New analysis method of TPC data using neural network

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In the experiments with MAIKo TPC, we can detect tracks of charged particles. A track is got as a pair of images in each event. It is necessary to analyze 2-dimensional images from TPC. Conventionally, we analyze with Hough transformation which is a method to find lines in images. This analysis requires complex algorithms and large computing power, and it takes much time. Recently neural networks are employed for image recognition. In this work, we developed new analysis method using neural networks. The new method made the analysis faster and more accurately than the conventional method.

KEYWORDS: neural networks, time projection chamber (TPC), active target, MAIKo TPC

1. Introduction

Time Projection Chambers (TPCs) are widely used to detect tracks of charged particles. We developed a TPC using a micro pixel chamber (μ-PIC) [1] named MAIKo (μ-PIC based active target for inverse kinematics.) [2] for unstable nuclei experiments. Figure 1 shows the schematic view of the MAIKo TPC. When charged particles pass through the detection gas filled in the MAIKo TPC, electrons are emitted along the particle tracks. These electrons are drifted downward by a drift electric field, gas-amplified on the surface on the μ-PIC. The anode and cathode electrodes of the μ-PIC were segmented into 256 strips which are arranged orthogonally. These strips are aligned at 400-μm intervals. Anode strips are parallel to x-axis and cathode strips are parallel to z-axis as shown in Fig. 1. Electrical signals induced by the amplified electrons are read out through the anode and cathode strips to determine the x and z position of the particle tracks. The vertical position of the tracks along the y-axis is determined from the drift time of the electrons. The 3-dimensional tracks are reconstructed from x, y, z-coordinates.

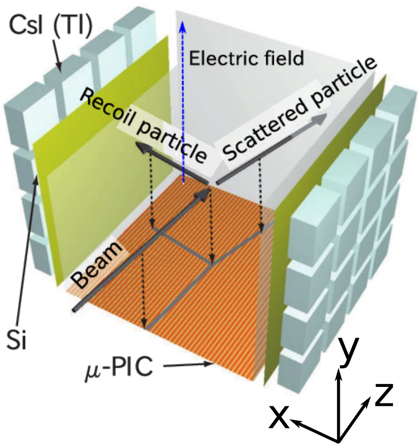

Fig. 1. Schematic view of the MAIKo TPC.

Incident particles are scattered by target particles in the sensitive volume of the TPC as shown in Fig. 1. Scattered particles goes to outside of the TPC and some recoil particles stop inside. Since reaction points are inside of the sensitive volume of the TPC, it is possible to detect low energy particle over a large solid angle. H_2 or He gas is widely used for a target gas but operation of TPC with pure H_2 or He gas is unstable and prone to discharge. Usually, quenching gas with high tolerance for electric discharge like CO_2 or iso-butane is mixed with a target gas for stable operation of the TPC although the quenching gas causes background events. Recently, the elastic and inelastic alpha scatterings on ^{10}C were measured with the MAIKo TPC at Research Center for Nuclear Physics, Osaka University. In this experiment, He (96%) was used as target gas and CO_2 (4%) was used as quench gas.

The track of charged particle is projected into a plane that is perpendicular to anode strips (anode image) and a plane that is perpendicular to cathode strips (cathode image). The MAIKo TPC outputs two images in each event. Figures 2 and 3 are examples of acquired images. These black-and-white images with 1024×256 pixels present drift times on the 256 strips of the anode and cathode recorded at every 10 ns for the duration of 10 ns $\times$ 1024 = 10.24 μs. Figure 2 shows the anode and cathode images from a ^{10}C + α event while Fig. 3 is from a background event due to the quenching gas. For the ^{10}C + α events, the energy and emission angle of the recoil α particles must be determined to obtain the spectroscopic information such as the excitation energy of ^{10}C and the scattering angle in the center-of-mass system. The energy of recoil is determined from the length of the track in the detection gas and the emission angle is determined from opening angle between the incident particle and the recoil α particle. To analyze the anode and cathode images, there are two steps.

- Distinguish ^{10}C + α events form background events.
- Extract the length and the emission angle of recoil α particles from anode and cathode images.

However, the conventional analysis requires a lot of efforts to select events and extract track information from the anode and cathode images. Therefore, we needed to develop a new analysis method using neural networks which are widely employed for image recognition in recent years.

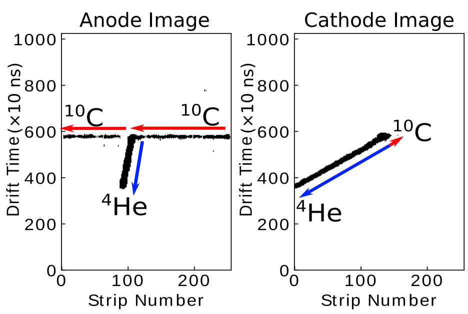

Fig. 2. Typical examples of the anode and cathode images recorded in a ^{10}C + α event

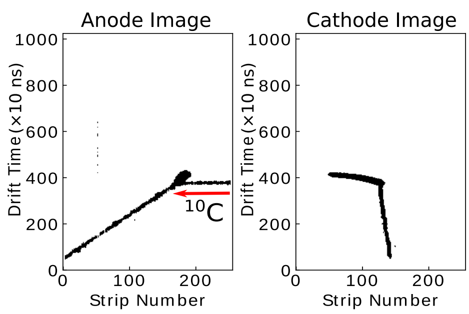

Fig. 3. Same with Fig. 2 but recorded in a background event.

2. Conventional analysis method

Conventionally, the Hough transformation was used in order to remove background events and to extract tracks. The Hough transformation is one of methods to find lines from an image. In the Hough transformation, a hit pixel in the image at (x_i, y_i) is transformed into a curved line in the (θ, r) parameter space (Hough space) according to Eq. (1).

$$r = x_i \cos\theta + y_i \sin\theta. \tag{1}$$

A point at (θ_i, r_i) in the Hough space specify a straight line in the original image as given by Eq. (2).

$$y = -\frac{x}{\tan\theta_j} + \frac{r_j}{\sin\theta_j}. \tag{2}$$

When the pixels in the anode or cathode image lie on a straight line, their transformed curves intersect at one point at (θ_j, r_j) in the Hough space. Thus, the intersection point in the Hough space gives the particle track according to Eq. (2).

It is possible to select the ^{10}C$+\alpha$ events by utilizing information about the straight lines extracted from the anode and cathode images such as length, angle, number, and position. Once the ^{10}C + α events are selected, the energies and anlges of the recoil α particles are determined from the images to calculate the excitation energies and the scattering angles in the center-of-mass system. However, the conventional analysis with the Hough transformation requires a complicated algorithm with many adjustable parameters, and the optimization of these parameters needs much efforts. It needs too much time to tune the parameters. It takes about 24 hours to optimize the parameters using 100 CPUs, and about 1 second to process the anode and cathode images from 1 event after the parameter optimization. The accuracy of the event selection was rated 89% using 3,000 events, which were tagged with human eyes.

3. New analysis method

The conventional analysis has problems of requiring complex algorithms and large computing power. It takes much time to analyze data from MAIKo TPC. We developed a new method using neural networks that are recently employed for image recognition. Using neural networks, it might be possible to recognize images considering many features of tracks at the same time without any complicated algorithms. Once a neural network trained, the neural network is able to recognize images faster and more accurately than the conventional analysis.

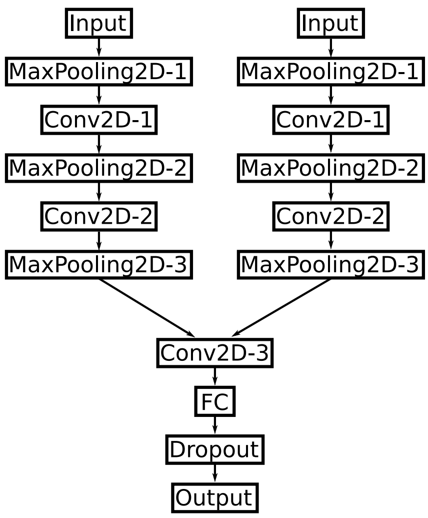

Fig. 4. Schematic structure of the neural network for the event selection.

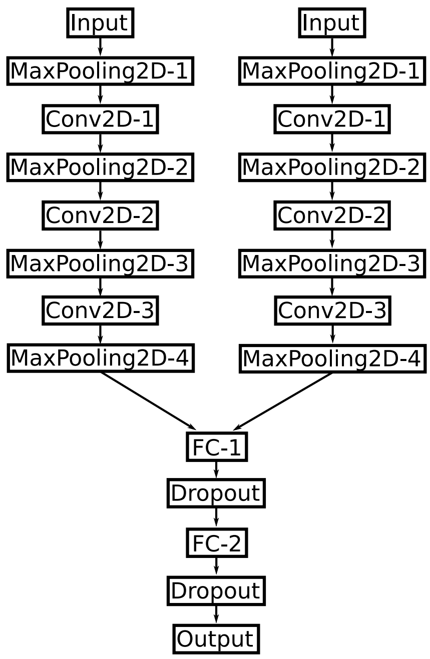

Fig. 5. Schematic structure of the neural network for the track extraction.

We used a convolutional neural network (CNN) that is useful for image recognition, because the data from the MAIKo TPC are images. Since the analysis consists of event selection and track extraction, we used two networks to analyze. Figures 4 and 5 show the networks for the event selection and the track extraction, respectively. Because the anode and cathode images have different features, the network has two branches. We inputted pair of images from MAIKo TPC to the neural network. The network for event selection has 16 layers and the network for track extraction has 21 layers. “Input”, “MaxPooling2D”, “Conv2D”, “FC”, and “Output” in Figs. 4 and 5 shows input layer, maxpooling layer, convolutional layer, full connection layer, and output layer respectively.

In event selection, we obtain a probability that this pair of images were taken in the ^{10}C + α event from output layer. If the probability was larger than 50%, the event was regarded as the ^{10}C + α scattering. This network was trained and evaluated with the data that was tagged by eye-scan. 2,700 events for training and 300 events for evaluation are used. In track extraction, the network outputted the coordinates of two endpoints of track where the ^{10}C + α scattering occurred and the recoil α particle stopped. This network was trained and evaluated with the data that was processed by the conventional method. 3,012 events for training and 1,554 events for evaluation were used.

We used Intel Core i7, Nvidia GeForce GTX 1080Ti, Ubuntu 18.04 LTS, and TensorFlow [3]+Keras [4].

4. Result

The neural network for the event selection trained 200 times for 2,700 events. It took about 26 minutes for training and about 1 second to process for 300 events. The accuracy of the event selection by the neural network evaluated by 300 events was 96%, while the accuracy by the conventional analysis was 89%. The neural network is able to select events faster and more accurately than the conventional method.

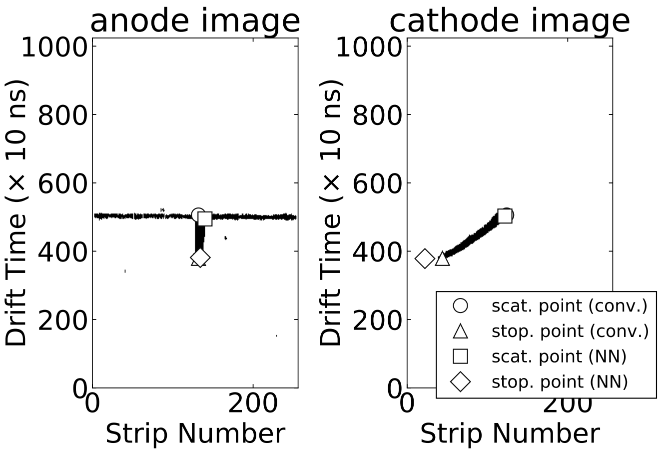

Fig. 6. Comparison of the track endpoints determined by the conventional method and the neural network.

The neural network for the track extraction trained 500 times for 3,012 events. It took about 270 minutes for training and about 2 seconds to process 1,554 events. The track endpoints determined by the neural network are compared with those by the conventional method in Fig. 6 in a typical event. The circles and triangles show the scattering and the stopping points determined by the conventional method, while the squares and rhombuses show the scattering and the stopping points determined by the neural network. The differences in the coordinates of the track endpoints determined by the conventional method and the neural network are about 4 mm in the standard deviation for 1,554 events. The processing time for the neural network to find the track endpoints became much shorter than the conventional method.

5. Conclusion

We developed a new method with neural networks to analyze the track images acquired by the MAIKo TPC. It was found that this new method made the event selection and the track extraction faster and more accurately than the conventional method with the Hough transformation.

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