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

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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 $\bar{p}p \rightarrow Y Y$

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

**Polarisation**

Proton angular distribution:

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

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

**Spin correlation**

Nucleon angular distribution:

$I(\theta_i, \theta_j) \propto \frac{1}{16\pi^2} (1 + \bar{\alpha}\alpha \sum_{i,j} C_{ij} \cos \theta_i \cos \theta_j)$
Reconstructing the Spin Observables

Spin observables can be extracted using Method of Moments:

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

Polarisation and Spin Correlation is given by:

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

\[
C_{ij} = \frac{9}{\alpha \alpha} \langle \overline{k_i} k_j \rangle = \frac{9}{\alpha \alpha} \frac{\sum_{m=1}^{N} \overline{k_{i,m}} k_{j,m}}{N}
\]

Erik Thomé, Elisabetta Perotti, Uppsala University
Reconstructing the Spin Observables

If \( \cos \theta_y \) is symmetric around 0 i.e.

\[
A_y(\cos \theta_y) = A_y(- \cos \theta_y)
\]

\[
A_{\bar{y}}(\cos \theta_{\bar{y}}) = A_{\bar{y}}(- \cos \theta_{\bar{y}}),
\]

the spin observables are obtainable without acceptance correction:

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

\[
C_{yy} = \frac{1}{\alpha \bar{\alpha}} \frac{\langle k_y k_y \rangle}{\langle k_y^2 \rangle \langle k_y^2 \rangle}
\]

\[
C_{ij} = \frac{1}{\alpha \bar{\alpha}} \frac{\langle k_i k_j \rangle - \langle k_i \rangle \langle k_j \rangle}{\langle k_i^2 \rangle \langle k_j^2 \rangle}, \quad i, j = x, z
\]
Simulation parameters

Simulations are done with feb17 release version.

- $\sim 10^6 \bar{p}p \rightarrow \Lambda\Lambda$ events
- Forward-peaking distribution
- Antiproton beam $p_\bar{p} = 1.642$ GeV/c
- Full $\bar{P}$ANDA Detector setup
- Ideal Pattern Recognition
- Ideal Hypothesis in Kalman filter
- Ideal Particle Identification
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 $\Rightarrow$ bad events/poor convergence
- Skews towards higher (lower) values $\Rightarrow$ errors over(under)estimated
- Skews in pull distributions $\Rightarrow$ bias in measurements
- Narrower (broader) normal distributions $\Rightarrow$ errors over(under)estimated
MC pull distribution (with Ideal Hypothesis)

**d1_mcpullpx {McTruthMatch==1}**

- **Entries**: 5057
- **Mean**: 0.01495
- **RMS**: 1.39
- **χ² / ndf**: 280.4 / 88
- **Constant**: 7.7 ± 375.2
- **Mean**: 0.014667 ± 0.009079
- **Sigma**: 0.015 ± 1.011

**d2_mcpullpx {McTruthMatch==1}**

- **Entries**: 5057
- **Mean**: 0.01495
- **RMS**: 1.39
- **χ² / ndf**: 267.6 / 76
- **Constant**: 7.7 ± 375.2
- **Mean**: 0.014667 ± 0.009079
- **Sigma**: 0.015 ± 1.011

**d1_mcpullpy {McTruthMatch==1}**

- **Entries**: 5057
- **Mean**: 0.002609
- **RMS**: 1.539
- **χ² / ndf**: 280.4 / 88
- **Constant**: 7.1 ± 352.1
- **Mean**: 0.002418 ± 0.018810
- **Sigma**: 0.015 ± 0.9954

**d2_mcpullpy {McTruthMatch==1}**

- **Entries**: 5057
- **Mean**: 0.002609
- **RMS**: 1.539
- **χ² / ndf**: 316.7 / 90
- **Constant**: 6.4 ± 313.9
- **Mean**: 0.002418 ± 0.018810
- **Sigma**: 0.015 ± 0.9954

**d1_mcpullpz {McTruthMatch==1}**

- **Entries**: 5057
- **Mean**: −0.009079
- **RMS**: 1.608
- **χ² / ndf**: 250
- **Constant**: 7.7 ± 361.4
- **Mean**: −0.009079 ± 0.01465
- **Sigma**: 0.015 ± 1.194

**d2_mcpullpz {McTruthMatch==1}**

- **Entries**: 5057
- **Mean**: −0.009079
- **RMS**: 1.608
- **χ² / ndf**: 320.4 / 84
- **Constant**: 7.7 ± 361.4
- **Mean**: −0.009079 ± 0.01465
- **Sigma**: 0.015 ± 1.194
MC pull distribution, (no Ideal Hypothesis)

**d1_mcpullpx {McTruthMatch==1}**

- Entries: 5850
- Mean: -0.0001141
- RMS: 1.558
- $\chi^2$/ndf: 265.4 / 92
- Constant: 6.5 ± 355.5
- Mean: 0.016775 ± 0.004426
- Sigma: 0.015 ± 1.254

**d1_mcpullpy {McTruthMatch==1}**

- Entries: 5850
- Mean: 0.02361
- RMS: 1.677
- $\chi^2$/ndf: 358.3 / 97
- Constant: 355.5 ± 6.9
- Mean: 0.01449 ± 0.016775
- Sigma: 0.016 ± 1.257

**d1_mcpullpz {McTruthMatch==1}**

- Entries: 5850
- Mean: -0.01108
- RMS: 3.129
- $\chi^2$/ndf: 378.4 / 83
- Constant: 367.2 ± 2.6
- Mean: -0.4551 ± 0.01689
- Sigma: 0.048 ± 3.198

**d0_mcpullpx {McTruthMatch==1}**

- Entries: 5850
- Mean: 0.01449
- RMS: 3.41
- $\chi^2$/ndf: 313.2 / 97
- Constant: 131.7 ± 2.6
- Mean: 0.03495 ± 0.04450
- Sigma: 3.198 ± 0.048

**d0_mcpullpy {McTruthMatch==1}**

- Entries: 5850
- Mean: -0.01108
- RMS: 3.333
- $\chi^2$/ndf: 358.3 / 97
- Constant: 134.9 ± 2.8
- Mean: -0.02937 ± 0.04291
- Sigma: 3.061 ± 0.048

**d0_mcpullpz {McTruthMatch==1}**

- Entries: 5850
- Mean: 2.436
- RMS: 3.129
- $\chi^2$/ndf: 636.2 / 86
- Constant: 2.6 ± 117
- Mean: 0.063 ± 2.441
- Sigma: 0.048 ± 2.901

**d0_mcpullpx {McTruthMatch==1}**

- Entries: 5850
- Mean: 0.01108
- RMS: 3.333
- $\chi^2$/ndf: 358.3 / 97
- Constant: 134.9 ± 2.8
- Mean: -0.02937 ± 0.04291
- Sigma: 3.061 ± 0.048
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 $p\pi^-$, $\bar{p}\pi^+$
- Select $|m_\Lambda - M(p\pi^-)| < 0.3$ GeV
- Vertex fit on all combinations of $p\pi^-$, $\bar{p}\pi^+$
  - Reject a candidate if $P(Vtxfit) < 0.01$
  - Select combination with smallest $\chi^2$
- Perform a 4 constraint fit on the $\bar{\Lambda}\Lambda$ candidates
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 $\Lambda$ and $\bar{\Lambda}$ in 4C-fit, treating $\bar{\Lambda}\Lambda$ as final state particles
4 Constraint Fit on $p p \rightarrow \Lambda \Lambda$

**d1_fitpullpx (FourMomFit_prob > 0.01)**

Entries 120804
Mean $-0.001289$
RMS 1.282
$\chi^2$/ndf 780.5 / 68
Constant 9460 ± 35.3
Mean $-0.001326 \pm 0.002915$
Sigma 1.012 ± 0.002

**d1_fitpullpy (FourMomFit_prob > 0.01)**

Entries 120804
Mean $-0.000557$
RMS 1.382
$\chi^2$/ndf 831.4 / 70
Constant 9423 ± 35.3
Mean $-0.001427 \pm 0.002933$
Sigma 1.016 ± 0.002

**d1_fitpullpz (FourMomFit_prob > 0.01)**

Entries 120804
Mean $-0.2752$
RMS 1.044
$\chi^2$/ndf 1437 / 68
Constant 9321 ± 35.6
Mean $-0.2754 \pm 0.0030$
Sigma 1.022 ± 0.003

**d0_fitpullpx (FourMomFit_prob > 0.01)**

Entries 120804
Mean $-0.003668$
RMS 1.058
$\chi^2$/ndf 462.4 / 77
Constant 9225 ± 33.9
Mean $-0.002365 \pm 0.003001$
Sigma 1.041 ± 0.002

**d0_fitpullpy (FourMomFit_prob > 0.01)**

Entries 120804
Mean $-0.001786$
RMS 1.057
$\chi^2$/ndf 593.9 / 69
Constant 9227 ± 34.2
Mean $-0.0029978 \pm 0.0001913$
Sigma 1.039 ± 0.002

**d0_fitpullpz (FourMomFit_prob > 0.01)**

Entries 120804
Mean $-0.2199$
RMS 1.068
$\chi^2$/ndf 462.4 / 77
Constant 9460 ± 35.3
Mean $-0.002365 \pm 0.003001$
Sigma 1.068 ± 0.003
Spin Correlation $C_{ii}$, using 4C fit output

Spin correlation error given by

$$\sigma_{C_{ij}} = \frac{9}{\alpha \alpha} \sqrt{\frac{1}{N - 1} \left( \langle k_i^2 k_j^2 \rangle - \langle k_i \rangle \langle k_j \rangle^2 \right)}$$
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 addition to DPM samples, following non resonant background channels are relevant:

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

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

A preliminary background study done on three samples with 10,000 events each

Events after selection

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{\Lambda}\Lambda$</td>
<td>2539</td>
<td>25.4 %</td>
</tr>
<tr>
<td>$\bar{p}p\pi^+\pi^-$</td>
<td>3538</td>
<td>36.4 %</td>
</tr>
<tr>
<td>DPM</td>
<td>8</td>
<td>0.08 %</td>
</tr>
</tbody>
</table>

To further suppress background, additional analysis steps needed.

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

Antiproton Flight Distance Significance

Signal
Background

Entries

\[
\begin{array}{|c|c|c|}
\hline
h_{FDS} & \\
\hline
\text{Entries} & 2539 \\
\text{Mean} & 219.5 \\
\text{RMS} & 209.7 \\
\hline
\end{array}
\]
Outlook

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

- Large background samples to be generated
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- How to proceed with Kalman filter?
- How to proceed with PID?

Thank you for your attention!
Backup
Acceptance functions

Acceptance used for $C_{zz}$