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FOML，a deep learning based fast online multi-track locating algorithm for MPGD with silicon pixel sensors

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Background

Mirco Pattern Gaseous Detector (MPGD) plays a vital role in particle detection at The Heavy Ion Research Facility in Lanzhou and the High-Intensity Heavy Ion Accelerator Facility. The MPGD has amplification structures of a few micron meters. However, the pad size of the readout plane does not match the high granularity due to limitations on the integration level of readout electronics. To address this, using silicon pixel sensors with a pixel size of a few microns to read the MPGD becomes a good candidate, but this produces a vast amount of data from silicon pixels. Therefore, we have developed a Fast Online Multi-Track Locating (FOML) algorithm based on deep learning approaches. Figure 1 demonstrates the HiBeam-SEE system, which is realized based on the TPC principle of pixel-chip gainless readout for precise localization of single-particle effects in integrated circuits.

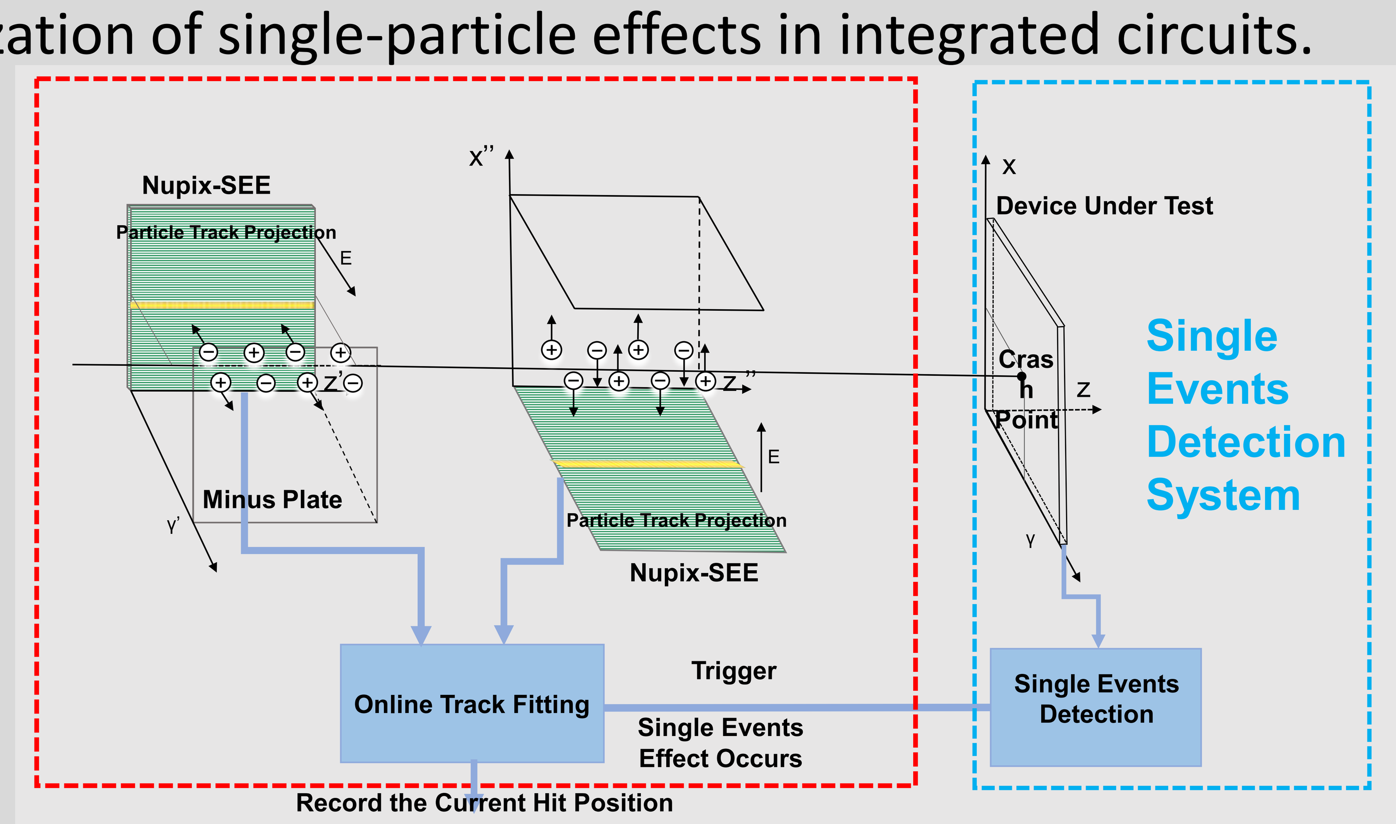

Figure 1 Heavy Ion Positioning System in HIRFL

Applications of Neural Networks in Physics

In physics research and applications, neural networks have excelled in pulse shape recognition, beam trajectory segmentation, and lesion detection in CT imaging. Examples include **CT reconstruction with CNN** methods proposed in [1], and end-to-end neural networks for feature extraction, regression of **beam trajectory paths by segmentation and fitting** proposed in [2]. This suggests that neural networks trained using large datasets have great potential for real-time trajectory localization.This is very much in line with the requirements for efficient detection and localization of detectors.

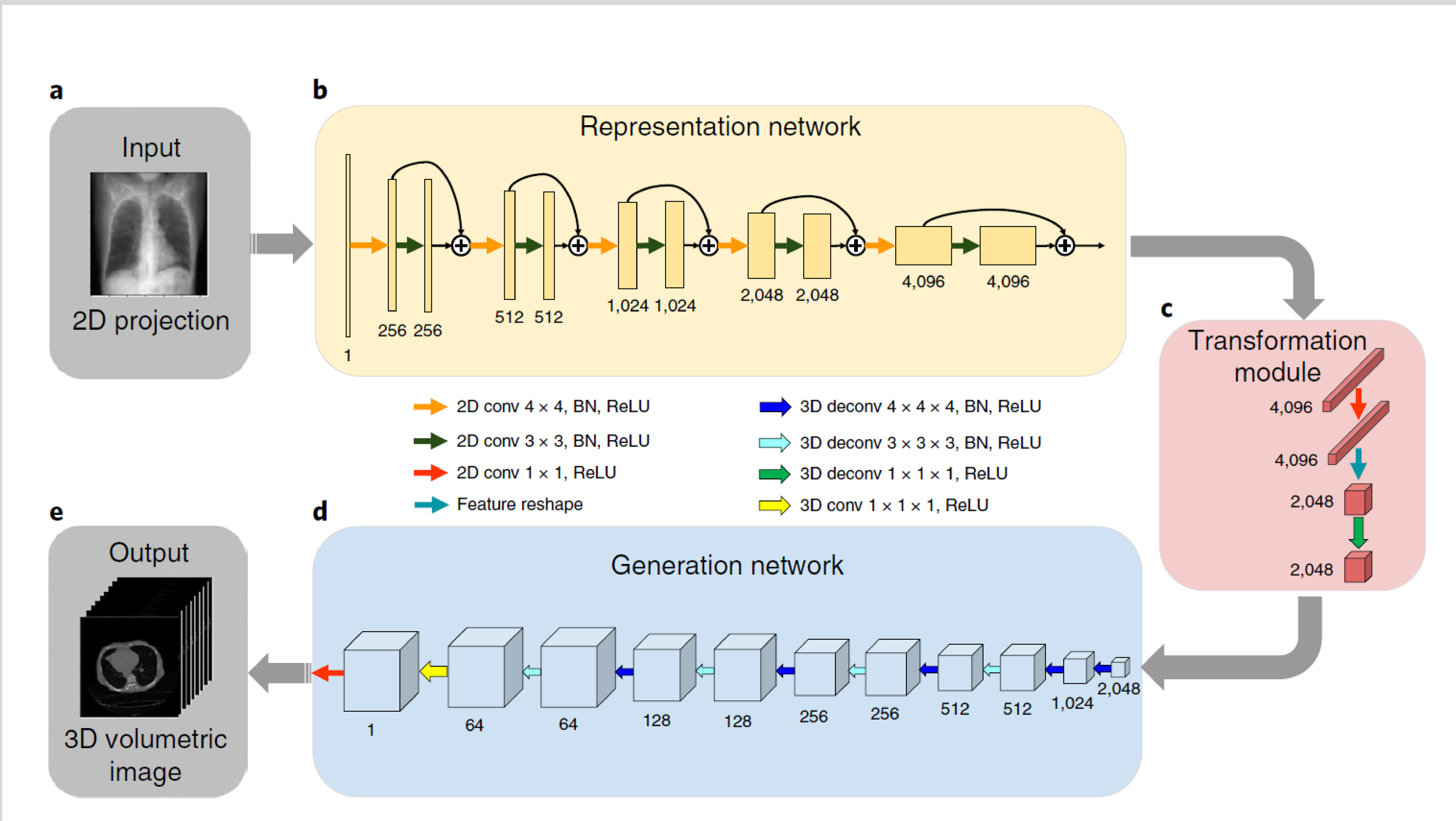

Figure 2 Deep learning based CT image reconstruction

Basic Architecture of FOML

The FOML we designed is also consistent with the classical detection model architecture, which consists of Backbone, Neck and detection head, respectively.

In our network, the Backbone part extracts the features of heavy ion images by reparameterization method to achieve implicit feature reuse while the model is more lightweight. Then, the outputs of several different stages in Backbone are used as inputs to Neck for more comprehensive information transfer and different levels of feature fusion through BiFPN network and attention mechanism module. Finally, the fused results are fed into the detection head for regression and classification calculations, outputting the results of category judgment and trail fitting for heavy ions. Among them, the design of detection head adopts the classical decoupling head structure, and the fused information is sent to the classification branch and regression branch for computation, which not only reduces the computational complexity of the model, but also improves the detection efficiency and accuracy of the model.

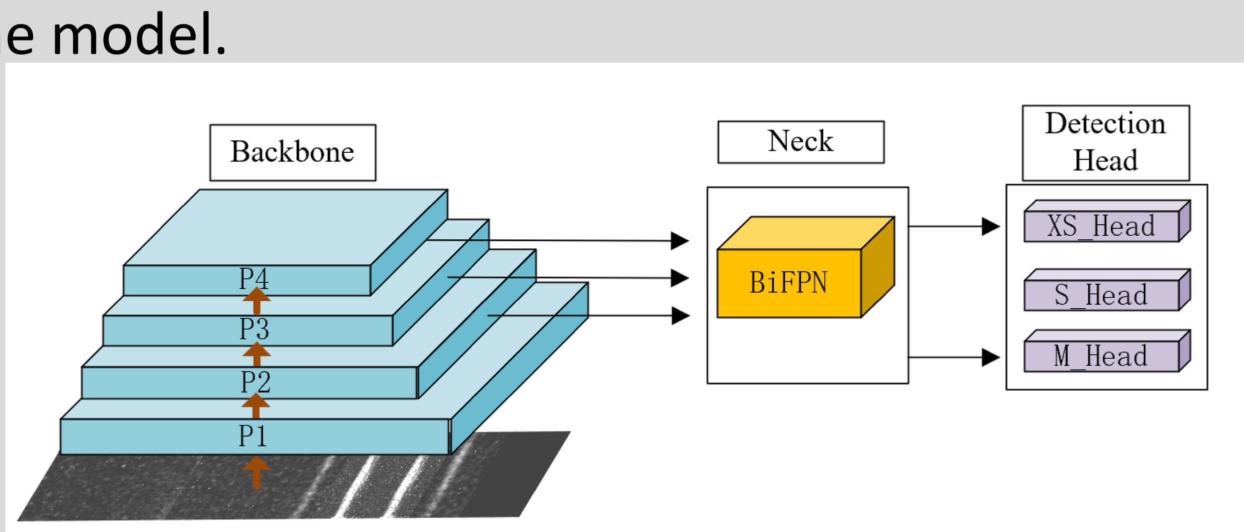

Figure 2 FOML Basic Structure Diagram

Key Indicators

Miss detection rate(%)	False detection rate(%)	Speed (fps)	positioning accuracy(μm)
0.32	0	452	1.81

Since reading MPGDs using silicon pixel sensors with pixel sizes of a few micrometers generates a large amount of silicon pixel data. We impose extremely high metrics on the deep learning-based FOML detection algorithm, especially in terms of leakage, false detection and detection speed. The above table makes a demonstration of the detection performance of FOML..

Conclusion

FOML was trained and tested on a dataset containing both actual and fused frames. The evaluation results show that FOML has a leakage rate of only 0.32%, no false detection rate, a processing speed of 452 fps, and a localization accuracy of 1.81 μm, which suggests that FOML can effectively meet the real-time detection requirements of microstructured gas detectors, demonstrating its great potential for real-time trajectory processing in detectors, and will be optimized for more application scenarios in the future.

References:
1.Shen L, Zhao W, Xing L. Patient-specific reconstruction of volumetric computed tomography images from a single projection view via deep learning[J]. Nature biomedical engineering, 2019, 3(11): 880-888.
2.Butanovs E, Zolotarjovs A, Kuzmin A, et al. Nanoscale X-ray detectors based on individual CdS, SnO2 and ZnO nanowires[J]. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 2021, 1014: 165736.