CENTER FOR ULTRA-WIDE-AREA RESILIENT ELECTRIC ENERGY TRANSMISSION NETWORKS

Real-time Event Identification through Low-dimensional Subspace Characterization of High-dimensional Synchrophasor Data

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Motivations

- Fast event identification is beneficial to improve system security and prevent cascading failures;
- Model-based methods depend on the accuracy of system parameter estimation, and data-driven methods attract more attentions;
- The limitations of existing data driven methods include:
  - Identify single type of events[1];
  - lack of physical interpretations[2-4];
  - complicated training models[2];
  - with a large dictionary size and expensive computations[2-4];
  - most are offline algorithms[3-4].

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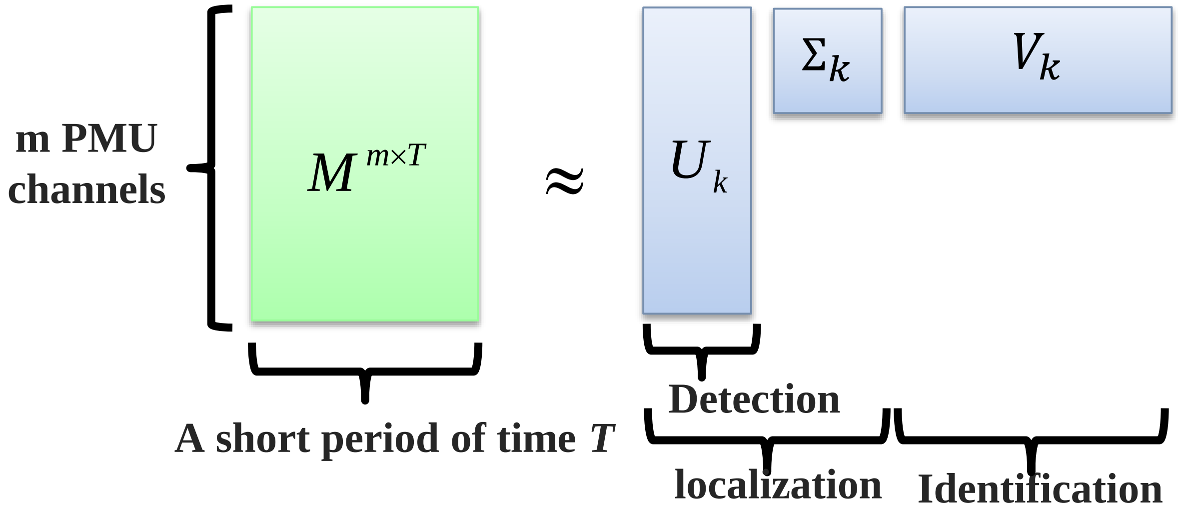
Features of our identification method

- Characterizing events through low-dimensional subspaces, which are related to the eigenvalues of power system state matrix;
- These subspaces of data matrix in 1 second can be efficiently computed by singular value decomposition (SVD);
- Our dictionary has a small size;
- Can be implemented in real time.

Problem Formulation

- Given the PMU measurements data $M^{m\times T}$, its low dimensional approximation can be obtained:

$$M^{m\times T} = U_k \Sigma_k V_k \quad k \ll T$$



U_k: Span the column subspace;
V_k: Span the row subspace;
Σ_k: The k largest singular values of $M^{m\times T}$.

Main Idea:

- Online track U_k to detect the abnormal event, and then localize by U_k, Σ_k and identify the type of event by V_k.

Event Identification through Subspace

- Identify an event by comparing the row subspace of the real-time spatial-temporal PMU data blocks with a dictionary of subspaces obtained from recorded PMU data with known event types.

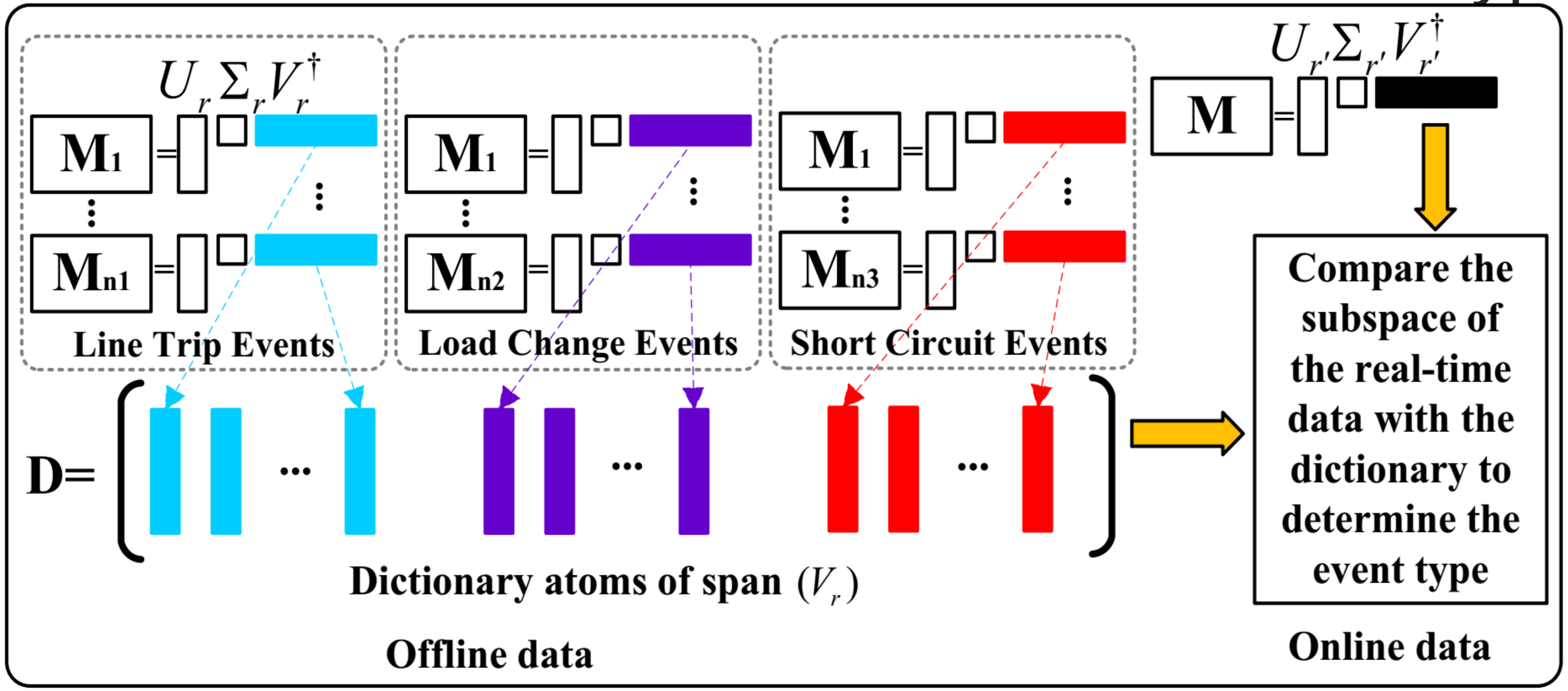


Fig. 1: Dictionary construction from historical datasets and real-time data identification through subspace comparison

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Event characterization through subspace

- Physically interpretation of subspace span(V_k) through linear system with an impulse input:

$$\begin{cases} x_{k+1} = Ax_k + Bu_0 \\ y_k = Cx_k \end{cases} \qquad (1)$$

  - In a short period of time, input u_0 can be ignored;

$$M_{m\times T} = [y_0 \quad y_1 \quad \cdots \quad y_T] \approx U_k \Sigma_k V_k$$
$$\approx \sum_{i=1}^{k} l_i{}^T x_0\, Cr_i \boxed{[\lambda_i \quad \lambda_i^2 \quad \cdots \quad \lambda_i^t]} \qquad (2)$$

  - Where λ_i, l_i are the i^{th}eigenvalue and left eigenvectors of matrix A;
  - r_i is the i^{th}right eigenvectors of matrix A;
  - Let $\beta^{\dagger}{}_k = [1, \lambda_k, \lambda_k^2, \ \ldots\ , \ \lambda_k^{\dagger}]$;
  - $\boxed{\text{Span}(V_k) = \text{span}(\beta^{\dagger}{}_k)}$.

Different type of events produces different eigenvalues, producing **different subspaces**.

Subspace Similarity Metric

- Subspace angle[7]

$$\theta(S_k, S_l) = arccos\sqrt{\frac{\| {B_k}^T, B_l \|_F^2}{\min(k,l)}}$$

  - Where B_k spans the subspace S_k with dimensionality k, while B_l spans the subspace S_l with dimensionality l.

- A small subspace angle $\theta(S_k, S_l)$ indicates a similar event type;
- The minimum angle θ^* between the online data and all the dictionary atoms $V_k^{i,j}$ points out the type of event;

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Detection and Location

- Detection indicator:

$$\varepsilon = \left\| y_t - U_k U_k^{\dagger} y_t \right\|_2$$

  - Where y_t is the online data at time t, $U_k U_k^{\dagger} y_t$ is estimated by column subspace U_k;
  - Once the threshold ε_0 is exceeded, it indicates the occurrence of event;
- Location indicator for the i^{th}bus:

$$\eta_i = \| (U_k \Sigma_k)_{i.} \|_2$$

  - Where $(U_k \Sigma_k)_{i.}$ is the i^{th} row of matrix $(U_k \Sigma_k)$;
  - Locate the most influenced buses by choosing the top k buses with the largest η_i, i=1,2…k.

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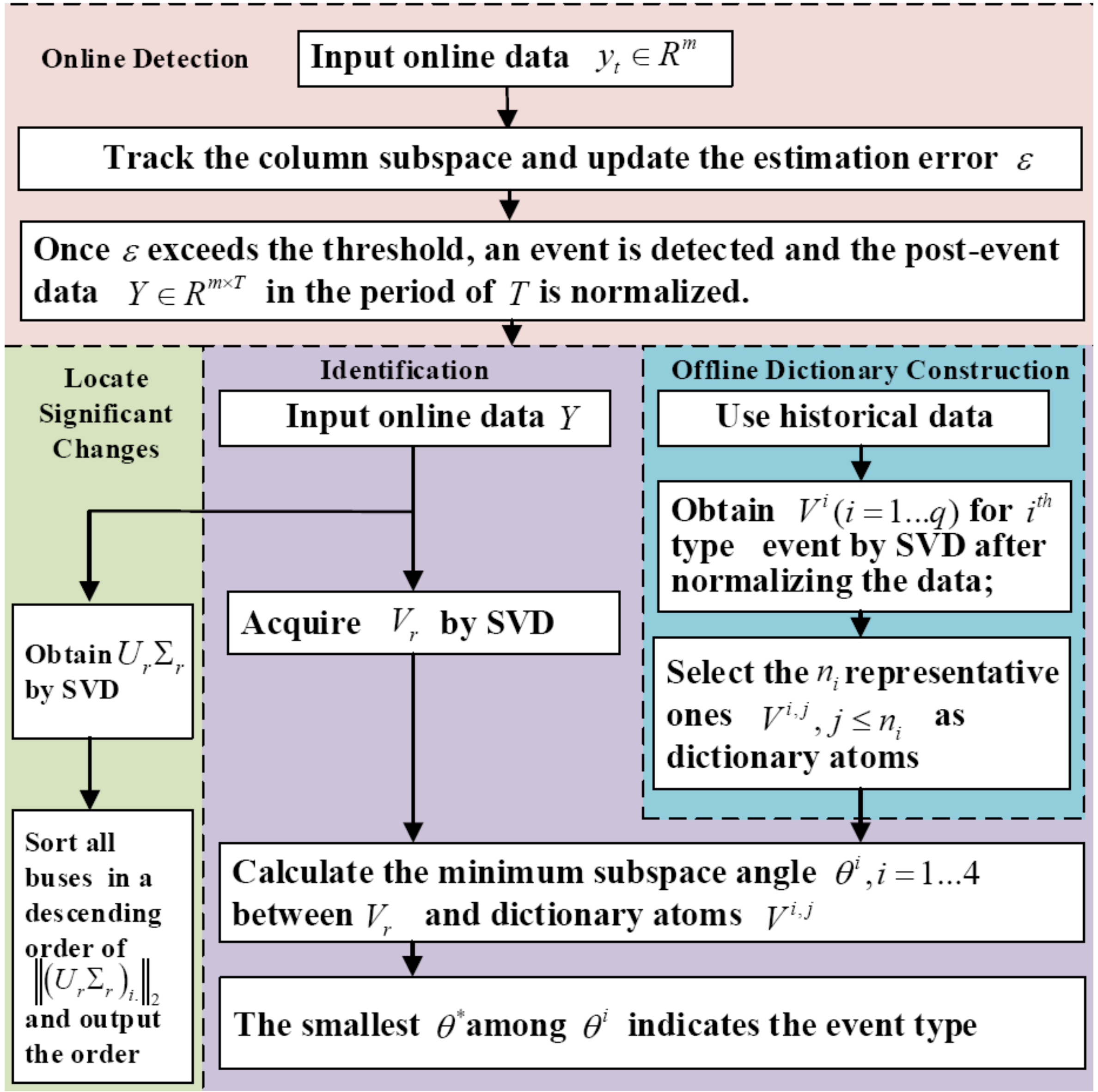
The Framework of Our Approach



Numerical Results

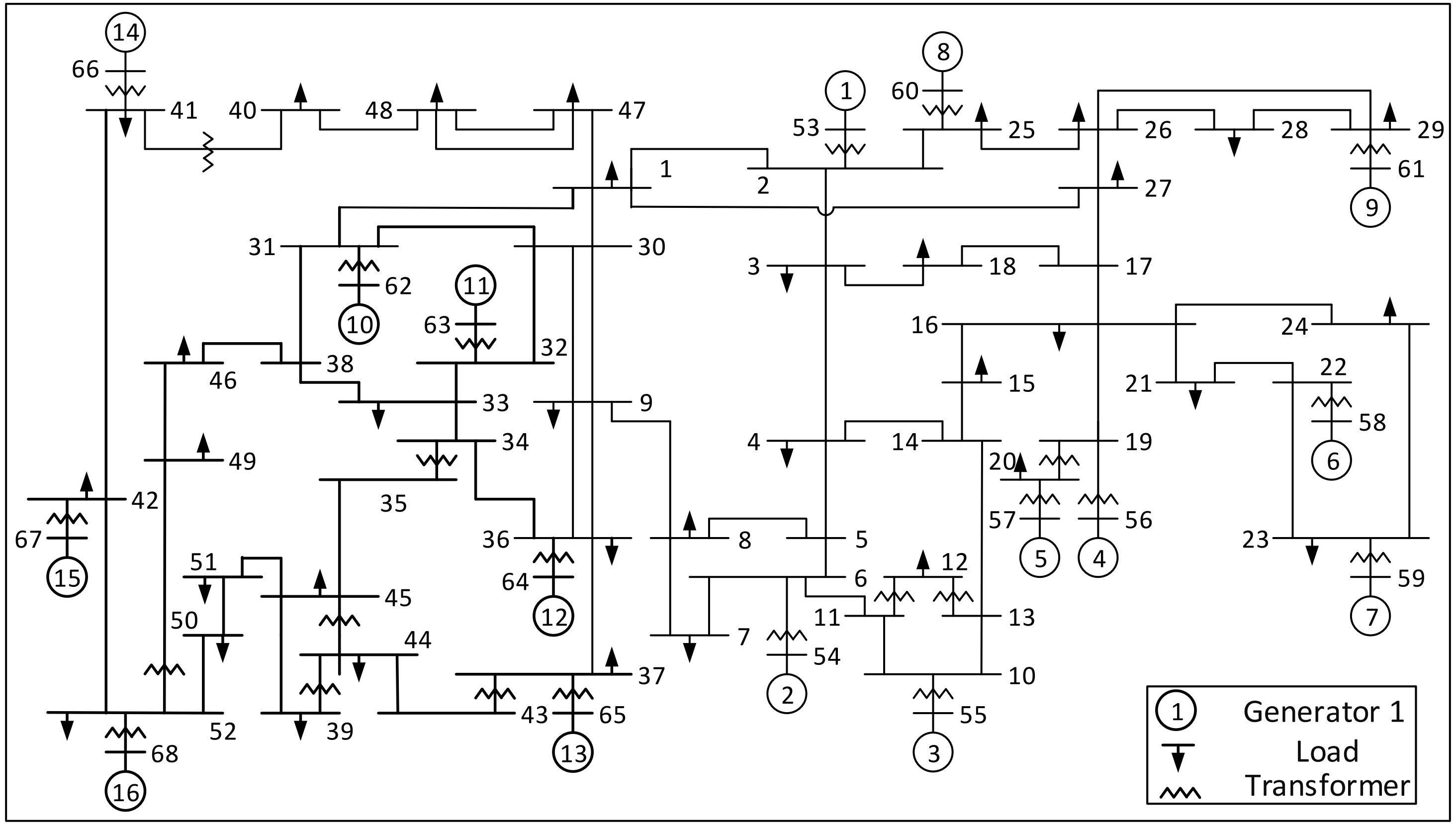


Fig.2 Topology graph of 16-machine 68 bus power system

- We test it in the 16-machine 68 bus power system through Power System Toolbox (PST);
- Sample frequency is 30 times / second;
- 380 testing cases: line trip, load change, three phase short circuit and generator trip events at various locations and on different initial conditions.

Dictionary Constructed offline

Table I Dictionary atoms for four types of events

Dictionary Type	The label of dictionary atoms
Line Trip	1-2, 4-14, 5-8, 12-11, 15-16, 30-32, 32-33, 33-34, 35-45, 42-41, 44-45
Short Circuit	2,3,8,12, 16, 25, 28, 31, 32, 33, 34 ,35, 36, 37, 39, 43, 44, 50, 53, 56, 59, 62
Load Change	15, 16, 24, 32, 41, 42, 47, 48
Generator Trip	1, 2, 10, 11, 13, 14, 15

- Step 1: offline construct dictionary atoms
  - **Line trip** : Labeled by the line between two buses;
  - **Load change** : Labeled by the bus number;
  - **Short circuit** : Labeled by the bus number;
  - **Generator trip**: Labeled by the number of the tripped generator;
  - In total: 42 dictionary atoms, each of which has the dimensionality of 30 by $r_{\max}^{1}$, are selected based on 190 training datasets.

[1] $r_{max} = 6$ is the maximum rank of data matrix

Identification Results

Table II Minimum subspace angles between a test case and the dictionary

Type Events \ Dictionary	Load Change	Line Trip	Short Circuit	Generator Trip
Load Change at bus 17	**2.6**°	10.8°	9.5°	9.8°
Line 7-8 is tripped	12.2°	**0.7**°	12.0°	3.0°
Short circuit at bus 36	13.5°	11.6°	**4.8**°	11.4°
Generator 5 is tripped	12.8°	2.2°	12.5°	**1.9**°

- Step 2: Online test four types of events
  - We utilized 1 second of data;
  - The subspace angles in Table II are the minimum one between online data and dictionary atoms of each type;
  - The bolder one, denoting the minimum one, points out the type of event.

Identification and Location Performance

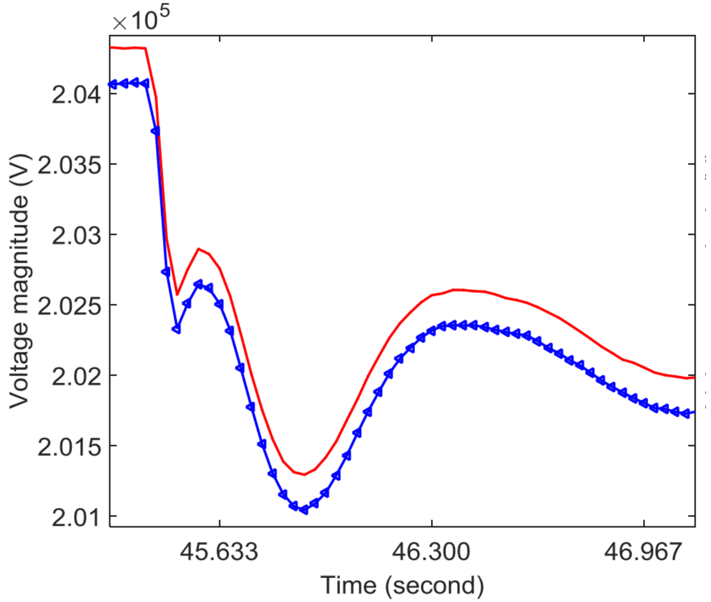
Table III Identification results of 380 testing datasets with different pre-conditions[1]

Type of event	IAR %	AR
Line Trip	100	1.7
Short Circuit	93.3	1.25
Load Change	100	1.5
Generator Trip	93.8	2.4

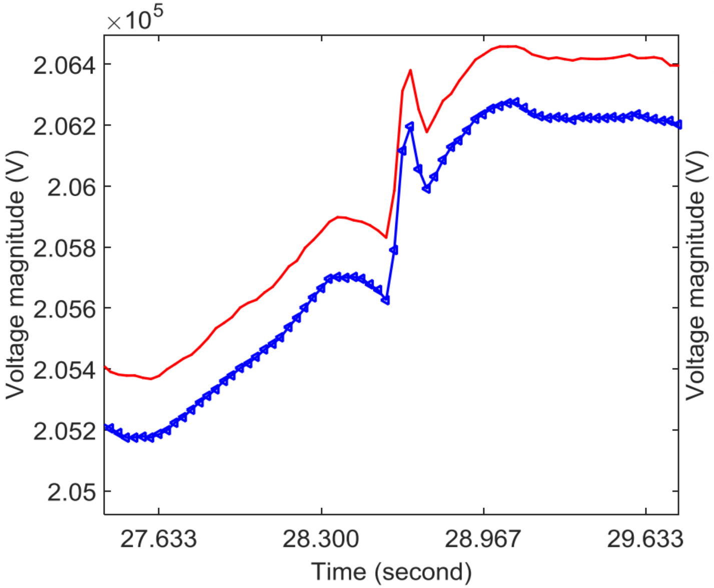
- Identification Accuracy Rate (**IAR**): the ratio of the number of accurately identified events to the total number of events;
- Average Rank (**AR**): the average rank of the correct bus location in descending order according to $\eta_i = \|(U_k \Sigma_k)_{i.}\|_2$. The correct bus denotes the bus that is closest to the location of the event.

[1] denotes the different operating conditions before the events and are measured by $\bar{\eta}_a^b = \frac{1}{L}\sum_{j=1}^{L} \frac{|P_j^b - P_j^a|}{|P_j^a|}$, where P_j^a denotes the active power on condition a and L is the total number of lines.

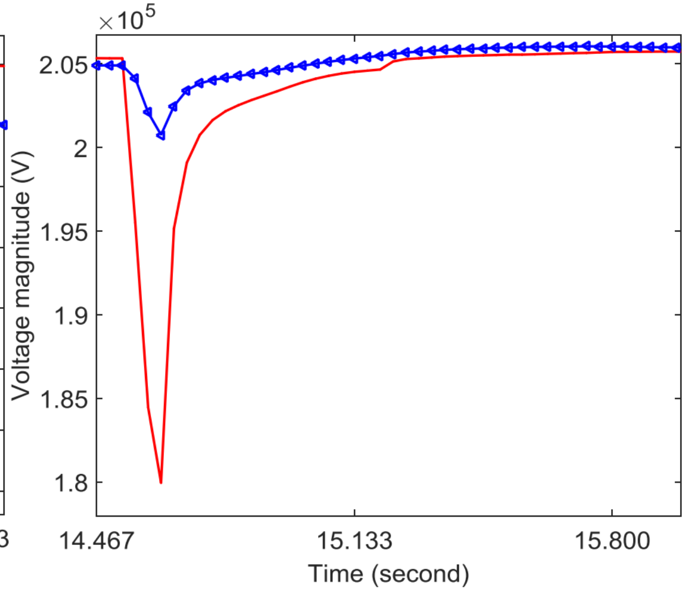
Results of ISO-New England



(a) Line A is tripped



(c) A Load Change Event



(d) A Fault Event

- 22 training dataset of the three types (a)-(c) are employed to construct a dictionary of 6 atoms;
- 10 testing datasets are successfully identified;
- Notice that exponential filters[1] ,are utilized to reduce noise before computing the subspaces in the training and testing datasets.

Identification Results

Table VI Minimum subspace angles between a test case and the dictionary atoms of three types of events in recorded PMU data

Dictionary Type / Events	Load Change	Short Circuit	Line Trip
Load Change 1	**4.08°**	16.91°	18.29°
Load Change 2	**3.12°**	20.81°	14.39°
Fault 1	24.95°	**6.33°**	23.86°
Fault 2	8.93°	**3.73°**	15.76°
Line Trip 1	7.25°	5.85°	**3.93°**
Line Trip 2	11.20°	30.21°	**4.27°**

- The minimum subspace angle of each row indicates the type of event.

Conclusions

- Our algorithm based on subspace can identify different types of events;
- It is efficient and only requires data in a short period of time;
- Can be implemented online algorithm and its requirements of storage is small;
- Both the simulated data and recorded PMU data validate the effectiveness;
- Further research will focus on identification of successive multiple events.

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