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# MULTIVARIATE EMPIRICAL MODE DECOMPOSITION BASED SIGNAL ANALYSIS AND EFFICIENT-STORAGE IN SMART GRID

Liu Liu<sup>1</sup>, Austin Albright<sup>1,2</sup>, Alireza Rahimpour<sup>1</sup>, Jiahui Guo<sup>1</sup>, Hairong Qi<sup>1</sup>, Yilu Liu<sup>1</sup>

<sup>1</sup>EECS, University of Tennessee, Knoxville, TN, USA

<sup>2</sup>EESRD, Oak Ridge National Laboratory, Oak Ridge, TN, USA

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# Introduction

# Introduction

- Wide-area measurement system (WAMS) provides rich information.
- Phasor measurement units (PMUs) have been widely deployed across North America.
- Huge amount of raw measurement data (collected by sensors) every second.

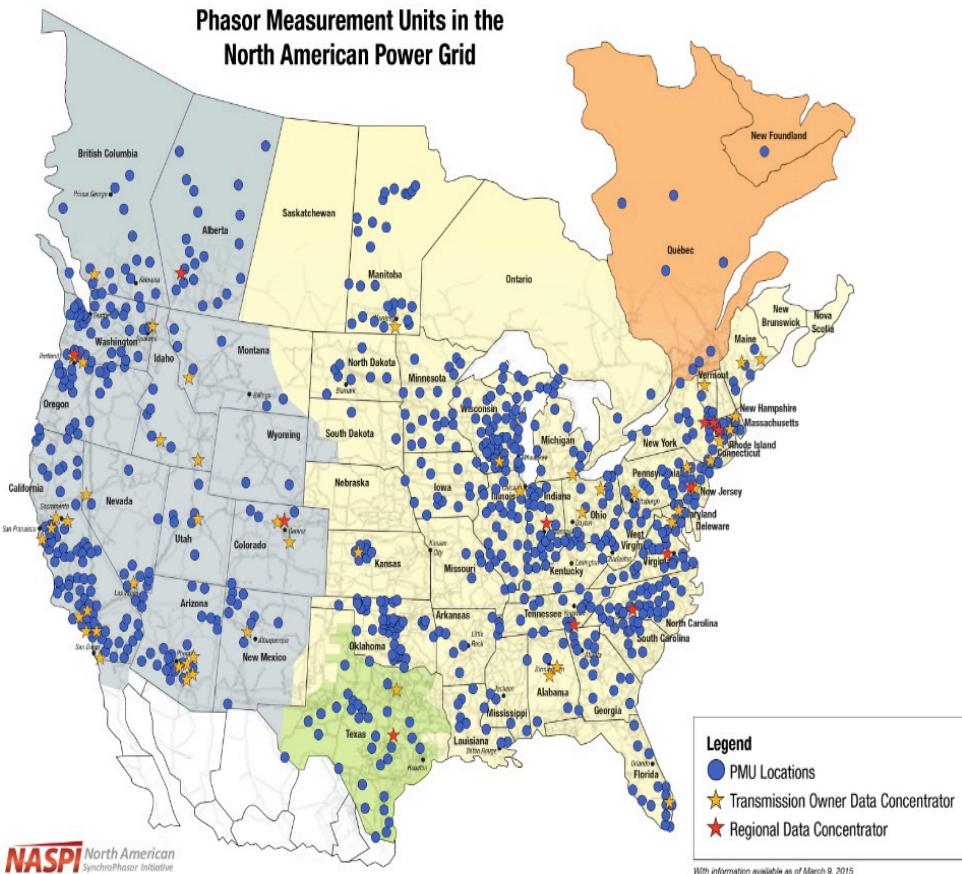


Figure 1. PMUs in North America

# Introduction

- Measurements heavily contaminated
  - noise (at transmission level and distribution level)
  - sensor node failures
  - cyber-attacks
- Challenging to provide reliable data analytics
  - extract useful information
  - reduce data storage

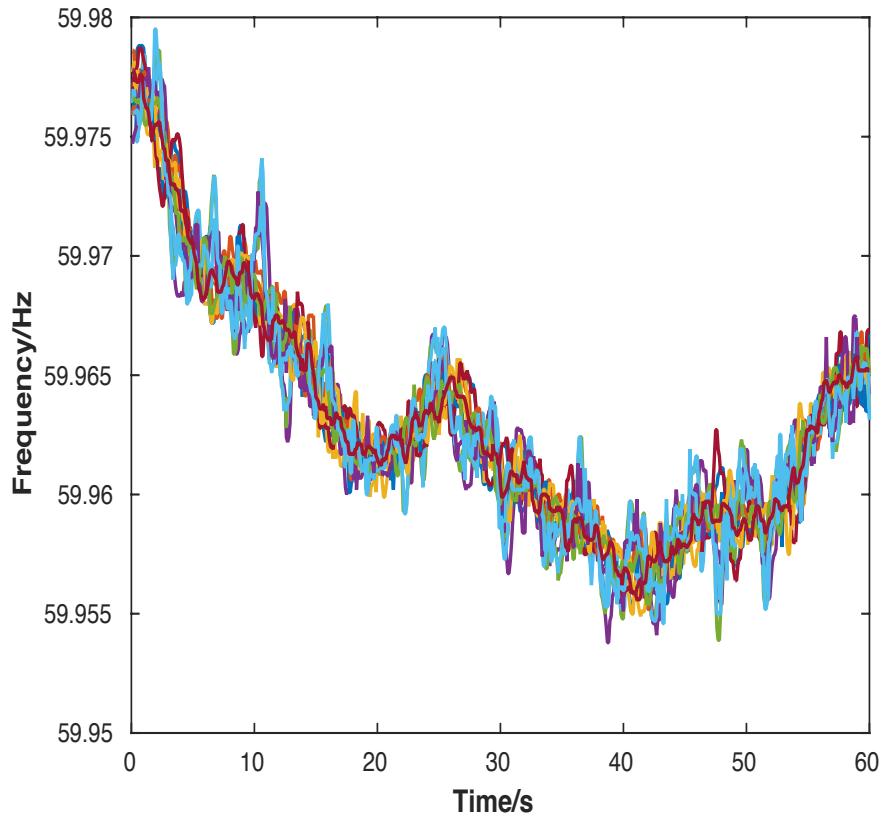


Figure 2. A clip of raw frequency records

# Introduction

- High fidelity compression has been addressed
  - lossless data compression for smart meters
  - compress disturbance data using wavelet-based algorithm
- Particularly, singular value decomposition (SVD) based approaches take the advantage of low-rank characteristic of multiple sensors.
  - spatial-temporal blocks (matrices)
  - thresholding the number of significant singular values

$$L \approx \hat{L} = \hat{U} \hat{\Sigma} \hat{V}^T \quad (1)$$

- Use  $\hat{L}$  to estimate the original data matrix  $L$

# Motivation

- Signal Decomposition (a better understanding of the signal)
  - retaining signal content
  - removing noise
- Related decomposition algorithms
  - Fourier
  - PCA
  - ICA
  - EMD
  - MEMD

# Proposed Framework

# Proposed Framework

- We propose a novel framework using Multivariate Empirical Mode Decomposition (MEMD): MEMD based Signal Analysis (**MSA**)

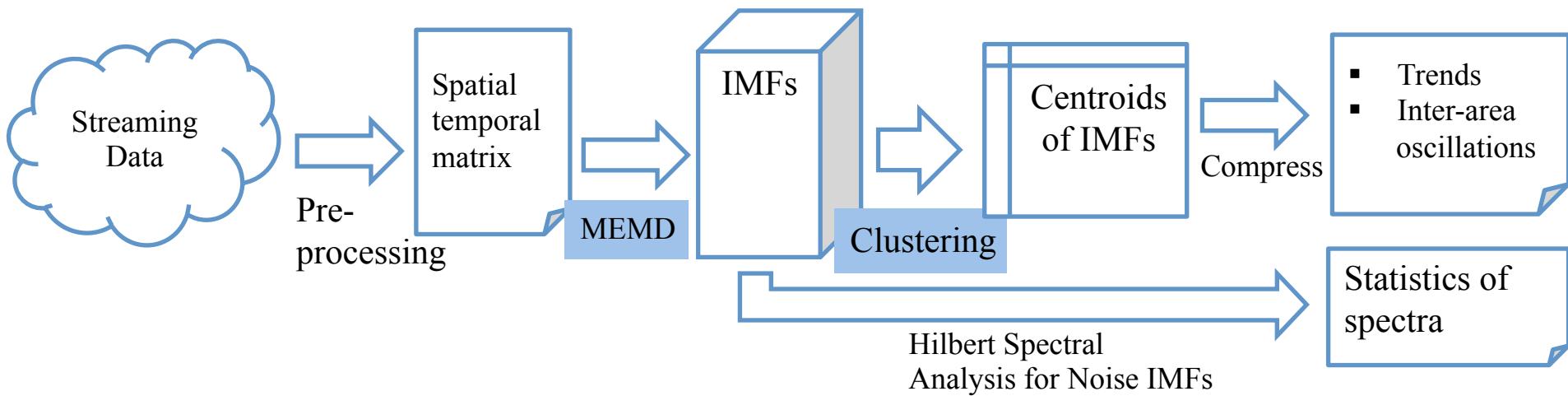


Figure 3. The framework of proposed MSA

# Proposed Framework

- Multivariate Empirical Mode Decomposition (MEMD) decomposes multi-channel signal  $X(t)$  into common intrinsic mode functions (IMFs):

$$X = \sum_{k=1}^N IMF_k + R \quad (2)$$

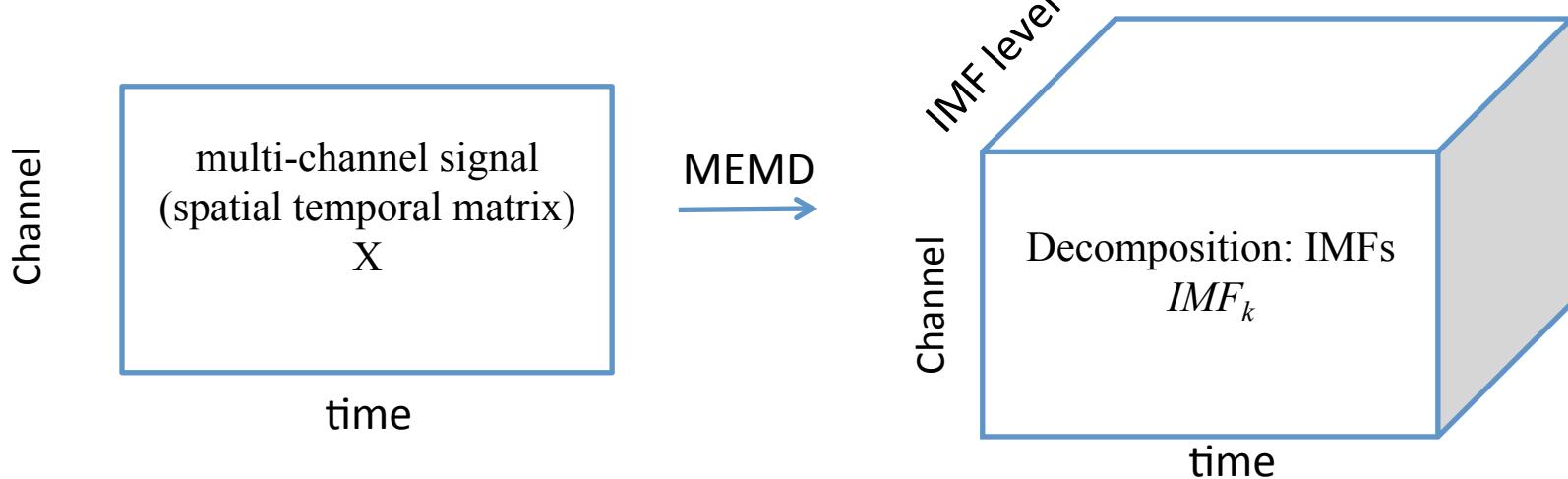


Figure 4. MEMD on data matrix

# Proposed Framework

- On individual IMF level, IMF for each channel is considered as a point in the data cloud
- The low-rank characteristic is interpreted as density of the data points
- Mean shift clustering finds the inner structure on each IMF level. The bandwidth is the mean of pair-wise “distance” between data points:

$$b_k = \alpha \frac{2 \sum_{i,j}^C \|IMF_k^{(i)} - IMF_k^{(j)}\|^2}{C(C-1)} \quad (3)$$

- IMFs are clustered into groups, each of which is represented by its centroid

# Proposed Framework

- We choose a threshold for the number of clusters empirically to determine the IMF is noise or not.

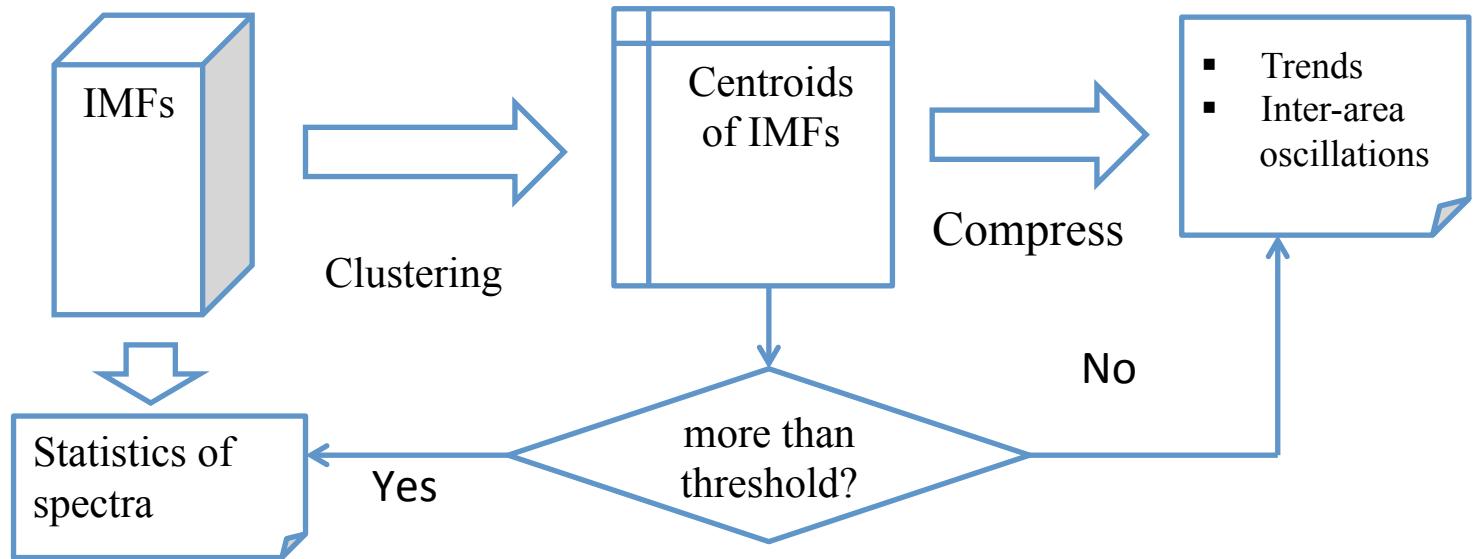


Figure 5. Data characterization and compression

# Experiments

# Experiments

Evaluate on both synthetic data and real-world WAMS data from FNET/GridEye

- Synthetic data
  - sampling rate of 10 Hz and duration of 1 min, 10 channels
  - three components: 0.015 Hz, 0.05 Hz, 0.2 Hz, peak-to-peak amplitudes of 0.01, 0.002 and 0.0005, respectively.
  - additive white Gaussian noise 20 dB
- FNET/GridEye data
  - sampling rate of 10 Hz and time window of 1 min
  - ambient data: 14 channels
  - event data: generation trip, 6 channels

# Experiments – Synthetic Data

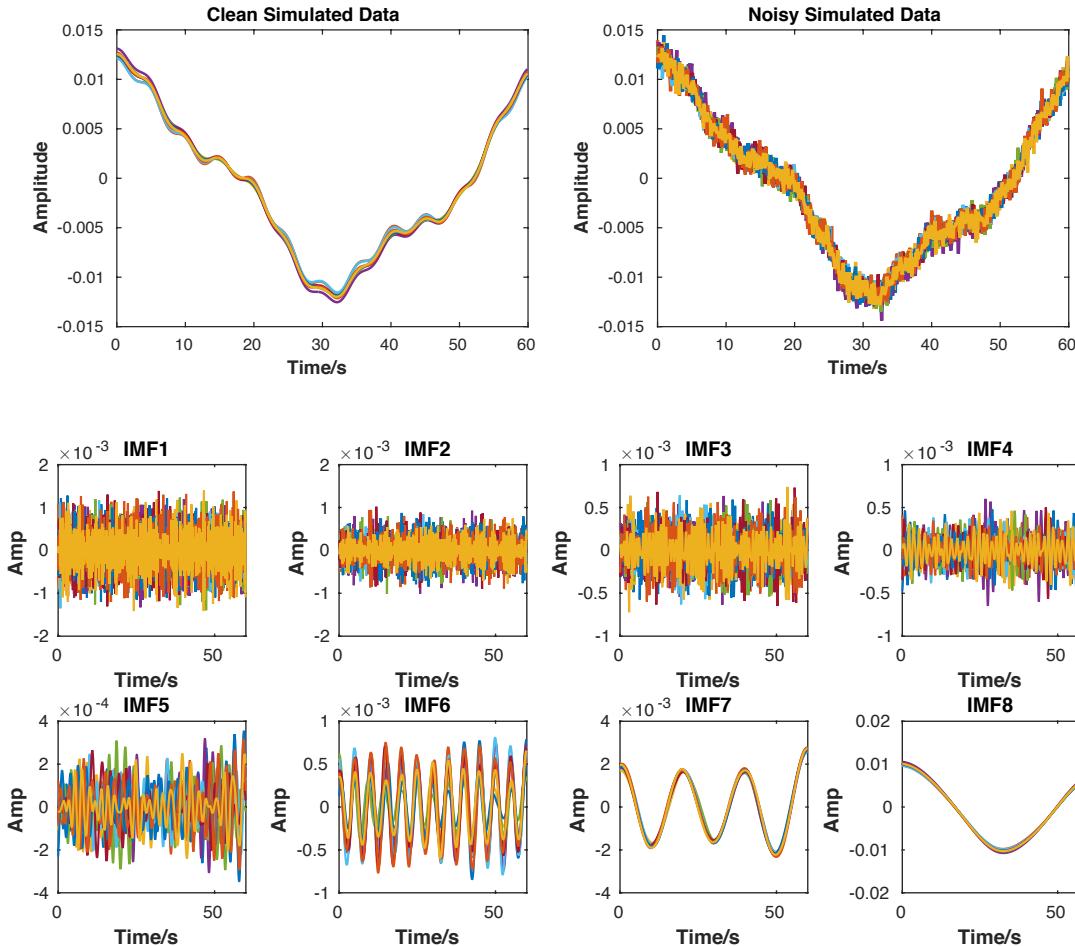


Figure 6. Synthetic data and adding noise

Figure 7. IMFs generated by MEMD

# Experiments – Synthetic Data

	IMF1, 2, 3, 4	IMF5	IMF6	IMF7, 8
# centroids	5	4	2	1

Table 1. Number of centroids

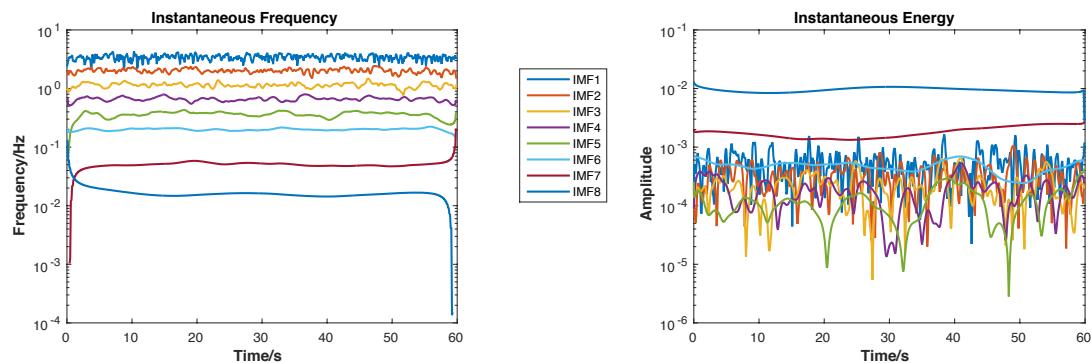


Figure 8. Hilbert-Huang transform of IMFs

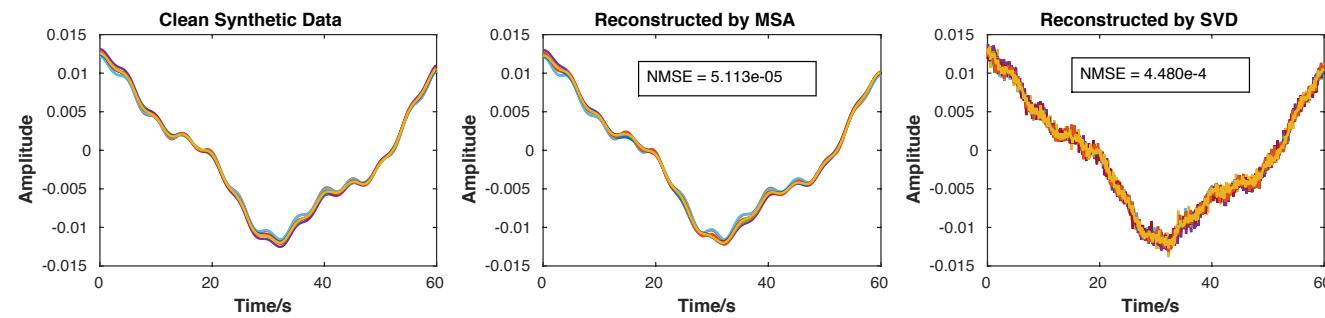


Figure 9. Reconstructions Comparison

# Experiments – Ambient Records

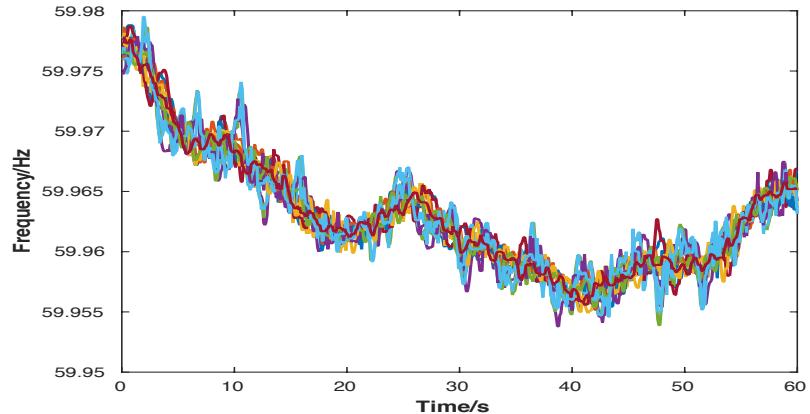


Figure 10. Ambient records of FNET/GridEye

Ambient	IMF1, 2, 3	IMF4, 5	IMF6	IMF7	IMF8, 9, 10
# centroids	7	6	4	3	1

Table 2. Number of centroids for ambient records

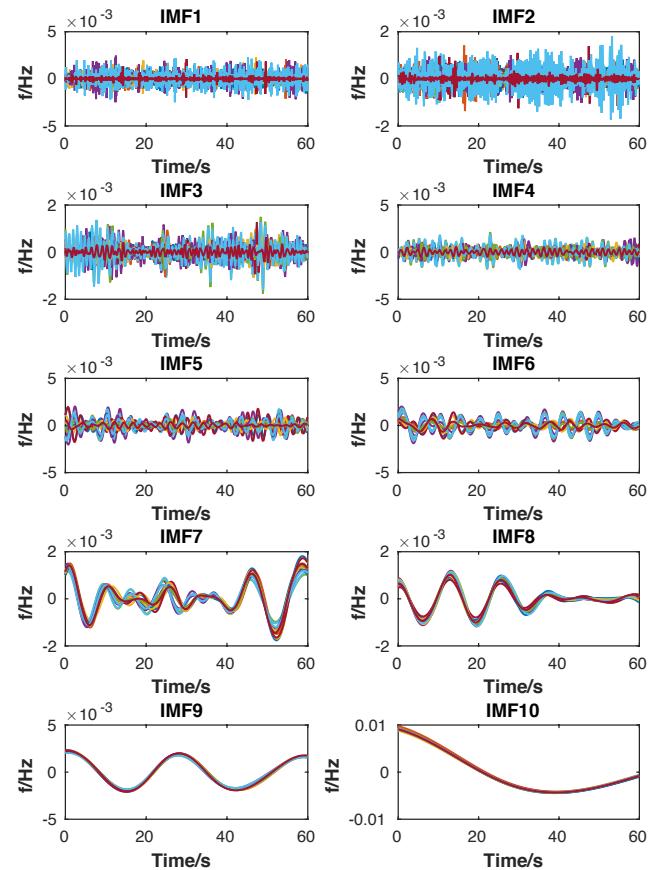


Figure 11. IMFs for ambient records

# Experiments – Ambient Records

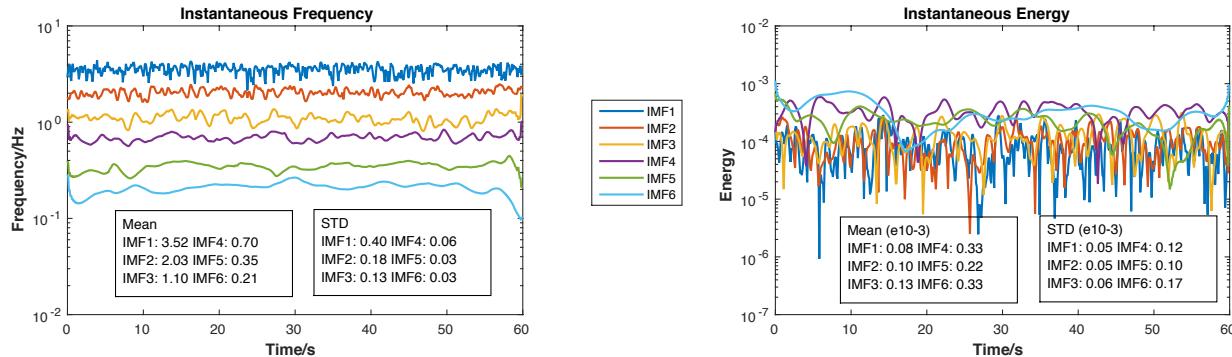


Figure 12. Hilbert-Huang transform of IMFs (ambient records)

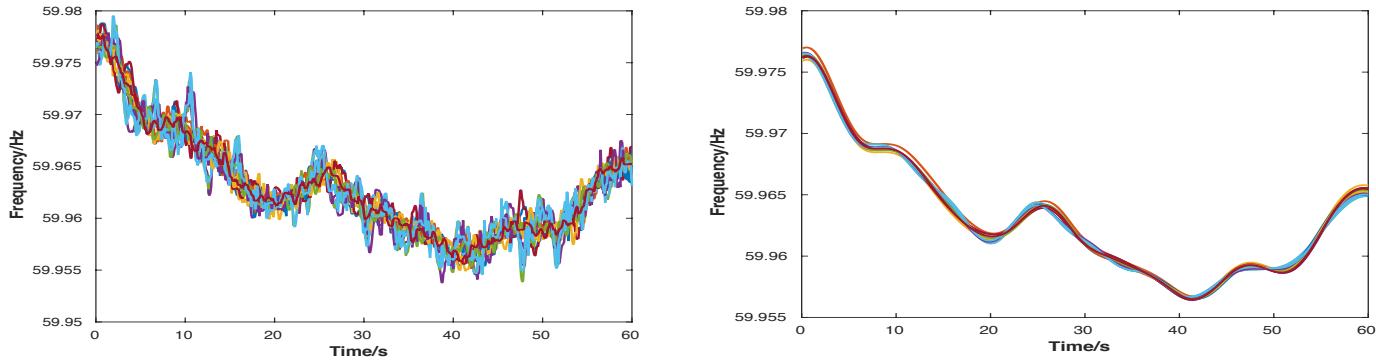


Figure 13. Reconstruction of ambient records

# Experiments – Event Records

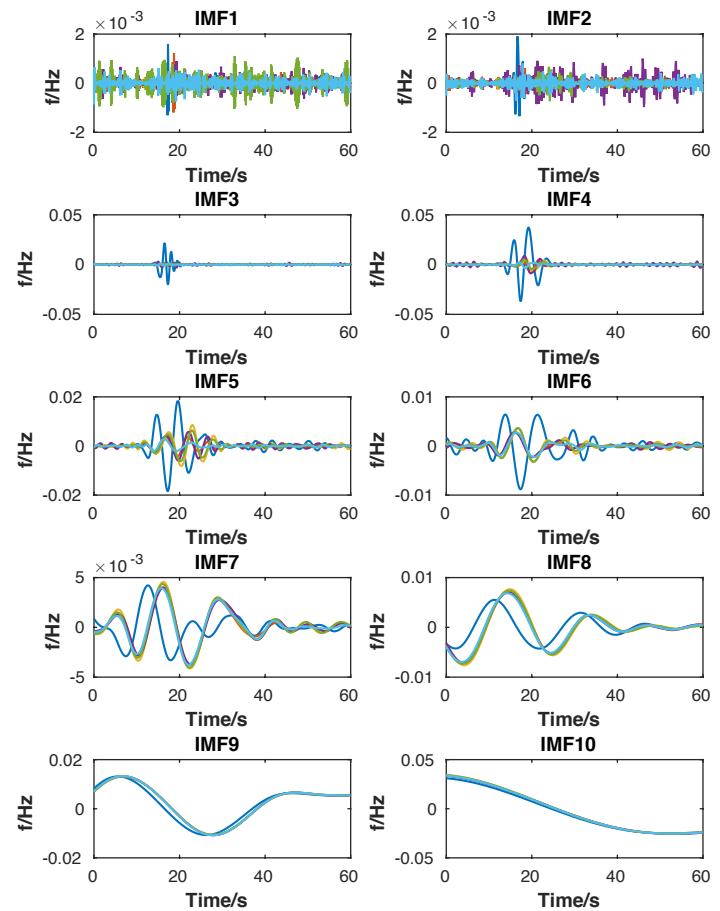
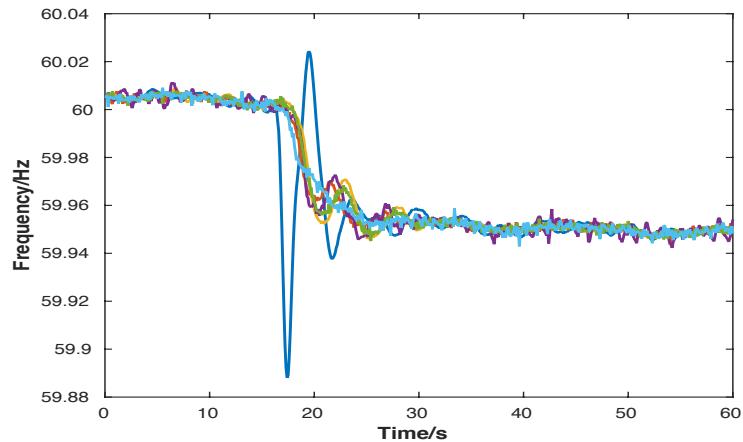


Figure 14. Event records of FNET/GridEye

Event	IMF1, 2, 3	IMF4	IMF5	IMF6 , 7, 8, 9	IMF10
# centroids	5	2	3	2	1

Table 3. Number of centroids for event records

Figure 15. IMFs of event records

# Experiments – Event Records

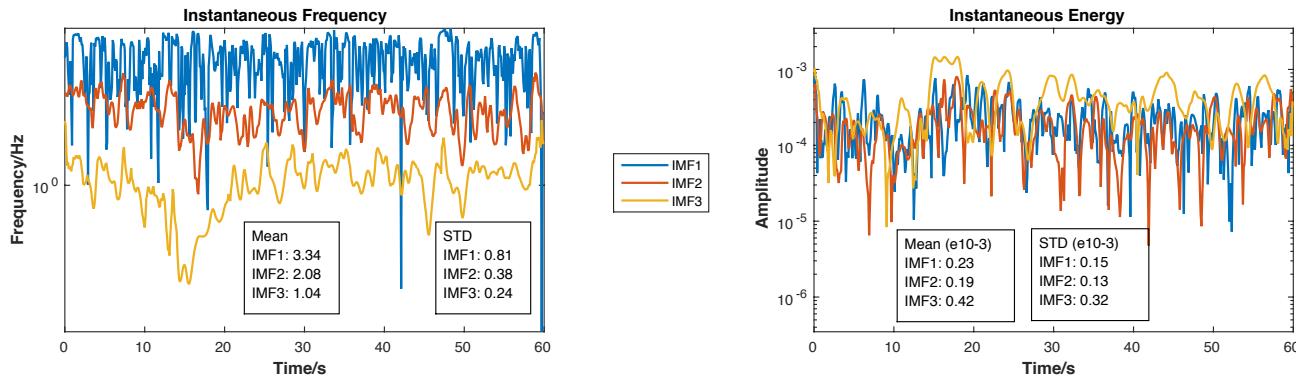


Figure 16. Hilbert-Huang transform of IMFs (event records)

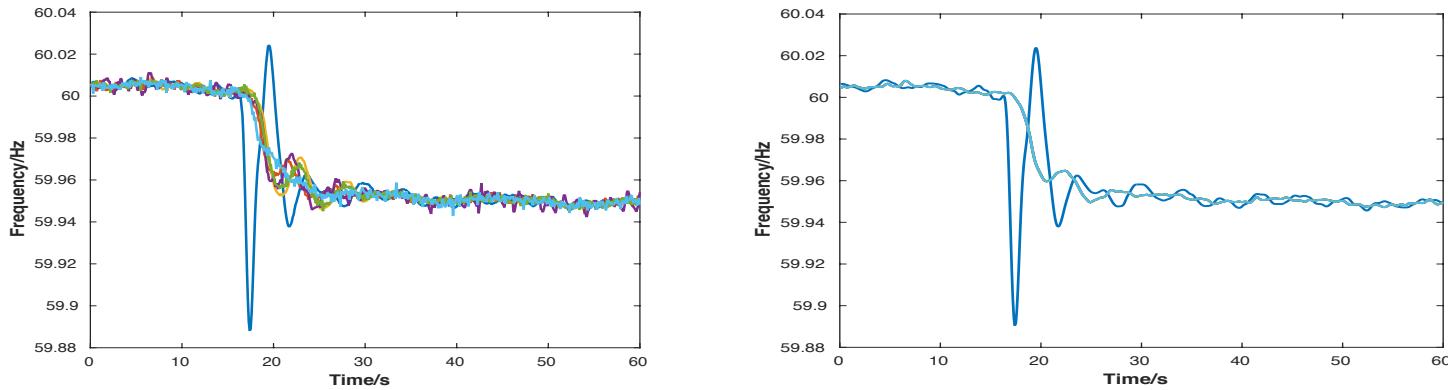


Figure 17. Reconstruction of event records

# Experiments – Compression

- The compression rate of ambient records is around 70% (14 channels) while the event records are not compressed due to fidelity of information.
- The overall compression rate can be approximated by that of ambient records since they are dominant.
- Empirically the compression rate is higher with more channels, provided the records follows the same pattern.

# Conclusion

# Conclusion

- We proposed MEMD based Signal Analysis (MSA) to address the problem of data characterization and compression effectively.
- The framework is totally data-driven and non-parametric.
- Also no prior knowledge needed
- Experiments on synthetic data and real-world records demonstrated its superiority.
- The compression can be better with more data involved.

**Thank you for your Attention!  
Questions?**