Accuracy improvement of avalanche photodiode based filter-less spectroscopy by deep learning

Masahiro Akiyama^{1*}, Takaya Ishikawa², Takashi Miyazaki¹

¹NIT Nagano College, 716 Tokuma Nagano-shi, Nagano 381-8550, Japan

²Chiba University, 1-33 Yayoi-cho Inage-ku Chiba-shi, Chiba 263-8522, Japan

*akiyama@nagano-nct.ac.jp

1. Abstract

In this paper, we report a highly sensitive filter-less spectroscopy method using an avalanche photodiode (APD) by deep learning. Many different band pass filters or grating methods are commonly employed. Electron multiplying charge-coupled devices (CCD) are commonly used for high sensitivity sensing. However, conventional devices consisting of filters or gratings provide a relatively huge system size. In addition, the light intensity diminishes at the filters/gratings. Previously, experimental measurements using the proposed APD-based spectroscopy method exhibits the sensing capability to detect and divide dual wavelength light without band pass filters or grating for applying fluorescence and excitation lights detection. However, the proposed spectroscopy method has a problem in calculation with noises. The noises lead an inaccurate answer. So we propose a new method with deep learning instead of the calculation for improving spectroscopy accuracy.

Keywords: Avalanche photodiode, Filter-less, Deep-learning

2. Introduction

Conventionally, fluorescent labels and an expensive fluorescent scanner are used for DNA analysis [1]. The fluorescent scanner requires a special light source with a band pass filter [2]. It is, in consequence, relatively bulky by the filters. On the other hand, the biochemistry field has need of a straightforward space-saving fluorescence detection system with filter-less [3, 4]. The filter-less systems are used characteristics of absorption coefficients(α) for sensing multi-wavelength fluorescence light.

Previously, we reported the APD-based filter-less

spectroscopy method by complex calculation [5]. The principle of this APD-based highly sensitive spectroscopy method is used the varying multiplication ratio that is decided by incident light wavelength. The wavelength controls running distance of photo-excited carrier by absorption coefficients(α), and this element decides multiplication ratio on fixed high electrical field. So we can easily notice the wavelength of single wavelength light. In this case, we use essential formula as follow,

$$M_{MIXV} = X_{\lambda_1} M_{\lambda_1 V} + X_{\lambda_2} M_{\lambda_2 V} + \dots + X_{\lambda_n} M_{\lambda_n V} \quad (1)$$

M_{MIXV} is a multiplication ratio at applying V voltage and the lighting several wavelengths (mixed light). $M_{\lambda_n V}$ is a multiplication ratio at applying V voltage and a lighting wavelength is λ_n [nm]. X_{λ_n} is photocurrent ratio by the λ_n wavelength light. We can establish formulas in each apply voltages as follows,

$$\begin{aligned} M_{MIXV_1} &= X_{\lambda_1} M_{\lambda_1 V_1} + X_{\lambda_2} M_{\lambda_2 V_1} + \dots + X_{\lambda_n} M_{\lambda_n V_1} \\ M_{MIXV_2} &= X_{\lambda_1} M_{\lambda_1 V_2} + X_{\lambda_2} M_{\lambda_2 V_2} + \dots + X_{\lambda_n} M_{\lambda_n V_2} \\ &\vdots \\ M_{MIXV_n} &= X_{\lambda_1} M_{\lambda_1 V_n} + X_{\lambda_2} M_{\lambda_2 V_n} + \dots + X_{\lambda_n} M_{\lambda_n V_n} \end{aligned} \quad (2)$$

M_{MIXV_n} is multiplication ratio at applying V_n voltage and lighting several wavelengths (mixed light). $M_{\lambda_n V_n}$ is multiplication ratio at applying V_n voltage and lighting the λ_n [nm] wavelength light. From these equations, we can get $X_{\lambda_1} \dots X_{\lambda_n}$ values by calculation as follows,

$$\begin{bmatrix} X_{\lambda_1} \\ X_{\lambda_2} \\ \vdots \\ X_{\lambda_n} \end{bmatrix} = \begin{bmatrix} M_{\lambda_1 V_1} & M_{\lambda_2 V_1} & \dots & M_{\lambda_n V_1} \\ M_{\lambda_1 V_2} & M_{\lambda_2 V_2} & \dots & M_{\lambda_n V_2} \\ \vdots & \vdots & \ddots & \vdots \\ M_{\lambda_1 V_n} & M_{\lambda_2 V_n} & \dots & M_{\lambda_n V_n} \end{bmatrix}^{-1} \begin{bmatrix} M_{MIXV_1} \\ M_{MIXV_2} \\ \vdots \\ M_{MIXV_n} \end{bmatrix} \quad (3)$$

However, the complex equations are not satisfied when the $M_{\lambda_n V_n}$ have a noise. There are several noises, in this

measurement system, that are shot noise of photocurrent, dark current noise, excess noise. So we change the calculation method to the deep learning for improving accuracy.

In this report, we divide dual wavelengths light that are blue and green lights for evaluating the accuracy. Our goal is classification at a noise level signal.

3. Experimental details

Figure 1 shows the measurement system. These incident lights (blue and green lights) have different wavelengths. So an APD makes different multiplication ratio. Thus this method can separate two types of light by using multiplication ratios of APD without band pass filters/gratings. In this measurement circuit, we employ APD (S6045-6), voltage source, and Pico ampere current meter (4200scs).

Fig. 1. Measurement circuit for photocurrent and dark current.

Firstly, the system measures dark current (I_d), and mixed photocurrent (I_p) characteristics for applied voltages in 1V steps (0 to 210 V) by Pico ampere current meter. The photocurrent ratio of blue and green light is changed 6 types that are 1:1, 1:0.1, 1:0.01, 1:0.001 and 1:0.0001. Secondly, the mixed multiplication ratio (M) is calculated by these currents (I_d , I_p , I_{p0}). The I_{p0} is photocurrent value when at applied 30 V. The I_p and multiplication ratios are calculated by next equations,

$$I_p = I - I_d \quad (4)$$

$$M = \frac{I_p}{I_{p0}} \quad (5)$$

Figure 2 shows I_p characteristics for applied voltage at each photocurrent ratios. The I_{p0} is around 1.3 and 0.6 μA when the ratio is 1:1 and 1:0.0001 respectively. The photocurrent values of “ratio 1” change 1 - 6 μA with random for making deep learning dataset. The I_p increase rapidly from 150 to 211 V. Figure 3 shows multiplication ratios for applied voltage at each photocurrent ratios.

Fig. 2. Mixed photocurrent – voltage characteristics at each photocurrent ratios.

Fig. 3. Multiplication ratios at each photocurrent ratios.

The multiplication ratios are increased from 30 V. The M data are clearly different at the ratio 1:1, 1:0.1. However, the M data are difficult to find different points at the ratio 1:0.01, 1:0.001, 1:0.0001 and 1:0. Figure 4 shows the dark current for apply voltage 6 times.

Fig. 4. Dark currents (I_d) – voltage characteristics.

The dark currents are different by dark current generation process. The dark currents have fluctuation noise that the noise value is 4 to 7 nA. The dark current consist of 4 types. They are diffusion current by minority carrier, generation current from crystal fault, surface leakage current, tunnel current. The carrier generation timing and place that are not the same. It makes fluctuation noise of the dark current. The dark current remove from the value. However, the fluctuation noise is existing in the photocurrent. In the other hand, the photocurrent of green is below 6 nA when the ratio is below 1:0.01 at 30V. So the fluctuation noise is almost same to the photocurrent of green when the photocurrent ratio at 1:0.01. It is indicated that the lights dividing is so difficult because the noise is almost same or bigger than green light signal when the photocurrent ratios are 1:0.01, 1:0.001, 1:0.0001 and 1:0. Our goal set classification Ratio(1:0.01) that the signal value is almost the same as fluctuation noise. If we achieve this goal it indicates this method can divide incident lights when there is a high noise. Next chapter, we try light classifying by deep learning at the ratios are 1:0.01, 1:0.001, 1:0.0001 and 1:0.

4. Data for deep learning

We measured the 6 types of photocurrent ratio 960 times each. So the total number of measurement times of photocurrent-voltage characteristic is 5760. 211 data of photocurrent value from I-V result is able to be obtained, so the total amount of data is 5760×211 . The data of deep learning has two types that are learning data and evaluation data. And learning data has two types that are practicing data and testing data. We set the dataset ratio that evaluating data ratio is 25% (1440), the practicing data ratio is 60% (3456) and testing data ratio is 15% (864). Figure 5 shows each percentage of the dataset for using deep learning. The following two types of data, the learning data, and the evaluation data, are required for analysis using deep learning.

Fig. 5. Percentage of the dataset for using deep learning.

5. Preprocess

In this deep learning, we use three types of preprocessing that are multiplication ratio (M) and the 1st derivative multiplication ratio ($\frac{dM}{dv}$) and the 2nd derivative multiplication ratio ($\frac{d^2M}{dv^2}$). The photocurrent data has two types of information that are total incident light power and the wavelength. However, the total incident light power is not necessary for classifying. So the photocurrent data are converted to multiplication ratio (M) with equation 5, the M data do not have the incident light power information, for highlighting the wavelength information. In addition, the M data is converted to the 1st derivative value ($\frac{dM}{dv}$) and the 2nd derivative value ($\frac{d^2M}{dv^2}$) for highlight wavelength information. Figure 6 shows the 1st derivative multiplication ratio – voltage characteristics.

Fig. 6. $\frac{dM}{dt}$ – voltage characteristics.

6. Classification by multilayer perceptron

This model is implemented using the PyTorch[6] default set (ver. 1.0.0) and trained with ADAM[7] optimizer using a batch size of 32 and 0.001 learning rate and betas=(0.9, 0.999) and default parameter setting. We decrease this learning rate in steps (stepsize400, gamma=0.1). We train the model for 1200 epochs. The model was trained until convergence. We use MLP (Multilayer Perceptron) for 6 type classification. We set three types of MLP model that are M , dM/dt , and d^2M/dt^2 type. The MLP has 5 layers that are an input layer and three hidden layers and an output layer. The input nodes number of

M , dM/dt and dM^2/dt^2 type is 211, 210 and 209 respectively. The first hidden layer, the node number is 150, set LeakyReLU (negative_slope=0.2) activation and Batch Normalization and dropout rate 0.25. The second hidden layer, the node number is 100, set LeakyReLU (negative_slope=0.2) activation and Batch Normalization and dropout rate 0.25. The third hidden layer, the node number is 50, set LeakyReLU(negative_slope=0.2) activation and Batch Normalization and dropout rate 0.25. The output layer has 6 nodes that are “Ratio(1:0)”, “Ratio(1:1)”, “Ratio(1:0.1)”, “Ratio(1:0.01)”, “Ratio(1:0.001)” and “Ratio(1:0.0001)”.

Figure 7 shows the MLP image of M type.

Fig. 7. The MLP image of M type.

7. Classification result

Table 1 shows the classification result. The classifications of Ratio(1:1) and Ratio(1:0.1) are classified by all preprocessing on this model with a high correct classification rate that is almost 1.0. The classification of Ratio(1:0.01) is classified by preprocessing of (a)(b)(c)(d). The second derivative preprocesses of (e)(f) deteriorates input data for Ratio(1:0.01). Especially, The Ratio(1:0) classification is classified by first derivative preprocess of (d). The dropout process support first derivative process of (d) and second derivative process of (f) for classifying. The best total correct preprocess is (d) that type is first derivative process with dropout.

Table 1. Classification result.

Preprocess (Dropout)	(a)M (no dropout)	(b)M (dropout)	(c)dM/dv (no dropout)	(d)dM/dv (dropout)	(e)d ² M/dv ² (no dropout)	(f)d ² M/dv ² (dropout)
Ratio (1:0)	0.8083	0.0833	0.4542	1.0000	0.8000	0.9125
Ratio (1:1)	1.0000	1.0000	1.0000	1.0000	0.9958	1.0000
Ratio (1:0.1)	1.0000	1.0000	1.0000	1.0000	0.9917	1.0000
Ratio (1:0.01)	1.0000	1.0000	0.9958	0.9958	0.0625	0.3250
Ratio (1:0.001)	0.0000	0.0000	0.0000	0.0000	0.0208	0.0000
Ratio (1:0.0001)	0.0000	0.0000	0.0000	0.0000	0.0125	0.0000
Total	0.6347	0.5139	0.5750	0.6660	0.4806	0.5396
Total without Ratio(1:0.001) Ratio(1:0.0001)	0.952075	0.770825	0.8625	0.99895	0.720825	0.809375

The total correct rate is 0.666. The total correct rate without Ratio (1:0.001) and Ratio (1:0.0001) is 0.99895.

8. Conclusion

The preprocess M can classify Ratio(1:1), Ratio(1:0.1), Ratio(1:0.01). The green signal value of Ratio(1:0.01) is almost the same with fluctuation noise. So we achieved our goal on this preprocess. It indicates this method can divide incident lights when there is a high noise. Moreover, the preprocess dM/dv can classify Ratio(1:0). It is indicated the dM/dv preprocess find the green light incident. The current Ratio(1:0) is almost the same Ratio(1:0.001) and Ratio(1:0.0001). The deep learning finds the characteristic by the derivative process. In this report, we can classify the noise level signal (Ratio(1:0.01)) with low multiplication ratio($M = 2$ to 3). We expect more accuracy improvement with high multiplication ratio. It indicated that the deep learning method can improve filter less APD based spectroscopy accuracy.

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