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ABSTRACT

A neural network is used for the impact parameter determination in ^{40}Ca+ ^{40}Ca reactions at energies between 35 and 70 AMeV. A special attention is devoted to the effect of experimental constraints such as the detectin efficiency. An overall improvement of the impact parameter determination of 25 % is obtained with the neural network. The neural network technique is then used in the analysis of the Ca+Ca data at 35AMeV and allows separation ofthree different class of events among the selected "complete" events.

1. Introduction

The increasing use of 4π multidetectors makes experimental heavy ion data more difficult to interpret without the help of theoretical calculations. Unfortunately, one of the key parameters of most calculations is the impact parameter which remains poorly known experimentally. Several attempts have been made to extract this quantity[1] using the charged particle multiplicity, the perpendicular momentum, the neutron number,etc... It turns out that, in the energy range under consideration here, all these methods, very efficient for peripheral reactions, failed for central collisions due to saturation of the observables. In order to use as much available information as possible, it would be interesting to combine several different observables. A promising step in this direction has been made recently using neural networks [2),3)]. Indeed, for ^{197}Au+ ^{197}Au at 600AMeV David et al[3)] have obtained an improvement by a factor of 4 in the impact parameter determination in central collisions with the use of a neural network compared to the use of a single observable. The goal of this paper, is to explore properties of a neural network at lower energies between 35 and 70AMeV. We will also take into account explicitly the experimental filter and restrict ourselves to measurable observables. Finally, the network will be applied to 35AMeV ^{40}Ca+ ^{40}Ca data collected at SARA(Grenoble, France)[4)].

2. Introduction to Neural Network

Let us start with a brief introduction on neural networks. For details and general background, the reader is refered to [5)]. By definition a neural network is an ensemble of highly connected cells. A cell is an entity which has one or several inputs, I_i, weighted respectively by ω_i, an activation threshold θ and gives an output according to a certain activation function f. Such a cell is represented on the top of figure 1. The output, S, of the cell is generated according to the equation:

$$S = f(\sum_i \omega_i I_i + \theta).$$

The activation functions used for each layers are displayed on the bottom of the figure 1. For a sake of simplicity, we have restricted ourselves to a three layer feed forward network. The first layer, which corresponds to the input layer, is composed of three cells, the median layer is called the hidden layer and contains 5 cells and finally the last one is a single cell output layer. Input cells receive the data from the outside (here the value of the physical observables) and the output cell gives the result (here an estimate of the impact parameter).

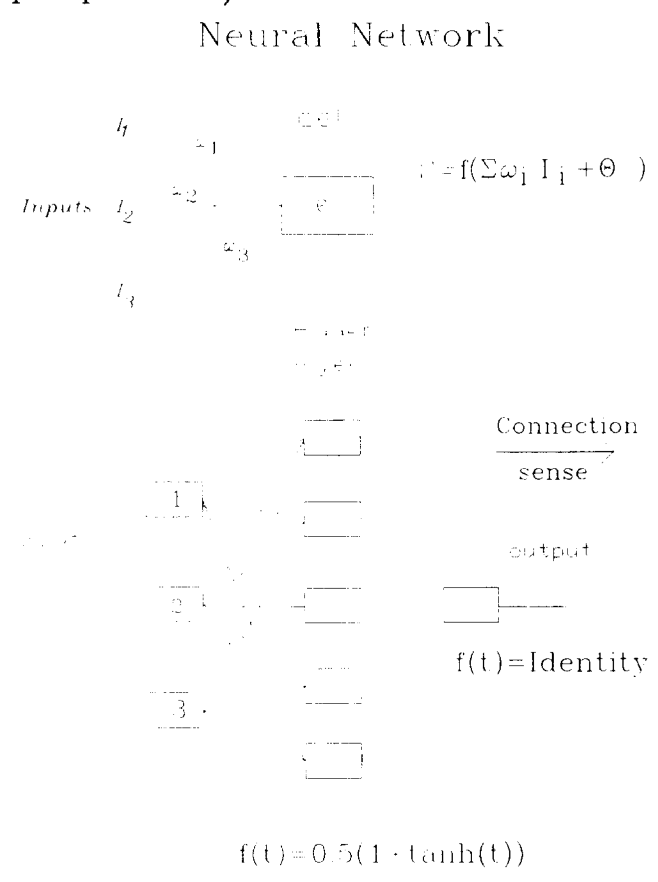

Fig. 1: schematic view of a cell (upper drawing) and of our network(lower drawing).

The use of a network is a two step process: a learning stage followed by an application stage. During the learning phase, the different parameters of the network

$(\theta,\ \omega)$ are determined. This is done with the help of a learning sample ie a sample for which inputs and the expected output are perfectly known. The parameters are then adjusted in order to minimize, according to the different weights and thresholds, the difference D between the calculated output, Out_{NN} and the known one, ξ for the whole training ensemble. The function D is defined in our work as

$$D(\omega_i, \theta_i) = 0.5(\sum_{\mu=1}^{n}(|\zeta^{\mu} - Out^{\mu}_{NN}|)^2)$$

where n is the total number of elements of the training sample. The details of the whole minimization procedure can be found in ref 3.

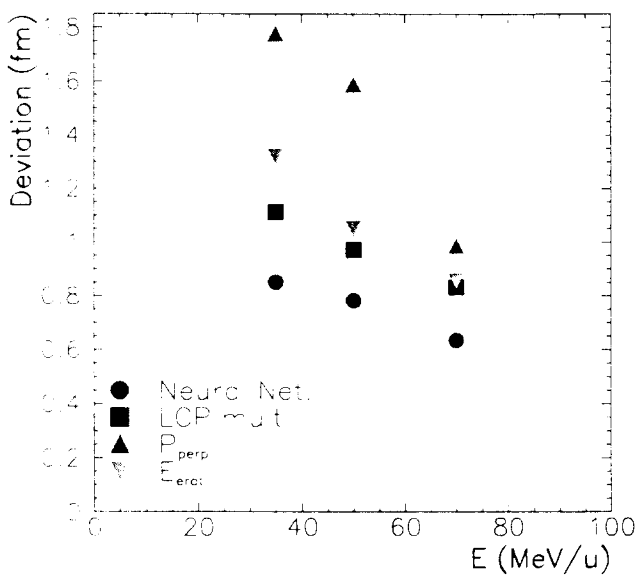

Fig. 2: Energy dependence of the deviation(see definition in the text) for Ca+Ca reactions obtained from QMD+Gemini.

In our case no real data are available to make a learning sample. A theoretical model has then to be used to generate this sample. A QMD dynamical calculation[7] coupled with Gemini[6] has been chosen. This hybrid model has already been very successful in reproducing many features of the $^{40}Ca+^{40}Ca$ reaction at 35AMeV[4]. The learning sample is composed of 1000 events uniformely distributed between 0fm and 8fm.

For this study, the three inputs that provide the most efficient combination of the available observables for $^{40}Ca+^{40}Ca$ at 35AMeV have been used. They are the charged particle multiplicity (CP), the perpendicular momentum (P_{perp}), and $E_{rat} = \frac{\sum P_t^2/2m}{\sum P_z^2/2m}$

3. Behaviour of our Neural Network

To compare the performance of the Neural Network (NN) with other commonly used methods, an observable is defined:

$$Deviation = \frac{1}{N}\sum_{i=1}^{N} |B_i^{QMD} - B_i^{var}|$$

which gives an estimate of the dispersion over the overall range of impact parameter. B^{var} stands for the impact parameter value determined using one of the following observables NN, CP, P_{perp}, E_{rat}.

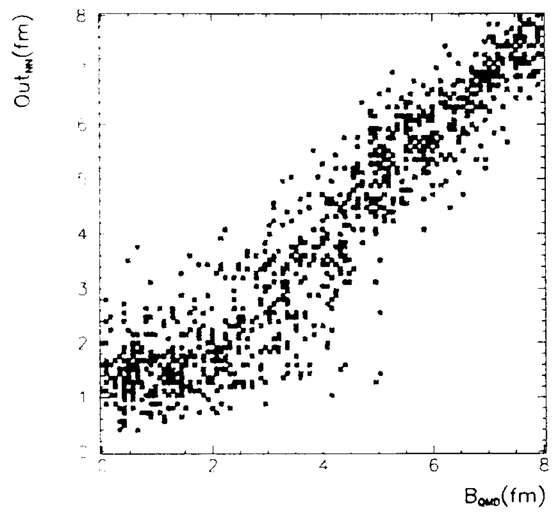

Fig. 3: Correlations between input impact parameter from QMD and the output generated by the network for Ca+Ca at 70AMeV.

For methods other than the neural network, let us explain the way the impact parameter is extracted. Using the training sample, the total distribution of a given observable (var) is cut into ten equal size bins for which the average impact parameter is calculated. Then, using a fit of a polynomial expression of these points, an impact parameter value $B^{var}$is associated to each value of the observable.

we have reported the results of such a comparison for Ca+Ca reactions as a function of the incident energy in figure 2.

For all energies, the neural network gives the lowest Deviation. It is the most accurate of the methods used here. It can be seen also that as the incident energy increases, the impact parameter determination becomes better. This true for all the different methods. Neverthless, in this model study, the neural network always allows an improvement around 25% compared to the others.

In figure 3, the correlation between the known impact parameter, B_{QMD}, and the neural network output, Out_{NN} is displayed for the Ca+Ca reaction at 70AMeV. This correlation is very good from 8fm till 1.5 fm. For the very central reaction, Out_{NN} saturates. This is due to the saturation of input observables for this central events.

It can also be seen that the dispersion around the mean increases with a decrease of the impact parameter.

In previous works, model calculations have been used without taking into account any experiemental filter. The effect of such filter is far from negligible and has the tendency to increasethe apparent fluctuations. The Amphora detector filter has been applied to study this effect. The result is presented in figure 4. As expected, the recognition by the neural network is poorer than without the filter. This clearly shows the necessity to use a network trained as closely to the experimental condition as possible.

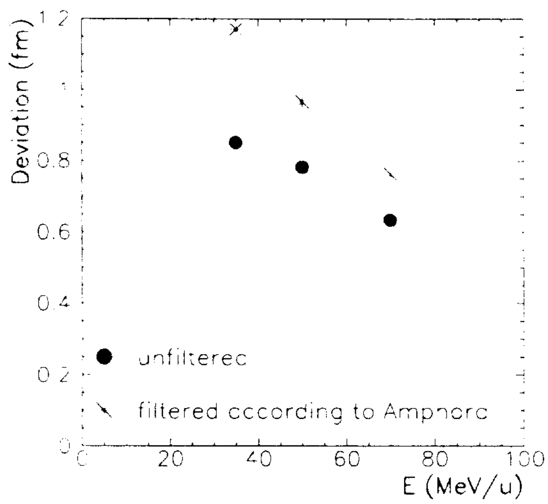

Fig. 4: Effect of a filter in the Neural Network performances.

4. Application on Real Data

The $^{40}Ca+^{40}Ca$ reaction at 35AMeV has been performed at SARA(Grenoble) using the Amphora multidetector system[4)]. The analysis was carried out focusing on "complete" events. These events which correspond to the more central ones, are defined as those for which:

- The effective charge particle multiplicity threshold > 10
- The detected $Z_{tot} > 85\%$ of total combined system Z

The network has been trained with filtered events generated by the model calculation. At this energy, the Out_{NN} distribution saturates around 2.5fm. A precise individual impact parameter determination at this energy by our network does not seem reasonable. Neverthless, we are going to separate the data into three groups according to Out_{NN}. The limits of these groups are $Out_{NN} \leq 3.2fm$, $3.2 < Out_{NN} \leq 4.4fm$ and $Out_{NN} > 4.4fm$ and have been chosen to make three equaly populated bins.

For these three different classes, the so called "Campi-plot"[8] has been generated. This plot allows exploration of the moments of the multiplicity distribution and has been suggested as a usefull means to identify for possible critical behaviour in de-excitation patterns. In figure 5, such plots are displayed for all events as well as for the 3 Out_{NN} classes.

Two peaks occur on the experimental contour plot in the pannel a) of Figure 5. One is located at large values of $lnZ_{max}$and small values of lnS'_2 and the other is located at small values of $lnZ_{max}$and large values of lnS'_2. Plots obtained for the different cuts in Out_{NN} show quite distinct behaviour. For the lower values of Out_{NN}, only the low lnS'_2 peak remain. On the other hand for higher Out_{NN} values, only the high lnS'_2 peak is present. This systematic nice behavior shows that neural network can be very useful in data analysis by allowing the grouping of events according to the correlation of several observables(here CP, P_{perp} and E_{rat}).

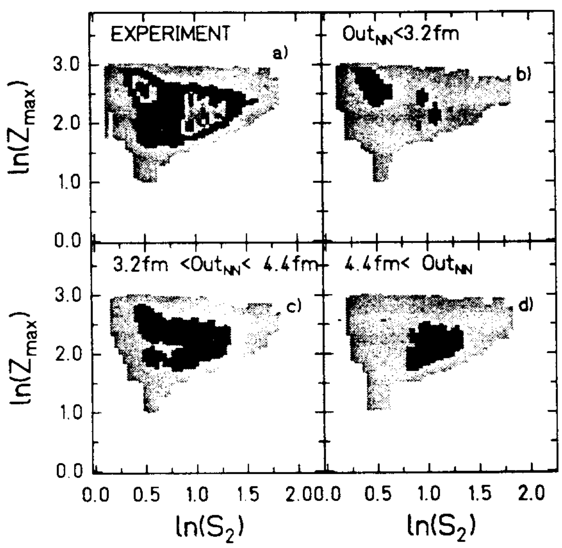

Fig. 5: Logarithmic distribution of Z_{max} vs $S'_2 = \frac{\sum_{i,z\neq Z_{max}} Z_i^2 M(Z_i)}{\sum_{i,z\neq Z_{max}} Z_i M(Z_i)}$. Each contour represents constant value units of relative $\frac{d^2Y}{dlnS'_2 Z_{max}}$ where Y is the yield. The outside contour level is at level 10, and each inner contour represents a progression in yield of 150.

5. Conclusion

In this contribution, the impact parameter recognition performance of a neural network in intermediate energy heavy ion collision has been studied. in model studies an improvement of about 25% is obtained compared to commonly used methods. Applied to real data, in this case $^{40}Ca+^{40}Ca$ reaction at 35AMeV, the network provides a clear separation of the different peaks obtained in the experimental Campi plots. This indicates that the neural network can be a valuable tool in data analysis. For such systems, it should be emphasized, however, that the impact parameter recognition is based on model calculations. Training the network would better be done using empirical data if this were possible.

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6. References

[1] M. Betty Tsang et al, Phys. Rev. C40 (1989)1685
[2] S.A. Bass et al, J. Phys. G: Nucl. Part. Phys. 20(1994)L21
[3] C.David et al, Phys. Rev. C51 (1995)1453
[4] K.Hagel et al, Phys. Rev. C50 (1994)2017
[5] B.Müller and J. Reinhardt, Neural Networks, (Springer,berlin 1991)
[6] B. Charity et al,Nucl. Phys. A483(1988)371
[7] T. Naruyama et al, Prog. Theor. Phys. 87 (1992)1367
[8] X.Campi, J. Phys. A 19, L917(1986)