Measurement Denoising Using Kernel Adaptive Filters in the Smart Grid

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Smart Grid

“The Smart Grid is a developing network of new technologies, equipment, and controls working together to respond immediately to our 21st century demand for electricity.”

From: www.smartgrid.gov
State Estimation

- "State Estimation processes telemetry data such as power measurements to obtain an estimate of the magnitudes and phase angles of bus voltages in the actual power systems."

From: www.etap.com
Smart Grid Security

• “Smart grids give clear advantages and benefits to the whole society, but their dependency on computer networks and applications, as well as on the Internet, makes our society more vulnerable to malicious cyber attacks with potentially devastating results.”

From: “ENISA Smart Grid Security Recommendations” (www.enisa.europa.eu)
false or malicious data

Images from: www.consumerenergyreport.com/smart-grid/ and www.capitalbusiness.me
The Problem

- State estimation is usually accompanied with bad data detection.
- Recently, false data injection attacks against the smart grid state estimation have been studied.
- It is possible to inject false or malicious data to the smart grid without being detected by bad data detection approaches.
The Problem

• The problem is, how to defend the smart grid against false or malicious data injection?

• Naturally, one possible strategy is to try to get rid of the injected false or malicious data in the system as early as possible.
Proposed Measurement Denoising for the Smart Grid

• In this paper, a measurement denoising module is proposed for denoising measurements and filtering out random false or malicious data, just ahead of state estimation in the smart grid.
• Adaptive filters are proposed to be employed in the measurement denoising. They can work in *prediction mode* to suppress noises.
Adaptive Filters for the Proposed Measurement Denoising

- Adaptive filters can adjust their coefficients dynamically to adapt to the signal statistics according to optimization algorithms.

- Consider an adaptive filter with $M$ adjustable coefficients in the proposed measurement denoising module.

$$y(n) = h(n)^T x(n)$$

$$x(n) = [x(n - D), x(n - D - 1), \ldots, x(n - D - M + 1)]^T$$

$$h(n) = [h_0(n), h_1(n), \ldots, h_{M-1}(n)]^T$$
Adaptive Filters for the Proposed Measurement Denoising

• Then the error sequence $e(n)$ can be formed as below, which can be used in optimization algorithms for updating the filter coefficients.

\[ e(n) = x(n) - y(n) \]

• Common adaptive filtering algorithms
  – Least mean squares (LMS)
  – Recursive least squares (RLS)
The LMS Algorithm for the Proposed Measurement Denoising

**Algorithm 1** The LMS algorithm for the proposed measurement denoising

\[ h(0) = 0 \]
\[ n = 1 \]
\[ \text{while } x(n) \text{ is available do} \]
\[ y(n) = h(n - 1)^T x(n) \]
\[ e(n) = x(n) - y(n) \]
\[ h(n) = h(n - 1) + \eta e(n) x(n) \]
\[ n = n + 1 \]
\[ \text{end while} \]
The RLS Algorithm for the Proposed Measurement Denoising

**Algorithm 2** The RLS algorithm for the proposed measurement denoising

- $h(0) = 0$
- $Q(0) = \lambda^{-1}I$
- $n = 1$

while $x(n)$ is available do

- $r(n) = 1 + \beta^{-1}x(n)^TQ(n-1)x(n)$
- $g(n) = \beta^{-1}Q(n-1)x(n)/r(n)$
- $y(n) = h(n-1)^Tx(n)$
- $e(n) = x(n) - y(n)$
- $h(n) = h(n-1) + g(n)e(n)$
- $Q(n) = \beta^{-1}Q(n-1) - g(n)g(n)^Tr(n)$
- $n = n + 1$

end while

- Regularization parameter
- Identity matrix
- Forgetting factor
Kernel Adaptive Filters for the Proposed Measurement Denoising

- Kernel adaptive filters, the adaptive filters in kernel spaces with improved performance, have been put forward in recent years.
- The kernel versions of the LMS and the RLS are called kernel LMS and kernel RLS.
- In kernel LMS, $y(n)$ is estimated by

$$y(n) = \eta \sum_{i=1}^{n-1} e(i) \kappa(x(n), x(i))$$

where $e(i)$ is the error term, $\kappa(u, v)$ is the kernel function, and $\eta$ is the learning rate.

Gaussian kernel

$$\kappa(u, v) = e^{-a\|u-v\|^2}$$

learning rate

kernel function

(example)
The kernel LMS Algorithm for the Proposed Measurement Denoising

Algorithm 3 The kernel LMS algorithm for the proposed measurement denoising

\[ e(0) = x(0) \]
\[ n = 1 \]
\[ \text{while } x(n) \text{ is available do} \]
\[ y(n) = \eta \sum_{i=1}^{n-1} e(i) \kappa(x(n), x(i)) \]
\[ e(n) = x(n) - y(n) \]
\[ n = n + 1 \]
\[ \text{end while} \]
Algorithm 4 The kernel RLS algorithm for the proposed measurement denoising

<table>
<thead>
<tr>
<th>Step</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( Q(0) = (\lambda \beta + \kappa(x(0), x(0)))^{-1} )</td>
</tr>
<tr>
<td></td>
<td>( z(0) = Q(0)x(0) )</td>
</tr>
<tr>
<td></td>
<td>( n = 1 )</td>
</tr>
<tr>
<td>While ( x(n) ) is available do</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( h(n) = [\kappa(x(n), x(0)), \ldots, \kappa(x(n), x(n-1))]^T )</td>
</tr>
<tr>
<td></td>
<td>( w(n) = Q(n-1)h(n) )</td>
</tr>
<tr>
<td></td>
<td>( r(n) = \lambda \beta^n + \kappa(x(n), x(0)) - w(n)^T h(n) )</td>
</tr>
<tr>
<td></td>
<td>( P(n) = Q(n-1)r(n) + w(n)w(n)^T )</td>
</tr>
<tr>
<td></td>
<td>( Q(n) = r(n)^{-1} \begin{bmatrix} P(n) &amp; -w(n) \ -w(n)^T &amp; 1 \end{bmatrix} )</td>
</tr>
<tr>
<td></td>
<td>( y(n) = h(n)^T z(n-1) )</td>
</tr>
<tr>
<td></td>
<td>( e(n) = x(n) - y(n) )</td>
</tr>
<tr>
<td></td>
<td>( z(n) = \begin{bmatrix} z(n-1) - w(n)r(n)^{-1}e(n) \ r(n)^{-1}e(n) \end{bmatrix} )</td>
</tr>
<tr>
<td></td>
<td>( n = n + 1 )</td>
</tr>
<tr>
<td>end while</td>
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Simulation

• The data set employed in the simulations includes the curve of the rotor speed of a generator, which is generated using the power system analysis toolbox (PSAT) 2.1.6 and the IEEE 14-bus test system.

• Three test cases:
  – Measurements with noises (noisy measurements)
  – Measurements with random false data injections
  – Measurements with both noises and random false data injections

• Additive Gaussian noise, manually added random false data
Simulation

- Parameters of the four adaptive filters (LMS, kernel LMS, RLS, and kernel RLS)
  - Number of taps: $M = 10$
  - Decorrelation delay: $D = 1$
  - Learning rate for LMS and kernel LMS: $\eta = 0.05$
  - Kernel: Gaussian kernel with $a = 0.1$
  - Forgetting factor for RLS and kernel RLS: $\beta = 1$
  - Regularization parameter for RLS and kernel RLS: $\lambda = 0.0001$

Note that this set of parameters is just chosen for this simulation. Other sets of parameters may also work and even better.
Simulation Results

Case 1
Measurements with noises
Simulation Results

Case 2
Measurements with random false data injections

- Measurements with random false data injections
  - Rotor speeds

Graphs showing:
- LMS
- Kernel LMS (better performance)
- RLS
- Kernel RLS (slightly better)
Simulation Results

Case 3
Measurements with both noises and random false data injections

- **LMS**
- **kernel LMS** (better performance)
- **RLS**
- **kernel RLS** (slightly better)
Introduction

The Proposed Approach

Simulation Results

Conclusion
Conclusion

- Measurement denoising has been proposed for the smart grid.
- As an improved version of adaptive filter, kernel adaptive filter has been proposed for measurement denoising.
- Simulation results show that kernel adaptive filters perform better in measurement denoising.
Thank you!