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Electron Image Reconstruction for Pixelated Semiconductor Tracking Detectors Based on Neural Networks

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Energetic electrons do not deposit their energy locally at their Point of Entry (PoE) into the detector volume but produce three-dimensional tracks. The energy deposition happens along these tracks, typically extending over several pixels. The structure of these tracks is caused by multiple scattering of the primary electron with the detector material and, therefore, statistically. The output of the pixelated semiconductor-based detector system is a binned two-dimensional projection of the energy deposition. However, to get images with a good spatial resolution, not the energy deposition into the detector volume is of interest but the PoE of the primary electrons into the detector volume.

We present a convolutional neural network (CNN) which reconstructs a frame-wise probability map. The probability describes for each physical pixel the probability that it contains a PoE map with values between zero and one. The CNN has no fully-connected layers and applies to different physical detector sizes without retraining. The basis of the CNN is a modified u-net [1]. The modular design of the CNN also enables the fast adaptation to different primary energies and physical pixel sizes via transfer learning.

Moreover, the CNN can be expanded by a super-resolution module to enable probability maps with subpixel resolution of a factor of four by four. The super-resolution shows its full power for primary energies below 120 keV. For these energies, the shape of the energy deposition arriving in the pixel structure is dominated by systematic effects like diffusion and repulsion and not by stochastic effects like multiple scattering. Therefore, a more precise reconstruction of the PoE is possible.

The training of the neural networks is realized in a highly automated pipeline which can be fed with data obtained by Monte Carlo simulation. A PoE reconstruction of individual PoEs requires the identifiability of tracks in the frames and no intensity images. Combined with the long individual tracks, each frame contains many pixels with no PoE and only a few pixels containing a PoE. The consequence is a so-called unbalanced data set. A specially designed loss function using the confusion matrix is used to handle this unbalanced data set. This loss function $\mathcal{L}$ contains three components [2]:

$$\mathcal{L}(g,p) = a \cdot TPR(g,p) + b \cdot TNR(\bar{g},\bar{p}) + c \cdot \Delta(g,\bar{g},p)$$

TPR is derived from the Rate of the True Positives of the confusion matrix, *TNR* from the Rate of the True Negatives, and Δ explicitly handles the difference between the number of PoEs of the prediction p and the ground truth g per frame. The inverse of the prediction and the ground truth are defined as $\bar{p} = 1 - p$ and $\bar{g} = 1 - g$. The prefactors a, b, and c can be individually adjusted to the used training set. The ratio between a and b should be in the ratio between pixels with PoE and pixels with no PoE. The choice of c should be between a and b or smaller. A too-large factor c potentially leads to disregarding the *TPR* and *TNR*. The choice of these prefactors has a large influence on the multiplicity, which describes the ratio between reconstructed PoEs and PoEs in the ground truth. A multiplicity of one means that each primary electron creates one reconstructed PoE on average.

The other parameter significantly influences the multiplicity is the applied threshold to the neural network's output. The applied threshold transfers the probability map into a binary response for each pixel. For a probability above the threshold, the binary response of a pixel is one, and for a probability below the threshold, the binary response is zero. Fig. 1a shows the influence of the applied threshold on the multiplicity and the modulation transfer function (MTF) value at 0.5 times the Nyquist frequency. With higher thresholds, the multiplicity decreases, and the MTF increases. For thresholds close to zero and larger than 0.85, the contrast, respectively, the statistic is worse, and it is impossible to determine the MTF via the slanted edge method [3]. Typically, the applied threshold is around 0.5. However, the choice of the applied threshold depends on the application. A higher threshold leads to a better resolution since only pixels are considered where the probability is high that the pixel contains a PoE. However, a higher threshold can only be used if the measurement statistic is high enough that it is tolerable not to consider pixels with a PoE with a lower probability containing a PoE.

Fig. 1b depicts the multiplicity and the MTF value at 0.5 times the Nyquist frequency for different primary electron rates for a constantly applied threshold. The multiplicity is one for very low particle rates since the event patterns are easily separable. With increasing rate, more overlapping events occur and, therefore, the ratio of pattern pile-up events increases rapidly. The consequence of pattern pile-up events is a decreasing multiplicity. The multiplicity is for low rates higher than one to compensate for the decrease. This ensures a multiplicity of one at the average primary particle rate of the training dataset. The MTF is constant up to a rate of 0.04 e - /pix/frame and decreases slowly for higher rates. Therefore, even with higher electron rates, the CNN is able to separate so-called pattern pile-up events and reconstruct the PoE of the individual contributing electrons. A pattern pile-up event is a cluster of adjacent pixels containing the energy deposition of two or more primary electrons.

Using the presented CNN to reconstruct frame-wise the PoE of individual primary electrons enables a high spatial resolution, which can be extended to subpixel resolution for lower primary energies. Application examples will be provided.

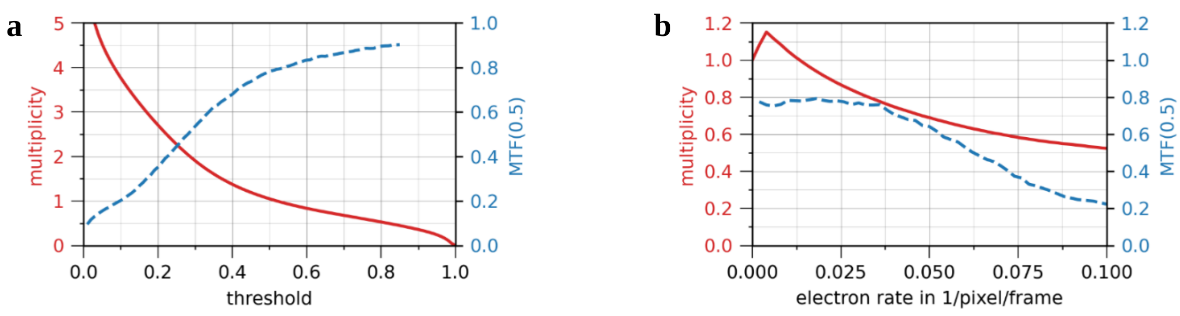

Fig. 1. Multiplicity (solid line) and MTF (dashed line) for a simulated primary energy of 300 keV. The MTF is obtained via the slanted edge method and graphed at 0.5 times the Nyquist frequency [3].
a: Quantities as a function of the applied threshold for a primary particle rate of 0.01 e/pix/frame.
b: Quantities as a function of the primary electron rate for an applied threshold of 0.5.

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