Searching the Higgs with the Neurochip TOTEM.\textsuperscript{*}

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We show that neural network classifiers can be helpful in discriminating Higgs production events from the huge background at LHC, assuming the case of a mass value $M_H \sim 200$ GeV. We use the high performance neurochip TOTEM, trained by the Reactive Tabu Search algorithm (RTS), which could be used for on-line purposes. Two different sets of input variables are compared.

1. Introduction

The Standard Model of elementary particle physics (SM) has been highly successfully sustained by a lot of experimental data up to now. In particular after the recent discovery of the top quark all its elementary building blocks have got a solid experimental confirmation, except the Higgs boson, albeit its essential role in the model. In fact, as it is well known, it provides the mechanism for breaking the electroweak symmetry, thus generating the masses of the gauge bosons and the fermions. The importance of the search for this missing element of the Standard Model is proved indeed by the fact that it is among the main motivations for the future colliders activity. At LEP2 the Higgs could be discovered for $M_H \leq 98$ GeV \cite{1}; in case of heavier mass we will have to wait for the Large Hadron Collider (LHC) at CERN, whose energy in the centre of mass will be $\sqrt{s} = 14$ TeV.

The experimental observation of the Higgs will be a difficult challenge especially because, as the SM predicts and detailed studies have confirmed \cite{2}, the signal, i.e. events characterized by the production of the Higgs boson, will be overwhelmed by background events, with multi-hadron production induced by strong interactions of quark and gluons. With this work we want to show that an artificial neural network (ANN) trained with a suitable choice of the input variables might be a valid tool to enhance the signal to background ratio. We consider the extraction of Higgs events from backgrounds in simulated data at LHC energies. In particular we consider two cases: in the first, shortly called off-line, a maximal set of information on each event is available; in the second, called on-line, only the knowledge about the transverse momenta of final state muons is available, as it is the case with the CMS muon spectrometer \cite{11}.

2. TOTEM and RTS

Neural networks, implemented as VLSI hardware, are being considered as good candidates to solve problems of time-critical and high quality pattern recognition in High Energy Physics (HEP)\cite{3,4}. The main benefit is speed, because of the massive parallel architecture. The cost is usually a very complex architecture, since common algorithms such as back-propagation, being derivative-based, require high precision computation\cite{4}. On the contrary the neurochip TOTEM has a simple structure as it implements a ”derivative-free” algorithm, based on an ap-
The approach to the training problem, where this is first transformed into a combinatorial optimization task and then solved by means of the heuristic method called Reactive Tabu Search (RTS) [4]. RTS builds up search trajectories in the space of the binary strings of length $L = N \cdot B$, into which $N$ weights, needed to configure a neural network, are suitably coded using $B$ bits per weight. The search is intended to locate the best “suboptimal” minimum on a cost surface by means of a sequence of elementary moves, each consisting of a single bit-flip in the string of weights. When a move is done, its inverse is forbidden for a prohibition period of $T$ successive steps (the Glover’s Tabu Search method [9]), allowing some amount of diversification in the search process. RTS remarkably enhances such diversification by dynamically adjusting the parameter $T$ through a simple mechanism that evaluates and reacts to the current local shape of the cost surface. As a result RTS escapes rapidly from local minima and cyclings and finds solutions even for low precision weights quite independently from any starting from starting point [9].

3. Data selection and analysis

At the energy of 14 TeV the dominant production mechanism of the Higgs in $p - p$ collision is the gluon-gluon fusion. For $M_H \sim 200$ GeV the Higgs particle decays predominantly into a vector gauge boson pair (ZZ,WW). Despite of the smaller branching fraction ($\Gamma_{H \rightarrow WW}/\Gamma_{H \rightarrow ZZ} \sim 3$) the so called gold plated channel

\[ p p \rightarrow H X \rightarrow Z^0 Z^0; X \rightarrow \mu^+ \mu^- \mu^+ \mu^- X' \]  

provides cleaner signal with a narrow four leptons invariant mass peak that for $M_H > 400$ GeV would be clearly distinguishable from ZZ continuum. As pointed out by several papers [3,2] this channel can be exploit in the wide mass range 130 GeV $\leq M_H \leq 800$ GeV [3,4] (with one Z being virtual for $M_H < 180$ GeV). For $M_H \geq 180$ GeV up to 400 GeV this channel is sensitive even at luminosities as low as $\sim 10^{35} pb^{-1}$ [1]. Thus we considered [1] as the signal in our simulation assuming a mass value of 200 GeV. In this case the main sources of background are the $t \bar{t}$ production:

\[ p p \rightarrow t \bar{t} X \rightarrow \mu^+ \mu^- \mu^+ \mu^- X' , \]  

with the 4 muons arising from semileptonic decay of the top and antitop, and the $Z b \bar{b}$ production:

\[ p p \rightarrow Z^0 b \bar{b} \rightarrow \mu^+ \mu^- \mu^+ \mu^- X' , \]  

with a muon pair arising from $Z^0$ decay and the other one from semileptonic $b$ and $\bar{b}$ decays. The cross sections for the three processes as calculated by the PYTHIA 5.7-JETSET 7.4 Monte Carlo code used to generate the data are:

\[ \sigma(pp \rightarrow HX \rightarrow ZZ \rightarrow 4 \mu X') = 2.7 \cdot 10^{-3} \text{ pb} \]  
\[ \sigma(pp \rightarrow t \bar{t} X \rightarrow 4 \mu X) = 7.7 \text{ pb} \]  
\[ \sigma(pp \rightarrow Z^0 b \bar{b} X \rightarrow 4 \mu X') = 5.7 \text{ pb}. \]

The signature of the channel [1] is characterized by two $\mu^- \mu^+$ pairs with large transverse momentum and invariant mass close to $M_{Z^0}$. In addition noticeably the production of hadrons is expected to be different in the signal and the background channels, due to a more copious generation of them by hard parton scattering in the [3] and [4] processes as compared to [1]. However the latter peculiar feature remains hidden because of the huge number (typically several hundreds at the LHC energy) of hadrons produced by hadronization of the two remnant partons and by multiple interaction per beam crossing. Consequently, in order to remedy, we choose to preprocess the data by the so called $k_\perp$ clustering algorithm citek. This algorithm consists of two steps. In the first one compares

\[ d_{ij} = 2 \min\{E_i^{2T_1}, E_j^{2T_2}\} \sqrt{(\eta_i - \eta_j)^2 + (\phi_i - \phi_j)^2} \]

with

\[ d_{iB} = E_i^{2T_1} , \]

where $E_{T_1}$ is the transverse energy of the $i^{th}$ particle with respect to the beam direction, $\eta_i$ is its pseudorapidity and $\phi_i$ is the azimuth angle with respect to the beam axis: a final state particle $i$ is attributed to the beam remnants (beam jet) if $d_{iB}$ is smaller than $d_{ij}$, otherwise it is attributed to a hard jet. In the second step, which is not of interest here, the particles belonging to hard jets are divided into different clusters.
3.1. Off line

Of course the ability of a neural network in discriminating signal from background events lies in the optimal choice of the physical variables. In this off-line analysis we use the following ten physical observables:

- $X_1 - X_4$ The transverse momenta of the four muons.
- $X_5 - X_8$ The invariant masses of the four different $\mu^-\mu^+$ pairs.
- $X_9$ The four muons invariant mass.
- $X_{10}$ The hadron multiplicity related to hard jets obtained with the $k_T$ algorithm.

3.1.1. Training and testing

The neural network we have configured on the neurochip Totem for the present work is a 10-20-1 feed-forward architecture. It has been trained using 4000 Higgs events, mixed with 2000 $t\bar{t}$ and 2000 $Zb\bar{b}$ events. Then it has been tested on a set of data completely different from the training one, made up according to the ratio of the cross sections of the three processes (4), (5) and (6).

The performance of the ANN has been evaluated by introducing the usual two variables purity ($P$) and Higgs discrimination efficiency ($\varepsilon$) defined as follows:

$$P = \frac{N_H}{N_H + N_B} ; \quad \varepsilon = \frac{N_H}{N_H}$$

where $N_H$ is the total number of Higgs events in the testing sample, $N_A$ is the total number of the accepted (i.e. correctly identified) Higgs events and $N_B$ is the total number of the accepted background events, i.e. events that are incorrectly identified as Higgs events. One can make a purity vs. efficiency plot by introducing a threshold parameter $l$ in the dynamical range [0,1] of the ANN output, so that if the ANN output $y$ for an event in the testing phase turns to belong to the subinterval $I_1 = [0,l]$, then that event is classified as a signal, otherwise if it turns to belong to the subinterval $I_2 = [l,1]$, then that event is classified as a background. Our results are reported in figure 1, where they are compared with those obtained using a simulated neural network trained by a classical backpropagation algorithm [14] for the same input variable [16].

3.2. On-line

As already pointed out, a main benefit of the hardware implementation of the neural networks is the speed: this is true for the neurochip Totem, while the faster Totem++ is on the way to meet even the requirements of employ even at the future LHC [13]. Taking this in mind, we examine the case when only the knowledge of the transverse momenta of the final muons is given, with uncertainty ($\delta P_t \sim \pm 0.15 P_t$), just like with the CMS muon spectrometer [11]. Moreover we set the two cuts on our four muon events, namely:

$$|P_t| > 5 \text{ GeV} \quad \text{and} \quad |\eta| \leq 2.4$$

where $\eta$ is the pseudorapidity of the muons. As input variables of our neural network we choose the following:

- $X_1 - X_4$ The transverse momenta of the four muons.
- $X_5 - X_8$ The transverse mass of the four different $\mu^-\mu^+$ pairs.
- $X_9$ The transverse mass of the four muons system.
- $X_{10} - X_{11}$ The eigenvalue of the transverse Parisi momentum tensor.

The transverse mass of a set of particles with transverse momentum $P_t^{(i)}$ is given by

$$M_t^2 = \left( \sum_{i=1}^{n} |P_t^{(i)}| \right)^2 - \left( \sum_{i=1}^{n} P_t^{(i)} \right)^2$$

while the transverse Parisi momentum tensor [17]...
is defined as
\[ A_{ij} = \frac{\sum_{k=1}^{4} P_i^{(k)} P_j^{(k)}}{\sum_{k=1}^{4} |P_i^{(k)}|}, \quad i, j = 1, 2. \] (10)

where \( P_i^{(k)} \) are the transverse components of the momentum of the \( k^{th} \) muon in the lab frame.

3.2.1. Training and testing

For the present case, like for the previous off-line one, we have implemented a feed-forward 11-32-1 neural network architecture on the neurochip TOTEM and we have followed exactly the same procedures, apart from the introduction of the cuts (8). The (preliminary) results are shown in figure 1 together with the off-line ones.

4. Conclusions

We have shown that neural networks as implemented on the chip TOTEM exhibit considerably high quality and high speed performances, probably not attainable by traditional statistical methods. Therefore they should be seriously considered and thoroughly investigated for effective use in physics experiments. We stress the fact that we gain a factor of about \( 10^3 \div 10^4 \) in the signal to background ratio.

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