Research on restoration method of nuclear pulse current signal of semiconductor detector based on artificial neural networks

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Abstract. The charge pulse generated by semiconductor detector caused by nuclear event carries nuclide and nuclear reaction information, but the amplified charge pulse amplitude is obviously weak and the noise is so large. Aiming at the difficulty of obtaining the charge signal pulse generated by the detector, a method for recovering the nuclear pulse current signal of semiconductor detector is proposed. Pulse recovery is divided into two parts: pulse shape recovery and pulse amplitude recovery. Point at the pulse shape, a shape recognition network of nuclear pulse current signal based on deep learning is proposed. For pulse amplitude, it can be obtained by Mexican straw hat wavelet forming algorithm. This algorithm can eliminate the baseline fluctuation caused by pulse stacking. The proposed shape recognition network of nuclear pulse current signal is composed of classifier and regressor. The classifier is used to judge whether the data contains a complete rising edge. The data containing the complete rising edge is sent to the regressor for prediction, so as to obtain the parameters related to the current pulse shape. The precision, recall and F-Measure of the classifier in classifying the test set are 98.88\%, 98.05\% and 98.33\%, respectively. The average absolute error of the regressor in predicting the parameters related to the current pulse shape is about 9 ns. The experimental results show that the proposed method can recover the shape and amplitude of the current signal.

1. Introduction
In semiconductor detectors, the energy loss of rays entering the sensitive layer of the detector produces a large number of electron hole pairs, and the current pulses formed by the movement of electron hole pairs with different points in the electric field have different characteristics. Therefore, the generation position of the electron hole pair can be determined by the shape of the current pulse. Therefore, the generation position of the electron hole pair can be determined by the shape of the current pulse. The incident depth of different types of particles in the detector is different, so the particle type can be determined by analyzing the position information generated by carriers. However, all charged particles of 1MeV are consumed in the sensitive layer, and 30000 electron hole pairs [1] are ionized on average. The amplitude of the amplified signal is still very small. Therefore, the fluctuation of internal noise of electronic devices will cause great interference to the signal. At present, transient current technology [2, 3] can capture current pulses, but this method requires accurate oscilloscope trigger setting and efficient high-frequency noise shielding [4], and the detected pulse amplitude is obviously weak and the noise is large. Therefore, the method of integrating current with capacitor as load opens up a new idea for the study of current pulse. After the current passes through the RC circuit, a voltage pulse is generated, and...
the shape of the current pulse will affect the rising edge of the voltage pulse. Therefore, this paper studies how to recover the current signal by using the voltage signal. Due to the relatively long time for the capacitor to release charge, the voltage pulses will randomly stack at high count rate, resulting in baseline fluctuation and pulse height change, which brings challenges to the recovery of current pulse signal.

In recent years, with the development of deep learning, most scholars began to pay attention to its application in the nuclear field [5, 6, 7, 8, 9, 10]. Chen Jun-Ling et al. [11] used neural network to recover the saturated signal waveform obtained from high-energy particles. Islami rad et al. [12] and Taheri et al. [13] trained different neural networks to identify the position of ray interaction through energy spectrum. In terms of pulse stacking, Regadio et al. [14] used neural network to solve the pulse stacking problem and estimate the pulse height; Fu et al. [15] used recurrent neural networks to recover the stacking pulses generated during the interaction between neutrons and gamma rays. It can be seen that the stacking problem can be solved by neural network, and then the pulse shape can be restored. According to the relationship between current pulse and voltage pulse, a neural network for current pulse shape restoration is proposed in this paper.

2. Current pulse recovery method

The current pulse is a stepped rectangular pulse. The recovery of the current pulse includes the recovery of the pulse shape and the recovery of the pulse amplitude. The pulse amplitude can be recovered by Mexican straw hat wavelet shaping algorithm, which can eliminate the influence of baseline fluctuation. The pulse shape can be recovered by nuclear pulse current signal shape recognition network.

2.1. Current pulses at different positions

The electron hole pair drifts to two stages under the action of electric field, which causes the change of induced charge on the electrode plate and forms a current pulse in the output circuit. The motion of the carriers of these two polarities before they are all collected determines the shape of the current pulse. Shockley Lamo [16, 17] theorem gives the relationship between the current pulse and the spatial distribution of the electric field inside the detector:

\[
I(t) = \frac{Q \mu E(X(t))}{X}
\]

(1)

Where Q is the charge deposited by electrons or holes; \( \mu \) is the mobility of carriers; \( E(X(t)) \) is the electric field strength; X is the distance between two plates. For planar detectors, the electric field is constant in the whole depletion region, so the value of current remains unchanged until the carrier reaches the plate. Due to the different drift velocities of electron and hole pairs, the collection time of holes and electrons with generation point \( x_0 \) can be expressed by \( t_n \) and \( t_p \):

\[
t_n = \frac{X - x_0}{\mu_n E}
\]

(2)

\[
t_p = \frac{x_0}{\mu_p E}
\]

(3)

Where, \( \mu_n \) is the mobility of electrons; \( \mu_p \) is the mobility of holes; \( x_0 \) is the distance from the carrier generation point to the negative plate.

Fig.1 shows the current pulses obtained from electron hole pairs at different generation points in a planar silicon P-I-N detector. The intrinsic layer thickness of P-I-N semiconductor detector is generally about 10mm, so the collection time of electrons and holes is generally on the order of 10^-7s.
Figure 1. The planar silicon P-I-N detector pair generates current pulses from electron hole pairs with different points.

Assuming that the time when electrons and holes move in the electric field at the same time is $t_1$ and the time when only one carrier moves in the electric field is $t_2$, the shape of the current pulse can be described by $t_1$ and $t_2$:

$$t_1 = \min\{t_p, t_n\}$$ (4)

$$t_2 = t_n + t_p - t_i$$ (5)

According to equations (2) - (5), $t_1$ of the pulse generated near the p pole or n pole of the detector sensitive area is approximately zero. In the middle of the sensitive region, there is a point where the pulse rise time is the shortest, and the time of electrons and holes arriving at the two plates is exactly the same, that is, $t_2$ is approximately zero. Therefore, both $t_1$ and $t_2$ can take zero, and the ratio of $t_1$ to $t_2$ changes with the change of carrier generation point.

2.2. Pulse shape analysis and recovery

The current pulse generated by the interaction between ray and semiconductor is transmitted from the detector to the amplification circuit. The equivalent circuit of detector and amplifier input is shown in Fig. 2. Where $I_0(t)$ is the current formed by the carrier motion generated by the ionization event in the depletion layer. $U(t)$ is the output voltage pulse of the detector, that is, the waveform at the input of the amplifier. $R$ and $C$ are equivalent resistance and equivalent capacitance.

$$H_{RC}(S) = \frac{U(s)}{I_0(s)} = \frac{1}{RCs}$$ (6)

In equation (6), the impact response of the system obtained by inverse Laplace transform is:
\[ h_{RC}(t) = \frac{1}{C} e^{-\frac{t}{RC}} \]  

(7)

In linear time invariant systems, the output signal can be represented by the convolution of the input signal and the system impulse response. The expression of voltage pulse is:

\[ U(t) = I_0(t) * h_{RC}(t) = I_0(t) * \frac{1}{C} e^{-\frac{t}{RC}} \]  

(8)

It can be seen from equation (8) that the voltage pulse is the result of the convolution of the current pulse and the system function, and the pulse shape of the current will affect the pulse shape of the voltage.

In order to make the variation characteristics of the output voltage easier to observe, the amplitude of the output voltage pulse is normalized, and the rising part of the waveform is intercepted for comparison, as shown in Fig. 3. The figure shows the voltage pulses obtained after current pulses of different shapes pass through RC circuit. As can be seen from Fig. 3 (a), when the current pulse duration is the same but the ratio of \( t_1 \) to \( t_2 \) changes, the voltage pulse shape changes with the change of \( t_1 \). As can be seen from Fig. 3 (b), when the ratio of \( t_1 \) to \( t_2 \) remains unchanged, the width of the rising edge of the voltage pulse becomes wider with the increase of the duration. Obviously, the shape of the rising edge of the voltage pulse reflects the shape of the current pulse. Therefore, by analyzing the shape of the rising edge of the voltage pulse, the shape of the current pulse can be obtained.

[Figure 3. Comparison diagram of voltage pulses amplified by current pulses of different shapes(a) with different duration but same ratio(b) with the same duration but different ratio]

The recovery method of current pulse shape is shown in Fig.4. After the current pulse passes through the RC circuit, a voltage pulse containing noise is generated. Because the existing technology can identify the number of pulses, but can’t judge whether the pulses are complete, it is necessary for the classifier to classify the voltage pulses containing noise and discard the pulse data without complete rising edge. The function of the regressor is to correct the accumulation and predict the parameters related to the current pulse shape. The network structure of classifier and regressor in Fig.4 is shown in summary 3.

[Figure 4. Recovery method of current pulse shape]
2.3. Pulse amplitude analysis and recovery

The current pulse has two amplitudes, and the relationship between the two amplitudes is given by equation (1). After one amplitude is known, another amplitude can be calculated according to the mobility of electrons and holes. It can be seen from equation (8) that there is a linear relationship between the amplitude of the voltage pulse and the amplitude of the current pulse. \( h_1 \) and \( h_2 \) can be used to represent the current pulse amplitude, and \( H_1 \) and \( H_2 \) can be used to represent the voltage pulse amplitude, as shown in Fig. 5.

![Figure 5. Pulse amplitude](image)

The amplitude of the unit current pulse and the amplitude of the unit voltage pulse are known. If the voltage pulse amplitude is obtained again, the amplitude of the current pulse can be obtained through equation (9).

\[
\frac{H_1}{h_1} = \frac{H_2}{h_2}
\]

However, in the case of high count rate, voltage pulses will randomly stack, resulting in baseline fluctuation and pulse height change. The Mexican straw hat wavelet shaping algorithm [18] can solve the problem of baseline fluctuation and obtain the amplitude of voltage pulse. Let the expression of the input pulse signal be as follows:

\[
X(t) = H \exp\left(-\frac{t}{\tau_0}\right)u(t)
\]

Where, \( H \) is the pulse signal amplitude; \( \tau_0 \) is the exponential decay constant; \( u(t) \) is the unit step function. The impulse response is:

\[
h(t) = \left[1 - \frac{t^3}{s^2} + \frac{3t}{s^2} \left(1 - \frac{t^2}{s^2}\right)\right] \exp\left(-\frac{t^2}{2s^2}\right)
\]

Where, \( s \) is the scale factor of wavelet transform.

\( y(t) \) can be expressed by the input signal \( x(t) \) and the system impulse response \( h(t) \), and its expression is as follows:

\[
y(t) = x(t) * h(t) = Hg\left(\frac{t}{s}\right)
\]

Where, \( g(t) \) is the mother small fundamental wave, and its expression is as follows:

\[
g(t) = (1-t^2) \exp\left(-\frac{t^2}{2}\right)
\]

\( h(t) \) in equation (11) is a quadratic smoothing function, so the convolution identity between the linear function and \( h(t) \) is equal to zero, that is, the convolution identity between the linear baseline
superimposed on the pulse and $h(t)$ is equal to zero. Obviously, when calculating the height of the formed Mexican straw hat wavelet pulse, the amplitude of the voltage pulse can be obtained without deducting the baseline, and then the amplitude of the current pulse can be obtained.

3. Data preparation

The data set used in this paper is generated by simulation. The simulation process is shown in Figure 4. The randomly generated current pulse signal generates voltage pulse with noise after passing through RC circuit. In this experiment, two data sets are generated. Each group of data in the data set contains 200 features. These 200 features are the sampling data of voltage pulses with a pass rate of 106 at a frequency of 100MHz. The duration of the sampled voltage pulses is $2\mu s$. The sampling point of data set A contains the voltage pulse generated by incomplete current pulse, which is used to train the classifier. The sampling points of data set B are all from the voltage pulse generated by the complete current pulse, which is used to train the regressor. Both data sets contain 20000 groups of data, which are divided into training set and test set according to the ratio of 7:3. The sampled voltage pulse data is given by equation (14).

$$U(t) = I(t) * e^{-\frac{t}{\tau}} + n(t)$$  (14)

Where, $g(t)$ is the mother small fundamental wave, and its expression is as follows:

Where $I(t)$ is the current generated by carrier motion; $n(t)$ is the white noise with a signal-to-noise ratio of 70 dB generated by the random number generator; $\tau$ is the exponential decay constant, with a value of 800.

Considering the influence of stacking, this paper sets the number of pulses contained in each group of data as 1-2. Therefore, the pulse shape of the current can be $t_1_1$, $t_2_1$, $t_1_2$ and $t_2_2$ these four parameters are described, that is, the four labels of dataset B. Where, $t_1_1$ represents the time when electrons and holes move in the electric field at the same time in the first pulse, $t_2_1$ represents the time when only one carrier moves in the electric field in the first pulse, $t_1_2$ represents the time when only one carrier moves in the electric field in the second pulse, $t_2_2$ represents the time when only one carrier moves in the electric field in the second pulse. When the number of current pulses is 1, use $t_1_1$ and $t_2_1$ indicates the parameters of the pulse. For each current pulse, the following two conditions need to be met:

1. The pulse duration is 200ns-400ns, i.e. $200\text{ns} \leq t_1 + t_2 \leq 400\text{ns}$;
2. Carriers may be generated at any position in the detector, that is, $t_1$ and $t_2$ take any ratio.

When the number of current pulses is 1, the pulse may appear at any position of the sampling window (For dataset a, the pulse can exceed the sampling window when it is on the leftmost or rightmost side; for dataset B, the pulse cannot exceed the sampling window when it is on the leftmost or rightmost side); When the number of current pulses is 2, two pulses are generated at random intervals. Such two pulses may appear at any position of the sampling window.

4. Network and training

4.1. Overall network design

In this paper, a shape recognition network of nuclear pulse current signal is proposed, which is composed of classifier and regressor, as shown in Fig. 6. Since the prior art can only identify the number of pulses and cannot identify the integrity of pulses, it is necessary to judge the integrity of the rising edge of voltage pulses before predicting the shape of current pulses. If the input sample has no complete rising edge, it will be divided into discarded samples, and this group of data will be discarded; If the input sample contains a complete rising edge, it will be divided into prediction samples, and this set of data will be sent to the regressor. The regressor processes the voltage pulse data from the classifier and finally outputs the parameters related to the corresponding current pulse shape.
4.2. Classification network and training
The classifier is a BP neural network with three hidden layers. The number of neurons in the hidden layer is 600, 200 and 50 in turn. Its structure is shown in Fig. 7. The classifier contains 200 inputs and 2 outputs. The samples can be divided into prediction samples and discarded samples.

\[
L = \frac{1}{N} \sum_{i} \left[ y_i \cdot \log(p_i) + (1-y_i) \cdot \log(1-p_i) \right]
\]  

(15)

Where, \( y_i \) is the label of the sample; \( p_i \) is the probability that the sample is predicted to be a positive class. In order to reduce the loss value, back propagation uses Adam optimization algorithm to update the network weight.

4.3. Regression network and training
The classifier is a BP neural network with two hidden layers. The number of neurons in the hidden layer is 600 and 200 in turn. Its structure is shown in Fig. 8. The regressor contains 200 inputs and 4 outputs to predict the current pulse shape.
The regressor is trained by data set B with a learning rate of 0.001. The root mean square loss function is used to calculate the difference between the real value and the predicted value to judge the effect of the network. The root mean square loss function is defined as follows:

\[
\text{loss} = (\hat{y}_i - y_i)^2
\]  

(16)

Where, \(\hat{y}_i\) is the predicted value of the sample; \(y_i\) is the label of the sample. Back propagation uses Adam optimization algorithm to update the network weight.

5. Evaluation index and result analysis

In this experiment, Pytoch is used to realize the network architecture, and training is carried out on Google colab.

5.1. Evaluating indicator

The performance of classifier is evaluated by accuracy, recall and F value. Accuracy rate refers to the percentage of positive samples in the results predicted as positive samples by the classifier, which is defined as follows:

\[
\text{Precision} = \frac{TP}{TP + TF}
\]  

(17)

Where, TP refers to the number of data belonging to this category correctly classified into this category, TN refers to the number of data not belonging to this category classified into this category, FP refers to the number of data belonging to this class wrongly divided into other classes, and FN refers to the number of data not belonging to this class correctly excluded. Recall rate refers to the percentage of the predicted positive samples in the actual positive samples, which is defined as follows:

\[
\text{Recall} = \frac{TP}{TP + FN}
\]  

(18)

F value is a harmonic average, taking into account the accuracy rate and recall rate. Its definition is as follows:

\[
F = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}
\]  

(19)
The evaluation indexes of regression network include root mean square error (RMSE), mean absolute error (MAE) and coefficient of determination (R Squared). Use $y_i$ and $\hat{y}_i$ I represents the label and predicted value respectively, $\bar{y}$ represents the average value of the label, and m is the number of samples, so the definition of evaluation index is as follows:

$$\text{RMSE} = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2}$$

$$\text{MAE} = \frac{1}{m} \sum_{i=1}^{m} |y_i - \hat{y}_i|$$

The smaller the value of MEA and RMSE, the higher the prediction accuracy and the better the prediction effect. R squared reflects the degree to which the independent variable explains the change of the dependent variable. The closer its value is to 1, the better the model fitting.

5.2. Result analysis

The test set is used to evaluate the performance of the network. The accuracy rate of classifier is 98.88%, the recall rate is 98.05%, and the F value is 98.33%. Table 1 shows the prediction performance of the regressor. The MAE of the predicted values are 9.8, 10.5, 8.4 and 9.6 respectively; RMSE were 15.0, 16.2, 18.9 and 19.4, respectively; R squared were 0.972, 0.966, 0.973 and 0.937 respectively. For the sampling frequency of 100MHz, the minimum step size is 10ns, while the MAE of the regressor is about 9ns. It can be seen that the relative error of the current pulse shape recovered by the trained regressor is small.

| Parameter | t1_1 | t2_1 | t1_2 | t2_2 |
|-----------|------|------|------|------|
| MAE       | 9.8  | 10.5 | 8.4  | 9.6  |
| RMSE      | 15.0 | 16.2 | 18.9 | 19.4 |
| R Squared | 0.979| 0.966| 0.973| 0.937|

Take any 100 groups of predicted values of t1_1, t2_1, t1_2 and t2_2 and compare them with the real values, as shown in Fig.9. The dots represent the real value and the triangles represent the predicted value of the regressor. The abscissa in Fig. 9 represents any set of values without actual physical significance, and the ordinate represents the real value or predicted value of this set of data. t1_1 and t2_1 in Fig. 9 (a) and Fig. 9 (b) are the two parameters of the first pulse, and t1_2 and t2_2 in Fig. 9 (c) and Fig. 9 (d) are the two parameters of the second pulse. The values of t1_2 and t2_2 of some data are zero, indicating that the number of pulses of this group of data is 1.
6. Conclusion

In this paper, the current pulse shapes generated by carriers with different generation points are compared, and the pulse shapes of current pulse and voltage pulse generated through RC circuit are compared and analyzed. It is found that the current pulse shape will affect the rising edge of voltage pulse. According to the relationship between current pulse shape and voltage pulse shape, a nuclear pulse current signal recovery method is proposed. The restoration of nuclear pulse current signal is divided into two parts: pulse shape restoration and pulse amplitude restoration:

1. For the current pulse shape, the nuclear pulse current signal shape recognition network can be used to recover the current pulse shape;
2. For the amplitude of current pulse, Mexican straw hat wavelet shaping algorithm can be used to recover, which can eliminate the influence of baseline fluctuation.

The shape recognition network of nuclear pulse current signal is composed of classifier and regressor, which is suitable for identifying no more than two pulse signals. The classifier is used to screen the qualified pulse waveform, and the regressor is used to correct the accumulation and return the relevant parameters of the current pulse shape. The accuracy, recall and F value of the classifier are 98.88%, 98.05% and 98.33% respectively. The average absolute error of the regressor for the prediction of current pulse shape related parameters is about 9ns. The experimental results show that the proposed nuclear pulse current signal shape recognition network can recognize the current pulse shape, and the pulse signal can be recovered according to the pulse shape and pulse amplitude.

References

[1] WANG jing-jin, FAN tian-min, QIAN yong-kang, et al. Nuclear Electronics. Atomic Energy Press, Beijing.

[2] Martini M, Mayer J W, Zanio K R. (1972) Drift Velocity and Trapping in Semiconductors—Transient Charge Technique. Elsevier, 3: 181–261.

[3] Eremin V, Strokan N, Verbitskaya E, et al. (1996) Development of transient current and charge techniques for the measurement of effective net concentration of ionized charges (Neff) in the space charge region of p-n junction detectors. Nuclear Instruments and Methods in Physics Research Section A, 372(3): 388–398.
[4] Praus P, Belas E, Franc J, et al. (2014) Electronic pulse shape formation in transient charge and transient current detection approach in (CdZn)Te detectors. IEEE Transactions on Nuclear Science, 61(4): 2333–2337. DOI: 10.1109/TNS.2014.2330070.

[5] JIN Shuang, LIU Xiaojing, CHENG Xu. (2021) Optimization method of CFD coarse grid numerical simulation based on neural network. Nuclear Techniques, 4(06): 77-83.

[6] CHEN Li, GU Min, ZENG Guoqiang, et al. (2017) Radon daughter subtraction algorithm for artificial radioactive aerosol based on neural network. Nuclear Techniques, 0(09): 45-49.

[7] Yu Liu, Jing-Jun, Zhu, Neil Roberts, Ke-Ming Chen, et al. (2019) Recovery of saturated signal waveform acquired from high-energy particles with artificial neural networks. Nuclear Science and Techniques, 30(10): 97-106.

[8] Hao-Ran Liu, Yu-Xin Cheng, Zhuo Zuo, et al. (2021) Discrimination of neutrons and gamma rays in plastic scintillator based on pulse-coupled neural network. Nuclear Science and Techniques, 32(08): 50-58.

[9] YU Zhi-xiang, CHEN Hai-long, LIAN Bing. (2020) Prediction of radon exhalation rate on the surface of in-situ leaching evaporation tank by BP neural network inversion. Nuclear Electronics and Detection Technology, 40(01): 178-183.

[10] Woldegiorgis S, Enqvist A, Baciak J. (2021) ResNet and CycleGAN for pulse shape discrimination of He-4 detector pulses: Recovering pulses conventional algorithms fail to label unanimously. Applied Radiation and Isotopes, 176: 109819.

[11] Jun-Ling Chen, Peng-Cheng Ai, Dong Wang, et al. (2020) FPGA implementation of neural network accelerator for pulse information extraction in high energy physics. Nuclear Science and Techniques, 31(05): 29-37.

[12] Islami rad S Z, Peyvandi R G. (2019) A novel and fast technique for evaluation of plastic rod scintillators as position sensitive gamma-ray detectors using artificial neural networks. Radiation Physics and Chemistry, 157: 1–5.

[13] Taheri A, Askari M, Sasanpour M T. (2020) A beta-gamma position-sensitive detector based on rod plastic scintillators and artificial neural networks. Journal of Instrumentation, 15(6).

[14] Regadio A, Esteban L, Sánchez-Prieto S. (2021) Unfolding using deep learning and its application on pulse height analysis and pile-up management. Nuclear Instruments and Methods in Physics Research, 1005(April): 165403.

[15] Fu C, Du fulvio A, Clarke S D, et al. (2018) Artificial neural network algorithms for pulse shape discrimination and recovery of piled-up pulses in organic scintillators. Annals of Nuclear Energy, 120: 410–421.

[16] Ramo S. (1939) Currents Induced by Electron Motion. Proceedings of the IRE, 27(9): 584–585.

[17] Mitra, P. (1970) Current to Conductors Induced by a Moving Point Charge. American Journal of Physics, 38(1): 112–112.

[18] Qin Z jian, Chen C, Luo J song, et al. (2018) A pulse-shape discrimination method for improving Gamma-ray spectrometry based on a new digital shaping filter. Radiation Physics and Chemistry, 145: 193–201.