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APPLICATION OF NEURAL NETWORKS TO SIMULATED DATA FOR LIQUID ARGON TPC'S*

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The paper presents the capability of a Liquid Argon TPC to distinguish between electrons and π^0's and also between proton, kaon and pion. Neutral pions are very dangerous background in the study of neutrino oscillations while hadronic identification is important to look for proton decay. The analysis was based on the data from Monte Carlo simulation and was achieved by means of Neural Networks. Two methods of analysis focus on the particle energy loss by ionization. One concerns electrons inside electromagnetic cascades, the other one decaying hadrons.

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1. Introduction

The ICARUS experiment [1] will start next year at the Gran Sasso laboratory in Italy. Its detector was first proposed by Carlo Rubbia in 1977 [2] and is based on Time Projection Chambers (TPC) filled with Liquid Argon. The two modules of the ICARUS detector are being installed and in the next step will be filled with 600 tons of Liquid Argon. The technology of this detector was checked in several tests and the results are very promising. Thanks to high energy resolution and very good granularity ICARUS will provide 3D imaging for tracking and calorimetric measurements. The high sensitivity of this type of detector will make it ideal to explore oscillations of neutrinos while a bigger detector would be perfect to look for nucleon decay [3].

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The Liquid Argon TPC was also proposed for the T2K experiment [4, 5] which will be realized at the Japanese Proton Accelerator Research Complex (J-PARC). T2K will be a second generation long-baseline neutrino-oscillation experiment. The most important measurement carried out there concerns the mixing angle θ_{13}.

The detector technique based on Liquid Argon is so interesting that there are many ideas for building a much bigger detector of this type in the future. They were presented at the dedicated workshop recently organized at Gran Sasso [6].

In order to study neutrino oscillations it is essential to distinguish between electromagnetic cascades produced by electrons and those which appear from π^0 decays which are the most dangerous background. In searching for proton decay the hadronic identification is important. These two problems will be discussed in the following chapters.

In the second chapter the software needed to perform the analysis is described. The third chapter focuses on the details of the electron/π^0 discrimination while the fourth concentrates on the proton decay identification. Finally, the last part of the paper is a summary and outlook.

2. Description of the method

All events used in our analysis were generated and reconstructed by the T2K-LAr software, which is a dedicated tool for a proposed Liquid Argon detector in T2K experiment. This software was mostly developed by A.Rubbia and his group. Generation of the Monte Carlo data was performed using a `G4T2K` generator based on the `Geant4` environment [7]. Generated events were mono-energetic, with no additional particles in the initial state and no noise. Particles were shot into the detector along one direction and events were fully contained. Reconstruction was done using the T2K-LAr `Qbatch` program.

In our analysis events were classified using the neural network library from the `ROOT` package [8]. We used simple Multilayer Perceptron networks with:

- Input layer — containing a number of neurons (inputs) which is dependent on the number of parameters used for classification.
- One hidden layer — the number of neurons in this layer was adjusted empirically (to maximize the quality of classification).
- Output layer — containing a number of neurons (outputs) which depends on how many types of particles we want to distinguish among.

Before starting the whole procedure, the set of the generated events was divided into two parts: training set and testing set. The training set contains, apart from parameters used as inputs for the neural network, also a value of true network output for each of the events. This set is used to train the neural network. The testing set is used to test the quality of the classification.

A very convenient way of testing the quality of the classification by a neural network is to use *purity-efficiency plots* (*cf.* Fig. 2). By gathering the network answers for all the events in the testing set, we get the distribution for the network output. To distinguish between two classes of events: signal (one of the particles) and background (the other ones), we need to establish a cut (threshold) on the distribution of the network output. Let us define the two variables for a given threshold applied to the network output:

1. Purity:

$$\text{Purity} = 100\% \, \frac{N_{\text{sig}}(\text{Output})}{N_{\text{bg}}(\text{Output}) + N_{\text{sig}}(\text{Output})}\,. \tag{2.1}$$

2. Efficiency:

$$\text{Efficiency} = 100\% \, \frac{N_{\text{sig}}(\text{Output})}{N_{\text{sig}}(\text{Input})}\,. \tag{2.2}$$

$N_{\text{sig}}(\text{Set})$ and $N_{\text{bg}}(\text{Set})$ are the numbers of signal and background events in a given set. Input is the set of the events which is being classified and Output is the set of the network answers which are above a given threshold. If the purity–efficiency curve is located higher on the plot — the quality of classification is better and the network can separate better the signal from the background.

The main uncertainty in the determination of the purity–efficiency curves comes from the uncertainty in the purity:

$$\sigma_{\text{purity}} = \sqrt{\sigma^2_{N_{\text{sig}}(\text{Output})}\left(\frac{\partial \text{purity}}{\partial N_{\text{sig}}(\text{Output})}\right)^2 + \sigma^2_{N_{\text{bg}}(\text{Output})}\left(\frac{\partial \text{purity}}{\partial N_{\text{bg}}(\text{Output})}\right)^2}\,. \tag{2.3}$$

In both parts of the analysis, e/π^0 discrimination and proton decay search, the basic parameter used as input for the neural network was the ionization signal from the wires. It is very well measured by the Liquid Argon detector [1].

3. Electron/π^0 discrimination

The best way to get the neutrino's signature in the *charged current (CC)* reactions is to measure the signal from the charged lepton in the final state. In the case of an electron in the final state, an electromagnetic shower is produced. The energy of the shower can be precisely measured due to the good energy resolution of LAr TPC. This is the reason why the CC events with the electron in the final state are the so called "golden channel" for Liquid Argon TPCs.

The electron signature is used to recognize CC interactions of neutrinos of two flavors:

- Electron neutrinos and their interactions:

$$\nu_e + n \rightarrow e^- + p \tag{3.1}$$

  which are important in the T2K experiment where the very low $\nu_\mu \rightarrow \nu_e$ oscillation signal will be searched for.

- Taon neutrinos and the:

$$\nu_\tau + N \rightarrow \tau + X \tag{3.2}$$

  reaction, where τ decays into an electron and two neutrinos occur with an 18% branching ratio. This reaction will be important in the ICARUS experiment (CNGS beam) where the $\nu_\mu \rightarrow \nu_\tau$ oscillations will be searched for.

A considerable background for *charged current* reactions are the *neutral current (NC)* interactions, where π^0 mesons are produced:

$$\nu_\mu + n \rightarrow \nu_\mu + \pi^0 + X\,. \tag{3.3}$$

In 98.8% of cases the π^0 in the final state of this reaction decays after traveling an infinitesimal way into two photons. Photons give rise to electromagnetic showers and can imitate electron or taon signals when one of the showers starts close to the interaction vertex. Confusion is possible especially in two situations:

1. One of the photons coming from a π^0 decay has very low energy and only the second one initiates the electromagnetic shower.

2. Showers produced by the two photons overlap.

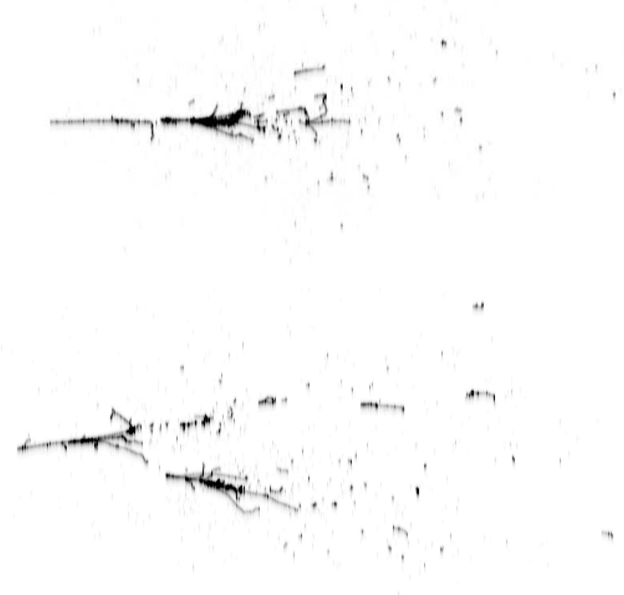

Fig. 1. Electromagnetic showers in the Liquid Argon TPC initiated by electron (upper part) and π^0 (lower part).

The mistake may also be made when a neutral pion decays into an e^+e^- pair and a photon (*Dalitz decay* in 1.2% of cases). Examples of electron and π^0 events in the T2K Liquid Argon TPC are shown in figure 1. Electron/π^0 discrimination has its aim to separate *charged current* and *neutral current* neutrino interactions.

A set of Monte Carlo electron and π^0 events was divided into two comparable parts: training set and testing set. The energy of the generated particles was set to 1 GeV because the average energy of the T2K experiment beam will be close to that value. The neural network discrimination method was applied by extracting some parameters from electron and π^0 events and feeding a simple neural network with them. The network has one output which gives us information which particle was recognized. Testing the quality of the classification by a neural network was performed using purity-efficiency plots. The basic parameter which was used was an average energy loss on several wires from the cascade beginning:

$$\left\langle \frac{dE}{dx} \right\rangle = \frac{1}{N} \sum_i \left(\frac{dE}{dx} \right)_i . \tag{3.4}$$

An electron gives an immediate ionization signal unlike the π^0 meson. π^0 decays into two photons that convert into e^+e^- pairs after an average distance equal to the radiation length in liquid argon ($X_0 = 14$cm). Before the shower starts to develop, the signal from an e^+e^- pair created by the conversion of a photon coming from a π^0 decay should be twice as high as the signal from a single electron. This fact is the main motivation for using the $\frac{dE}{dx}$ as a parameter. The number of wires taken into account in calculating the average energy loss was adjusted to have the purity and efficiency as high as possible. Results of the neural network analysis (2-2-1 network) using only $\frac{dE}{dx}$ information are represented by the lowest purity-efficiency curve in Fig. 2. They are promising but one can obtain better results by extracting more information from the events in the detector.

To improve the quality of classification, additional parameters were used as input variables for neural network. These parameters are the results of the shape analysis of electromagnetic showers produced by electrons and π^0's. Some of the variables which were added to the analysis are listed below:

1. Average width of the event in the wire plane.

2. Total number of reconstructed electron tracks in the electromagnetic cascade.

3. Length of the track with the largest number of hits.

4. Average radius of the event in the space.

5. Average angle between the direction of the primary particle and the reconstructed hits in the space.

Adding the parameters from topological analysis of events gave a considerable improvement in the quality of the classification. Results of using the 7-2-1 network with $\langle\frac{dE}{dx}\rangle$ and topological parameters used as inputs are represented by the middle purity-efficiency curve in Fig. 2.

Assuming that we know the location of the primary vertex of the neutrino interaction (the point where the electron or π^0 was produced) we can further improve the quality of classification. This was done by using an additional parameter to feed the neural network: $x_{\rm ion}$. The value of $x_{\rm ion}$ is the distance between the location of the primary vertex and the point where the first ionization signal was registered by the detector. Using the $x_{\rm ion}$ parameter gives us very big improvement in classification. It is illustrated by the highest purity–efficiency curve in Fig. 2. Although adding $x_{\rm ion}$ is essential, we should stress that the information about the location of the primary vertex is often unavailable, especially at low neutrino energies.

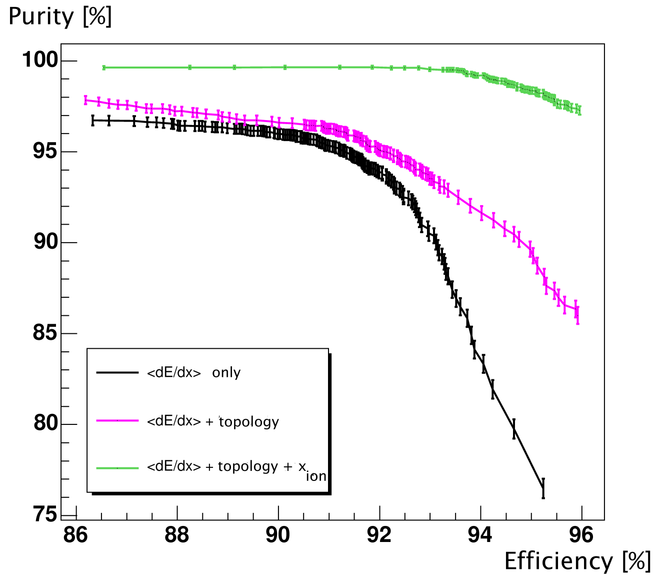

Fig. 2. Purity-efficiency plots for three levels of the analysis.

4. Proton decay

Proton decay is predicted by many Grand Unification Theories. Although the newest data from Super-Kamiokande confirm the exclusion of the simplest group SU(5) [10], there are many other interesting symmetries in which proton decays very naturally [11]. The golden channel for Liquid Argon is $p- > K^+\nu$ [12] which is favored by SUSY. For this channel one event observed in the LAr TPC is enough to prove that proton decays.

Initially 2000 of events for each particle type (proton, K^+ and π^+) were generated inside the detector. In the simulation particles with kinetic energy of 1 GeV were traveling in the direction of the longest side of the detector. They were allowed to loose their energy until they stopped only via ionization of Liquid Argon. All the particles were fully contained inside the detector.

As was mentioned before, a standard three layer perceptron of neural network was used. In that case there were three output nodes, related each to one particle type. The input layer consisted of 9 neurons, each one corresponding to the energy loss on one wire, starting from the track end. For improving the quality of the network's result the last wire was not taken into account. For this wire the area from which ionization electrons are collected was often smaller than the one for other wires.

The correction for energy loss in each of the 9 wires was made by considering the angle between the particle track and the wires. Figure 3 shows the energy distribution for the total energy loss. For each particle the network efficiency recognition was always above 90% and the contamination from other particles was below 10% when the electronic noise was not taken into account.

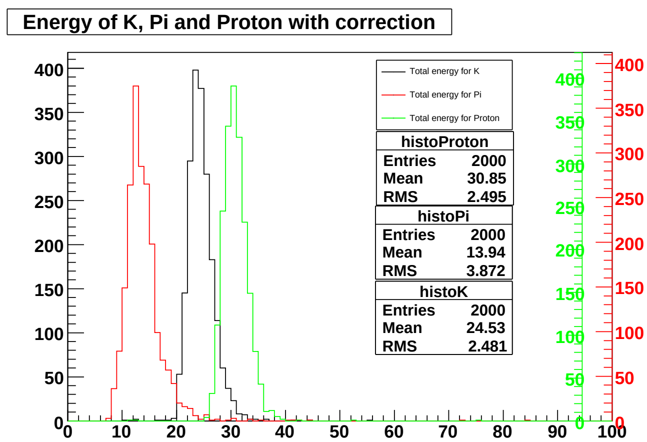

Fig. 3. Energy distribution for the total energy loss in 9 wires for the three particles (π^+, K^+, p) using the corrected energy loss.

Finally, the influence on particle identification by changing the geometry of neural network was checked. In order to receive faster response only one input instead of nine was used. It turned out that the sum of six energy losses in six wires, was enough for the net to give a good result and optimized the calculation time.

5. Summary and outlook

In our analysis we applied neural network techniques — a very efficient way of classification of events. These techniques were used for e^-/π^0 discrimination and particle identification for proton decay. We found that the $\frac{dE}{dx}$ information is crucial for the discrimination of the particles. We also found that some additional parameters describing the topology of the events can be very useful, especially in electron/π^0 distinction.

The preliminary results are promising. Our plan is to improve the analysis by using some other classification algorithms: in particular more advanced types of neural networks (ontogenic neural networks). It is also important to apply our classification techniques to the ICARUS T600 detector where the wire geometry is different from that of the T2K-LAr detector. The first data from running the T600 detector on the CNGS beam are expected in 2007 and will give a great opportunity to test our analysis. Making the algorithms useful for analysis using real data requires knowledge of the detector noise. It is our purpose to test the quality of classification on events with noise. Applying our techniques to Monte Carlo data for the T600 detector implies using a different event generation software. Adjusting our software to accept FLUKA [9] generated data is then one of our future tasks.

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