 CMS NOTE 1997/050

The Compact Muon Solenoid Experiment

CMS Note

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17 June 1997

Neutral pion rejection in the CMS $PbWO_4$ crystal calorimeter using a neural network. The dependence of neutral pion rejection factor on crystal's off-pointing angle.

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Abstract

We study the Neural Network approach for γ/π^0 separation in the CMS $PbWO_4$ crystal calorimeter, and investigate the dependence of π^0 rejection on crystal's off-pointing angle. It is shown that there is no strong dependence of the rejection power on the value of the off-pointing angle.

1 Introduction

For a precision ECAL, the principal benchmark reaction is H $\rightarrow \gamma\gamma$. Therefore, the key physics requirements for a precision ECAL at LHC are: (1) the best possible energy resolution, (2) adequate θ angular resolution for photons at high luminosity, and (3) efficient photon identification (ID) and jet background rejection.

The CMS $PbWO_4$ calorimeter is now at an important stage in its design. The detector parameters must be optimized and finalized this year to meet all of the physics requirements for energy and angular resolution, with uniform acceptance and high photon ID efficiency covering the full pseudorapidity range. The engineering design of the calorimeter may then be completed in time for the start of crystal production in 1998.

In this note we present results on a study of the separation of γs from π^0s, using a neural network approach. The simulation program used is CMSIM, the full detector simulation package for CMS. We have carried out an extensive series of simulation runs including: (1) two particle types: γ and π^0; (2) three energies: 25, 50 and 75 GeV; (3) three off-pointing angle's, θ_{op}, values: 0°, 1.5° and 3°; (4) three regions in theta angle: 25-40 degrees, 40-63 degrees and 63-90 degrees; (5) 11 shifts in the longitudinal vertex position: from -10 cm to 10 cm with 2 cm steps. About 10,000 single-particle events are needed to train the neural net at each point in parameter space and to produce the final results. In total for this investigation we generated about 600 files containing 6 million events. Fermilab has provided a five-processor DEC Alpha EV5 server dedicated for this purpose.

The immediate goal of this investigation is to determine the optimal design value of the off-pointing angle. Recent CMS designs have used an off-pointing angle value equal to 3°. The introduction of an off-pointing angle is necessary to eliminate gaps between the crystals that can be "seen" by particles from the interaction region, and to improve the acceptance for photons with good energy resolution. However, recent simulation studies by S. Shevchenko [1] have shown that photon position resolution is rather sensitive to the choice of θ_{op}. The degradation of the position resolution for larger θ_{op}-values is understood to be due to the transformation of the large longitudinal shower fluctuations into the transverse shower profile fluctuations. Since the lateral energy deposition profile is used for photon position measurement, the transverse shower fluctuations strongly affect the position accuracy. Therefore, it is important to figure out how the introduction of off-pointing angle may affect the γ/π^0 separation.

2 Neural Network Analysis and Results

For the neural network analysis, we use the JETNET 3.0 package [2]. A simple neural network with 13 input layers, one hidden layer and one output neuron has been used. The neurons have a Sigmoid activation function. The use of the neural network proceeds in two phases. A learning phase is carried out first, to optimize the weights between the neurons. A second phase with different simulated samples is then used for testing, to evaluate the performance of the trained neural network. We utilize two-thirds of each sample of 10,000 events for training, and the remaining one-third for testing the rejection power, with an efficiency for correctly identifying photons fixed at 90%.

An important aspect of a network's performance is its ability to generalize to independent samples drawn from the same population as the training sample. During training, we periodically monitor the network's generaliztion ability by comparing the network's discrimination perfomance on the independent training and test samples. Figure 1 shows the evolution of this performance during the training of 75 GeV 1.5° off-pointing angle sample, and demonstrates good generalization ability.

We compared the two most popular neural net training algorithms, namely, Back-Propogation updating [3] and Manhattan updating [4]. The best results were obtained for the Manhattan updating algorithm with a learning rate parameter β equal to 0.01.

As an input for the neural network, we have chosen the following 13 variables based on the energy deposited in a 3×3 crystal matrix centered on the crystal with the largest deposited energy:

1-9) Nine crystal's energies in 3×3 crystal matrix.

10,11) Two 'center of gravity' variables

$X_{COG} = \sum_{i=1}^{9} E_i X_i / \sum_{i=1}^{9} E_i$

$Y_{COG} = \sum_{i=1}^{9} E_i Y_i / \sum_{i=1}^{9} E_i$

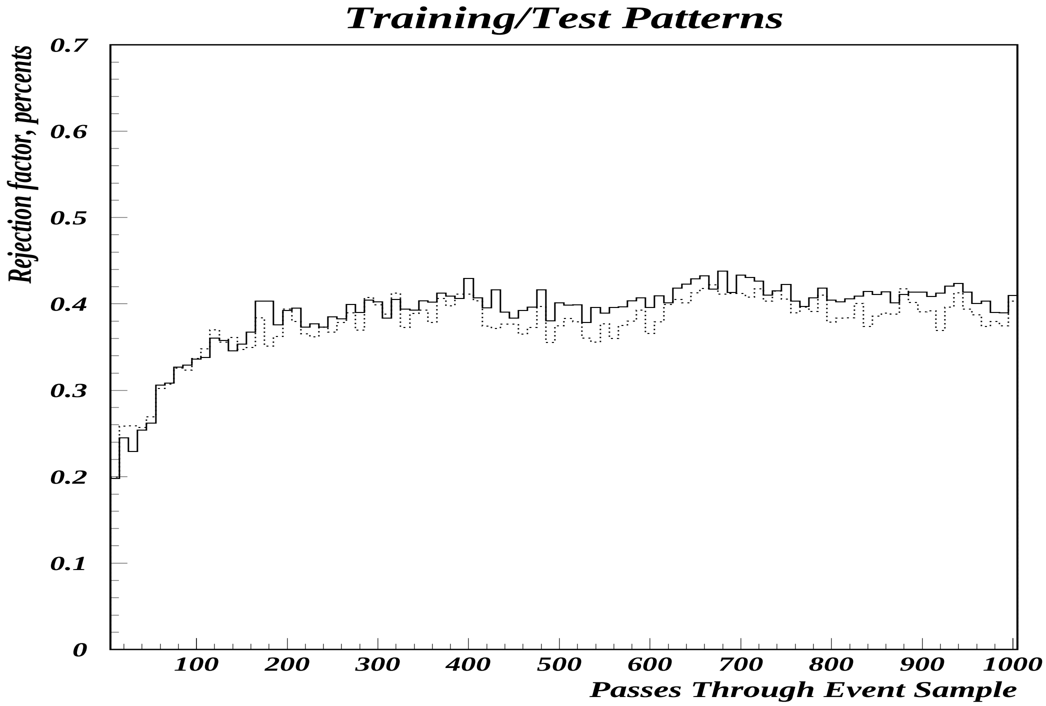

Figure 1: Plot of evolution of the network performance for training (solid line) and test (dotted line) patterns over 1000 iterations through the 75 GeV and 1.5° off-pointing angle sample. The vertical scale shows the fraction of overlapping $\pi^0 \to \gamma\gamma$ decays that are rejected with a cut chosen to accept 90% of single photons.

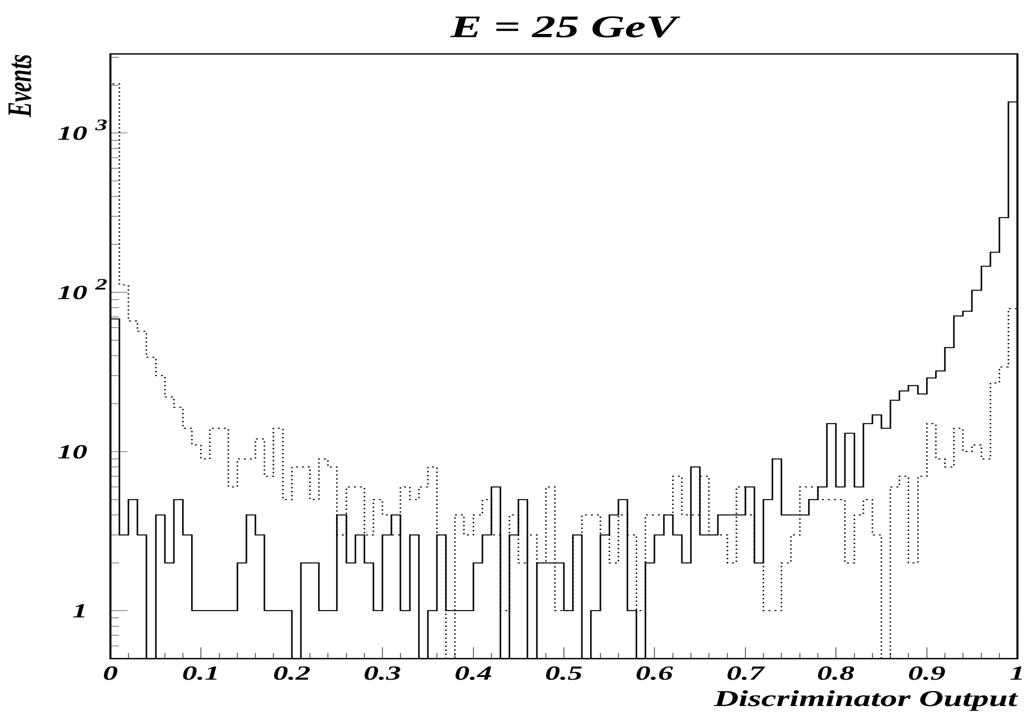

Figure 2: Distributions of discriminator output values for single γ's (solid line) and single π^0's (dotted line) for the 25 GeV and 3° off-pointing angle sample. The vertical scale is logarithmic.

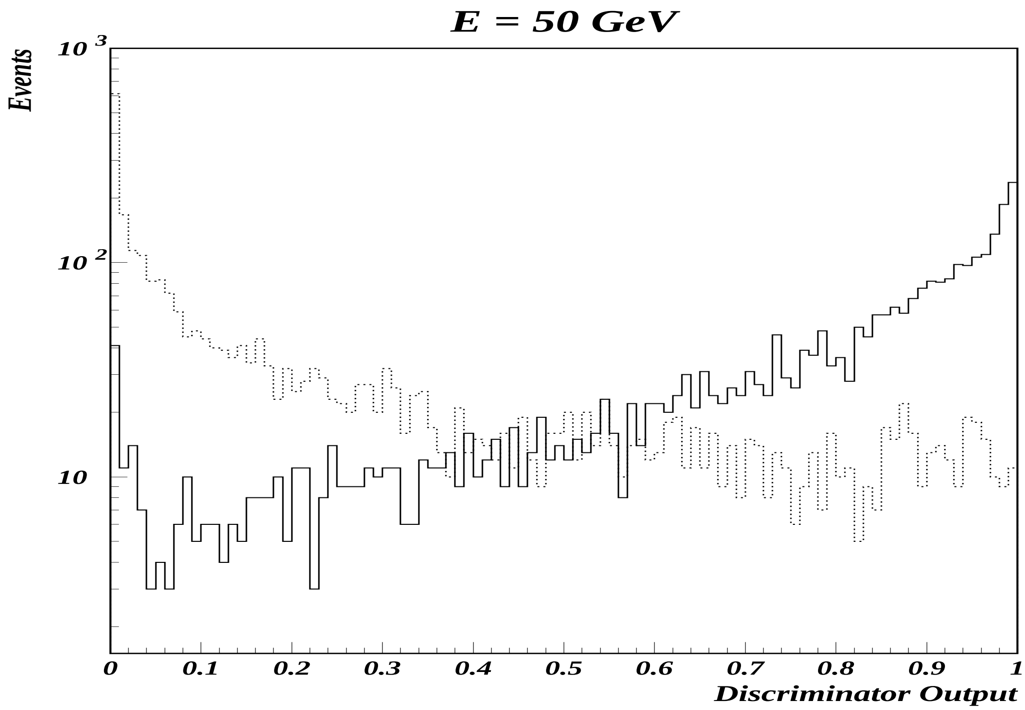

Figure 3: Distributions of discriminator output values for single γ's (solid line) and single π^0's (dotted line) for the 50 GeV and 3° off-pointing angle sample. The vertical scale is logarithmic.

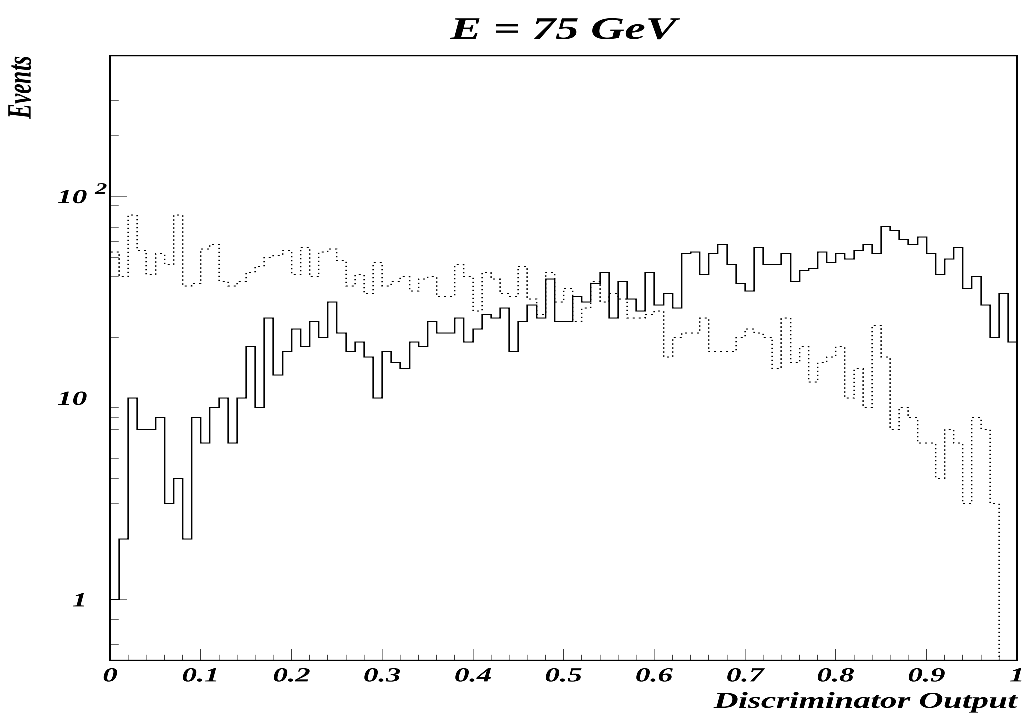

Figure 4: Distributions of discriminator output values for single γ's (solid line) and single π^0's (dotted line) for the 75 GeV and 3° off-pointing angle sample. The vertical scale is logarithmic.

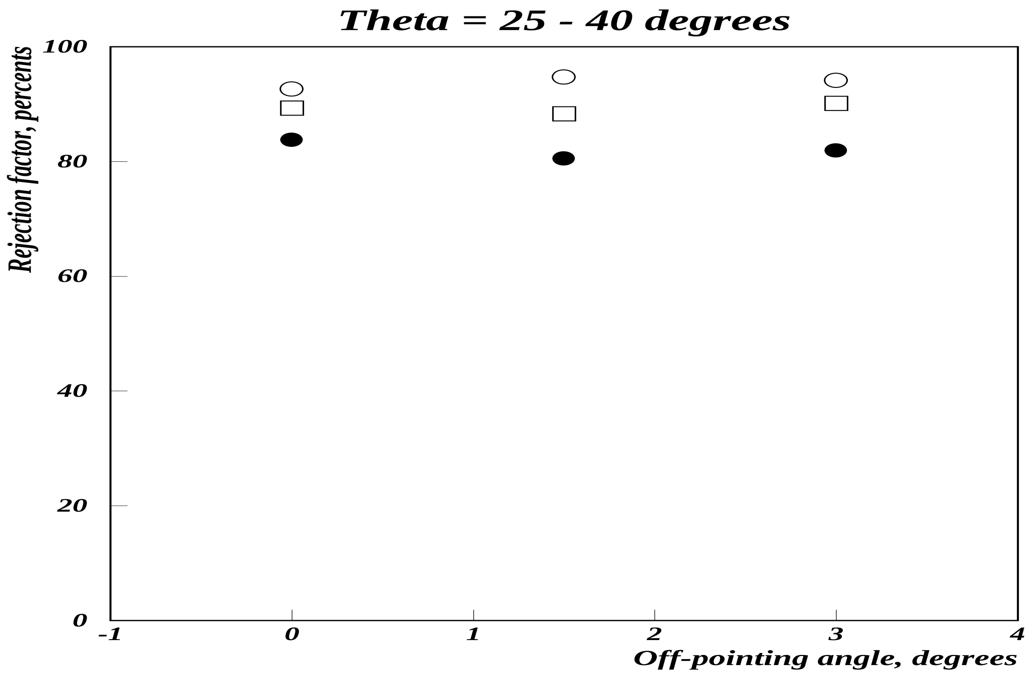

Figure 5: The fraction of π^0s rejected as a function of off-pointing angle in theta angle's region 25 - 40 degrees for different particle's energies: open circles - 25 GeV; open squares - 50 GeV and closed circles - 75 GeV. The vertical scale shows the fraction of overlapping $\pi^0 \to \gamma\gamma$ decays that are rejected with a cut chosen to accept 90% of single photons.

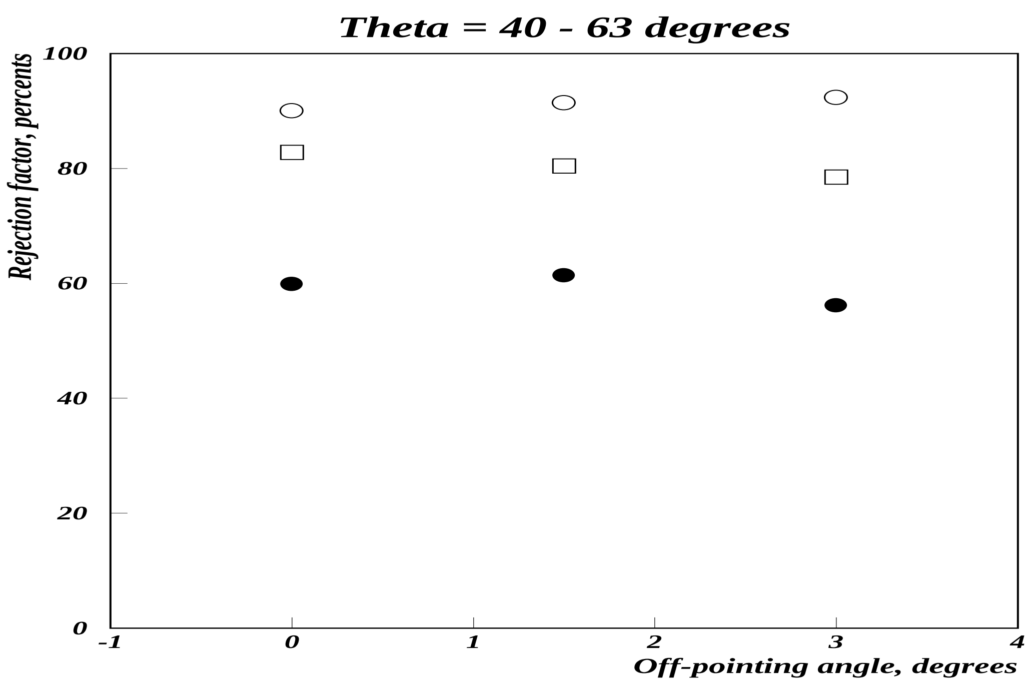

Figure 6: The fraction of π^0s rejected as a function of off-pointing angle in theta angle's region 40 - 63 degrees for different particle's energies: open circles - 25 GeV; open squares - 50 GeV and closed circles - 75 GeV. The vertical scale shows the fraction of overlapping $\pi^0 \to \gamma\gamma$ decays that are rejected with a cut chosen to accept 90% of single photons.

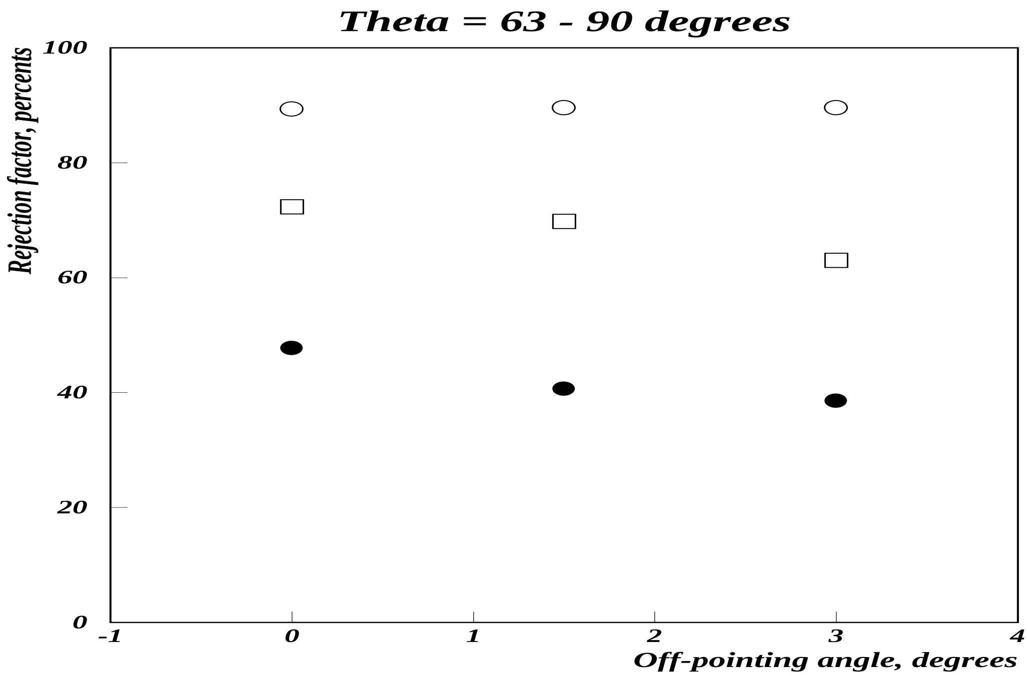

Figure 7: The fraction of π^0s rejected as a function of off-pointing angle in theta angle's region 63 - 90 degrees for different particle's energies: open circles - 25 GeV; open squares - 50 GeV and closed circles - 75 GeV. The vertical scale shows the fraction of overlapping $\pi^0 \to \gamma\gamma$ decays that are rejected with a cut chosen to accept 90% of single photons.

12,13) Two 'width' variables

$X_W = \sum_{i=1}^{9} E_i(X_i - X_{COG})^2/E_i$

$Y_W = \sum_{i=1}^{9} E_i(Y_i - Y_{COG})^2/E_i$

Figures 2-4 show a comparison of the final discriminator output distributions for simulated photons and neutral pions for different energies and 3° off-pointing angle. As expected the discrimination is better for lower energies. The fraction of π^0s rejected as a function of off-pointing angle are shown in Figures 5-7 for different particle's energies and different theta angle regions. A cut applied on the discriminator output is chosen to give a photon efficiency of 90%. The main results are the following:

- The rejection power obtained with neural network approach is at least as good as has been obtained by a χ^2 method [5], but the neural network approach needs much less simulation time than χ^2 method.
- There is no strong dependence of the rejection power on the value of the off-pointing angle.

3 Acknowledgments

We would like to thank Sunanda Banerjee for his help with the CMSIM installation, and the Fermilab Computer Division for their help and support in providing the DEC Alpha server that made this simulation study possible.

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