New analysis method of TPC data using neural network

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In the experiments with TPC, we can detect tracks. A 3-dimensional track is projected into 2-dimensional planes. It is necessary to analyze 2-dimensional image data from TPC. Conventionally, the analysis is used Hough transformation. This analysis requires a lot of efforts. These days, neural networks are attracting attention. In this work, we develop new analysis method using neural networks. By using new method, analysis can be performed faster than the conventional method.

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

1. Introduction

These days, Time Projection Chamber (TPC) is widely used to detect tracks of charged particles. We developed Mu-PIC based Active target for Inverse Kinematics . (MAIKo) TPC [2] using Micro Pixel Chamber (μ-PIC) [1] for unstable nuclei experiments. Figure 1 shows the overview of MAIKo TPC. A detection gas is filled in TPC. When charged particles pass through the gas, electrons emitted. The electrons are drifted in the direction (downer arrow) of the readout surface by a drift electric field (upper arrow) and the tracks are detected. The μ-PIC has 256 of anode strips and cathode strips which are arranged orthogonally. These strips are aligned at 400-um intervals. Anode strips are parallel to x-axis in Fig. 1 and cathode strips are parallel to z-axis.The signals induced by the drifted electron are read out through the anode and cathode strips which provide the 2-dimensional position (x-axis and z-axis) of the particle tracks. The vertical position (y-axis) of the tracks are determined from the drift time of the electrons. The 3-dimensional tracks are reconstructed from x, y, z-coordinates.

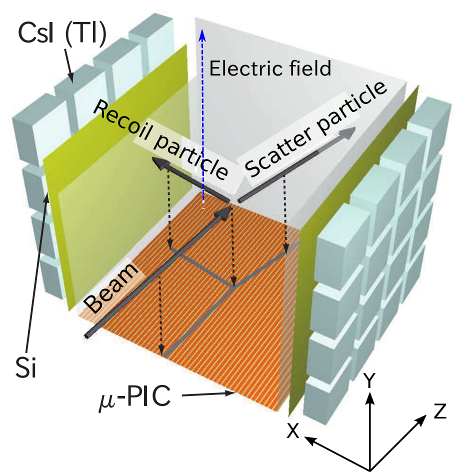

Fig. 1. MAIKo TPC の概観

MAIKo TPC is the active target that a detection gas is used for a target gas. By using the active target, incident particles scatter with target particles in the detector. It is possible to detect low energy particles with a large solid angle. He or H_2 that is widely used for a target gas has low discharge resistance. Normally, CO_2 or iso-butane that has high discharge resistance is used for a quench gas and mixed with target gases. The events that incident particles are scattered with quench gases are background events. The elastic and inelastic alpha scatterings on ^{10}C were measured with MAIKo

TPC at Research Center for Nuclear Physics, Osaka University (RCNP). In this experiment, He (96%) was used as target 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). MAIKo TPC outputs two images by one event. μ-PIC has 256 anode strips and 256 cathode strips, and measure waveform by 1,024 samples in 100 MHz. The resolution of an image from MAIKo TPC is 256 × 1,024. Figures 2 and 3 are examples of measured data at RCNP. Figure 2 is the event that a incident particle scatter with He and Fig. 3 is the event that a incident particle scatter with quench gas.

In a scattering experiment, it is necessary to determine the energy and emission angle of the scattering particles. The energy is determined from the length of a track. The emission angle is determined from tracks of the incident particle and the scattering particle. To extract the information of tracks, there are two steps.

- Select events scattered with target and background events.
- Extract the length and the emission angle from images.

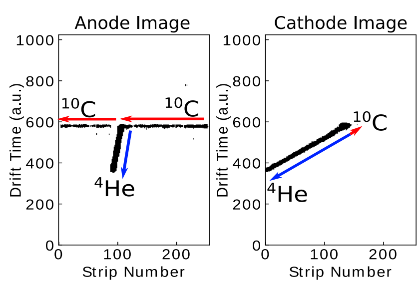

Fig. 2. ^{10}C + ^{4}He の散乱事象

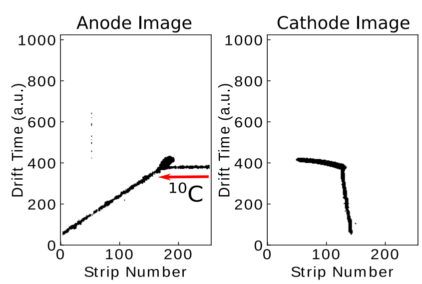

Fig. 3. ^{10}C とクエンチガスとの散乱事象

There are a lot of efforts to select events and extract information of tracks. So, we developed faster analysis method using neural networks that are attracted attention in image recognition.

2. Conventional analysis method

Conventionaly, the Hough transformation was used in order to remove background from data. The Hough transformation is one of methods to find lines from a image. Hough 変換を用いたアルゴリズムによって行ってきた。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 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 events scattered with He by using conditions of the length, the angle, the number, and the location of tracks. The energy and the scattering angle is determined from them. This method using the Hough transfomation needs complicated condition branches with many parameters. It needs too many times to tune the parameters.

It takes about 1 day to tune the parameters using 100 CPUs. It takes about 1 second by 1 event to process the images after the parameter tuning. The selection ability is evaluated by 3000 data that is judged by human eyes. The accuracy, that is ratio of judgement correctly, is 89%.

3. New analysis method

There is a problem that the conventional method needs complicated condition branches and much machine power. We develop new method using neural networks that are recently attracting attention for image recognition. Using neural networks, it is may possible to recognize images with not using complicated condition branches, but handleing many signatures. Onec a neural network trained, it is able to recognize images fast. Using features of neural networks, it is expected to realize higher accuracy and faster recognition speed than the conventional method.

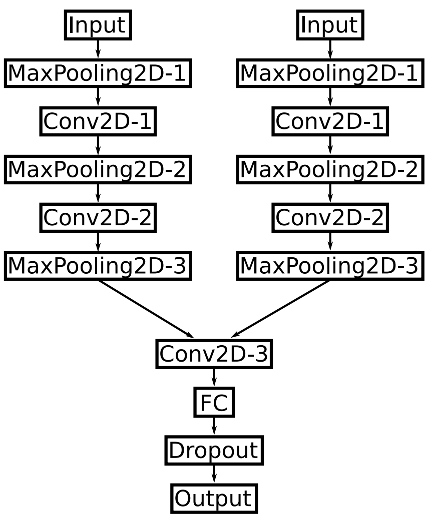

Fig. 4. This neural network selects events scattered with a target.

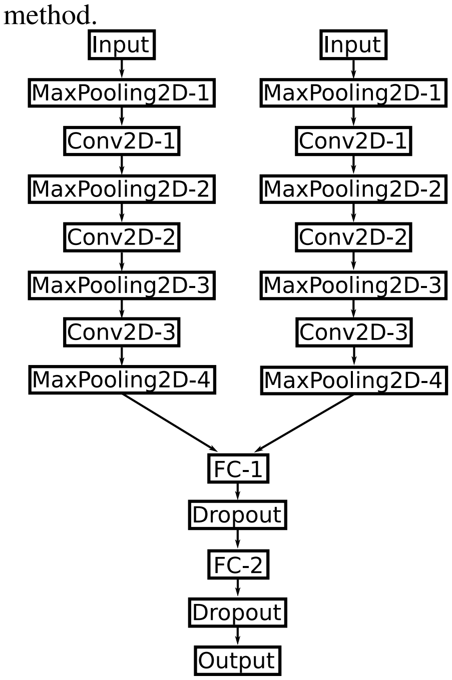

Fig. 5. This neural network extracts imformation of tracks from images.

We use Convolutional Neural Network (CNN) that is useful for image recognition, because the data from MAIKo TPC are images. CNN is the network that has convolutional layers. The analysis has two steps that are event selection and track extraction. We use two network to analyze. Figures 4 and 5 show the network that selects events and that extracts imformation of tracks.

The neural network for event selection is inputed pair of images from MAIKo TPC and outputs probability of event scattered with a target. If the probability is bigger than 50%, the event is judged scattered with a target. Because the anode image and cathode image has different features, the network has two branches. This network trained and was evaluated with the data that is judged by eye-scan. 2,700 events for training and 300 events for evaluation are used.

The neural network for track extraction is also inputed pair of images from MAIKo TPC and outputs coordinates of points at that a incident particle scattered and at that recoil ^{4}He stopped. This network trained and was evaluated with the data that is determined by the conventional method. 3,012 events for training and 1,554 events for evaluation are uesd.

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

4. Result

The neural network for 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 evaluated by 300 events that are used for evaluation of the conventional method is 96%. New method is able to select events in higher accuracy that the conventional method. It takes shorter time to tune parameters and to process than the conventional method.

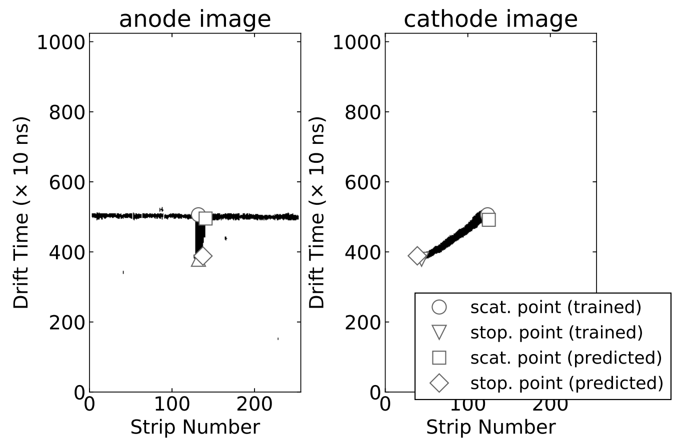

Fig. 6. This figure shows comparision of coordinates determined by the conventional method and the neural network.

The neural network for track extraction trained 500 times for 3,012 events. It took about 270 minutes for training and about 2 seconds to process for 1,554 events. Comparision of coordinates determined by the neural network and the conventional method is shown in Fig. 6 with a tipical image. The circle point and the triangle point is a scattering point and a stopping point determined by the conventinal method. The square point and the rhombus point is a scattering point and a stopping point determined by the neural network. The difference between points of conventinal method and neural network is about 4 mm in root mean squared error for 1,554 events. It takes shorter time to tune parameters and process than the conventional method.

5. Conclusion

We developped the new method with neural networks to replace the conventional method with Hough transformation. The new method selects and extracts in high accuracy and processes faster than the conventional method. Neural networks are usefull to analyze data of TPC.

References

[1] A. Ochi, T. Nagayoshi, T. Tanimori, T. Nagae, and M. Nakamura, Nucl. Instrum. Methods Phys. Res. A **471**, 264 (2001).

[2] T. Furuno, T. Kawabata, H. Ong, S. Adachi, Y. Ayyad, T. Baba, Y. Fujikawa, T. Hashimoto, K. Inaba, Y. Ishii, S. Kabuki, H. Kubo, Y. Matsuda, Y. Matsuoka, T. Mizumoto, T. Morimoto, M. Murata, T. Sawano, T. Suzuki, A. Takada, J. Tanaka, I. Tanihata, T. Tanimori, D. Tran, M-, Tsumura, and H. Watanabe, Nucl. Instrum. Methods Phys. Res. A **908**, 215 (2018).

[3] A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mané, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng, (2015). `https://tensorflow.org`

[4] F. Chollet, et al., (2015). `https://keras.io`

[5] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Proceedings of the IEEE **86**, 11, 2278 (1998).

[6] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume **1**, 1097 (2012).