Identifying Overlapping Successive Events Using a Shallow Convolutional Neural Network

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I. Introduction

Cascading failures involve complicated physical mechanisms, which cannot be accurately represented by a single model. People are motivated to prevent cascading failures at an early stage by efficient event identification. Existing identification approaches have limitations: 1) only for single events or multiple events with minor overlapping, 2) require a large number of training datasets, 3) offline, but in reality insufficient successive events are available, and events occur close in time and location.

II. Problem Formulation

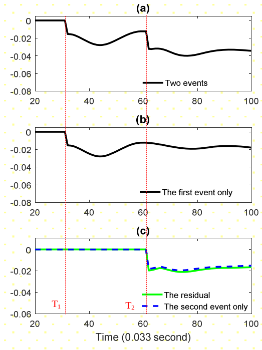


Fig. 1 Voltage magnitude of the bus when a line trip following a generator trip occurs nearby

Challenges:

a. Successive events are **overlapping** in Fig. (a)-(c),

b. Historical successive events are **insufficient** .

Goals:

a. Identify **overlapping** events within seconds.

b. Only using **single** events as training data.

c. **Robust** to insufficient training data.

III. Feature Extraction

$M_{t_0}^{t_0+T-1}, M_{t_0+1}^{t_0+T}$ are data matrices of PMU channels in the sequential windows of period T from t_0, and $M_{t_0}^{t_0+T-1}$ of rank r can be approximated by $M_{t_0}^{t_0+T-1} \approx U_r \Sigma_r V_r^{\dagger}, U_r \in C^{m\times r}, V_r \in C^{m\times r}$ contain the singular vectors and $\Lambda_r = diag(\sigma_1, \cdots, \sigma_r)$ collects the first r singular values. As there exists an operator A that $y_t = A\, y_{t-1}$, we have

$$M_{t_0+1}^{t_0+T} = A M_{t_0}^{t_0+T-1} \qquad (1)$$

Define the eigenvalues $\lambda_1, \cdots, \lambda_r$ of A and singular values $\sigma_1, \cdots, \sigma_r$ of $M_{t_0}^{t_0+T-1}$ as the *dominant features*.

IV. Online Prediction-Subtraction

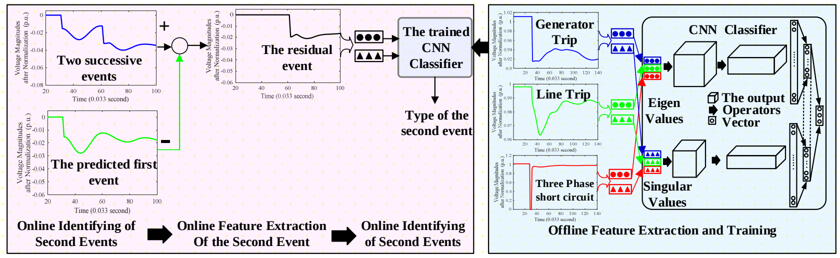
Let the ith event occurs at $T_i, \mathrm{i} = 1,2$. After the second event occurs, there are still impacts of the first events in the measures $M_{T_2}^{T_2+\tau}$. These impacts $\bar{M}_{T_2}^{T_2+\tau}$ can be predicted by dynamic mode decomposition (DMD) or other ones.

$$\tilde{M}_{T_2}^{T_2+\tau} = M_{T_2}^{T_2+\tau} - \bar{M}_{T_2}^{T_2+\tau} \qquad (2)$$

Then the residual data $\tilde{M}_{T_2}^{T_2+\tau}$ can represent the second event only.

Therefore, the features of the second event can be extracted from $\tilde{M}_{T_2}^{T_2+\tau}$.

V. Training and Testing of the Proposed CNN



VI. Numerical Results

Simulated datasets are generated by Power System Simulator for Engineering (PSS/E) in the IEEE 68-bus power system. Identification Accurate Rate (IAR) is the ratio of correctly identified events to the total events.

A. IAR of the Second Events

Table. 1 The performances of CNN-F and CNN-T on 1627 second events

Second Event Type	Time Interval	CNN-F[1] NS[2]	CNN-F[1] NP[2]	CNN-T[1] NS[2]	CNN-T[1] NP[2]
IAR (%)	0.5	85.5	**93.1**	80.1	61.0
IAR (%)	1	84.7	**95.0**	81.9	67.7
IAR (%)	1.5	88.2	**92.4**	85.9	78.2
IAR (%)	2	87.4	**92.6**	74.7	70.8

1: CNN-T, CNN-F represent the CNN with time series as inputs and extracted features as inputs respectively.

2: Not Subtract (**NS**) means using the measurements $M_{T_2}^{T_2+\tau}$ after time T_2; Subtract the Prediction (**SP**) means using the residual $\tilde{M}_{T_2}^{T_2+\tau}$ in (2).

- The proposed CNN-F with SP achieves a better performance.

B. Robust to Small Training Data

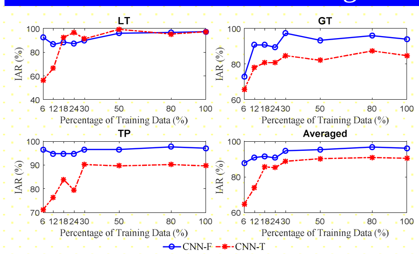


Fig. 2 The performances of CNN-F and CNN-T when partial training datasets are available

- CNN-F with SP is more robust to the small training data than CNN-T.

C. Robust to Delays in Event Detection

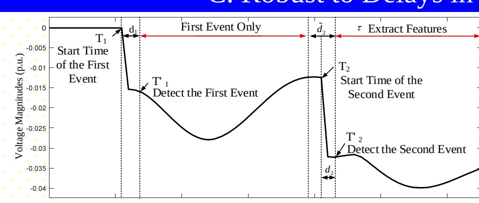


Fig. 3 Sequence of events due to time delay

Table. 2 The IAR of CNN-F when the start time of the ith event have d_i time delay

(d_1, d_2)	(200,33)	(200,100)	(200,167)
IAR (%)	92.2	95.0	90.5
(d_1, d_2)	(300,33)	(300,100)	(300,167)
IAR (%)	95.4	94.4	94.1
(d_1, d_2)	(500,33)	(500,100)	(500,167)
IAR (%)	88.7	91.1	86.1

- The proposed CNN-F is robust when T_1 and T_2 are delayed by d_1 and d_2.

VII. Conclusions

- The proposed two-layer CNN classifier is able to identify successive events in real-time, is more robust to small training data than the CNN-T with time series as inputs, and is robust to delays in event detection.

Acknowledgement

- This research is supported in part by the ERC Program under NSF EEC-1041877 and the CURENT Program, and NSF Grant 1508875

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