Principal Component Analysis for Neural Electron/Jet Discrimination in Highly Segmented Calorimeters

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Abstract. A neural electron/jet discriminator based on calorimetry is developed for the second-level trigger system of the ATLAS detector. As preprocessing of the calorimeter information, a principal component analysis is performed on each segment of the two sections (electromagnetic and hadronic) of the calorimeter system, in order to reduce significantly the dimension of the input data space and fully explore the detailed energy deposition profile, which is provided by the highly-segmented calorimeter system. It is shown that projecting calorimeter data onto 33 segmented principal components, the discrimination efficiency of the neural classifier reaches 98.9% for electrons (with only 1% of false alarm probability). Furthermore, restricting data projection onto only 9 components, an electron efficiency of 99.1% is achieved (with 3% of false alarm), which confirms that a fast triggering system may be designed using few components.

INTRODUCTION

By 2005, the LHC will be colliding protons of 7 TeV at periods of 25 ns. This collision frequency will produce an enormous amount of data that shall be analyzed by an online multistage triggering system, in order to reject the huge background noise of the experiment. One of the detectors to be placed around a collision point of the LHC is ATLAS, for which the trigger system is being designed in three levels of analysis. For the triggering system, calorimeters play an important role. Both electromagnetic (e.m.) and hadronic sections are highly-segmented into cells, in order to provide a detailed energy deposition profile for incoming particles. The second-level (L2) trigger system will have access to full calorimeter granularity in the restricted areas of the detector for which significant signal can be observed. These are the regions of interest (ROIs), which are identified by the first-level (L1) system (3).

In this paper, an electron/jet discriminator for the L2 system is developed using neural processing over calorimeter information. In these simulations, a ROI for the e.m. calorimeter comprised three segments, with each one formed by a matrix of 12x12 cells, while the hadronic section comprised 4 segments formed by 4x4 cells each. Figure 1 illustrates such arrangement. More recent updates on the calorimeter system show different granularity for the e.m. segments and only three segments for the hadronic section. However, as from recent studies, these changes proved not to be very significant in terms of the efficiency achieved by the neural discriminator (4).

As depicted in Figure 1, a ROI in the calorimeter was described by 496 cells, which makes the discrimination between electrons and jets a very complex task. As speed is one of the main issues of the L2 system, the reduction of this high dimensionality of the input data space is very attractive. Principal component analysis (2) has extensively been used for data compaction in a variety of applications. However, as the calorimeter system provides a highly-segmented readout of particle interactions, in this paper principal component analysis is performed on each calorimeter segment. This alternative approach avoids extracting principal components from grouped calorimeter data, which is typically performed, as some of the outermost cells of each calorimeter segment may provide important discriminating information in spite of their poor signal to noise ratio. By extracting segmented principal components, one expects an improvement in the overall performance of the discriminator, when original data are projected onto just a few components. This would allow a fast and highly efficient triggering system to be designed.

PRINCIPAL COMPONENT ANALYSIS

The principal component analysis (PCA) is based on the Karhunen-Löeve series. PCA aims at finding a set of M orthogonal vectors in input data space that account for

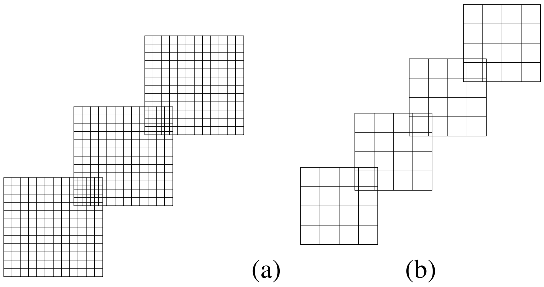

FIGURE 1. The electromagnetic (a) and hadronic (b) sections.

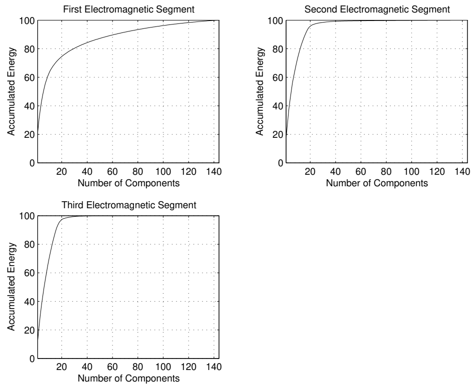

FIGURE 2. Cumulative energy of the first principal components of the electromagnetic segments.

as much as possible of the data's variance. Thus, the differences in classes of events originally present in the data set may still be identified by projecting data of the original N-dimensional input space onto the M-dimensional subspace spanned by these vectors. This would perform a dimensionality reduction with the preservation of the information spread around the full input space, as normally M << N.

The extraction of these components can be made by classical or neural methods. In the classical method, the components are the eigenvectors of the autocorrelation matrix of the random process under consideration, sorted by the decreasing order of the corresponding eigenvalues. Alternatively, a neural network can be used, and the training phase may be supervised or non-supervised (2).

Figures 2 and 3 show the cumulative energy (in percentage of the total energy in the segment) of the first principal components, when data compaction is performed on each segment. It can be clearly seen that the main calorimeter information is preserved in just a few components, which allows a significant compaction ratio to be achieved.

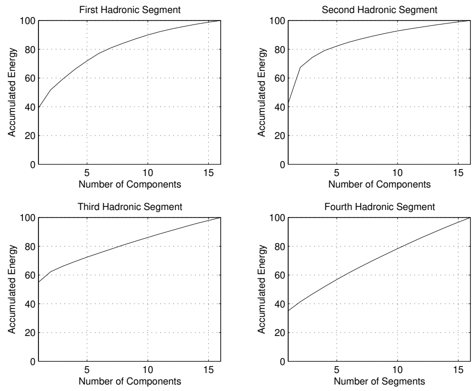

FIGURE 3. Cumulative energy of the first principal components of the hadronic segments.

NEURAL DISCRIMINATION

For the classifier design, a three layer fully-connected feedforward neural network was trained (using the backpropagation method (2)) to separate electrons from jets. The hyperbolic tangent was the activation function for all neurons. The number of input nodes of the final classifier was dependent on the number of principal components selected. The single hidden layer was composed of 33 neurons, whereas the output layer had just one neuron.

The whole L2 simulation data set contained 2528 electrons and 685 jets. This data sample was split into two to form the training and testing sets. Data normalization for e.m. segments was performed by dividing the energy samples of each cell by the total energy deposited in the full e.m. calorimeter. For the hadronic section, there was no need to apply any normalization scheme.

Considering only 33 components, the neural discriminator achieved an electron efficiency of 98.9% for the testing set, with less than 1% of false alarm probability (jets misclassified as electrons). Table 1 shows how these 33 components were distributed among the calorimeter segments. It confirms that the extraction of segmented principal components was able to reveal the important information of the hadronic and the two outer e.m. segments, from which almost all of such important components were extracted. The high performance of the classifier can be observed from Figure 4, which shows the particle distributions of the network output. Target values were arbitrarily chosen as -1 for electrons and 1 for jets.

Another attractive result was found by selecting just 9 components[1]. Obviously, this further compaction in-

[1] These 9 components were chosen according to a relevance study (1) that showed the main components for the neural discrimination process.

Table 1. The distribution of the 33 components among calorimeter segments.

Segment	Electromagnetic Components	Hadronic Components
First	2	7
Second	4	7
Third	4	7
Fourth	-	2

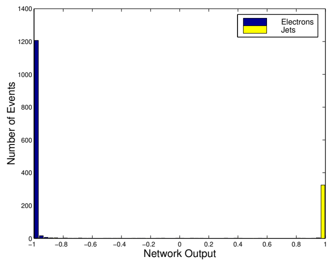

FIGURE 4. Output of the neural discriminator.

creases the false alarm probability, which becomes 3%, for the same level of electron efficiency. However, this slight deterioration in discrimination performance may be worth the considerable increase in processing speed such reduced set of components provides.

These results may be compared to others obtained from different design approaches using the same data set (see Table 2). It is shown that segmented principal component analysis outperforms a variety of methods, among which neural processing on non-segmented components, full input data space and topological data description in terms of concentric ring sums. It also outperforms classical analysis from matched filters (5).

CONCLUSIONS

It can be seen from Table 2 that the extraction of principal components for each segment of the calorimeter system performs much better than the non-segmented extraction of components. Projecting data onto 33 segmented principal components proved to be even better than a direct neural processing over the whole group of calorimeter cells, when data compaction of any kind is not realized. Thus, the segmented principal component analysis not only compacts efficiently the original data input space, enabling to reduce the processing time for the online operation, but also improves the neural discrimination efficiency. It should also be noted that the segmented principal component approach may be combined with topological methods, for improving the overall performance. This approach is presently under investigation.

Table 2. Comparison to other methods of discrimination.

Method used for Discrimination	Electron Efficiency (%)	Misclassified Jets (%)
Neural Network using 33 Non-segmented principal components*	72.4	39
Matched Filters	76.0	32
Neural Network directly on energy cells	97.9	10
Neural Network using 9 components	99.1	3
Neural Network with topological mapping (Rp) and rings(6)	98.7	2
Neural Network using 33 components	98.9	1

* These components were extracted from grouped data.

Envisaging an even faster processing speed, a more compact design using just 9 components proved to be feasible, as the discrimination performance was only slightly deteriorated. An implementation of such compact triggering system is being attempted using digital signal processing (DSP) technology.

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