A machine learning approach for mass composition analysis with TALE-SD data

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Abstract. The TALE experiment is a Telescope Array Low-energy Extension constructed to observe cosmic rays with energies down to $10^{16.5}$ to clarify the origin of the second knee and the energy of the galactic to extragalactic CRs transition. TALE consists of 10 high-elevation fluorescence detectors and 80 scintillation counters in an area of 21 km$^2$. The key of data interpretation is the mass composition of cosmic rays, and we report on a machine learning approach of mass composition analysis that utilizes waveform data of TALE scintillation counters.

1 Introduction

1.1 Telescope Array experiment
The Telescope Array (TA) experiment is the largest cosmic ray observatory in the northern hemisphere designed to detect ultra high energy cosmic rays is deployed in Millard County, Utah, USA. It mainly observes ultra high energy (above $\sim 10^{18}$ eV) cosmic rays, using both Fluorescence Detectors (FD) and scintillator Surface Detectors (SD). There are 507 SDs with about 700 km$^2$ effective detection area and the 3 FD stations, which are called Black Rock Mesa (BRM), Long Ridge (LR) and Middle Drum (MD). The FD telescopes cover the sky above the SD array from 3$^\circ$ to 31$^\circ$ in elevation. The general map of the TA detectors is shown in Fig. 1a.

1.2 Telescope Array Low-energy Extension (TALE)
The Telescope Array Low-energy Extension (TALE) detectors are designed for the energy threshold of the experiment to be well below $10^{16.5}$ eV. We call the bend in the energy spectrum around $10^{17}$ eV as the "second knee" and consider that the feature suggests a galactic-to-extragalactic transition of cosmic ray origin. The motivation of the TALE experiment is to clarify the origin of the feature measuring the energy spectrum and mass composition of cosmic rays around $10^{17}$ eV. To observe lower energy showers, TALE utilizes 10 FDs with elevation angles higher than that of TA-FD, from 31$^\circ$ up to 59$^\circ$. In addition 80 SDs with denser grids are also installed near the MD site. The full details of the detectors may be found in [1]. For this analysis, we report on a machine learning approach of mass composition analysis that utilizes waveform data of TALE-SD array. The layout of TALE detectors is shown in Fig. 1b.

2 TALE-SD mass composition analysis

2.1 Monte Carlo (MC) simulation and Event selection criteria
We generate cosmic ray air showers using CORSIKA-based MC simulation code developed for TA [2] in this analysis. QGSJETII-04 [3] and Geant 4 are used for air shower simulation and detector response simulation, respectively. The MC input parameters are given in Table 1. The simulated air shower is reconstructed using TALE-SD software [4]. Only events that pass the event selection criteria shown in Table 2a below are used in the analysis. The number of Monte-Carlo events after the selection are 17,121 events (proton) and 17,262 (iron), respectively.

<table>
<thead>
<tr>
<th>Table 1: MC simulation dataset</th>
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<tbody>
<tr>
<td>primary</td>
</tr>
<tr>
<td>MC simulation</td>
</tr>
<tr>
<td>interaction model</td>
</tr>
<tr>
<td>primary energy</td>
</tr>
<tr>
<td>zenith angle</td>
</tr>
<tr>
<td>azimuthal angle</td>
</tr>
<tr>
<td>TALE-SDs</td>
</tr>
<tr>
<td>Number of generated event</td>
</tr>
<tr>
<td>Number of selected event</td>
</tr>
</tbody>
</table>

2.2 Composition-sensitive parameters
The advantages of the TALE-SD array are its high statistics and high uniform sensitivity compared to FD. If we analyze mass composition analysis using TALE-SD data, we can apply the result to cosmic ray energy spectrum and
Figure 1: (a) General map of the TA experiment site. The locations of the TA-SDs are shown as red circles and the locations of the three TA-FD stations are indicated by light blue circles. Yellow circles show the location of the TALE-SDs. The TALE-FD station is located at the MD site. (b) The layout of the TALE detectors. Open square boxes (□) represent the locations of the TALE-SDs and blue circle (•) correspond to the MD/TALE-FD station. Black boxes (■) represent the locations of the TA-SDs.

anisotropy analysis.

A schematic view of an air shower arriving at the surface is shown in Fig. 3. As shown in this figure, air showers arrive at the surface with 3 characteristics: lateral distribution, curvature, and thickness. Using TALE-SD software and simulated proton and iron air showers, we search and extract 22 parameters [5, 6] that exhibit 3 characteristics. The parameters’ histograms are shown in Fig. 4.

Table 2: (a) Event selection criteria (b) $N_{\text{thickness}}$ selection (SD selection)

(a)

\[
N_{\text{SD}} \geq 5, \quad N_{\text{thickness}} \geq 1, \\
\chi^2_{\text{geometry}} / \text{d.o.f.} \leq 4, \quad \chi^2_{\text{Bulk}} / \text{d.o.f.} \leq 2, \\
\left( \sigma^2_0 + \sin^2 \theta \sigma^2_0 \right)^{0.5} \leq 2.5 \text{ deg.}, \\
\sigma_{S_{\text{rec}}}/S_{600} \leq 0.25, \\
0^\circ \leq \theta_{\text{rec}} \leq 45^\circ.
\]

(b)

$\text{recorded waveform} \leq 2.56 \mu s$ (128 bin)
$N_{\text{bin}}(\geq 15 \text{ FADC count})$ is more than 2.
$N_{\text{bin}}(\geq 45 \text{ FADC count})$ is more than 1.
No saturation in recorded signal (upper/lower) within the range of $400 \ m \leq r \leq 700 \ m$. 

and simulated core positions, respectively. Red one is ray.

Figure 3: A schematic view of the development of an air shower around the surface. Dashed line and black arrow are shower plane and shower axis, respectively. Purple, red and blue arrow indicates "lateral distribution", "thickness" and "curvature" of air showers, respectively.

Figure 2: Simulated core position distribution for TALE-SD array. ○, ● and •/,• indicates TALE-SD array, TALE-FD and simulated core positions, respectively. Red one is (a)proton and blue one is (b)iron. "Entries" indicates the number of generated events.

Figure 4: 22 parameters by the TALE-SD array histograms. Proton MC is shown with red lines and iron MC is shown with blue them. "Entries" indicates the number of events.
3 Machine learning approach

3.1 Neural network details

We have developed a machine learning model to take advantage of the high-statistics TALE-SD data for mass composition analysis. The machine learning model that we use is a binary classification to discriminate between proton and iron cosmic ray events by MC simulation as shown in the Fig. 5. The input vector $\alpha$ consists of 22 normalized parameters. Output value $\beta$ is a numerical values from 0 to 1, with 0 being labeled as proton and 1 as iron. The output value $\beta$ is determined to be proton if it is less than 0.5, and iron if it is greater than 0.5.

The machine learning model details are shown in Table 6. We use two activation functions (a hyperbolic tangent and a sigmoid). To eliminate learning bias, the same number of events are prepared for proton and iron air showers. All data are split into training, validation, and test data at a ratio of 8:1:1.

![Figure 5: Machine learning model outline](image)

![Figure 6: Machine learning model details](image)

<table>
<thead>
<tr>
<th>primary</th>
<th>proton</th>
<th>iron</th>
</tr>
</thead>
<tbody>
<tr>
<td>All data</td>
<td>17120</td>
<td>17120</td>
</tr>
<tr>
<td>Training data</td>
<td>13696</td>
<td>13696</td>
</tr>
<tr>
<td>Validation data</td>
<td>1712</td>
<td>1712</td>
</tr>
<tr>
<td>Test data</td>
<td>1712</td>
<td>1712</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Adam</td>
<td></td>
</tr>
<tr>
<td>Loss function</td>
<td>Cross-Entropy Error (CEE)</td>
<td></td>
</tr>
</tbody>
</table>

3.2 The prediction of the machine learning model

The performance of the trained machine learning model was evaluated using all test data. The result is shown in Fig. 7. The red line represents the model’s prediction on test data where the answer is proton ($\beta = 0$), and the blue line represents the model’s prediction on test data where the answer is iron ($\beta = 1$). Classification matrix for all test data are shown in Table 3. The percentage of those that predicted that the answer is proton is 68.9%, and the percentage of those that predicted that the answer is iron is 65.4%. The overall accuracy is determined by the average of these values, which is 67.1%.

![Figure 7: The response distribution of the test data to the machine learning model](image)

4 Conclusion

We search and extract 22 parameters that depend on primary cosmic ray for cosmic ray mass composition analysis using TALE-SD array. Using these parameters, we have developed a binary classification machine learning model to discriminate proton and iron cosmic rays by MC simulation. The classification accuracy of the machine learning model is currently 67.1%. To improve the accuracy, it is planned to add information for each detector, search for new parameters, and use a Graph Neural Network.

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References


[4] K. Sato, for the Telescope Array collaboration, "Cosmic ray energy spectrum in the 2nd knee region measured 

[5] P. Abreu et al., "A Search for Photons with Energies Above $2 \times 10^{17}$ eV Using Hybrid Data from the Low-
Energy Extensions of the Pierre Auger Observatory", 


Full Authors List: Telescope Array Collaboration


Table 3: Classification matrix for all test data in Fig. 7. The percentage of cosmic-ray events considered to be of proton origin if the output value $\beta$ is less than 0.5, and of iron origin if the output value is greater than 0.5, is shown in brackets.

<table>
<thead>
<tr>
<th>answer \ prediction</th>
<th>proton(0 $\leq \beta &lt; 0.5$)</th>
<th>iron(0.5 $\leq \beta \leq 1$)</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>proton(0 $\leq \beta &lt; 0.5$)</td>
<td>1180 (68.9%)</td>
<td>532 (31.1%)</td>
<td>1712</td>
</tr>
<tr>
<td>iron (0.5 $\leq \beta \leq 1$)</td>
<td>593 (34.6%)</td>
<td>1119 (65.4%)</td>
<td>1712</td>
</tr>
<tr>
<td>total</td>
<td>1773</td>
<td>1651</td>
<td>3424</td>
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