VERITAS and Source Direction Reconstruction

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Outline

- Background
  - VERITAS
  - Gamma ray astronomy
- Source direction reconstruction
  - Geometric method
  - Displacement method
- Displacement method implementation
  - Lookup table
  - Multivariate analysis
  - Analytical function
VERITAS

Very Energetic Radiation Imaging Telescope Array System

Four 12 meter telescopes in southern Arizona

High energy gamma rays

Detect Cherenkov light from air showers
Gamma Ray Air Showers

High energy gamma ray strikes atmosphere

Chain reaction:

- Energetic photons undergo pair production
- Energetic particles emit photons
Relativistic particles emit Cherenkov radiation
Cherenkov radiation detected by telescopes
Image features can inform us about incident photon

Shape and orientation indicate arrival direction
Direction points to source of gamma rays
Can thus create gamma ray map
Geo Method

Geometric method
Requires shower image from multiple telescopes
Find intersection of major axes
Disadvantage: imprecise at large zenith angles because axes are close to parallel
Disp Method

Displacement method

Characteristic angular distance between source and shower

Distance depends on size and shape of image
Disp Method

Related to the ratio between width and length of image

The longer the length, the greater the disp

Other parameters (size, zenith angle, altitude, etc) also affect disp
Disp Method
Geo initially used, but large zenith angles were problematic.

Disp method was implemented with six-dimensional lookup table.

Size, length, width, zenith angle, azimuth angle, PedVars level.

Low statistics problem; some bins empty.

Problems at small zenith angles.
Geo and Disp
Geo and Disp Combined

Combine the methods, weighted by zenith angle $z$

$$\text{geo} \cdot (1 - w) + \text{disp} \cdot w$$

$$w = \exp\left(-12.5 \cdot (\cos(z) - 0.4)^2\right)$$

Small zenith angle uses geo
Large zenith angle uses disp
Geo and Disp Combined
Room for improvement for disp method

Replace lookup table with multivariate analysis (MVA)

TMVA is a root library for performing MVA with machine learning techniques

Neural networks, boosted decision trees, support vector machines, and more

Boosted decision trees (BDT) has achieved best performance
TMVA and BDT

- MVA input variable: var1
- MVA input variable: var2
- MVA input variable: var3
- MVA input variable: var4

Root node

- $x_i > c_1$
- $x_i < c_1$
- $x_j > c_2$
- $x_j < c_2$
- $x_j > c_3$
- $x_j < c_3$
- $x_k > c_4$
- $x_k < c_4$

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TMVA and BDT

Boosting: create forest of trees; use average estimate

Each additional tree learns from previous

Many parameters to be adjusted to maximize performance

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<th>Parameter</th>
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TMVA and BDT

Given length, width, size, loss, and time gradient variables
Takes 1-2 hours to run
Monte Carlo set with over 1 million events at each zenith angle
BDT Results

Output deviation for method: MVA_BDT_500_d8_tmva_z65 (test sample)
BDT Results
BDT Results

Disp calculation with BDT

- Best-90% RMS vs. \( \cos(\text{zenith}) \)
Analytical Approach

BDT seem to have reached performance limit
BDT also quite slow
Try something more transparent and faster
Find an analytic function that predicts disp
My research suggests a starting point of:

\[ A \left(1 - \frac{\text{width}}{\text{length}}\right) \]

The parameter \( A \) depends on many factors: altitude of shower, elevation of the detector, the zenith angle of the event, energy of the incident gamma ray, and more. Use this as a base, add in other variables in various ways, find best fit
Analytical Approach

\[
\text{disp} = \log(\text{size}) \cdot \left[ A + B \cdot \left( 1 - \frac{\text{width}}{\text{length} + C \cdot \text{loss} \cdot \log(\text{size})} \right) \right]
\]

\[
A = -0.00796032;
\]
\[
B = 0.203981;
\]
\[
C = 0.0973756;
\]
Analytical Results

ratio:trueDisp

diff:trueDisp
Analytical Results

Disp Calculation

Best-90% RMS vs Cos(zenith)
Analytical Results

Analytical function not as effective as BDT
Faster than BDT
Including TimeGrad information may improve results
Simply adding analytical output to BDT methods did not improve performance, but combining it in another way may still be useful
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