Feasibility of Using Neural Networks as a Level 2 Calorimeter Trigger for Jet Tagging

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Several of the expected decay modes of the Higgs particle will result in jet formation. We propose to incorporate a second level trigger into the SDC detector, using neural network VLSI hardware, to tag such Higgs decay modes. The input to the neural network will be the energy depositions in both the barrel and endcap regions of the calorimeter. The neural network's output would be a value representing the degree of correlation between the observed energy distribution and the type of physical scattering that has occurred. Preliminary results indicate that neural networks may be of use in tagging jet decays of the Higgs particle.

1. Introduction

The SSC will produce $\sim 10^8$ events per second, at design luminosity, with the majority of these events being of no interest. The question then becomes how to eliminate these uninteresting events. Hardware triggers can be designed to select certain physics processes which exploit their characteristics. Events that pass these hardware triggers would be sent to external storage devices. The proposed SDC detector for the SSC will, in fact, have three levels of trigger, with each successive trigger further pruning the data sample that is to be selected.

One particular characteristic of certain events, for example jets, will be the presence of large energy depositions in relatively small volumes of the calorimeter with the remainder of the calorimeter being relatively "quiet". The calorimeter readout of the SDC detector, when it is unfolded into a two dimensional LEGO plot, resembles the grayscale pixel readout of an image.

Artificial Neural Networks (ANNs) have been shown to be useful in pattern recognition problems[1]. Therefore the same techniques that are successfully used for pattern recognition problems in other areas can be applied to the calorimeter readout from the SDC detector with the patterns of interest being jets and/or isolated lepton signals. ANNs have already been successfully applied, off-line, to problems in high energy physics[2]. However, in these problems the number of input nodes is much less than the number of inputs that would be present in an ANN used for triggering on jets.

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2. Simulation

To test the whether ANNs could in fact be used as part of the triggering system for the SDC detector, a Monte Carlo simulation was undertaken. The simulation process consisted of several steps with the steps being:

- Generation of minimum bias events and jet events using the ISAJET[3] Monte Carlo program.

  The default values for the ISAJET parameters were used in the generation of both types of events. Equal numbers of both types of events were generated for use in training and testing of the ANN. After their generation, for each event, the event tracks were traced into the calorimeter. For a straightforward testing of the feasibility of using ANNs, the total energy of each track was deposited in the appropriate calorimeter cell.

  The calorimeter was segmented using the largest cell size in the EM endcap region of the SDC detector[4], 0.2 in η, the pseudo-rapidity variable, and 0.2 in ϕ, the azimuth angle about the beam axis. Only the barrel and endcap regions of the calorimeter were considered, as the energy density for the forward calorimeter would be very high. Thus tracks having an $|\eta|$ greater than 3.0 were discarded. This leads to an event that can then be characterized by a 30 x 32 pixel array. Typical minimum bias events have very little energy deposition in the barrel and endcap sections of the calorimeter while jet events have very large energy depositions in these calorimeter sections.

- Training of the ANN.

  A commercial neural network program, NeuralWorks Professional II/Plus[5], was used for this study. The ANN was configured with 960 input nodes, 1 hidden layer of 1100 nodes, and an output layer consisting of a single node. A hyperbolic tangent was used for the sigmoid function. The output of the ANN was supposed to be either -1 for a min-bias event or +1 for a 2-jet event. After their initial randomization, the connection weights between the various layers were determined using the back-propagation method. The training set events were presented in a random order to the network by the neural net program. The network was allowed to train until the RMS error reached the desired value.

- Testing of the ANN.

  After the training was completed, a set of events, which the network had not previously seen, was presented to the network to see how well the network had been trained. The output of the network was considered to be correct if its output value was within 0.5 of the desired result.

3. Results

As mentioned above the ANN was trained using a back-propagation algorithm. There was no attempt at pruning the number of hidden layer nodes or even of augmenting their numbers.

The initial training of the ANN was with 150 events, 75 min-bias and 75 2-jet events. The network reached the desired RMS error within 3000 epochs. The results of this training are detailed in Table I. As would be expected the ANN had reasonable success on the training set. However on the test data set of 500 events, the success rate was not as good. Because of the large number of interconnection weights to be determined, in all likelihood the training data set was too small.

Table I

	Number of Events	Number Identified	Percentage
Training Set			
Min-bias Events	75	75	100.0
2 Jet Events	75	67	89.3
Test Set			
Min-bias Events	250	249	99.6
2 Jet Events	250	165	66.0

To test whether this in fact was the case, the ANN was trained on the 500 event set and then tested on another data set of 650 events. It should be noted that the ANN trained in less than half the number of epochs as in the previous training. The results of this training are detailed in Table II. As can be seen these results were better for both the min-bias and jet events.

Table II

	Number of Events	Number Identified	Percentage
Training Set			
Min-bias Events	250	248	99.2
2 Jet Events	250	241	96.4
Test Set			
Min-bias Events	325	316	97.2
2 Jet Events	325	286	88.0

An examination of the failed events did not reveal any topological pathology that would cause the ANN to mistakenly identify the events.

4. Conclusions

Even though the above results are preliminary, it appears that ANNs can be used to identify jet structures, at a reasonable level, in the barrel and endcap regions of the SDC calorimeter.

However further work is needed to address the following questions:

- What should the number of nodes be in the hidden layer?
- How many hidden layers should the ANN have?

- What are the optimum values for the momentum and learning rate parameters?
- Has a large enough training set been used?

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