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Optimal Filtering for Grid Event Detection from Real-time Synchrophasor Data

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Abstract

This paper shows the use of optimal filter estimation for real-time data processing to automatically detect dynamic transient effects in phasor data produced in a synchrophasor vector processing systems. The optimal filters are estimated on the basis of phasor data where no disturbances are present and the estimation problem is formulated as a least squares optimization. Event detection bounds are computed from variance estimates and events are detected by formulating conditions on the number of consecutive samples for which the filtered phasor signals are outside of the bounds. Event detection is illustrated on the phasor data obtained from a microPMU system developed by Power Standards Lab.

Keywords: Event Detection, Synchrophasor Data, Grid Monitoring, Estimation, C37.118

1 Grid Monitoring

The intensification of distributed renewable energy resources, along with the deployment energy storage systems to buffer intermittent energy production, has motivated the need to monitor power flow and power quality more accurately in the electricity grid. Complementary to the traditional Supervisory Control And Data Acquisition (SCADA) systems, synchrophasor vector processing systems implemented in (protection) relays, digital fault recorders and specialized Phasor Measurement Units (PMU) can produce time synchronized measurements of 3 phase AC amplitude and phase angle (phasor) of voltage and currents [2].

The enormous volumes of synchronized time stamped data produced at 60Hz sampling by PMUs provides a clear challenge for data management and provides new opportunities for power systems control and protection [13, 14, 3]. Manual observations of PMU data time sequences to observe trends or possibly detect anomalies in the data quickly becomes a unwieldy task. It has been recognized that automated or semiautomated data analysis techniques to identify faults [9], out-of-step conditions [12], power generation anomalies [17], detect PMU data events on multiple PMUs [20], state estimation [11] and possibly extract (dynamic) knowledge from such events [18] are highly desirable. Such applications greatly automate the data management

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task associated to analyzing PMU data and improve automated grid monitoring capabilities [10].

Algorithms for calculation of phasors, local system frequency and rate of change of frequency (RoCoF) that follow the guidelines of the (recent) IEEE Standard C37.118 [4, 8] are abundant. Especially the accuracy of phasor measurement under dynamic conditions, that include transient effects due to load switching, has been improved by dynamic phasor estimates that use (weighted) least squares, discrete-time (moving average) filtering and/or advanced algorithms based on discrete Fourier transforms [2]. Local signal processing (edge processing) of PMU data that exploits the same computational and processing capabilities of PMUs is important to reduce the need to transmit high frequency PMU data to a central repository for analysis and event detection.

This paper describes local synchrophasor based real-time data processing algorithm to automatically detect dynamic transient effects in AC voltage and current signals analyzed by a synchrophasor vector processing systems. The basic output of the algorithm is the time stamp when a dynamic event was detected. The approach is based on real-time discrete-time filtering of phasor data (amplitude and phase angle) to create optimal Filtered Rate of Change (FRoC) signals for each phasor and postulate an event detection algorithm based on the dynamic response of the FRoC signals. The idea of using phasors directly for event detection has been addressed in earlier work [5, 16, 15]. However, optimality of the FRoC signals is addressed in this paper by (recursive) least squares estimation of the parameters of a linear discrete-time filter that minimizes the variance of the FRoC signals for both angle and amplitude data of the phasor for event detection.

It is shown that such optimal filtering of phasor data will lead to FRoC signals that have much better variance properties than the RoCoF signals based on the rate of change of the bus frequency [7] produced by the PMU. The smaller variance properties are achieved by the optimal filter that estimates the dynamics of the noise on the phasor data due to sensor and grid dynamics and can be used to detect the start time of dynamic transient effects in phasors more accurately. For the practical illustration of the algorithm, real-time PMU data acquisition is implemented on a Raspberry PI computer running Python packages under Linux, receiving C37.118 format data from the microPMU system [19], developed by Power Standards Lab as an extension to the well-established low voltage PQube instrumentation by Power Sensors Ltd. It is shown how real-time processing of the phasor data received by C37.118 can be used for local event detection on the basis of data obtained during several local events measured by the microPMU.

2 Synchrophasor Data

2.1 Synchrophasor Data Representation

To explain the basic terminology and the use of phasor data for event detection, consider a measurement of a AC signal $x(t)$, which is either a voltage or current signal. In an ideal steady-state operating mode, the signal $x(t)$ is a pure sinusoidal signal $x(t) = A\cos(2\pi ft + \delta)$ with an amplitude A, frequency f, and phase offset δ. Using the phasor representation, the signal $x(t)$ is represented by the real part of the complex number $x(t) = \mathrm{Re}\{Ae^{2\pi ft}e^{j\phi}\}$ where $X = Ae^{j\phi}$ denotes the phasor of $x(t)$.

Although this is an accurate representation of a steady-state sinusoidal signal, any changes in the signal $X(t)$ with respect to the pure sinusoidal representation would mean that the amplitude A and frequency f would change with respect to time. To characterize these time variations we may write $x(t) = A(t)\cos(2\pi f_0 t + \phi(t))$ where $\phi(t) = f_e(t)t + \delta$ denotes a time varying phase shift formulated as a time varying frequency error $f_e(t)$ with respect to the nominal frequency f_0 of the AC signal $x(t)$. This defines the (time varying) frequency of the AC signal as

$$f(t) = f_0 + \frac{d}{dt}\phi(t) = f_0 + f_e(t) + t\frac{d}{dt}f_e(t) \tag{1}$$

and makes the phasor a time-varying signal

$$X(t) = A(t)e^{j\phi(t)} \tag{2}$$

with respect to the nominal AC frequency f_0.

2.2 Rate of Change in Synchrophasor Data

The phasor data $(A(t), \phi(t))$ are estimated and exported by a PMU measuring device at regular time interval $t_k = k\Delta_T$, where $f_s = 1/\Delta_T$ denotes the sampling frequency. The typical sampling frequency is given by $f_s = 60$Hz for updates on the phasor at each cycle of an AC sigal $x(t)$ in an electricity grid with a nominal AC frequency of $f_0 = 60$Hz. The phasor data consisting of amplitude $A(t_k)$ and phase angle $\phi(t_k)$ are communicated, along with an accurate GPS measurement time t_k for data processing.

A popular signal for event detection, also often exported by the PMU, is the rate of change of frequency (RoCoF) signal

$$RoCoF(t_k) = 60 \cdot (f(t_k) - f(t_{k-1})) \tag{3}$$

that can be represented as the discrete-time filtered signal $RoCoF(t_k) = F(q)f(t_k)$ where $F(q)$ is a discrete-time derivative filter represented by the "transfer" function

$$F(q) = \frac{1 - q^{-1}}{60} = \frac{q - 1}{60q} \tag{4}$$

where q is use to denote the discrete-time shift operator $qx(t_k) = x(t_{k+1})$ and $q^{-1}x(t_k) = x(t_{k-1})$. Although the filter $F(q)$ and the resulting RoCoF signal is indeed a viable signal for detecting changes in the frequency $f(t_k)$, it is highly susceptible to noise on the actual phase angle estimate $\phi(t_k)$.

It is clear from (1) that differentiation or a discrete-time derivative of the phase angle $\phi(t_k)$ is required to obtain an estimate of frequency $f(t_k)$, whereas an additional discrete-time derivative is needed to obtain $RoCoF(t_k)$. A more careful design of the filter $F(q)$ is needed to obtain a signal suitable for event detection that is robust to noise on the phase angle estimate $\phi(t_k)$. Furthermore, time varying changes in the phase angle estimate $\phi(t_k)$ is only one part of the phasor. Time varying changes in the amplitude $A(t_k)$ of the phasor $X(t_k)$ in (2) must also be taken into account to properly detect events.

3 Signal Processing for Event Detection

3.1 Optimal Filtering

To set up the framework for the construction of optimal filters to process the discrete-time sampled phasor data $X(t_k)$ in (2), we consider an unobservable discrete-time event signal $d(t_k)$. The event signal $d(t_k)$ can only be observed via noisy observations of the phasor data $(A(t_k), \phi(t_k))$ characterized by

$$\begin{array}{rcl} A(t_k) & = & G_A(q)d(t_k) + n_A(t_k) \\ \phi(t_k) & = & G_\phi(q)d(t_k) + n_\phi(t_k) \end{array} \tag{5}$$

where $G_A(q)$ and $G_\phi(q)$ denote unknown dynamic systems that filter the effect of the common event signal $d(t_k)$ on both the amplitude $A(t_k)$ and phase $\phi(t_k)$ of the phasor $X(t_k)$. The noise $n_A(t_k)$, $n_\phi(t_k)$ on the signals in (5) is characterized by filtered white noise signals

$$\begin{array}{rcl} n_A(t_k) & = & H_A(q)e_A(t_k) \\ n_\phi(t_k) & = & H_\phi(q)e_\phi(t_k) \end{array} \tag{6}$$

where $H_A(q)$ and $H_\phi(q)$ denote unknown dynamic systems that model filter the white noises $e_A(t_k)$, $e_\phi(t_k)$ and model the spectral content of the output noise on the data in (5). As such, we may assume that $H_A(q)$ and $H_\phi(q)$ are spectral factorizations of the noise spectrum and are stable and stably invertible filters [1]. We assume that the white noises $e_A(t_k)$, $e_\phi(t_k)$ are uncorrelated with an unknown variance without loss of generality to formulate the estimation problem of the optimal filters to process the phasor data $(A(t_k), \phi(t_k))$.

To illustrate the idea of optimal filtering, we consider the amplitude signal $A(t_k)$ only, as the approach to filter $\phi(t_k)$ will be similar. Formulating a filtering $F_A(q)$ of the amplitude data $A(t_k)$ leads to the estimate $\hat{d}(k) = F(q)A(t_k) = F(q)G_A(q)d(t_k) + F(q)H_A(q)e_A(t_k)$ where it can be observed that choosing $F_A(q) = G_A(q)^{-1}$ would lead to a perfectly constructed event signal $d(t_k)$, but susceptible to a filtered noise signal $F(q)H_A(q)e_A(t_k)$ that may be arbitrary bad. Furthermore, such a choice is only possible if the dynamics $G_A(q)$ is known and invertible. An example of this approach is the choice of the filter $F(q)$ for the RoCoF signal in (4), where an attempt is made to approximate the inverse of integration (differentiation) to process a step-wise change in the bus frequency due, resulting in high frequency noise amplification.

Instead, choosing $F_A(q) = H_A(q)^{-1}$ would lead to

$$\hat{d}_A(t_k) = F(q)G_A(q)d(t_k) + e_A(t_k) \tag{7}$$

and constitutes a filtered version of the event signal $d(t_k)$ perturbed by only a white noise signal. The properties of a white noise signal can now be used to formulate an event detection algorithm that exploits the correlation between subsequent measurements of $\hat{d}(t_k)$ over time. More details on the actual event detection will be given in the next section, first we focus on the construction of the filter $F_A(q) = H_A(q)^{-1}$.

The possibility to choose a filter $F_A(q) = H_A(q)^{-1}$ is motivated by the fact that $H_A(q)$ is a spectral realization of the spectrum of the noise $n_A(t_k)$ in (5). It is well known that such a filter $H_A(q)$ can always be realized by stable and stably invertible filters $F_A(q) = H_A(q)^{-1}$ [1], guaranteeing the existence of the stable filter $F_A(q)$. As $H_A(q)$ is unknown, we proposed two crucial steps to compute a filter $F_A(q)$ that is able to approximate the inverse of the noise dynamics $H_A(q)$:

1. Select N data points of phasor data of $A(t_k)$ where *no* event was present, e.g. $d(t_k) = 0$.
2. Select an (optional) filter $L_A(q)$ to filter the phasor amplitude data. The filter $L_A(q)$ is used to emphasize certain frequency ranges where event detection is important. For example, a high pass filter $L_A(q)$ will avoid detection of offsets on the amplitude $A(t_k)$.

The selection of N data points where no event is present in step 1 can be by manual inspection of the data or based on the event detection algorithm summarized later. Clearly, this first step is required for the initialization and calibration of the event detection algorithm. The ability to include a user-specified filter $L_A(q)$ in step 2 above provides an extra design step in the event detection. In addition, a carefully designed filter $L_A(q)$ can make the approximation of the inverse of the noise dynamics more easier to achieve. With the help of the two steps above, (7) reduces to

$$\hat{d}_A(t_k) = F_A(q)L_A(q)A(t_k) = F_A(q)L_A(q)H_A(q)e_A(t_k) \tag{8}$$

where is can be observed that an approximation of the inverse of the (filtered) noise dynamics $L_A(q)H_A(q)$ by $F_A(q)$ would now lead to a white noise $\hat{d}_A(t_k)$. Parametrizing the filter $F_A(q)$ in an Moving Average format

$$F_A(q) = 1 - f_1q^{-1} - f_2q^{-1} - \cdots - f_nq^{-1} \tag{9}$$

allows $\hat{d}_A(t_k)$ in (8) to be written in a linear regression form

$$\begin{aligned} \hat{d}_A(t_k, \theta) &= A(t_k) - f_1A(t_{k-1}) - f_2A(t_{k-2}) - \cdots - f_nA(t_{k-n}) \\ &= A(t_k) - \theta\varphi_A(t_k) \end{aligned}$$

where $\theta = \begin{bmatrix} f_1 & f_2 & \cdots & f_n \end{bmatrix}$ and $\varphi_A(t_k) = \begin{bmatrix} A(t_{k-1}) & A(t_{k-2}) & \cdots & A(t_{k-n}) \end{bmatrix}^T$. A maximum likelihood estimator $\hat{\theta}_A^N$ that minimized the variance

$$\hat{\theta}_A^N = \min_{\theta} \frac{1}{N} \sum_{k=1}^{N} \hat{d}_A(t_k, \theta)^2$$

over N time samples is now simply given by the Least Squares estimate

$$\hat{\theta}_A^N = \left[\frac{1}{N} \sum_{k=1}^{N} A(t_k)\varphi_A(t_k)^T \right] \left[\frac{1}{N} \sum_{k=1}^{N} \varphi_A(t_k)\varphi_A(t_k)^T \right]^{-1} \tag{10}$$

and reduces the optimally filtered detection signal $\hat{d}_A(t_k, \hat{\theta}_{LS}^N)$ to a white noise signal if indeed $F_A(q, \hat{\theta}_{LS}^N) \approx (L_A(q)H_A(q))^{-1}$. Increasing the order n of the filter $F_A(q, \theta)$ in (9) increases the design freedom of achieving this approximation, while the user chosen filter $L_A(q)$ can simplify the objective to achieve the approximation for a given value of the order n [6].

3.2 Event Detection

The properties of a white noise signal can now be used to formulate an event detection algorithm that exploits the correlation between subsequent measurements of $\hat{d}(t_k)$ over time. Using $E\{\cdot\}$ to denote the expectation operator, the white noise signal $e_A(t_k)$ in (6) satisfies

$$E\{e_A(t_k)e_A(t_k - \tau)\} = \begin{cases} \lambda & \tau = 0 \\ 0 & \tau \neq 0 \end{cases}$$

indicating that subsequent values of $e_A(t_k)$ are uncorrelated.

The optimal filter $F_A(q, \hat{\theta}_A^N)$ found by minimizing the variance of the filtered event signal $\hat{d}_A(t_k, F_A(q, \hat{\theta}_A^N))$ in the case of no event ($d(t_k) = 0$) and an order n large enough to satisfy $F_A(q, \hat{\theta}_A^N) \approx (L_A(q)H_A(q))^{-1}$ ensures that

$$\begin{aligned} \hat{d}_A(t_k, \hat{\theta}_A^N) &= F_A(q, \hat{\theta}_A^N)L_A(q)A(t_k) \\ &\approx e_A(t_k) \end{aligned}$$

is also a white noise signal in the case of no event. This allows us to formulate an event detection algorithm on the premise of assuming normal distributions for the $\hat{d}_A(t_k, F_A(q, \hat{\theta}_A^N))$ signal and exploiting the following information.

Consider N data points of phasor data of $A(t_k)$ where *no* event was present, e.g. $d(t_k) = 0$. These N data points are typically *not* the same as the N data points without event on which the parameter $\hat{\theta}_A^N$ was estimated to allow cross validation [6]. With the computed optimal filter $F_A(q, \hat{\theta}_A^N)$ we can now compute a variance estimate

$$\hat{\lambda}_A = \min_{\theta} \frac{1}{N} \sum_{k=1}^{N} \hat{d}_A(t_k, \hat{\theta}_A^N)^2, \quad \hat{d}_A(t_k, \hat{\theta}_A^N) = F_A(q, \hat{\theta}_A^N) A(t_k) \tag{11}$$

Assuming that the numerical values of $\hat{d}_A(t_k, \hat{\theta}_A^N)$ are generated by a normal distribution, the probability that

$$|\hat{d}_A(t_k, \hat{\theta}_A^N)| > 3\sqrt{\hat{\lambda}_A} \tag{12}$$

is less then 0.3% for a particular value of t_k. Although checking if (12) is satisfied for event detection, there is still a small probability of false event detection at each time stamp t_k that may lead to may false event alarms over a large number of data points that is generated by a PMU. Assuming, in addition, that $\hat{d}_A(t_k, \hat{\theta}_A^N)$ is a white noise signal with uncorrelated samples, the probability that

$$|\hat{d}_A(t_l, \hat{\theta}_A^N)| > 3\sqrt{\hat{\lambda}_A}, \quad l = k, k+1, \ldots, k+m-1 \tag{13}$$

for m *consecutive* time stamps t_l, $l = k, k+1, \ldots, k+m-1$ will be even smaller, typically 0.3^m%. The event criterion in (13) clearly will lead to much less false event alarms at the price of a small delay of m consecutive samples. The delay is often negligible, as choosing $m = 6$ would only lead to 0.1 sec delay at $f_s = 60$ Hz sampling, while reducing false alarm probability significantly.

If an event does occur on the amplitude measurement $A(t_k)$ of the phasor $X(t_k)$, the filtering leads to a signal

$$\begin{aligned} \hat{d}_A(t_k) &= F_A(q, \hat{\theta}_A^N) L_A(q) A(t_k) \\ &\approx F_A(q, \hat{\theta}_A^N) L_A(q) G_A(q) d(t_k) + e_A(t_k) \end{aligned}$$

with an optimal filter $F_A(q, \hat{\theta}_A^N)$ accurate enough to satisfy $F_A(q, \hat{\theta}_A^N) \approx (L_A(q) H_A(q))^{-1}$. Since $\hat{d}_A(t_k)$ is now the sum of a filtered event signal $F_A(q, \hat{\theta}_A^N) L_A(q) G_A(q) d(t_k)$ and a white noise $e_A(t_k)$, we may expect that not only (12), but also (13) will be satisfied. Depending on the dynamics of $F_A(q, \hat{\theta}_A^N) L_A(q) G_A(q)$ and the duration of the event signal $d(t_k)$, the absolute value of the signal $|\hat{d}_A(t_k)|$ may stay out of the bound $3\sqrt{\hat{\lambda}}$ for a larger number of consecutive samples. This allows one to increase the value of m in (13), while reducing the probability of false event detection.

It should be pointed out that the LS estimate in (10) can be updated (recursively) each time a set of N data points is available where no event was detected. For now, the LS estimate serves as a calibration of the optimal filter $F_A(q, \hat{\theta}_A^N)$ to reduce the amplitude $A(t_k)$ measurements of the phasor $X(t_k)$ to white noise $\hat{d}_A(t_k, \hat{\theta}_A^N)$ for event detection. The exact same procedure for choice of a data filter $L_\phi(q)$ and computation of optimal filter $F_\phi(q, \hat{\theta}_\phi^N)$ with event detection can be applied to the angle $\phi(t_k)$ measurements of the phasor $X(t_k)$ in parallel.

4 Event Detection on Phasor Data from a µPMU

4.1 Data collection from micro-PMU system

The Power Standards Lab (PSL) micro-PMU (µPMU) [19] includes a PQube instrument that contains measurement, recording, and communication functionalities along with a remotely-mounted micro GPS receiver, and a power supply. These devices can be connected to single- or three phase secondary distribution circuits up to 690V (line-to-line) or 400V (line-to-neutral), either into standard outlets or through potential transformers (PTs). The devices continuously sample AC voltage and current waveforms at 256 or 512 samples per cycle and can produce 3 phase phasor data $X(t_k)$ at sampling rates of 60 or 120 Hz.

The phasor data data is streamed in real-time to a client computer using IEEE C37.118 standard over the Ethernet using TCP port 4713. The client computer used for data acquisition here is a Raspberry PI model B+ that acts as an interface between the data source (µPMU) and the data archive server (OSIsoft server). An overview of the hardware setup used for real-time C37.118 data acquisition from the µPMU into the Raspberry PI is shown in Fig. 1.

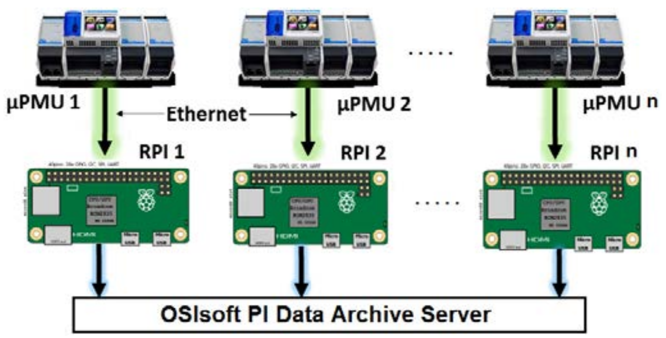

Figure 1: Hardware setup for data processing and archival.

Due to the flexible computing environment on the Raspberry PI, real-time event detection can directly be implemented via Python. Socket programming is used to read data from the TCP port 4713 in a predefined frame-size. The µPMU-Raspberry PI act as a server-client application that communicate C37.118 data using sockets.

4.2 Decoding the C37.118 Data in Real-time

A popular way to process C37.118 data is the use of OpenPDC[1] by Grid Protection Alliance (GPA), but here we decode data directly in the Python application used to read data from the TCP port 4713. The Synchrophasor measurements are tagged with the UTC time corresponding to the time of measurement usually consisting of three numbers: a second-of-century (SOC) count, a fraction-of-second (FRACSEC) count, and a message time quality flag as in [4]. The synchrophasor consists of four message types: data, configuration, header, and command. The first three message types are transmitted from the µPMU that serves as the data source, and the last (command) is received by the µPMU. All message frames start with a 2-byte SYNC word then followed by FRAMESIZE word (2-byte), IDCODE (2-byte), a time stamp consisting

[1] http://openpdc.codeplex.com/

of a second-of-century (SOC, 4-byte)[2] and FRACSEC (4-byte), which includes a FRACSEC integer (24-bit) and a Time Quality flag (8-bit).

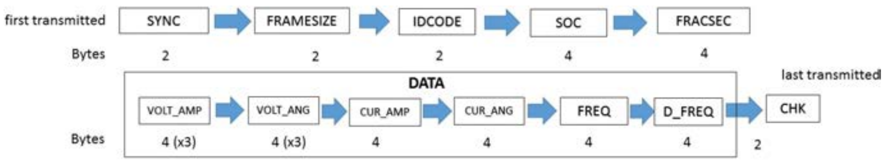

Figure 2: Data frame byte transmission of C37.118 data

The SYNC word provides synchronization and frame identification. The IDCODE positively identifies the source of a data, header, or configuration message, or the destination of a command message. All data frames terminate in check word (CHK) which is a CRC-CCITT. This CRC-CCITT uses the generating polynomial $X16 + X12 + X5 + 1$ with an initial value of 1 (hex FFFF) and no final mask. All frames are transmitted exactly as described with no delimiters and an illustration of an example frame transmission order is shown in Fig.2.

4.3 Application of event detection

For demonstration purposes, single phasor voltage amplitude $A(t_k)$ and angle $\phi(t_k)$ data are collected from the Engineering Building at UCSD via a µPMU. The data used for demonstration of event detection was collected over the course of 48 hours at 60Hz sampling (approx. 10^6 data points) while a tornado warning was issued in San Diego in the afternoon of January 6, 2016.

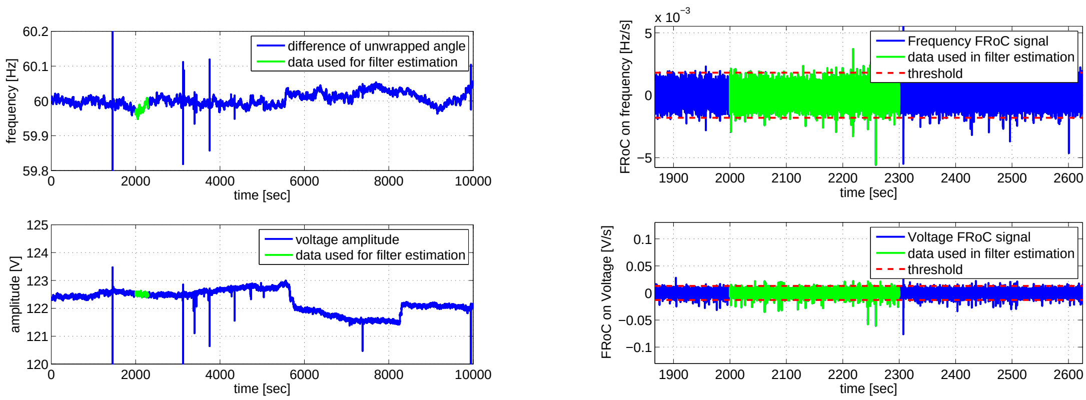

Figure 3: Left: part of the full phasor data (frequency and amplitude) with indication of data use for filter estimation. Right: zoomed-in version of the FRoC signal for both frequency and amplitude data in the neighborhood of the data used for filter estimation.

For the optimal filter estimation, the data filter $L_A(q)$ on the voltage amplitude data $A(t_k)$ was chosen as a first order high pass Butterworth filter with a cut-off frequency of 0.1Hz to avoid detection of low frequency (off-set) disturbance events. The voltage phase data $\phi(t_k)$

[2]The SOC count is a four (4) byte binary count of seconds from UTC midnight (00:00:00) of January 1, 1970, to the current second representing a 32-bit unsigned integer.

limited between $[-180, 180]$ deg was first properly unwrapped to $\phi_u(t_k)$ and then reduced to

$$f_e(t_k) = 2\frac{f_s}{160}(\phi_u(t_k) - \phi_u(t_{k-1}) + 60$$

to obtain a frequency estimate on which the same data filter $L_\phi(q) = L_a(q)$ was applied for optimal filter estimation. Only a small part of the data of just 5 minute length ($N = 18000$) is used for the estimation of the optimal filter paremeters $\hat{\theta}_A^N$ and $\hat{\theta}_\phi^N$ of an $n = 20$th order MA filter, while a neighboring set of points of also 5 minute length is used to estimate the variance estimates in (11) that will serve as event detection bounds. An zoomed-in version of the available data set along with the estimate of the event detection bounds is given in Fig. 3.

Based on the estimated optimal filters that generated the FRoC signal and the variance bounds, event detection is initiated if $m = 20$ consecutive samples of $\hat{d}_A(q, \hat{\theta}_A^N)$ or $\hat{d}_\phi(q, \hat{\theta}_\phi^N)$ are outside the bounds $3\sqrt{\hat{\lambda}_A}$, $3\sqrt{\hat{\lambda}_\phi}$. Based on the requirement of $m = 20$ consecutive samples, 3 significant events are detected in the phasor data and an overview of the events are depicted in Fig. 4.

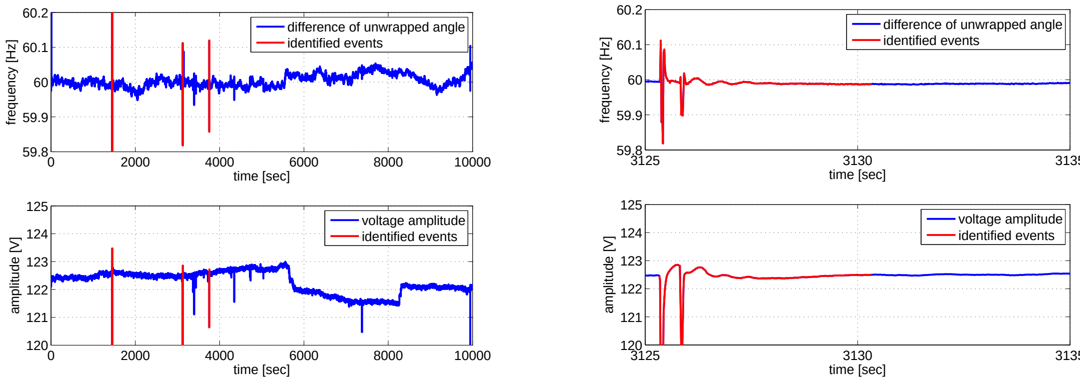

Figure 4: Left: part of the full phasor data (frequency and amplitude) with indication of events detected on the data (colored red). Right zoomed-in version of the 2nd event detected in the data showing oscillations on the frequency and several voltage dips.

Although there are other "spikes" seen in the data, these do not signify the detect events as they do not satisfy the event detection criteria. These events signify the disturbances on the grid that can explicitly be seen on the phasors of the power signal.

5 Conclusions and Future Work

Optimal filters which can be used to formulate filtered rate of change phasor signals can be estimated on the basis of phasor data where no disturbances are present via a straight-forward least squares optimization. The resulting variance bounds give rise to event detection algorithms that check for the number of consecutive samples for which the filtered phasor signals are outside the variance bounds. The resulting procedure is applied to actual phasor measurement data obtained from a microPMU system developed by Power Standards Lab and shows realistic event detection for various frequency (angle) and voltage disturbance events. Our future work will implement the event detection algorithm in real-time, either in the PMU firmware or an external client computer, to monitor and automatically detect events in the electricity grid.

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