

The non-linear signal domain selection using a new quality function in neural net training

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Abstract

Applying cuts in the space of event parameters is the traditional technique for background rejection in high energy physics. Obtained by considering the simulation of signal and background events, particular values of these cuts are used to reach required balance between efficiency of signal detection and background rejection.

Modern experiments in high energy accelerator physics and astrophysics are operating with multidimensional parametric spaces. Thus, the problem of the best cut selection is of vital interest. Frequently used rectangular cuts are usually too restrictive and can deteriorate the shape of selected multivariate signal distribution. With the aid of the proposed method, it is possible to obtain smooth nonlinear shape of signal cluster which optimizes the ratio of signal to noise. The search of the best γ -cluster on the data files of Crab nebula detection by Atmospheric Cherenkov Telescope of Whipple collaboration proves the superiority of neural techniques upon traditional methods.

1. Introduction

The rates of interesting events, expected at LHC and in astrophysics experiments, are negligible as compared with background events. Therefore, a key to successful analysis is the reduction of the data volumes in such a way that the maximum sensitivity to a new physics is preserved and the maximum immunity to noise is achieved [1].

The “cuts” (mostly linear) performed on multidimensional distributions of measurements are usually used in collider experiments analysis to enlarge the significance of statistical conclusions concerning the existence of new phenomena. Usually, it is difficult to outline the desired “best” signal domain where it is possible to detect the significant abundance of signal events over background distribution. The signal domain, multidimensional decision surface, can be nonlinear and its selection is an unsolved problem yet without knowing the signal and background distribution shapes.

It is proposed to use the neural net training the experimentally obtained pure background and mixed signal

and background samples. A new objective function is introduced instead of the classification score.

2. The new neural algorithm for background rejection

Significant processes in high energy astrophysics has been made in the unambiguous detection of the Crab Nebula at TeV energies by the Whipple collaboration [2]. Huge background is caused by isotropically distributed flux of charged cosmic rays in this experiment. The main technique to reject this background is applying multidimensional linear cuts on measured Cherenkov image parameters, as introduced by Hillas [3].

To prove the existence of neutral particles from celestial sources, one looks for an abundance ($N_{on} - N_{off}$) of events coming from the direction of a possible source (N_{on}) compared with the control measurement, when pure background is registered (N_{off}). As the expected fluxes are very weak (the ratio of signal to background does not exceed 0.01), it is necessary to answer the following question: is the detected abundance a real signal or only a background fluctuation? The measure (level) of statistical significance used in γ -ray astronomy is so-called criterion size (σ) [4]:

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$$\sigma = \frac{N_{\text{on}} - N_{\text{off}}}{\sqrt{N_{\text{on}} + N_{\text{off}}}} \quad (1)$$

The greater σ , the lesser the probability that the detected excess is caused by a background fluctuation. After selecting the “ γ -like” events from rat data (both from the ON and OFF samples), the criterion takes the form:

$$\sigma = \frac{N_{\text{on}}^* - N_{\text{off}}^*}{\sqrt{N_{\text{on}}^* + N_{\text{off}}^*}} \quad (2)$$

$N_{\text{on}}^*, N_{\text{off}}^*$ are the numbers of events which passed data selection cuts. As shown in Ref. [5], the use of σ as objective function, helps us to outline realistic nonlinear shape of γ -cluster and enlarge σ , compared with the technique used in the Whipple Observatory (supercuts), proposed in Ref. [6] and then improved in Ref. [7]. New methods of net training on simplified problem of nonlinear cluster detection and on a new piece of Crab data are illustrated in following section.

3. Results

The 2:4:2:1 feed-forward network is used to detect the 2-dimensional cluster with radial symmetry (see Fig. 1). Training samples consist of 450 “background” events, uniformly distributed in a unit square. Fifty “signal” events generated according to radial symmetric Gaussian distribution with mean = 0.5 and $\sigma = 0.03$ were added to one of the background samples. The goal of the algorithm is to find a two-dimensional cluster maximising this objective function (2). Fig. 1 presents the results of cluster search for 1 + 1 random search strategy.

Obtained “chromosomes” were used as a “pool” for genetic algorithm, the results of which are presented on Fig. 2. Both “mutations” and “crossovers” give a rise to the objective function.

Data, obtained on the Crab Nebula in December 1993 using the Whipple Collaboration 10 m Cherenkov Imaging telescope, were used in the analysis. The database consisted of 19 On/Off pairs, with total on-source time of

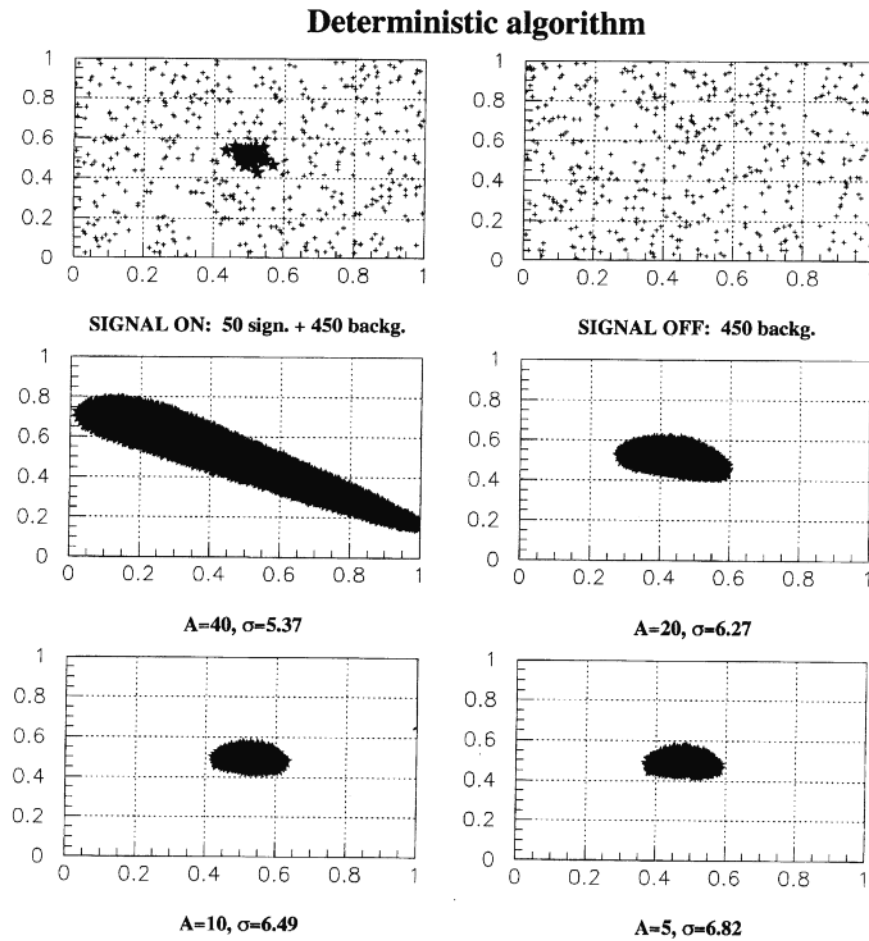


Fig. 1.

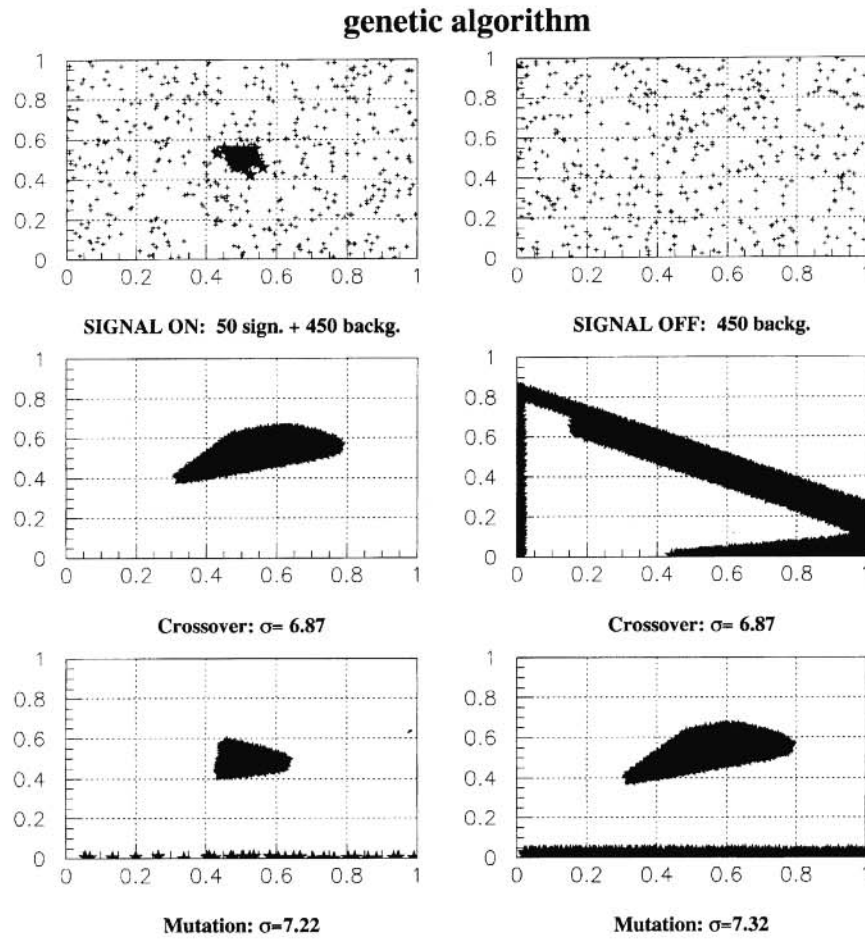


Table 1
WHIPPLE Crab detection, 1993

	N_{on}^*	N_{off}^*	σ	DIFF	DIFF/ N_{off}^*
SUPERCUT	1710	866	16.6	844	0.97
NN, 4:3:1	1552	707	17.8	845	1.2

473 min. The standard “supercuts” effect was 16.6σ on this database; this increased up to 17.8σ after optimization using the neural network (see Table 1). While this is not in itself a very marked improvement in sensitivity, it is, nevertheless, encouraging that some improvement is obtainable, particularly, as the improved shape of the γ -ray domain can be readily explained [8].

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