APPLICATION OF NEURAL NETWORK FOR PHOTON-HADRON DISCRIMINATION IN A PRESHOWER DETECTOR IN HIGH ENERGY HEAVY ION COLLISIONS

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Abstract

Using a combination of a preshower detector and a charged particle veto, it is shown that the neural network method is able to provide satisfactory discrimination between photons and hadrons in the case of extremely high particle density produced in the forward region of heavy ion collisions at the LHC energy.

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1 Introduction

Neural network has been extensively used to solve problems of high degree of complexity, such as feature classification, image processing, pattern recognition, combinational optimization etc. Many topics encountered in high energy physics consist of similar problems of classification and pattern recognition and artificial neural network methods have been successfully applied to solve them [1]. One of the specific examples is to discriminate different type of shower particles in a calorimeter [2]. But these applications are mostly limited to situations where the particle multiplicity is low and chances of overlap of hadron and photon showers are negligible.

In heavy ion collisions at ultra-relativistic energies one faces the problem of detection of particles in a very high multiplicity environment. In particular, for photons, which are conventionally detected using calorimetric techniques [3], it becomes increasingly difficult to separate fully developed showers in the forward pseudorapidity ($\eta$) region because of high particle density. In such situations photon studies have been limited to the measurement of spatial distribution using a preshower detector [4]. Such a detector consists of a converter (usually 3 $X_0$ thick lead plates) followed by a finely granular sensitive medium e.g., scintillator pads or gas cells. The sensitive medium responds to electromagnetic shower particles generated in the converter. This technique considerably reduces the possibility of overlap of showers.

Even with the use of a preshower detector photons need to be discriminated from hadrons which also produce signal in the sensitive medium. Most of the charged hadrons, while passing through the detector, deposit energy equivalent to the Minimum Ionising Particle (MIP) in the sensitive medium and are usually confined to one pad. Photon signal, on the other hand, corresponds to several MIPs depending on the number of shower particles and spreads to several cells. After clustering of pad hits, hadron rejection is achieved by applying a suitable threshold (taken usually equivalent to 3 MIPs) on the cluster signal. Clusters having signal above threshold are more likely photon candidates and are referred as "$\gamma$-like" clusters.

Impurity in the photon sample due to hadron contamination should be less than a few percent above 3 MIP threshold, arising from the tail of the MIP distribution, if all hadrons behaved as MIPs. However a sizeable fraction of hadrons interacts in the converter (3 $X_0$ thick lead is equivalent to $\sim 10\%$ of interaction length) and generates signal which looks like photon shower. These
hits cannot be filtered by the application of threshold. Two closely moving hadron tracks may also mimick a photon signal. Upstream conversion of photons in the intervening material close to target may lead to more than one cluster on the detector. Hadron interactions in the converter and extra photon clusters constitute a large contamination in the photon sample. It is therefore necessary to use new approaches using information which provide improved discriminatory properties between hadron and photon signals in a preshower detector.

Charged Particle Veto (CPV) detector placed in front of an electromagnetic calorimeter has been used in tagging charged hadrons and for separating photons [3]. Similar arrangement can be attempted with preshower detector also. Both the CPV and the preshower detector respond to incident charged particles but the CPV, by its design, will be insensitive to photons. Thus charged particles can be vetoed by comparing the signals in the two detectors. However in a high multiplicity environment difficulties arise in the use of proper algorithm for vetoing because of two reasons:

(i) Finite separation between the preshower detector and the CPV and multiple scattering in the converter destroys the one-to-one correspondence in coordinates between the cells hit by a charged particle in the two detectors, and

(ii) closeness of hadron and photon tracks in high particle density environment results in a large probability of vetoing photon clusters, thereby reducing the efficiency of photon detection.

In the present article we explore the applicability of neural network (NN) methods with several inputs representing the discriminatory properties between hadrons and photons and compare their performances with the results of simpler vetoing algorithms. We present simulation results for a realistic case of a preshower detector expected to measure the spatial distribution of photons in heavy ion collisions at the LHC energy. Preliminary results have been presented elsewhere [5].

2 Detector Simulation

The preshower detector under study consists of 3 $X_0$ thick lead converter with cells of gas proportional chamber as the sensitive medium. The detector covers typically one unit of pseudorapidity in the forward cone and is arranged in the
form of rectangular matrices of gas cells, so that each cell is surrounded by eight neighbours in a $3 \times 3$ matrix. Considering the estimated particle density in Pb + Pb collisions at the LHC energy, we have used square cells of 1 cm size and 8 mm depth. A CPV having the same granularity as the preshower part has been placed in front of the converter, the cells being back-to-back with the preshower cells. The detector is placed at 6 meter from the interaction point. No other material has been placed in the intervening space.

The response of the preshower detector and the CPV has been simulated using GEANT3.21 simulation package [6]. For a systematic investigation of the usefulness of vetoing algorithms, two different cases have been studied:

(a) single particles: photons and positive pions at specific energies of 1 GeV, 2 GeV, 5 GeV and 10 GeV.

(b) event generator: particles generated from VENUS 4.12 event generator [7] for central ($b < 2$ fm) Pb + Pb collisions at the LHC energy. Particle multiplicity in VENUS events is one of the highest among all the event generators currently being used for detector simulation studies at LHC energy [8]. Hence for detector design it provides one of the worse case scenarios.

GEANT results in the form of energy deposition in gas cells have been used for clustering and photon measurement. Cells having energy deposition less than that equivalent to 0.2 MIP are not considered, this level being taken as the detector noise. No attempt has been made to include the response of gas proportional chamber. Nearest neighbour clustering algorithm has been used to find out photon and hadron clusters. A fraction of photon and hadron tracks produces more than one cluster. Clustering of CPV hits has not been attempted.

An efficient photon-hadron discrimination algorithm should be able to select all the clusters ($N_{\gamma}^{\text{cls}}$) bearing photon identity from the total number of clusters ($N_{\text{cls}}$) found on the preshower detector. The discrimination is usually achieved by computing some observable and applying a threshold. Number of clusters above such a pre-selected discrimination threshold is called $\gamma$-like clusters ($N_{\gamma-\text{like}}$). This contains majority of photons and some contaminants which reduce the purity of the photon sample.

For a quantitative description of the effectiveness of these algorithms, we define the following two variables:
\[ \epsilon_s = \frac{N_{\gamma,th}^{\gamma,th}}{N_{\gamma}^{\gamma}} \]
\[ f_p = \frac{N_{\gamma,th}^{\gamma,th}}{N_{\gamma-like}} \]

where \( \epsilon_s \) is photon selection efficiency, \( f_p \) is the fractional purity of the photon sample and \( N_{\gamma,th}^{\gamma,th} \) is the number of photon clusters above the threshold.

The photon selection efficiency discussed here is different from the photon counting efficiency \( \epsilon_\gamma \) described in Ref. [4]. \( \epsilon_\gamma \) will be smaller than \( \epsilon_s \) by a factor which takes into account the conversion probability of photons in lead and also the loss (or gain) of clusters due to particular clustering algorithms used and because of high multiplicity effects.

By adjusting the discrimination threshold it is possible to obtain a highly pure sample of photons, but the efficiency of selection will be small. On the other hand if one wants to retain most of the photons in the sample (i.e., high selection efficiency) then the purity of the sample will be lower. In practice the tradeoff is dictated by physics considerations, a photon sample having at least 80% purity being considered reasonable for the study of particle production and fluctuation on event-by-event basis.

\section{Vetoing Algorithms}

Depending upon the discriminatory properties of different variables obtained for different types of particles, one can use suitable algorithm to separate them. In the absence of a charged particle veto, hadrons are filtered using a threshold on the cluster signal [4]. Fig. 1 shows \( \epsilon_s \) and \( f_p \) as a function of threshold on cluster signal for the case of particles from VENUS event generator. Applicability of this method is severely limited if photon samples with purity in excess of 70% are desired, photon selection efficiency falling sharply from 94% for 70% purity to a paltry 55% for 80% purity.

Vetoing of charged particles using information from CPV hits depends critically on the algorithms selected. Following two algorithms, which may be successful in low multiplicity environments, have been tried here:

(a) If signal in the CPV cell directly opposite to the cluster maximum in
the preshower part is non-zero, then veto the cluster (referred as Veto-1).

(b) If total CPV signal in $3 \times 3$ matrix opposite to the cluster maximum is non-zero then veto the cluster (referred as Veto-9).

Combining the veto and threshold on cluster signal one can select photon samples with varying efficiency and purity. Results for both the vetoing methods are also presented in Fig. 1. The Veto-1 method is able to reject only a small number of clusters, resulting in a relatively high photon selection efficiency at the cost of purity. Still this method performs better than simple threshold on the cluster signal at higher purity, giving 10% higher selection efficiency for the desired 80% purity. The Veto-9 method rejects lots of clusters including those of photons. Hence even though purity of $\gamma$-like clusters may be high, efficiency of photon selection is always low and never more than 65%. In this respect Veto-1 method is more useful.

4 Neural Network

Although the use of a CPV and a simple vetoing algorithm helps to improve the performance of the preshower detector, the efficiency is far too less to be of practical use. Hence it is imperative to search for more intelligent algorithms like neural networks which can utilize maximum information of the shower profile and provide improved discrimination of photons from hadrons.

4.1 Setup and Training

We setup a standard feed-forward network using upto 21 inputs derived from preshower and CPV hits of each observed cluster of photons and hadrons. Two approaches have been followed for training and testing the network.

(A) *Hidden Layer Approach*: This approach has been used quite extensively in pattern recognition work. Here we use a 3-layer network with upto 21 inputs in the hidden layer and one in the output layer. JETNET 3.4 NN package has been used for this approach [9].
Different algorithms e.g., standard backpropagation algorithm, Manhattan updating and Langevin method have been tried for training the network. The standard back-propagation algorithm has been found to be most effective in the present case. The training parameters used in this algorithm are: learning parameter = 0.2, momentum (\( \alpha \)) = 0.05, network temperature = 1.

Training involves the determination of weights by minimizing the error function \( (F(x) - F_{\text{known}})^2 \),

where \( F(x) \) is the response to the inputs \( x \) and is also a function of the weights applied to the network. The response function used is the sigmoid function:

\[
F(x) = \frac{1}{1 + e^{-x}} \tag{1}
\]

Target output values \( (F_{\text{known}}) \) for photon and hadron samples used were 1 and 0 respectively.

(B) **Functional Expansion Approach:** In this method, we scale each variable \( (x_k) \) in the range \((-1, 1)\), where \( k \) varies from one to the number of inputs for each cluster [10]. It is then expanded using orthonormal functions,

\[
f(x_k) = w_{1k}x_k + \sum_{i=1}^{n}(w_{2ki}\sin(i\pi x_k) + w_{3ki}\cos(i\pi x_k)) \tag{2}
\]

where \( w \) is a set of weights and \( n \) the order of expansion. We have used \( n=4 \) for the present study. The transformed input quantities are then summed to form

\[
X = \sum_{k=1}^{l} f(x_k) + w_0 \tag{3}
\]

where \( l \) is the total number of inputs.

The classifier function used here is also a sigmoid function given by,
The target output values are the same as for hidden layer case. In the present study most of the results are obtained using approach (A). The effectiveness of approach (B) is described only in the context of results for the event generator case.

### 4.2 Inputs

Using GEANT simulation results and clustering on the preshower part as described in Sec. 2, following variables are extracted for each cluster to be used as NN input:

(i) signal strengths in 9 cells ($A_1$ to $A_9$) around the cluster maximum of the preshower detector,

(ii) signal strengths in 9 cells in CPV ($A_{10}$ to $A_{18}$) around the cells situated opposite to the cluster maximum mentioned in item (i).

(iii) total number of cells affected by the cluster in the preshower part of the detector ($A_{19}$).

(iv) total signal strength of the preshower cluster ($A_{20}$) (= sum of $A_1$ to $A_9$),

(v) total energy deposition in 9 CPV cells around the cluster maximum in the preshower part ($A_{21}$) (= sum of $A_{10}$ to $A_{18}$).

Comparison of all the inputs for photons and hadrons have been made to study their discriminatory properties. Fig. 2 displays inputs $A_{19}$ and $A_{20}$ for photons and for $\pi^+$'s at 2 GeV. The discriminatory behaviour of input $A_{20}$ is significant. This is the reason that threshold on cluster signal has been used earlier for hadron rejection in a preshower detector [4].
4.3 Preprocessing

The numerical values of the input variables vary widely from each other e.g., the numerical value of cluster signal in eV units in the preshower part \((A_{20})\) is about 10000 times higher than the number of cells affected \((A_{19})\). Such a large variation leads to the application of non-uniform weightage while processing through the network. It is therefore necessary to preprocess the inputs to bring them in the same scale before applying to the network.

We have used two preprocessing techniques:

(i) a simple method, in which the inputs are multiplied with suitable factors to keep all of them in the same scale \((0\text{ to } 1)\). The result using this method of preprocessing has been discussed in Ref. [5].

(ii) use of Principal Component Analysis (PCA) technique [11].

The PCA method is based on eliminating the correlation existing among the input variables. A matrix is formed having columns equal to the number of inputs in a cluster and rows equal to the number of clusters. This matrix is then replaced by a matrix of the same dimensions, where the elements are modified in such a way that the correlations are lost.

No preprocessing is applied for the functional link method, because the inputs are automatically scaled into \((-1,1)\) range as the first step of processing in this approach.

5 Performance of the Network

The performance of the network is evaluated by the two quantities, photon selection efficiency \(\epsilon_s\) and purity \(f_p\) defined earlier. We describe the results for different approaches below.

5.1 Hidden Layer Approach
5.1.1 Single particle case

Tracks of photons and $\pi^+$'s, 40000 each of particular energy, were simulated through GEANT, half of them being used in training the network and another half for testing the network. All the clusters originating from photon and hadron tracks are identified as photon and hadron clusters respectively. For Pb + Pb collisions at the LHC energy the ratio of charged particle multiplicity and photon multiplicity is close to one, hence we have studied the properties of the network for equal population of photons and hadrons.

Fig. 3 shows the NN output spectra for particles with energies of 1 GeV and 10 GeV respectively. Even though the inputs vary considerably, the use of sigmoid function in the network produces outputs which are peaked around 0 and 1. The NN output values of clusters can be used for discriminating the two types of particles by applying proper threshold.

We have calculated photon selection efficiency and purity for different thresholds applied to the NN output. This is shown in Fig. 4 for different particle energies.

With a threshold of 0.55, we observe that 99% of the input clusters originating from photons can be filtered. The purity of the detected photon samples decreases from 94% for 1 GeV particles to 85% for 10 GeV particles. At higher energies chances of splitting of clusters increases. Extra clusters not having proper CPV inputs remain as contaminants, thus reducing the purity of the photon sample.

5.1.2 Event generator case

GEANT results for particles from the VENUS event generator have been processed through the clustering routine, and the outputs for each cluster preprocessed by the PCA technique before using them as the inputs to the network. All particles in the event including neutral hadrons have been retained.

Because of high particle multiplicity, each event gives a large number of clusters. The clusters are assigned the particle identity of the track depositing energy on the cluster maxima. If both a photon and a hadron hit the same cell, we consider it as a photon hit. This treatment is different from the method adopted
in case of single particles, where the clusters are tagged according to the identity of the incident track only. All particles other than photons are considered as contaminants in the photon sample. If the photon track is shifted considerably (0.1 unit in $\eta$ or $10^0$ in azimuthal angle) from the original direction while forming the cluster, then we tag the cluster as a contaminant. This constraint is imposed from the consideration of acceptable distortion in the measured pseudorapidity distribution of photons.

For the present study we have used training sample of about 60000 clusters obtained from 10 events and another set of about 90000 clusters from 15 events for testing the performance of the network.

We have also studied the effect of different sets of inputs on the performance of the network. Results have been obtained for 9 ($A_1$ to $A_9$), 18 ($A_1$ to $A_{18}$) and 21 ($A_1$ to $A_{21}$) input cases. NN output spectra for 9- and 21- inputs are shown in Fig. 5. It is clearly seen that the discrimination is better with 21 inputs. Detailed comparison of the performance in various cases is discussed in the next section.

5.2 Functional Link Method

Performance of the functional link method has been studied for particles from the event generator using 21 inputs. Fig. 6 shows the output spectrum of the network. Appearance of two distinct peaks in the network output spectrum suggests that the output can be satisfactorily used for hadron-photon discrimination. The efficiency and purity values are quite close to those obtained from the hidden layer approach with 21 inputs.

6 Discussions and Summary

Photon-hadron discrimination thresholds (either the cluster signals or the NN output values) can be adjusted to provide various pairs of values of $\epsilon_s$ and $f_p$. Fig. 7 summarizes the results of all the methods investigated in the present work.

In general photon selection efficiency drops sharply with increasing demand
on purity of the sample in excess of 70%. At any given purity level, the efficiencies for various methods vary approximately according to the following trend:

\[
\text{cluster signal} < \text{Veto-1} < 9\text{-input NN} < 18\text{-input NN} < 21\text{-input NN}
\]

Veto-9 method is not at all suitable in high multiplicity environments. The NN method using detailed information on the shower profile (9-input case) even without the use of CPV can provide much better hadron rejection than the method using only the threshold on cluster signal. Thus for 80% purity 9-input NN method gives a selection efficiency of 76% compared to 55% for the cluster threshold method. Considering the three NN cases (9-, 18- and 21-inputs) in the hidden layer approach, it is found that the performance improves as more inputs are included. However improvement from 18-input case to 21-input case is marginal, most likely because inputs \(A_{20}\) and \(A_{21}\) are correlated with other inputs.

For the desired 80% purity of photon sample we obtain selection efficiency of 88% using 21-input NN method in both the approaches. This is a very significant improvement, particularly considering the fact that with only 55% photon selection efficiency (as obtained by threshold on the cluster signal) event-by-event physics might not have been possible.

Now that a trail has been found, one needs to chart the course further. The functional link method is computationally faster and simpler to implement. One needs to study this in more detail as one will be required to process large volumes of data in LHC experiments. Studies are in progress on the use of improved clustering routine to reduce the chances of splitting of clusters and better discriminatory variables as NN inputs. An important aspect under study is the effect of increasing the CPV cell size. Occupancy of CPV cells is typically a factor of 4 lower than the preshower part. If CPV cell size can be increased without affecting the performance of the network, this will considerably reduce the cost of the detector. Results of these investigations will be reported in future publications.

In summary neural network technique has been used to separate photon clusters from the mixture of photon and hadron clusters in a preshower detector in high energy heavy ion collisions. The results have been obtained from the simulated output using a preshower configuration including a charge particle veto. The difference in the profile of the energy deposition in the detector by photons and by hadrons are used for the discrimination. Two techniques of training, one using standard 3-layer network architecture and the other using the functional
transformation of the inputs give similar results. The method is particularly useful in providing filtered photon samples of high purity. For photon samples with 80% purity, selection efficiency close to 90% can be easily obtained. This is almost 30% higher than those obtained by applying threshold on the cluster signal and simple vetoing algorithms.

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Figure 1: Selection efficiency and purity of photons as a function of threshold on the cluster signal. Filled circles represent the results of simple case without using CPV hits, open circles and open squares represent respectively the results of Veto-1 and Veto-9 methods.

Figure 2: Input variables $A_{19}$, $A_{20}$ for 2 GeV single particles ($\gamma$ and $\pi^+$) illustrating the different responses for photon-hadron discrimination.
Figure 3: NN output spectra for the case of single particles at 1 GeV and 10 GeV energies. Solid line represents photon clusters and the dashed line represents pions.

Figure 4: Efficiency and purity as a function of threshold on NN output in single particle case at different energies.
Figure 5: NN output spectra, for particle clusters from VENUS event generator, obtained by using 9 and 21 inputs in the hidden layer approach after PCA pre-processing. Solid line represents photon clusters and the dashed line represents contaminants.
Figure 6: NN output spectra in the functional link method for particle clusters from VENUS event generator. Solid line represents photon clusters and the dashed line represents contaminants.
Figure 7: Photon selection efficiency and purity obtained after applying different discrimination thresholds in the case of particles from the event generator. For hidden layer NN method, the results for 9, 18 and 21 inputs are separately shown. The continuous lines are drawn only for joining the points.