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Learning-based change point detection for robust and accurate nuclear counting

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1. Introduction

The radiation monitoring system has been deployed in nuclear facilities to guarantee radiological safety and homeland security [1]. This is mainly because it allows us to continuously measure radioactivity levels in space. One of the key parts of the system is obviously the nuclear counting process which estimates count rates from stochastic signals received by radiation detectors. Here, the signals following Poisson law [2] make this process non-trivial since they generally show different fluctuation characteristics (i.e. variance) on the fly. Considering this property, lots of smoothing filters for stable and accurate counting process have been widely explored and also adopted in the real-world system.

In the literature, a bunch of moving average filtering methods [3,4], based on simply averaging a signal sequence in a window, are applied to radiation monitoring systems because those methods are not only straightforward but highly powerful count rate estimators to some extent. In early approaches, the window size of the filter is predefined and fixed while neglecting trends of signals. In a decade, some of the adaptive filtering approaches [5,6] are developed in which the window size, a significant factor determining the compromise between accuracy and response time, is adjusted depending on trends of signals (i.e., steady state and sudden change). Note that detecting the change points among these trends is the most significant procedure as the change point can be interpreted as a start point of the window to calculate current and future estimates. Mostly, state-space models [6] tracking changes in statistical features such as mean, variance, and spectrum are exploited in existing adaptive filtering approaches. However, this is problematic in practice as neither true signal distributions nor types of variation are known a priori. Also, it necessarily requires hand-craft tuning by users for each use case.

Recently, deep learning-based methods with neural networks have achieved great performance in the fields of signal processing, computer vision, and natural language processing [7,8]. In general, it is well known that extracting feature representation with such learning methods leads to robust and accurate predictions. At the same time, changing point and anomaly detection related research are carried out with notable results [9,10]. In contrast, to the best of our knowledge, learning-based methods still have not been considered for nuclear counting yet. In this paper, toward data-driven change point detections suited to real-world nuclear counting, a learning-based change point detection model with training schemes is elaborated. Experiments on feasible radioactive events are performed and the method is evaluated in terms of both quantitative and qualitative performances.

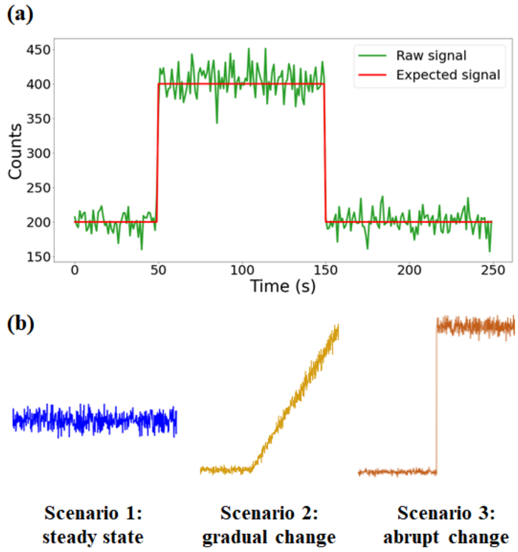

Fig. 1. (a) Illustration of nuclear counting in which the expected signal should be estimated from raw signals. (b) Typical trends of nuclear counting signals.

2. Methodology

As shown in Fig. 1(a), nuclear counting is to estimate accurate nuclear counts (red line) from raw signals (green line). Accurate change point detection is required to improve the counting process. In this section, the overall method for model architecture, post-processing, training procedures, and the experimental setup is explained in detail. Firstly, nuclear counting dataset is described, and then the proposed change point detection model and training scheme are demonstrated. Next, the evaluation metrics are summarized to prove the model's capability. In addition, the baseline model for comparison is explained lastly.

2.1 Nuclear counting dataset

According to the properties of radioactive materials disintegration, nuclear counting signals can be modeled by the Poisson law [1] as below:

$$P(N = n) = e^{-(\lambda\Delta t)} \frac{(\lambda\Delta t)}{n!} \tag{1}$$

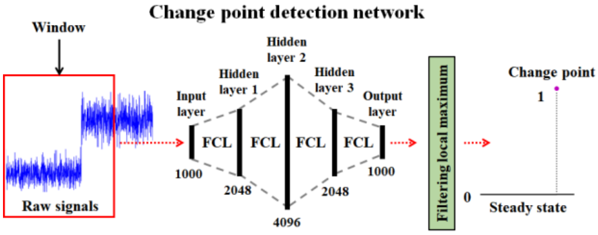

Fig. 2. The overall framework of the proposed learning-based change point detection method. Fully connected layers are abbreviated as FCL, and all numbers right below layers indicate the size of each layer.

where n is counts, λ is count rates, and Δt is time interval. The specificity of this Poisson law is that mean and variance of the Poisson distribution are the same. As illustrated in Fig. 1(a), nuclear signals with high intensity exhibit large fluctuation imposing serious difficulties in precise breakpoint detection.

In this paper, 200,000 sequences of nuclear counting signals paired with labels of change status are produced and used for this experiment. The scenarios including stable state, and gradual/abrupt changes of the nuclear counts are considered as shown in Fig. 1(b). The size of each sequence is 1,000 time points. We used 70% of the data for training, 15% for validation, and 15% for testing.

2.2 Change point detection model and training scheme

The overall framework of the proposed method is illustrated in Fig. 2. The model takes raw signals in a window with a size of 1,000 and then generates a change status of each time point. After the model's inference, a curve of resulted status is constructed and local maximums are selected as the final change points. Here, '1' denotes the change point and '0' denotes the steady state.

The change point detection model architecture is a neural network composed of four fully connected layers followed by the Rectified linear unit (ReLU) for activation. Exceptionally, Sigmoid function is used in the last layer. Figure 2 demonstrates visualized network's structure including the size of layers.

In this paragraph, training schemes are described. The problem formulation can be regarded as a multi-label classification task. Given K labels ($k \in K$), the network generates one logit ($\hat{y}_i^k$) per label (k) and class (i). As a loss function, cross-entropy loss (L) for multi-label is used as follows:

$$L = -\sum\sum \hat{y}_i^k log\hat{y}_i^k + (1-\hat{y}_i^k)\log(1-\hat{y}_i^k) \qquad (2)$$

where k is time points and i is change status in this problem. For minimizing loss, Adam optimizer is used for training. The learning rate is initialized as 0.1 and the batch size was set as 8. All weights of fully connected layers are initialized using a normal distribution. All computations are performed on a single GPU (NVIDIA GTX 1070) along with Pytorch framework. The network is trained for 200 epochs in total.

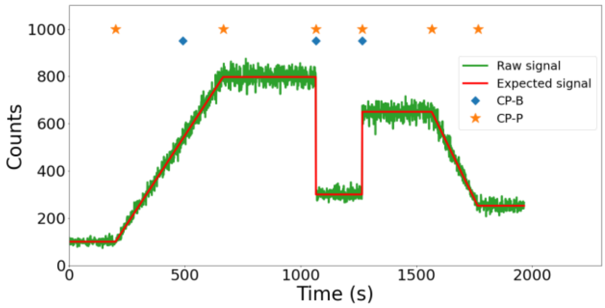

Fig. 3. Results of change point detection on nuclear counting dataset with baseline and proposed methods. CP-B denotes change points by the baseline method and CP-P denotes the points by the proposed method.

Evaluation metrics	Baseline method	Proposed method
Accuracy	65.61%	96.83%
Precision	57.24%	95.95%

Table 1. Quantitative performances of the proposed method in comparison with baseline method.

2.3 Evaluation metric

Quantitative performance measures of the detection are implemented with respect to both the precision and accuracy of predicted change points with corresponding labels. Here, a toleration distance τ is introduced to determine the correctness of predictions. Concretely, detected change points can be regarded as corrected ones if the following two conditions are met: 1) The detected change point a is the closest to true point b. 2) the difference between a and b is smaller than the toleration distance τ ($|a-b| < \tau$). In this experiment, τ is set to 20.

2.4 Baseline method for performance comparison

As a baseline model compared to the proposed method, the state-space model is used which simply detects change points by tracking changes in the mean and variance. Concerning the estimated mean, the changing state S^t at time t can be formulated by following Eq. (3):

$$S^t = \begin{cases} Change, & \text{if } |\hat{\lambda}^{t+1} - \hat{\lambda}^t| > \alpha \\ Stable, & otherwise \end{cases} \qquad (3)$$

where $\hat{\lambda}^t$ indicates the estimated count rate at the time t within an arbitrary buffer window, and α is a threshold of changes. Also, detecting change points via estimated variance follows the same procedure as in eq. (3). With extensive parameter exploration, the best threshold α and size of the buffer window can be found.

3. Results

Figure 3 shows the visual comparison of change point detections. As expected, the Baselined method tends to miss some change points, i.e. transition from steady state to linear growth, since it can detect only obvious variations of statistical properties. On the other hand, the proposed method achieves high accuracy and precision for the most of transitions. At the same time, the results show the robust capability of the proposed model. Further, the quantitative evaluation is summarized in Table 1. It shows that the proposed method outperforms the baseline method by a large margin for both accuracy and precision.

4. Conclusions

This paper presents the learning-based change point detection method for boosting adaptive smoothing filters. Inspired by multi-label classification tasks, the model can predict change points at each time point. To this end, the network architecture composed of fully connected layers along with the training scheme is well elaborated. Experiments on the nuclear counting dataset show that the proposed method greatly improves the accuracy and precision of change point detection, both quantitatively and qualitatively. In the future, the performance will be evaluated for the actual nuclear dataset.

REFERENCES

[1] G. F. Knoll, *Radiation Detection and Measurement*, 4th ed. Hoboken, NJ, USA: Wiley, pp. 65–105, 2010.

[2] G. Apostolopoulos, “On-line statistical processing of radiation detector pulse trains with time-varying count rates,” *Nuclear Instruments and Methods in Physics Research. A*, vol. 595, pp. 464-473, 2008.

[3] V. Arandjelovi´c, A. Koturovi´c, and R. Vukanovi´c, “A generalization of the preset count moving average algorithm for digital rate meters,” Nucl. Instrum. Methods, *Phys. Res. A*, vol. 481, pp. 769–772, 2002.

[4] R. Coulon, V. Kondrasovs, K. Boudergui, and S. Normand, “Moving sources detection algorithm for radiation portal monitors used in a linear network,” *IEEE Trans. Nucl. Sci.*, vol. 61, no. 4, pp. 2189–2194, 2014.

[5] H.-J. Jeong, et. al, “Statistical approaches to forecast gamma dose rates by using measurements from the atmosphere,” *Radiation Protection Dosimetry*, pp. 1–9, 2008.

[6] R. Coulon, J. Dumazert, V. Kondrasovs, and S. Normand, “Implementation of a nonlinear filter for online nuclear counting,” *Radiat. Meas.*, vol. 87, pp. 13–23, 2016.

[7] X. Feng, Y. Jiang, X. Yang, M. Du, and X. Li, "Computer vision algorithms and hardware implementations: A survey.", *Integration 69*, pp. 309-320, 2019.

[8] D. Otter, J. Medina, and J. Kalita, "A survey of the usages of deep learning for natural language processing." *IEEE transactions on neural networks and learning systems*, 2020.

[9] S. Aminikhanghahi, D. Cook, “A survey of methods for time series change point detection,” *Know. Inf. Syst.*, vol.51, no. 2, pp. 339-367, 2017.

[10] V. Chandola, A. Banerjee, and V. Kumar, “Anomaly detection for discrete sequences: A survey,” *IEEE Trans. Knowl. Data Eng.*, vol. 24, no. 5, pp. 823–839, 2012.