PMU Event Detection and Classification

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Objective

Improve classification accuracy of smart grid events based on data from individual PMU data in real-time while minimizing costly false positives[1].

Introduction

Phasor Measurement Units (PMUs) are increasingly playing an important role in smart grid automation. They provide high-resolution, high-quality, real-time, time-synced, voltage and phase angle measurements on electrical grids. Traditionally they have been used to capture measurements and monitor systems. More recently however, researchers have been exploring the use of the data collected from these devices in the prevention of service disruption through real-time autonomous event detection and intervention.

Previous Recent Feature Extraction from Single PMU

- Classical
- Observation/visual exploration
- Statistical
- None (raw-data)

Proposed Shapelet Feature Extraction

- Exact computationally infeasible
- Efficient heuristic exists based on SAX encoding

Data

Data is a matrix of simulated voltage and frequency measurements taken at a resolution of 60 Hz 0.5s before and 1.5s after PMU reported disturbance, and classes are labeled as follows:

- Fault
- Generation Loss
- Load switching off
- Load switching on
- Reactive power switched on
- Reactive power switched off
- Synchronous motor switching off

Features from Observation

- Slope Sequence (S²)
  \[ \lambda(n) = \frac{x(n + K) - x(n - K)}{2K} \]
- Domain-specific Shapelets (Dshapelet)
  - centered on first global extreme
  - user-specified window size

Figure 1: Example Shapelets

Classical Features

- Discrete Fourier Transform (DFT)
  \[ X(k) = \frac{1}{N} \sum_{n=0}^{N-1} x(n)e^{-j2\pi kn/N} \]
- Discrete Wavelet Transform (DWT)
- Fast Variant of discrete S transform features (FDST)
  \[ S_k = \begin{cases} \frac{1}{m} \sum_{k=0}^{m-1} V_k W_{k',k} e^{j2\pi k'/m} & \text{if } k' = k \\ 0 & \text{otherwise} \end{cases} \]
  \[ V_k = e^{-j\left(\frac{2\pi}{3}\right)k} \]
  \[ W_k = e^{-j\left(\frac{2\pi}{3}\right)k}, k = 0, 1, \ldots, (m - 1) \]

Statistical Features

- Median v. Mean: \( F_1 = \frac{\text{median} - \text{mean}}{\text{median}} \)
  where \( \text{median} = |V(n) - V| \)
- Difference median and mean difference: \( F_2 = V - V \) where \( V(n) = |V(n + 1) - V(n)| \)
- Variance distribution: \( F_3 = \frac{\text{var}}{\text{nump}} \) where \( \text{nump} \) is the minimum number of points that could account for 60% of the variance of \( V \).
- Change distribution: \( F_4 = \frac{\text{median}}{\text{mean}} \) where \( \text{median} \) is the minimum number of points that could account for 80% of the total change

Preliminary Results

Normalizing both voltage and frequency, and performing no other feature extraction, I was able to achieve perfect classification in both Fault and Generation Loss classes with readily available off-the-shelf classifiers—namely SVM and Gaussian Process. Further, I was able to achieve a higher accuracy than that reported by [2] on all 7 classes together. Shapelet feature extraction, however, has not yet shown promising results. We will continue to experiment with shapelets by a combination of:

- experimenting with alternative distance metrics (algorithm currently uses normalized euclidean distance)
- tuning parameters

I intend to also continue improving on the SVM/Gaussian Process classifier mentioned above with an emphasis on minimizing false positives.

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Table 1: Confusion Matrix of Preliminary 7-class results

References