Multiple Event Detection and Recognition through Sparse Decomposition

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Outline

- **Motivation and Goals**
- **Background**
- **Challenges**
- **Sparse Decomposition**
- **Experimental Evaluation**
- **Conclusion**

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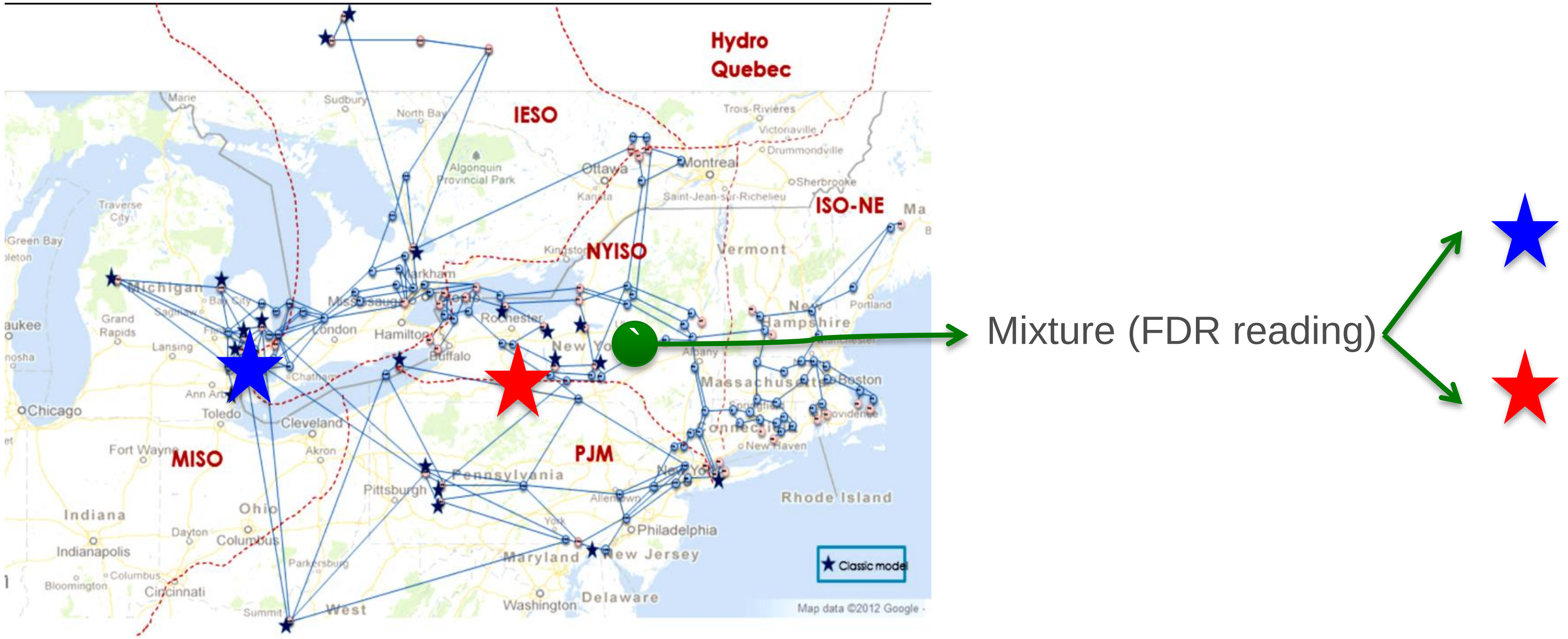
Motivation

- **Cascading or simultaneous faults/events (multiple events)** are common problems that may lead to large area blackout. (e.g., August 2003 U.S. northeastern blackouts and the July 2012 India blackouts).
- No existing works can efficiently handle multiple event detection, especially for large scale power systems.

Goals

- **When, Where, What:**

  To *detect*, *recognize* and *localize* each single constituent event from multiple sources using data collected from the ultra-wide-area monitoring networks (e.g., FNET).



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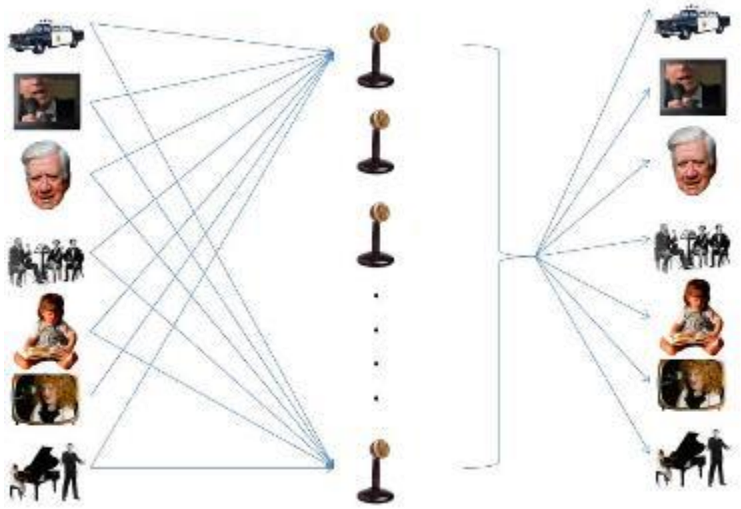
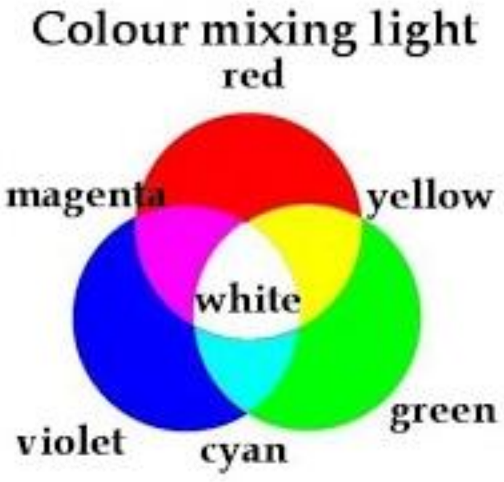
Background: Mixture and Unmixing

- **Mixture cases**
  - ❖ The cocktail party problem (speaker identification), color unmixing …



Sources Mixtures Separated sources



Event Unmixing

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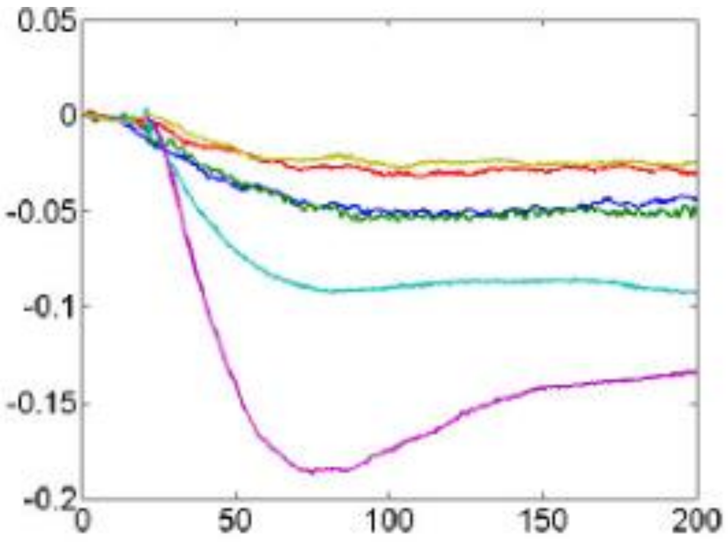
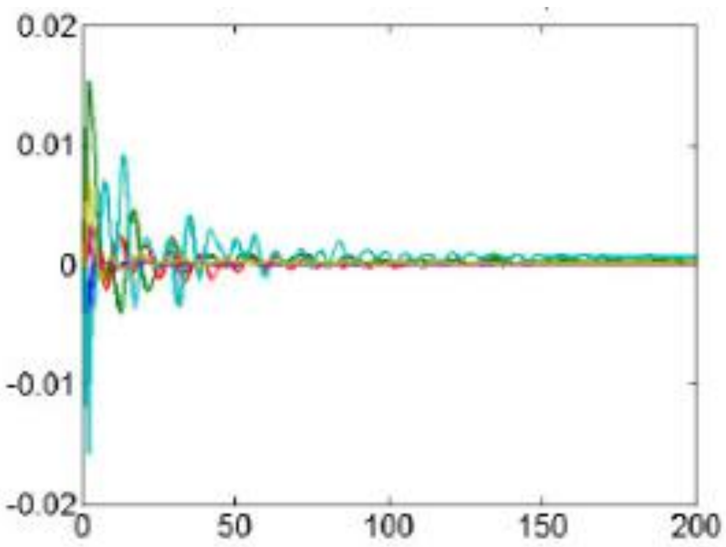
Root Event Signatures

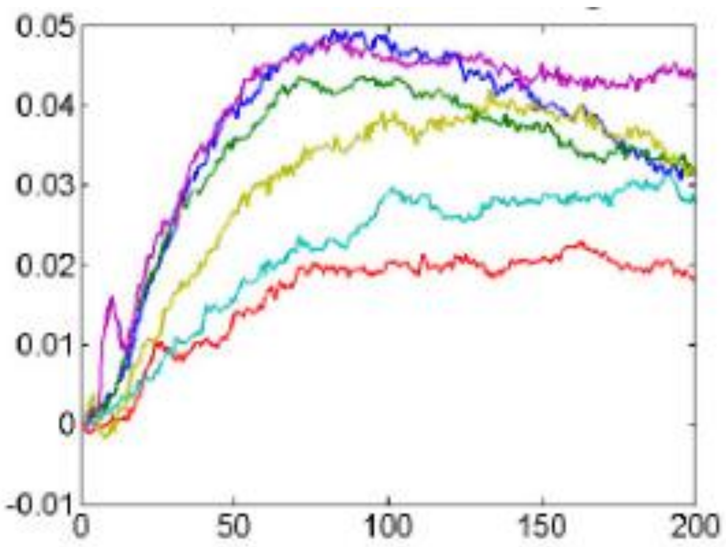
Generator Trip (GT)



Line Trip (LT)



Load Shedding (LS)



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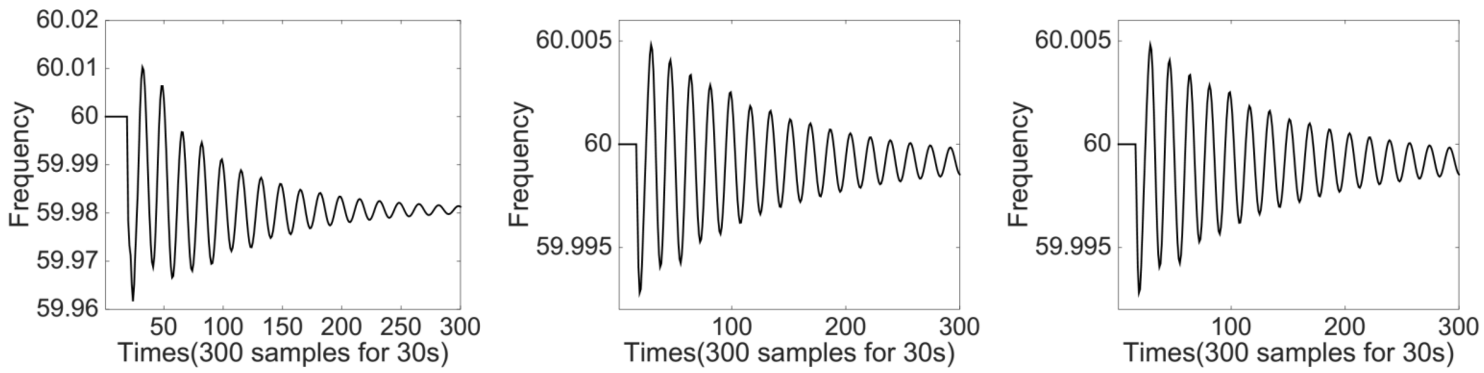
Challenges

- **Oscillation**
- **Inter-class Similarity**
- Intra-class Variance
- Nonlinear
- Unbalance

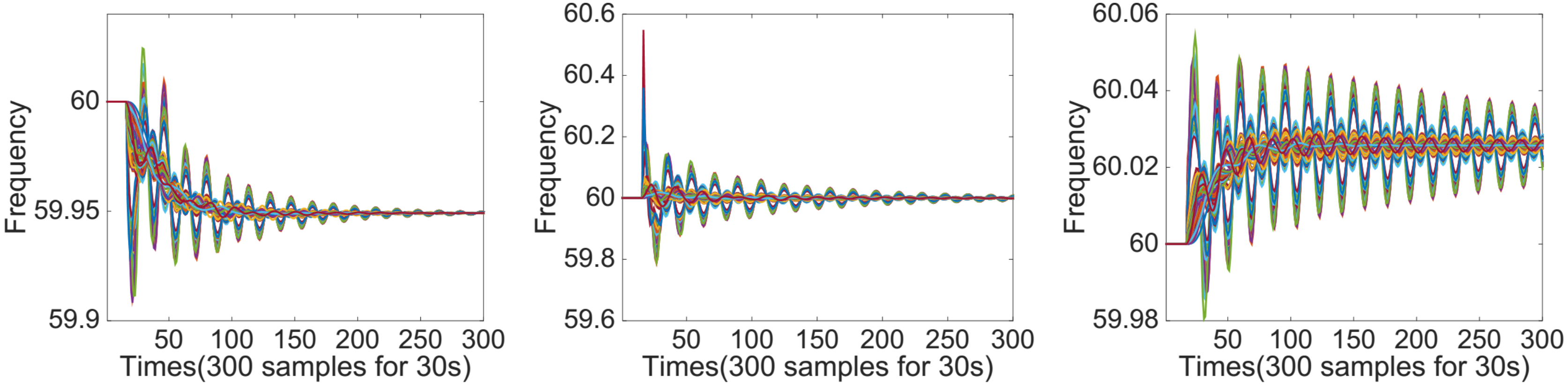


(a) GT (b) LT (c) LS

Frequency signals display similar patterns responding to different single events

Challenges

- Oscillation
- Inter-class Similarity
- **Intra-class Variance**
- Nonlinear
- Unbalance

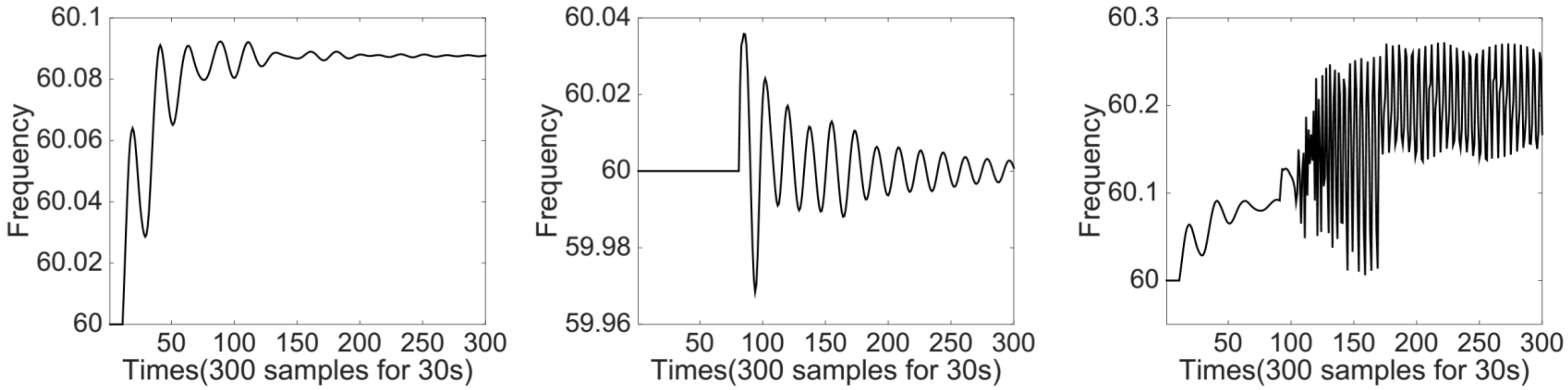


(a) GT (b) LT (c) LS

Frequency signals on several buses (plotted in different colors) responding to the same event

Challenges

- Oscillation
- Inter-class Similarity
- Intra-class Variance
- **Nonlinear**
- Unbalance



(a) LS (1s) (b) LT (8s) (c) LS (1s) + LT (8s)

Illustration of the nonlinear characteristic: (a) single event case: an LS occurred at the 1st sec; (b) single event case: an LT occurred at the 8th sec; (c) concatenated event with the same LS occurred at the 1st sec and the LT at the 8th sec

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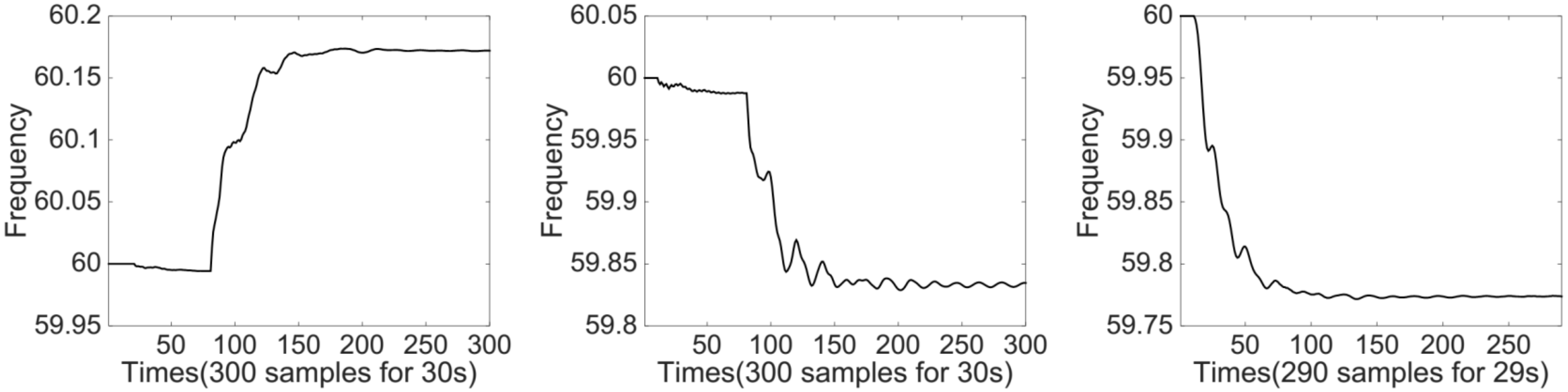
Challenges

- Oscillation
- Inter-class Similarity
- Intra-class Variance
- Nonlinear
- **Unbalance**

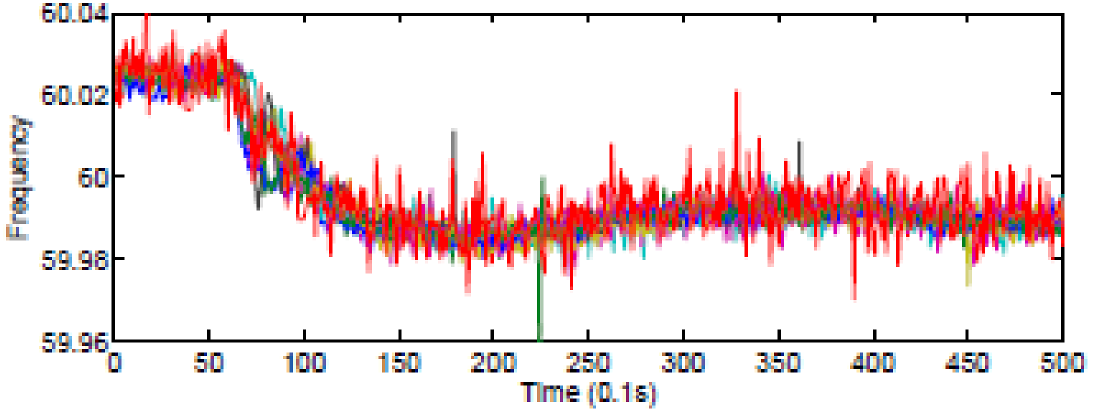


(a) GT (2s) + LS (8s) (b) GT (1s) + GT (8s) (c) GT (1s) + LT (7s)

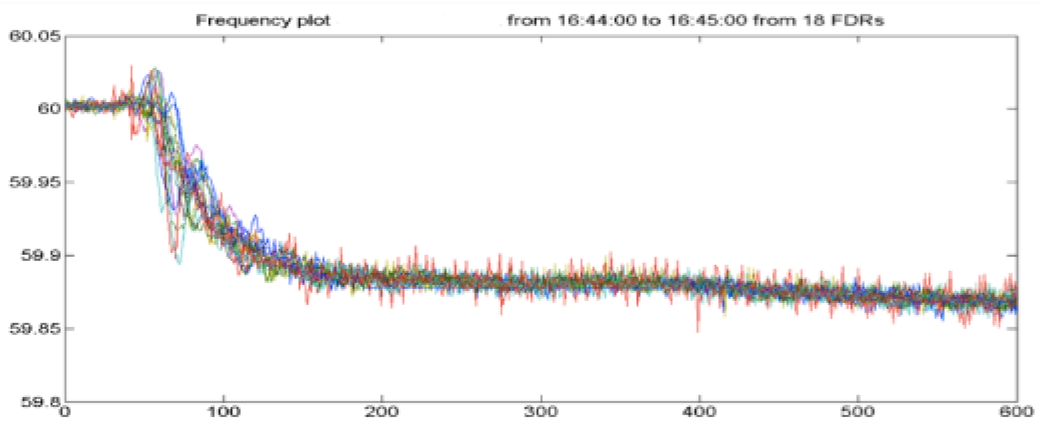
Three cases with unbalanced events: (a) concatenated events with a small GT occurred at the 2nd sec and a large LS at the 8th sec; (b) concatenated events with small GT at the 1st sec and large GT at the 8th sec; (c) concatenated events with a large GT at the 1st sec and a small LT at the 7th sec.

Challenges

- **Single Event vs. Multiple Event**



Plots of 10 raw FDR signals without denoising



Plots of 18 raw FDR signals without denoising

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Rationale – Event Unmixing

- **The key idea**
  - Linear mixture analysis has been widely used due to its effectiveness and simplicity, where the sensor readout at a single location is given by

$$\mathbf{s} = \mathbf{D}\mathbf{a} + \mathbf{n}$$

s: an l-element column vector, the measured mixture or **observation**

D: an $l \times c$ source matrix with each column indicating a **root event signature**

a: a $c \times 1$ column vector (**abundance vector)**, indicating the mixing coefficients satisfying certain constraints

n: the noise vector

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Algorithm – Sparse decomposition

- Given **s** (mixture observations), **D** (dictionary/the signature matrix), how to solve the "**a**" ?

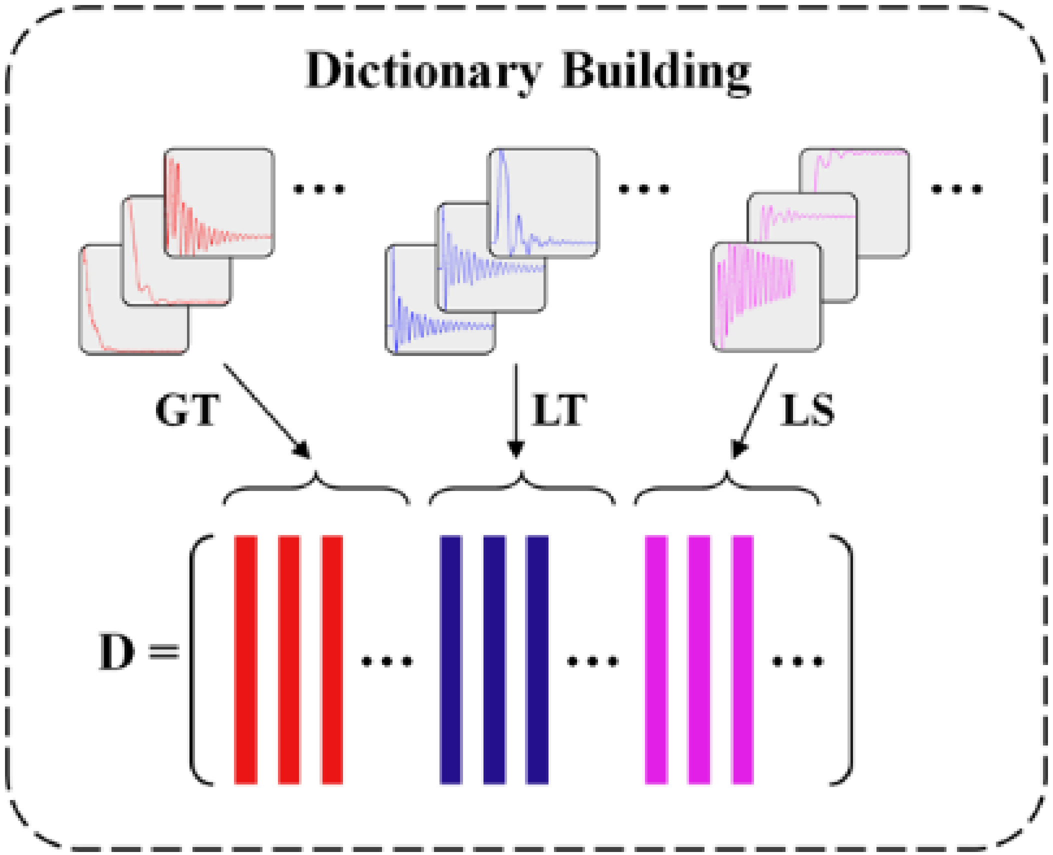
$$\mathbf{s} = \mathbf{D}\mathbf{a} + \mathbf{n}$$

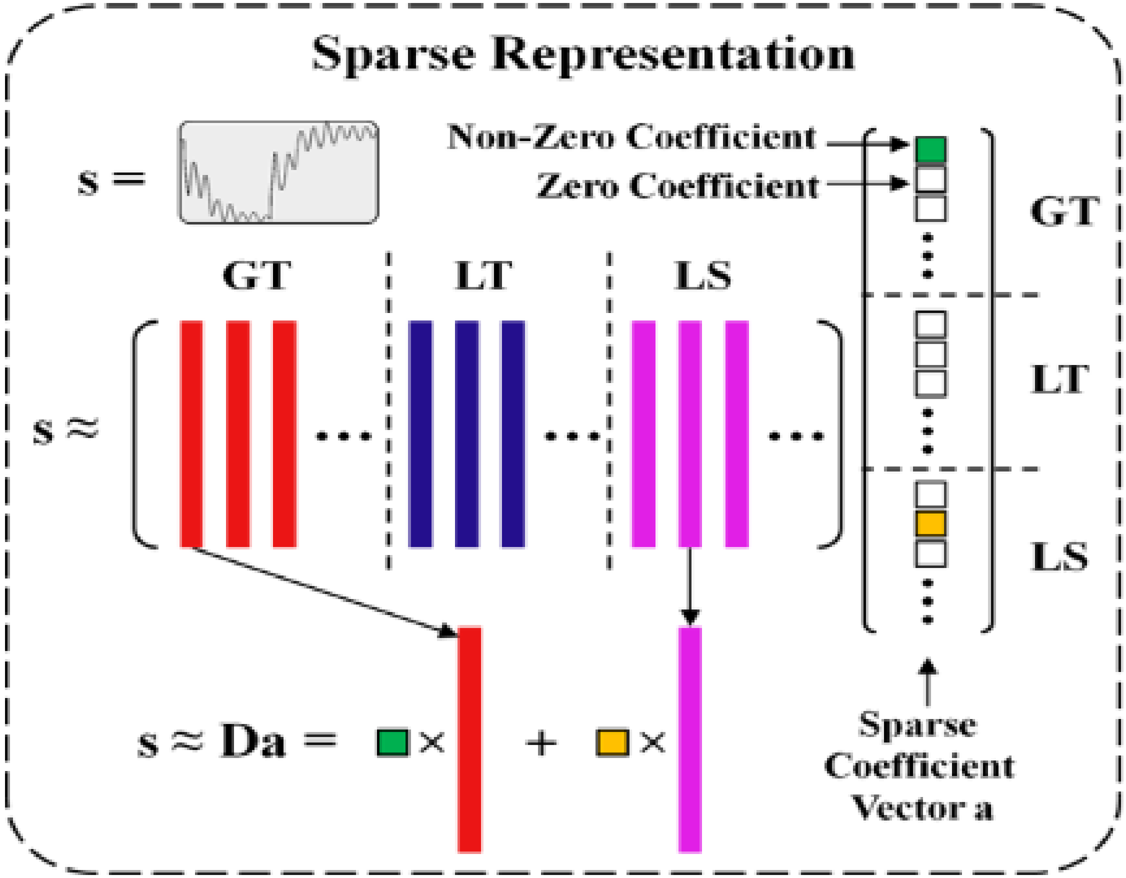
- Traditional methods fail to solve the coefficient vector **a**, such as LS, UFCLS.
- We propose the sparisty and non-negative constraints.

$$\arg\min_{\mathbf{a}} \left\{ \|\mathbf{s} - D\mathbf{a}\|^2 + \lambda \|\mathbf{a}\|_1 \right\}$$
$$\text{s.t. } \mathbf{a} \succeq 0$$

Because only a few components/ signatures should be involved in a mixed signal, **a** should be sparse--- a few non-zero elements. l_1-norm minimizes the number of non-zero elements in **a**.

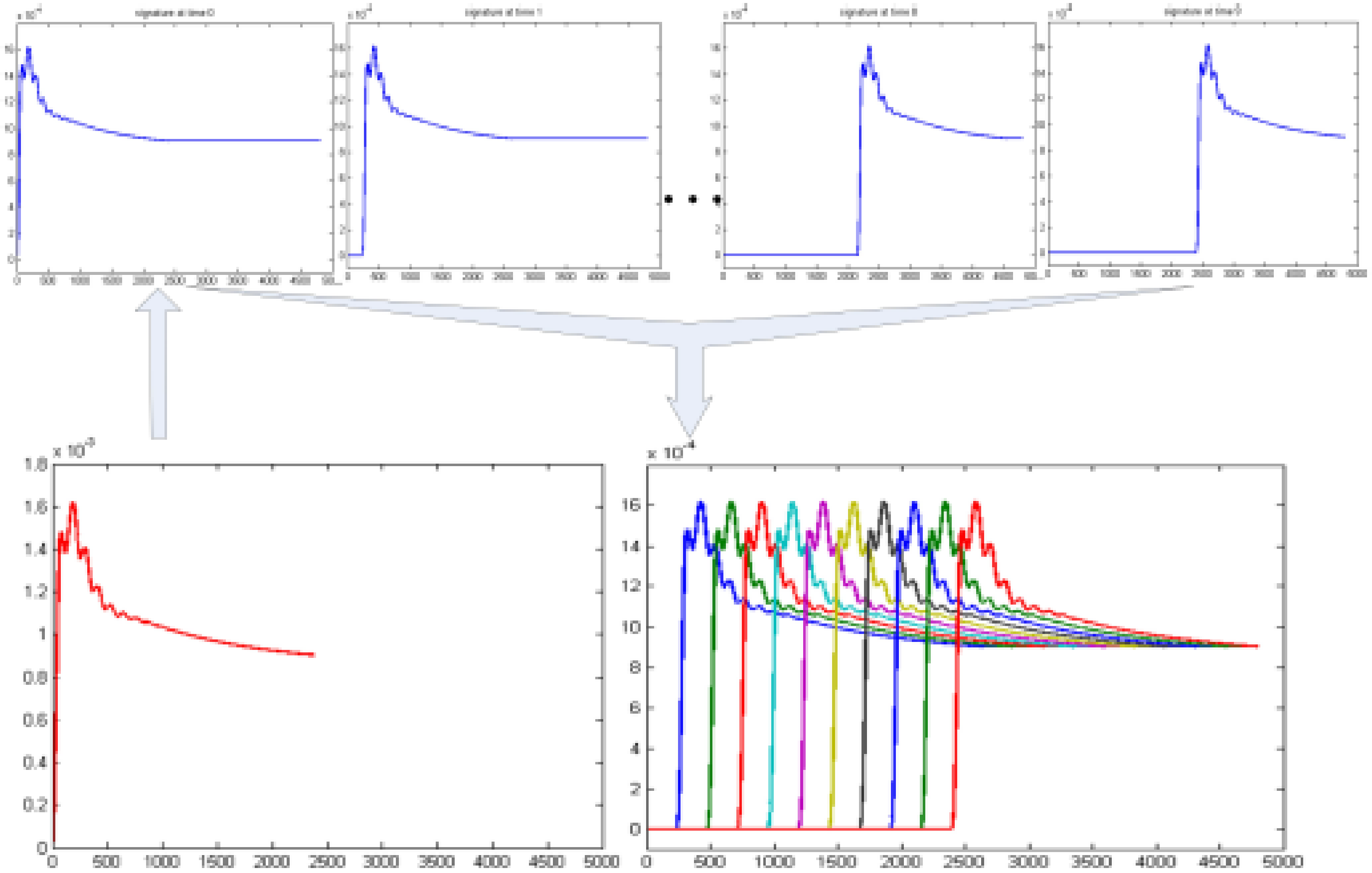
The Whole Flow





Dictionary Building

- **Temporal localization: shift each root event**



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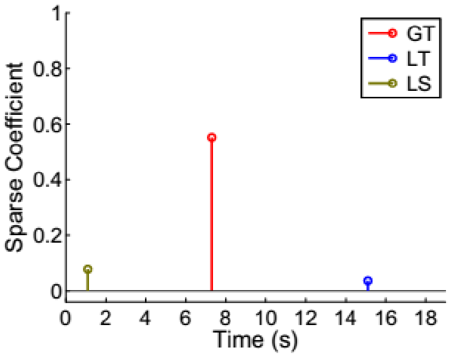
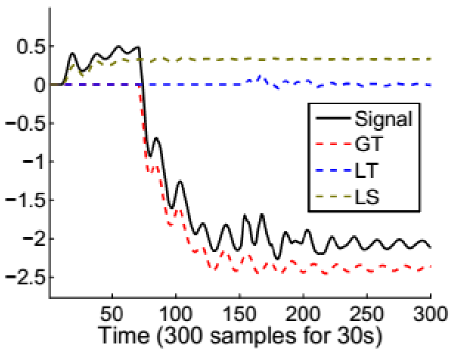
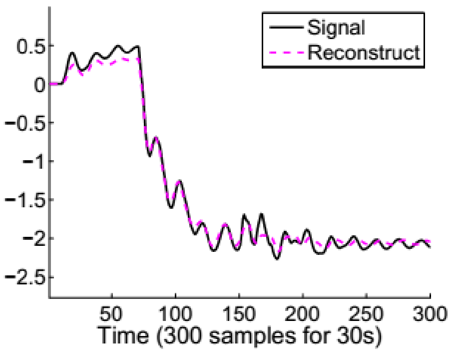
Experimental Evaluation

- **Simulated Event on NPCC testbed**
  - ❖ Triple event case







Ground truth:
- **LS (1sec)**
- **GT (7sec)**
- **LT (15sec)**

Detection:
- **LS (1.10sec)**
- **GT (7.29sec)**
- **LT (15.11sec)**

	Number of tests	DA (%)	FA (%)	RPR (%)	OTD (s)
S1C	144	100	0	100	0.123
M2C	115	95.65	2.17	98.64	0.193
M3C	138	91.55	0.97	98.15	0.202

S1C: single event cases
M2C: double event cases
M3C: triple event cases

DA: detection accuracy
FA: false alarm rate
PRR: root-pattern recognition rate
OTD: occurrence time delay

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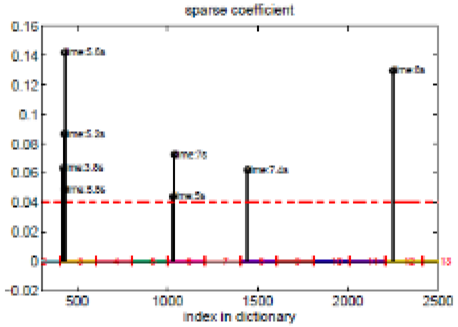
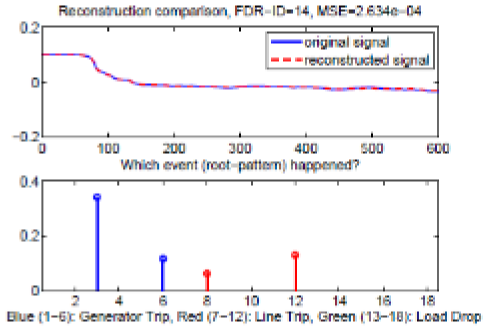
Experimental Evaluation

• Real Event

- ❖ **Two generator trips (event3 and event4) were successfully detected from 16 out of 18 FDRs and two line trips were successfully detected from 17 out of 18 FDRs.**
- ❖ **Each FDR detected the events with different time delay which can be further utilized for event spatial localization purpose.**

Event detection on FDR 14

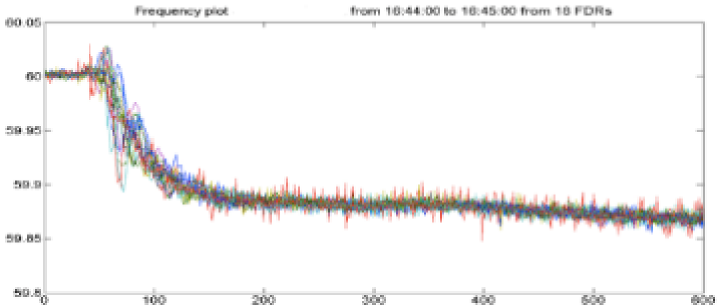




Each individual event is temporally localized on different FDRs!

FDR	1	2	3	4	5	6
GenTrip3	5.4s		4.0s	7.0s	5.2s	4.6s
GenTrip6	6.2s	4.2s	3.2s	7.6s	4.6s	4.2s
LineTrip8	9.2s	7.2s	7.8s	7.6s	9.0s	6.2s
LineTrip12	7.2s	6.2s		5.6s	6.4s	7.4s
FDR	7	8	9	10	11	12
GenTrip3	4.4s	4.0s	4.6s	4.2s	4.0s	4.2s
GenTrip6	6.4s	3.8s	6.8s	4.0s	6.0s	5.4s
LineTrip8	6.8s	5.6s	8.6s	6.0s	6.6s	8.6s
LineTrip12	7.2s	5.8s	7.2s	6.0s	6.6s	7.2s
FDR	13	14	15	16	17	18
GenTrip3	5.0s	5.6s	4.2s		3.6s	4.4s
GenTrip6	4.2s	7.0s	3.8s	4.4s	3.2s	7.8s
LineTrip8	9.0s	7.4s	6.8s	7.6s	7.8s	6.2s
LineTrip12	7.0s	8.0s	7.2s	7.4s	5.8s	6.4s

Plots of 18 raw FDR signals without denoising. (Denoising is necessary before performing event detection algorithm!)



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Conclusion

- **Sparse Decomposition**
  - ❖ **A novel interpretation of the frequency signal in power grid**
  - ❖ **Decomposition of linear mixture constrained by sparsity**
- **Multiple Event Detection**
  - ❖ **Detection of cascading events with different types**
  - ❖ **Temporal localization of events**
- **Test on Simulated and Real Cases**
  - ❖ **High efficiency and accuracy**

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