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Missing data recovery by exploiting low-dimensionality in synchrophasor measurements

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Problem Motivation

- Phasor Measurement Units:

  High sampling rate: 30/60 samples/second

  Usually multi-channel: measure bus voltage phasors, line current phasors, and frequency.

- PMU data is considered a source of *Big Data* in power systems.
- *Missing Data* affect applications such as state estimation and disturbance identification.

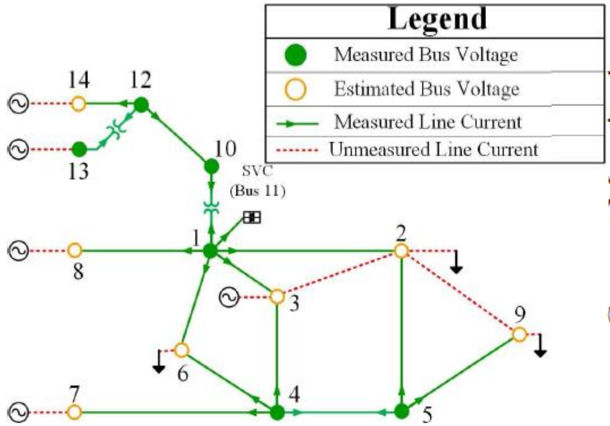
Developing *reliable and computationally efficient* PMU data recovery methods.

Low-rank Property of PMU Data

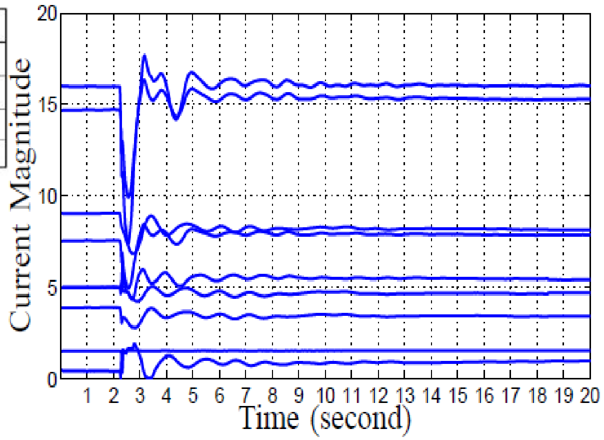
- Existing missing data recovery: interpolation from measurements in the same channel.
- Our approach: Analyze PMU data of multiple time instants collectively from PMUs in electrically close regions and distinct control regions.
- Process *spatial-temporal blocks* of PMU data for tasks such as missing data recovery, data compression and storage, disturbance triggering, detection of data substitution attacks.
- Key feature: *low-rankness* of PMU data blocks. (also observed in Chen & Xie & Kumar 2013, Dahal & King & Madani 2012.)

Low-rank Property of PMU Data

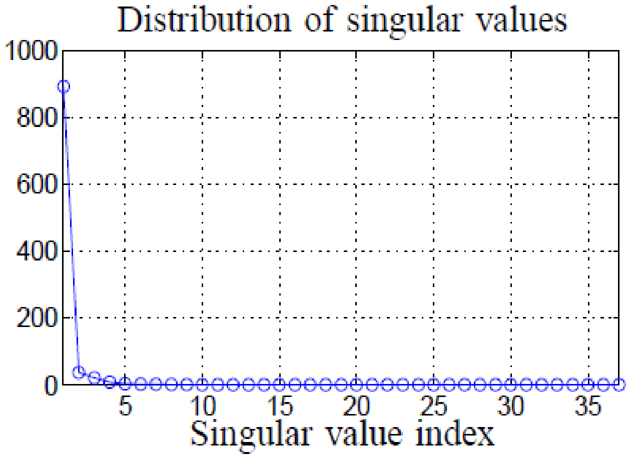
- 6 PMUs measure 37 voltage/current phasors. 30 samples/second for 20 seconds.
- Singular values decay significantly. Mostly close to zero. Singular values can be approximated by a sparse vector.
- Low-rankness also used in Chen & Xie & Kumar 2013, Dahal & King & Madani 2012 for dimensionality reduction.



PMUs in Central NY Power System



Current magnitudes of PMU data



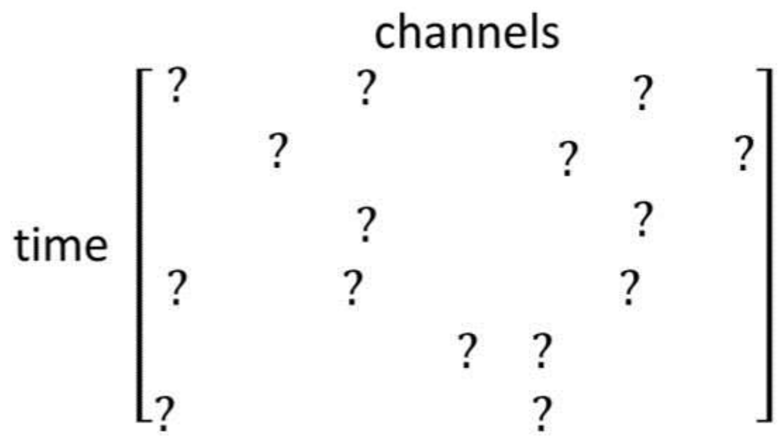
Singular values of the PMU data matrix

Missing data recovery in low-rank PMU data matrix

- **Our approach**: leverage low-rankness of PMU data blocks.

Low-rank matrix completion Problem!

Quite a few recovery algorithms exist.



Low-rank matrix with missing entries

Low-rank Matrix Completion Methods

Nuclear norm minimization (Fazel 2002), recover the missing data by solving a convex program:

$$\min_{X} ||X||_*$$

Singular Value Thresholding (Cai 2010), *iteratively* solve a modified version of the nuclear norm minimization problem:

$$\min_{X} \tau||X||_* + \frac{1}{2}||X||_F^2$$

s.t. X is consistent with the observed entries.

$||X||_*$ = sum of singular values of X

$||X||_F^2$ = sum of the absolute squares of all entries of X

OLAP (Online Algorithm for PMU Data Processing)

OLAP can fill in the missing data in *real-time*.

OLAP continuously updates dominating singular values and singular vectors. The new data is viewed as a linear combination of existing singular vectors.

OLAP is adaptive to the dimension change of the subspace. Disturbances in the power system can cause the dimensionality of a PMU data matrix to vary rapidly with time.

Gao, Wang, Ghiocel, and Chow, IEEE Transactions on Power Systems, 2016

Theoretical Analysis of PMU Data Recovery by Low-rank Matrix Completion Methods

The locations of missing PMU data are usually correlated.

- *Temporal* correlation: loss of consecutive measurements in one PMU channel.
- *Spatial* correlation: loss of measurements in multiple PMU channels simultaneously.

Theoretical guarantee of low-rank matrix completion when the locations of missing points are correlated.

Although the locations of the missing entries of a rank-r matrix are temporally or spatially correlated, all missing entries can be correctly recovered as long as $O(n^{2-\frac{1}{r+1}} r^{\frac{1}{r+1}} \log^{\frac{1}{r+1}} n)$ entries are observed.

Gao, Wang, Ghiocel, and Chow, IEEE Transactions on Power Systems, 2016

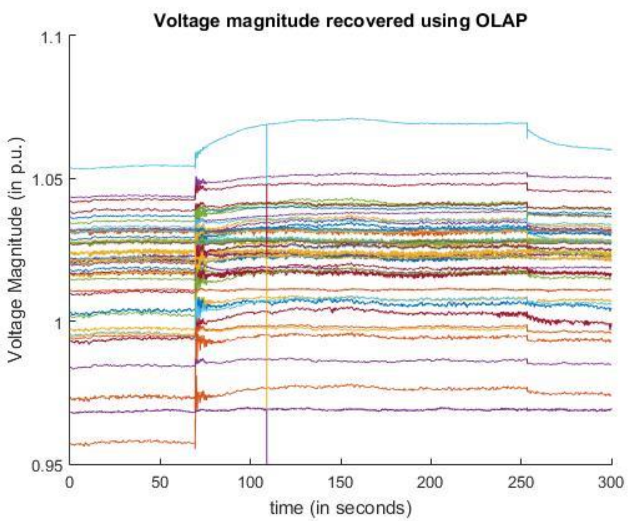
Data Recovery

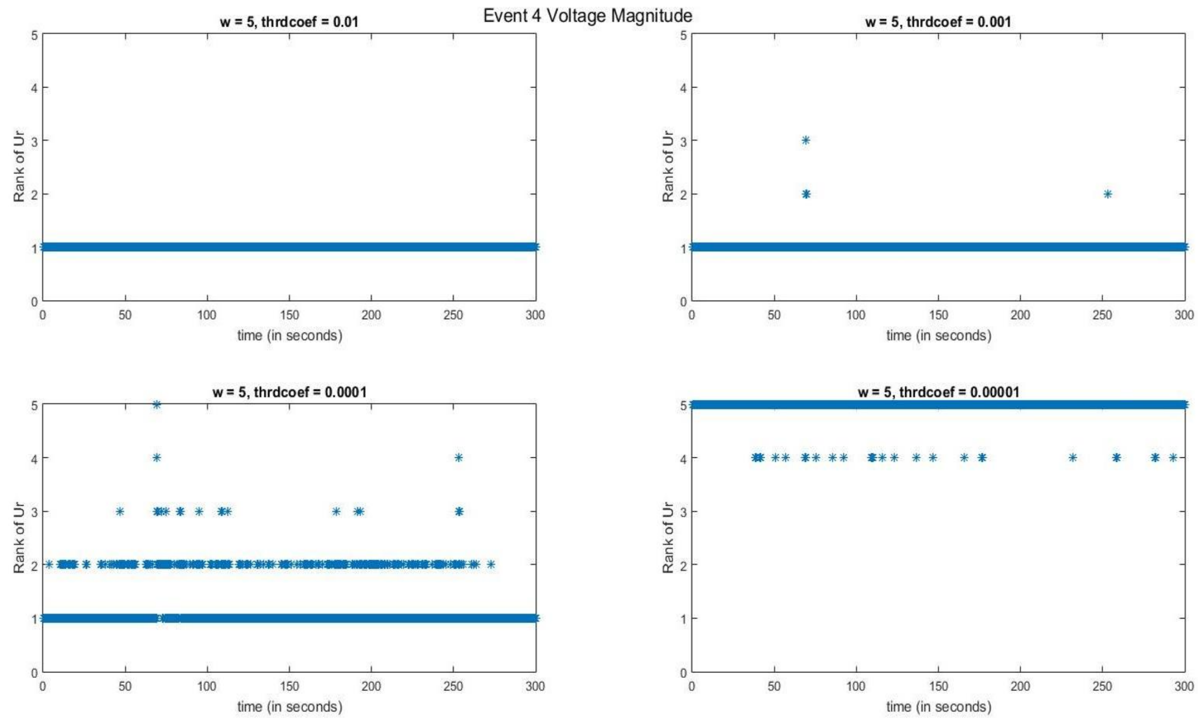
- Tested: Ten 5-minute data segments of NYS PMU data during grid disturbances.

- Recovered:
  - Voltage magnitude (53 channels)
  - Voltage angle (53 channels)
  - Frequency (53 channels)
  - Current magnitude (264 channels)
  - Current angle (264 channels)

OLAP Results

Varying the threshold parameter for the OLAP algorithm allows the submatrix rank to vary.



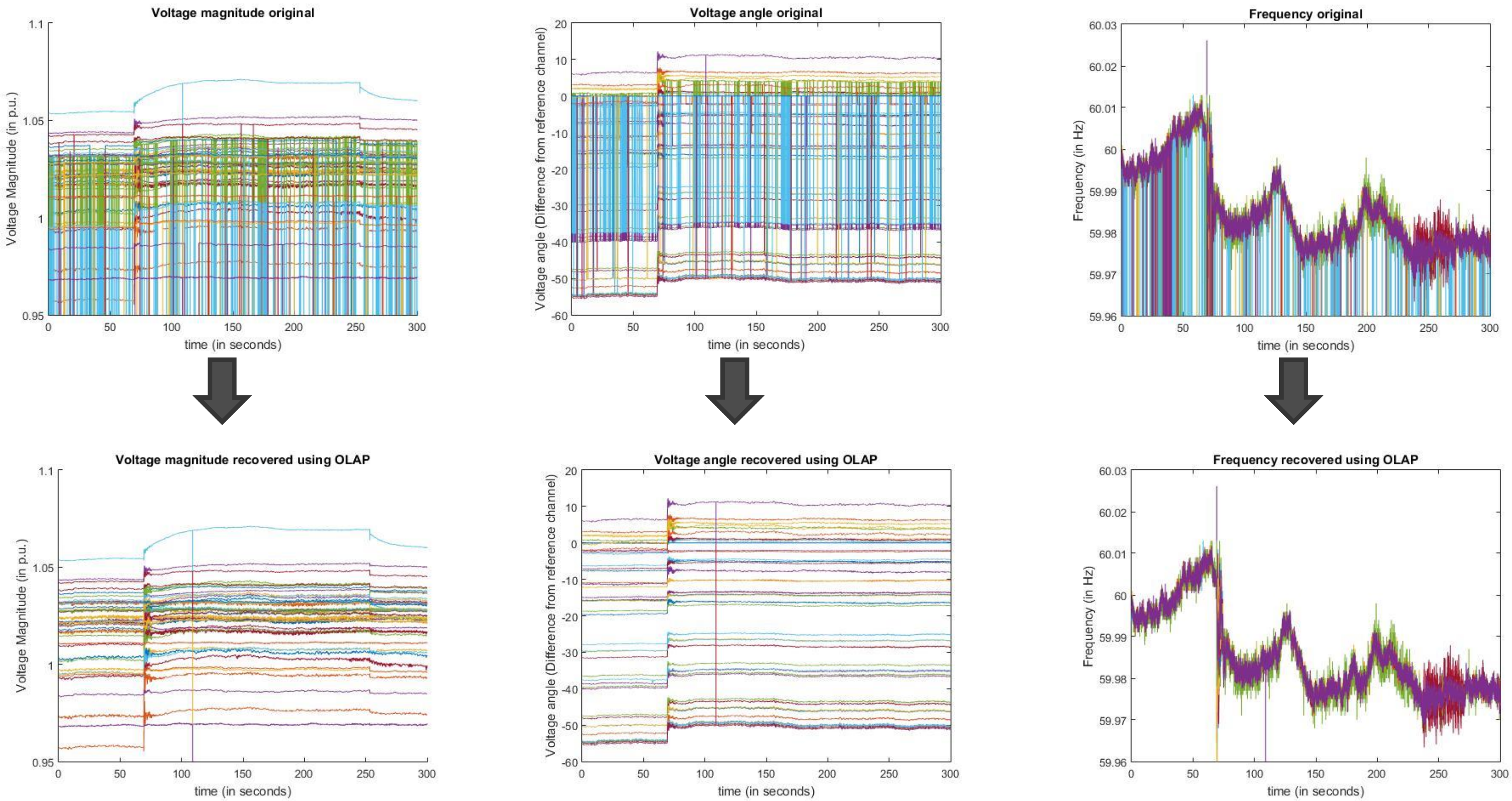


Computation time (2.60 GHz Intel Core i5 with 16 GB RAM):

	Voltage magnitude	Voltage angle	Frequency	Current magnitude	Current angle
OLAP	1.305 secs	1.327 secs	1.239 secs	8.121 secs	9.113 secs

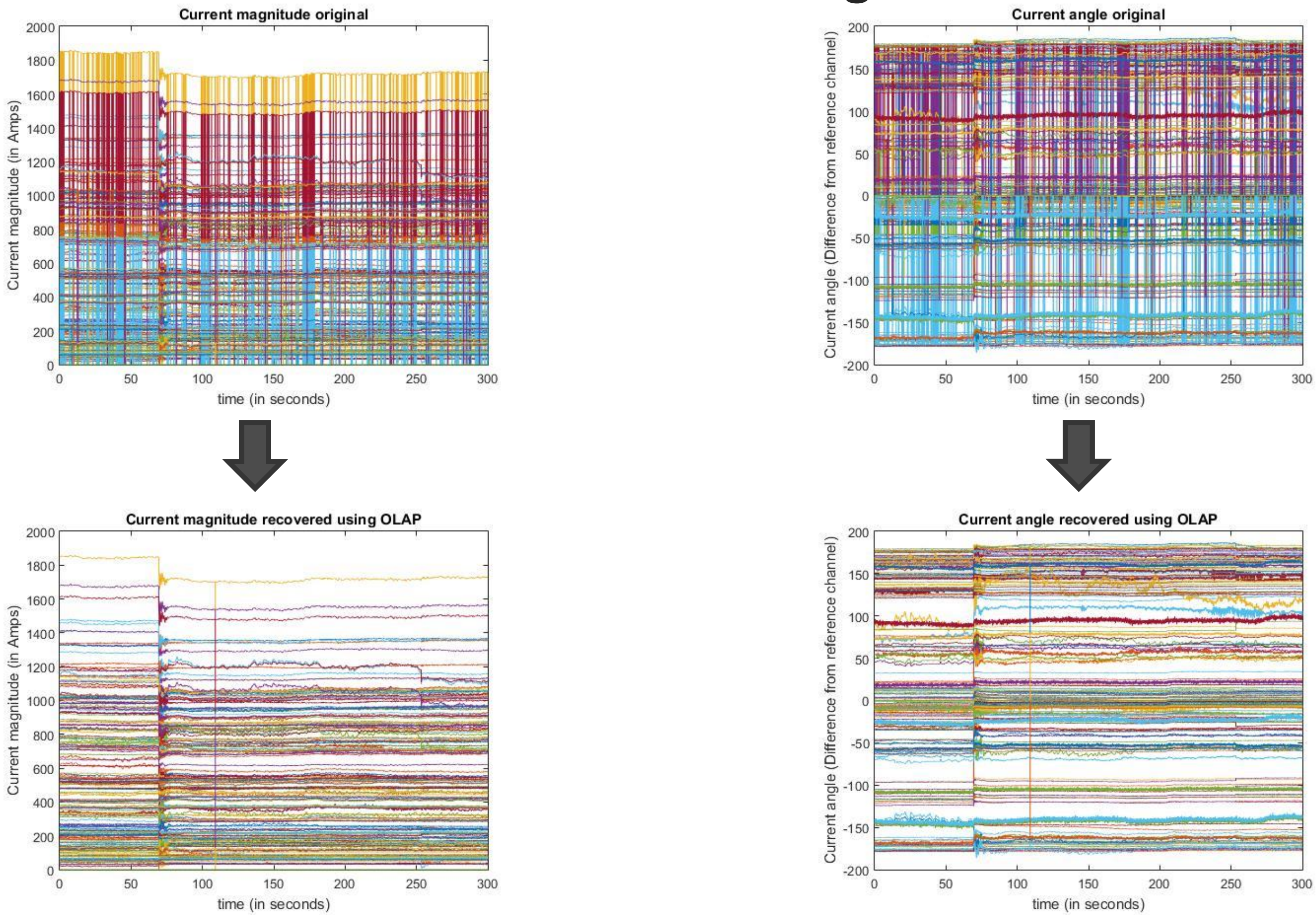
Data Recovery Results

Data recovery of a NYS disturbance for voltage magnitude, voltage angle, and frequency.



Data Recovery Results

Data recovery of a NYS disturbance for current magnitude and current angle.



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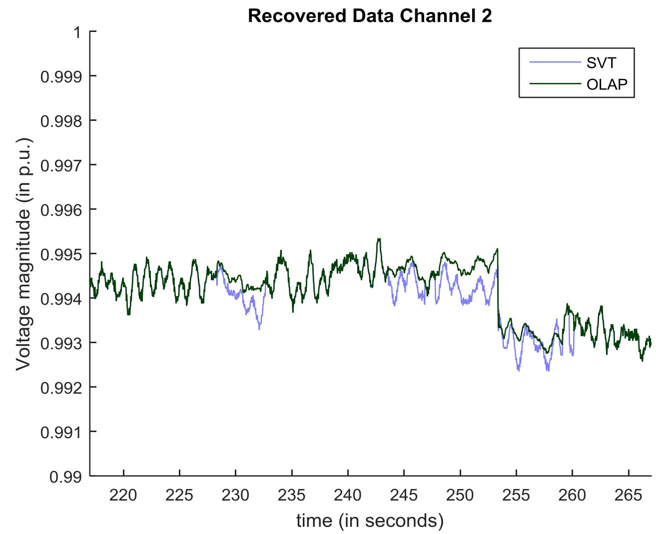
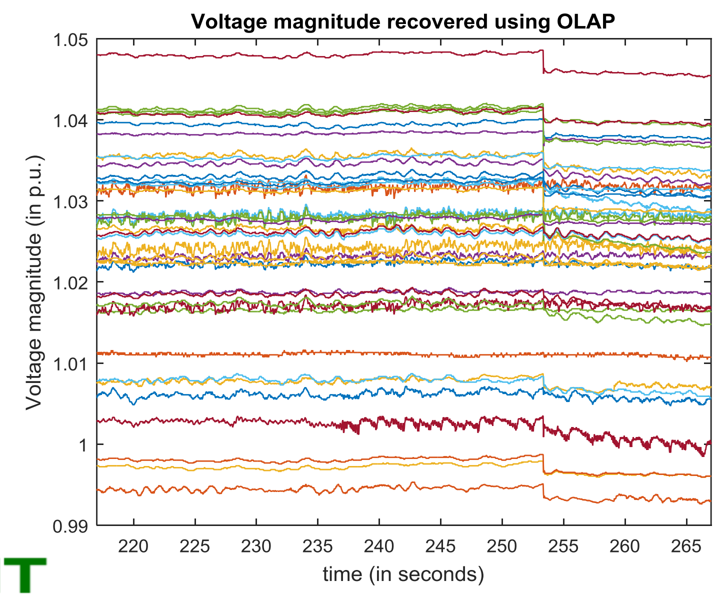
Recovery Results – Consecutive data drops





OLAP and SVT both successfully recovered a capacitor switching event when filling in missing data.

Recovery Results – Numerous data drops

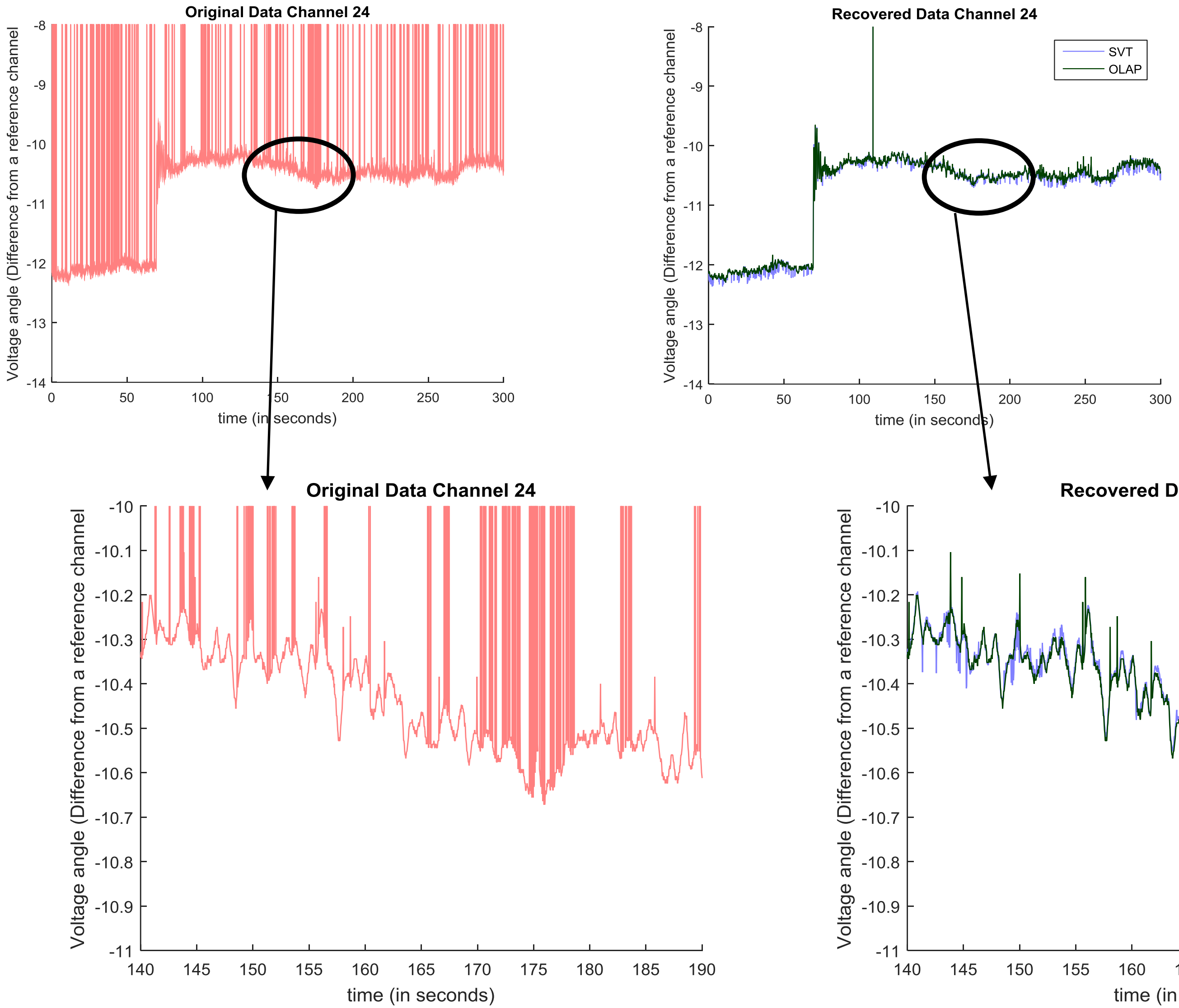
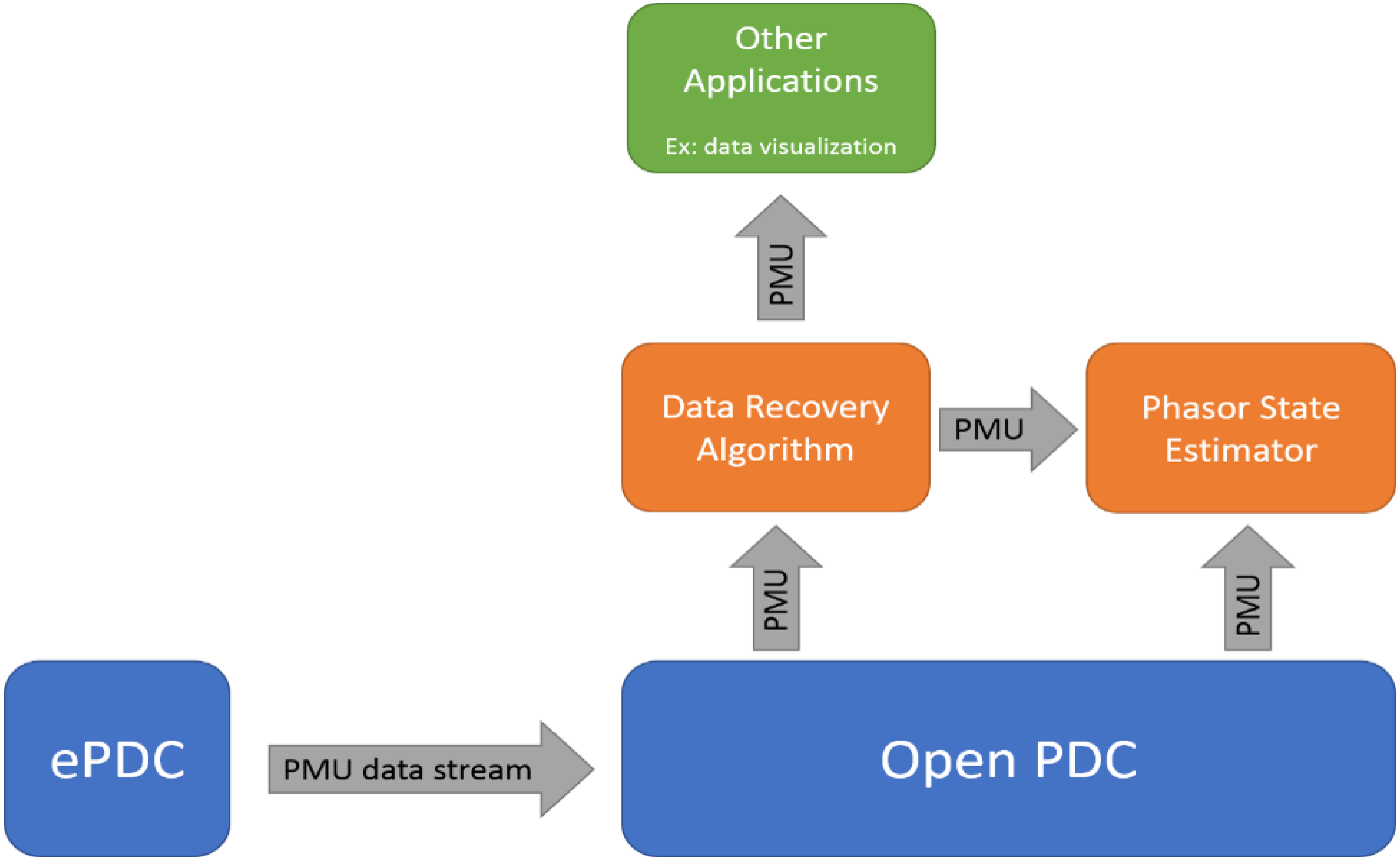


Illustration of data recovery results for OLAP and SVT when there are a large number of data drops.

Data Recovery Challenges

- Pre-processing:
  - Bad data check
  - Angle unwrapping
- Input parameters:
  - Especially hard to determine for SVT

Real-time OpenPDC Implementation



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Conclusions

- Missing data recovery by exploiting low-dimensional structures in PMU data.
- Both offline and online missing data recovery methods are reported.
- Missing PMU data was successfully recovered, even in cases of consecutive data drops or numerous data drops.

References

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Questions?