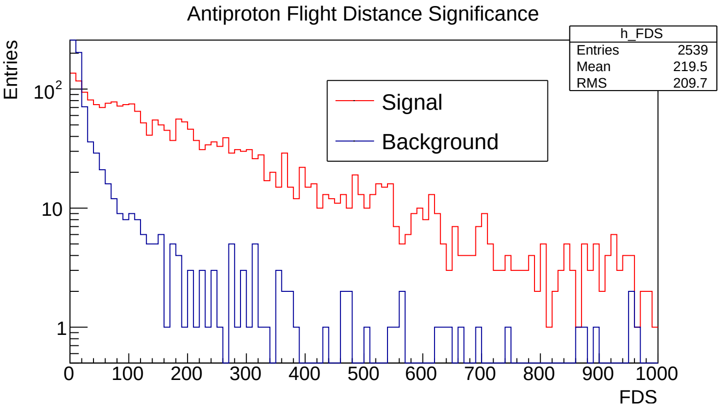
A preliminary background study done on three samples with 10.000 events each

Events after selection		
$\overline{\Lambda}\Lambda$	2539	25.4 %
$\overline{p}p\pi^{+}\pi^{-}$	3538	36.4 %
DPM	8	0.08 %

To further suppress background, additional analysis steps needed.

- Cut on 4-constraint χ^2 distribution optimized for maximum $S/\sqrt{B}$
- Cut on vertex displacement *e.g.* flight distance significance z/σ_z

Vertex cut



Antiproton Flight Distance Significance
h_FDS
Entries 2539
Mean 219.5
RMS 209.7
Signal
Background
Entries
10^2
10
1
0
100
200
300
400
500
600
700
800
900
1000
FDS

Outlook

- Large background samples to be generated
  - DPM
  - Non resonant $\pi^+\pi^- p\overline{p}$
- Update $\overline{\Xi}\Xi$ analysis with new tools
- Memo currently being written
- How to proceed with Kalman filter?
- How to proceed with PID?

Outlook

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Thank you for your attention!

Backup

Acceptance functions

Acceptance used for C_{zz}