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DiCCA with Discrete-Fourier Transforms for Power System Events Detection and Localization

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Abstract: Large wide-area power grids monitoring systems generate a large amount of phasor measurement unit (PMU) data. Single variable analysis methods are often applied to the relative phase angle difference (RPAD) between two PMU locations for event detection. However, the possible locations of the events cannot be identified by such methods. In this paper, dynamic-inner canonical correlation analysis (DiCCA) based discrete Fourier transform method is proposed to detect events in the PMU data and identify the possible locations of the events. A case study on a real PMU dataset demonstrates the effectiveness of the proposed method.

Keywords: dynamic-inner canonical correlation analysis, discrete Fourier transform, latent variable modeling, PMU data, event detection

1. INTRODUCTION

With increasingly more complex power grids and the introduction of more distributed generations, a continuous monitor over the power system is required to improve its efficiency and reliability. This trend has led to a wide application of phasor measurement units (PMU). Phasor measurement unit is an electrical device which provides a real-time measurement of current, voltage, frequency and phasor angle across the power system. The electrical quantities collected from PMUs can provide useful insights about power system dynamics that can be used for state estimation, disturbance monitoring, stability analysis and event identification. In addition, the data collected by the PMUs can be transmitted and stored at rates up to 60 times per second. Therefore, the large amounts of data generated by PMUs can be used for comprehensive event detection and analysis.

Among all the applications on PMU data, one important application is disturbance detection. Various methods for disturbance detection have been proposed. Tate (2008) proposed a method using finite impulse response (FIR) for transient detection. The work presented in Foruzan et al. (2017) and Khan et al. (2015) applied detrended fluctuation analysis for fast event detection. Negi et al. (2017) proposed to use the computation of spectral kurtosis on the sum of intrinsic mode functions for event detection. As discussed in Allen et al. (2013), some important "events of interest", such as transmission line reclosing and tripping can be characterized as low frequency oscillations below 2Hz in the relative phase angle difference (RPAD) between two PMU locations (Rogers (2012)). Therefore, the detection of these events is equivalent to the detection of low frequency oscillations. In addition, the purpose of differencing the phase angles of two stations is to eliminate common drifts or trends between them, so the sudden oscillations in one of the stations can stand out better.

Several methods have been proposed in literatures that perform low frequency oscillations detection. A straightforward way is to perform discrete Fourier transform on RPAD pairs between all stations. To detect transient events, DFT can be applied to a relative small window of samples instead of the whole sequence. Low frequency oscillations can be detected by focusing on dominant frequency components in the range $0 \sim 2$Hz. The disadvantage of this method is that the number of PMU pairs increases quadratically with the number of PMU locations. As a result, the computational complexity will also increase. In addition, there is no way to identify the possible locations of the events, since two stations have the same contribution to the corresponding RPAD. Other methods that have been proposed to detect oscillations include matrix-pencil fitting, zero crossings of the time series or autocovariance function (ACF) (Liu et al. (2007); Kedem and Yakowitz (1994); Thornhill et al. (2003)). Matrix-pencil fits a sum of damped sinusoids to the RPAD data, and the low frequency oscillations are detected based on the significantly high value of the sinusoids amplitude. Zero crossings of the time series checks the intervals between the zero crossings of a time series, while zero crossings of ACF checks the intervals between the zero crossings of the ACF. In both cases, the intervals should have similar length to the oscillation period when an oscillation exists. The advantage of ACF over the time series itself is that the impact of noise is reduced in ACF method. However, all of these methods are designed for single variable and have similar disadvantages as the discrete Fourier transform method.

In this paper, a DiCCA based DFT method working on multi-variables is proposed. DiCCA is applied to extract latent dynamic variables in the multivariate time series data. It extracts a set of lower dimensional dynamic latent variables with descending predictabilities from a set of higher dimensional variables (Qin and Dong (2017)). Since oscillating components in the data are highly predictable, they will be extracted by the first few dynamic latent variables. Then, discrete Fourier transform is applied to each dynamic latent variable to detect low frequency oscillations, and the station that has the largest contribution to the dynamic latent variable can be identified as the possible location of the events.

The remainder of the paper is organized as follows. Section 2 reviews the DiCCA method. Section 3 presents the proposed DiCCA based discrete Fourier transform method. The case study on real PMU dataset in Section 4 demonstrates the effectiveness of the proposed method. Conclusions are drawn in Section 5.

2. DYNAMIC-INNER CANONICAL CORRELATION ANALYSIS

Dynamic-inner canonical correlation analysis (DiCCA) was proposed to model high dimensional time series data. It extracts a set of dynamic latent variables with descending predictabilities, such that the important dynamics are guaranteed to be extracted first.

Denote $\mathbf{x}_k$ as a sample vector of m variables and t_k as the first dynamic latent variable at time k. The predictability of a time series $\{t_k, k = 1, 2, \cdots, N\}$ can be defined as the correlation between t_k and $\hat{t}_k$, where $\hat{t}_k$ is the prediction of t_k from the past values and can be expressed as

$$\hat{t}_k = \beta_1 t_{k-1} + \beta_2 t_{k-2} + \cdots + \beta_s t_{k-s} \tag{1}$$

Higher correlation indicates smaller angle between t_k and $\hat{t}_k$, which in turn indicates higher predictability. On the other hand, lower correlation indicates larger angle between t_k and $\hat{t}_k$, which in turn indicates lower predictability. Therefore, the maximal predictability of t_k can be achieved by maximizing the correlation between t_k and $\hat{t}_k$, which can be written as

$$\max \quad \frac{\sum_{k=s+1}^{N} t_k \hat{t}_k}{\sqrt{\sum_{k=s+1}^{N} t_k^2}\sqrt{\sum_{k=s+1}^{N} \hat{t}_k^2}} \tag{2}$$

Denoting t_k as a linear transformation of $\mathbf{x}_k$ as

$$t_k = \mathbf{x}_k^T \mathbf{w},$$

such that

$$\begin{aligned}\hat{t}_k &= \beta_1 t_{k-1} + \cdots + \beta_s t_{k-s} \\ &= \mathbf{x}_{k-1}^T \mathbf{w} \beta_1 + \cdots + \mathbf{x}_{k-s}^T \mathbf{w} \beta_s \\ &= [\mathbf{x}_{k-1}^T \cdots \mathbf{x}_{k-s}^T](\boldsymbol{\beta} \otimes \mathbf{w})\end{aligned}$$

Combining Equation (1) and (2), the objective function of DiCCA can be presented as

$$\max \quad \frac{\mathbf{w}^T \mathbf{X}_{s+1}^T \mathbf{Z}_s (\boldsymbol{\beta} \otimes \mathbf{w})}{||\mathbf{X}_{s+1}\mathbf{w}||||\mathbf{Z}_s(\boldsymbol{\beta} \otimes \mathbf{w})||} \tag{3}$$

where $\otimes$ denotes the Kronecker product, and the data matrices are defined as

$$\mathbf{X}_i = [\mathbf{x}_i \ \ \mathbf{x}_{i+1} \ \ \cdots \ \ \mathbf{x}_{N-s-1+i}]^T \quad \text{for} \quad i = 1, 2, \cdots, s+1$$
$$\mathbf{Z}_s = [\mathbf{X}_s \ \ \mathbf{X}_{s-1} \ \ \cdots \ \ \mathbf{X}_1]$$

The weight vector $\mathbf{w}$ and the coefficients of the prediction model (1) can be found by solving the objective function (3). After extracting the first dynamic latent variable, the data matrix $\mathbf{X} = [\mathbf{x}_1 \ \ \mathbf{x}_2 \ \ \cdots \ \ \mathbf{x}_N]^T$ is deflated as

$$\begin{aligned}\mathbf{X} &:= \mathbf{X} - \mathbf{t}\mathbf{p}^T \\ \mathbf{t} &= [t_1 \ \ t_2 \ \ \cdots \ \ t_N]^T \\ \mathbf{p} &= \mathbf{X}^T\mathbf{t}/\mathbf{t}^T\mathbf{t}\end{aligned}$$

and the deflated $\mathbf{X}_i$'s can be formed from the deflated $\mathbf{X}$ accordingly. Next, the deflated data matrices are used to extract the second dynamic latent variable. This procedure can be repeated to extract more latent variables.

The DiCCA algorithm has several advantages. First,tThe number of dynamic latent variables required to extract all the dynamics in the data are guaranteed to be smaller than the number of variables m. Second, it guarantees that the most predictable component is extracted first. Since oscillating components are highly predictable, DiCCA is able to extract them in the first few latent variables. Therefore, the analysis of the oscillations in high dimensional time series can be transformed into the analysis of low dimensional *principal time series* formed by the first few latent variables.

3. DISCRETE FOURIER TRANSFORM BASED ON DICCA

Discrete Fourier transform provides a frequency domain representation of a sequence $s_0, s_1, \cdots, s_{N-1}$. The transformation is defined as

$$S_k = \sum_{j=0}^{N-1} s_j e^{-i2\pi kj/N} \quad \text{for } k = 0, 1, \cdots, N-1 \tag{4}$$

In addition, the discrete Fourier transform is invertible. Therefore, given the discrete Fourier transformation of a sequence as $S_0, S_1, \cdots, S_{N-1}$, the original sequence can be calculated by inverse discrete Fourier transformation defined by

$$s_k = \frac{1}{N}\sum_{j=0}^{N-1} S_j e^{i2\pi kj/N} \quad \text{for } k = 0, 1, \cdots, N-1 \tag{5}$$

S_k can be interpreted as the coefficient of the complex sinusoid at the corresponding frequency. Parseval's theorem shows that

$$\sum_{k=0}^{N-1} |s_k|^2 = \frac{1}{N}\sum_{k=0}^{N-1} |S_k|^2 \tag{6}$$

Therefore, $|S_k|^2$ can be interpreted as the spectral density at the corresponding frequency. If there exits a k such that $|S_k|^2$ is significantly higher than $|S_j|^2$ for $j \neq k$, then there are significant oscillations in the original signal $s_0, s_1, \cdots, s_{N-1}$. Therefore, oscillations in the signals can be detected by detecting spikes in the spectral density functions.

Since "events of interest" in a power system can be characterized as low frequency oscillations, a straightforward method is to use discrete Fourier transform. Assume there are M PMU locations, then the discrete Fourier transform method works as follows.

- Calculate $M(M-1)/2$ RPAD pairs
- Perform discrete Fourier transformation on each RPAD pair and detect spectral density spikes in the range $0 \sim 2$Hz.
- Each detected spike corresponds to an event

Therefore, the number of discrete Fourier transformations needs to be performed increases quadratically with the number of PMU locations. However, even though there are $M(M-1)/2$ RPAD pairs, there are only $(M-1)$ degrees of freedom, and the number of transformations do not match the degrees of freedom.

We present a possible solution to this problem. Let $X(k)$ denote the phase angle at location k. First, we calculate the discrete Fourier transformation of $(M-1)$ relative phase angle differences of $X(k) - X(k-1)$, for $k = 2, 3, \cdots, M$. Then the discrete Fourier transformation of the RAPD between any 2 locations i and j, $i > j$ can be calculated as

$$DFT(X(i) - X(j)) = \sum_{k=j+1}^{i} DFT(X(k) - X(k-1))$$

where DFT represents the discrete Fourier transformation.

After an event is detected, it would be desirable to find the possible location of the event. However, the discrete Fourier transformation cannot identify the location, since 2 stations contribute equally to the RAPD, and hence contribute equally to the discrete Fourier transformation results. Similarly, other oscillation detection methods work on signal RPAD pair also have this problem and cannot identify the possible locations of the events. To address this problem, a oscillation detection on multivariate is necessary to analysis the interactions among variables and identify the possible locations of events. Therefore, the following method is proposed for events detection and possible location identification, which is a combination of DiCCA and discrete Fourier transformation.

- Perform DiCCA on $M(M-1)/2$ RAPD pairs and extract l dynamic latent variables
- Perform discrete Fourier transformation on each l dynamic latent variable and detect spectral density spikes in the range $0 \sim 2$Hz
- For each dynamic latent variable, the PMU location contributes most to the corresponding DiCCA loading is identified as the root cause of the event.

This method has several advantages. First, DiCCA guarantees that the number of dynamic latent variables extracted is fewer than the degrees of freedom of the variables. Since the degrees of freedom of the $M(M-1)/2$ RPAD pairs is $(M-1)$, there are at most $(M-1)$ dynamic latent variables. Therefore, the number of discrete Fourier transformation required is at most $(M-1)$. Second, the magnitude of the each element in the loading vector $\mathbf{w}$ indicates the contribution of each RPAD pair to the dynamic latent variable, which is equivalent to the contributions of 2 PMU stations corresponding to the RPAD pair. Therefore, it is reasonable to roughly identify the PMU station that makes the highest contribution to the latent variable as the possible location of the events. The effectiveness of this method will be demonstrated in the next section.

4. CASE STUDY ON PMU DATASET

4.1 PMU Data

In this case study, we have data collected from 6 PMU locations (Station1-Station6) downloaded from $http://www.nrel.gov/docs/fy15osti/61664-1.zip$. The correspondence between the 15 paired RPAD variables (V1-V15) and the phase angles at 6 stations (Station1-Station6) are summarized in Table 1. For example, $V15$ is equal to the phase angle of Station1 minus the phase angle of Station2.

There are 108,000 samples in total and the sampling rate is 30Hz. In DiCCA modeling, the first 81,000 samples are used as training dataset, and the last 27,000 samples are used as testing dataset. All the 15 variables are differentiated first to remove the direct current offset to facilitate the detection of oscillatory events in the low frequency range.

4.2 DiCCA Modeling Results

In DiCCA modeling, the order is selected such that there is no dynamics in the prediction errors of the dynamic latent variables, and the number of dynamic latent variables is selected such that there is no dynamics in the residuals. In this case, the order is selected as 74 and the number of dynamic latent variable is selected as 5. The R^2 values (coefficient of the determination) of the prediction model (1) for each dynamic latent variable are plotted in Fig.1.

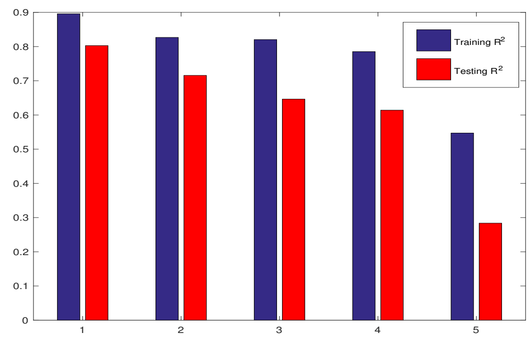


Fig. 1. R^2 for the prediction model of each dynamic latent variable in training and testing datasets

The blue bars are the R^2 for each dynamic latent variable of the training dataset, and red bars show the R^2 for each dynamic latent variable of the testing dataset. R^2 gives a measure on how good the fit is for a prediction model. R^2 closing to 0 indicates that the prediction model fits the data poorly, and R^2 closing to 1 indicates that the prediction model fits the data well. From Fig.1, we can see that all the R^2 values are significantly above 0, which again indicates that there are dynamics in the extracted dynamic latent variables and the prediction model fits well. In addition, R^2 decreases monotonically for both training and testing datasets. This agrees with the objective of

Table 1. Correspondence between V1-V15 and Station1-Station6

	Station1	Station2	Station3	Station4	Station5	Station6
Station1		-V15	-V13	-V10	-V6	-V1
Station2	V15		-V14	-V11	-V7	V2
Station3	V13	V14		-V12	-V8	-V3
Station4	V10	V11	V12		-V9	-V4
Station5	V6	V7	V8	V9		-V5
Station6	V1	V2	V3	V4	V5	

DiCCA that dynamic latent variables are extracted with descending predictability. In addition, the similar trends between the training R^2 and testing R^2 indicates the training dataset gives a good representation of the system.

Fig.2 shows the plots of loading vectors $\mathbf{w}_1 \sim \mathbf{w}_5$, where w_i corresponds to the loading vector for the i^{th} dynamic latent variable. From the plots of the loading vectors, the contribution of each Station to the dynamic latent variables can be identified. For example, $V5 \sim V9$ contribute most to the first dynamic latent variable. From Table 1, we can see that $V5 \sim V9$ are all in the row corresponding to Station 5. Therefore, compared to all the other stations, Station 5 contributes most to the first dynamic latent variable. Similarly, we can determine the station that has the highest contribution to the other dynamic latent variables. The results are summarized in Table 2, where DLV_i corresponds to the i^{th} dynamic latent variable. When an

Table 2. Stations and dynamic latent variables correspondence

	DLV_1	DLV_2	DLV_3	DLV_4	DLV_5
Station with the most contribution	5	2	3	1	6

event is detected based on a dynamic latent variable, the station with the most contribution can be identified as the possible location of the event.

4.3 Event Detection and Localization

After DiCCA modeling, discrete Fourier transform is applied to each dynamic latent variable to detect "events of interest". Since some events are transient, applying discrete Fourier transform to the entire dynamic latent variable sequence will cause miss detection. Therefore, in order to capture transient oscillations, discrete Fourier transform is performed on a time window of 300 samples (10 seconds), and the window moves every 150 samples until the sequence ends. The maximum magnitudes in the range $0 \sim 2$Hz for each window are saved, and the windows with the maximum magnitudes above 3.5 standard deviation from the mean are identified to have low frequency oscillations, or the "events of interest" (Allen et al. (2013)).

Fig.3 shows the magnitudes of frequency peaks in the range of $0 \sim 2$Hz for all time windows. The solid line represents the mean of the peaks and dashed line represents the 3.5 of deviations above the mean. It can be seen from Fig.3 that 5 peaks are above the the 3.5 deviation line and are detected as events. These 5 peaks correspond to the $223^{rd}, 288^{th}, 348^{th}, 536^{th}, 537^{th}$ time window. Since $V5 \sim V9$ contribute most to the first dynamic latent variable, it is suspected that oscillations exist in $V5 \sim V9$ in these five time windows.

Fig.4 shows $V5$, and the associated differentiated phase angle at Station 5 and Station 6 in the five time windows detected according to the first dynamic latent variable. $V6 \sim V9$ look similar to $V5$, therefore, they are not plotted here.

The same procedure is applied to other dynamic latent variables to detect new events that have not been detected by previous latent variables and identify the possible event locations. All the windows detected with events and the corresponding possible locations are summarized in Table 3.

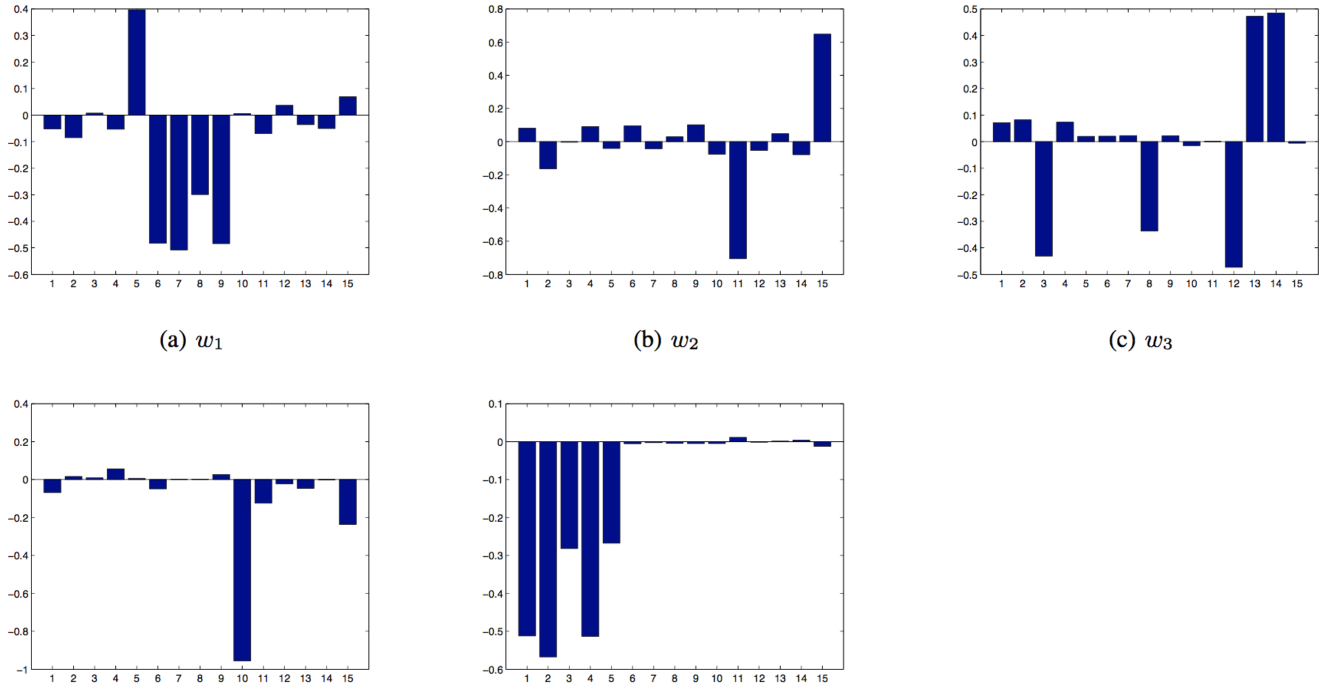
Table 3. Windows detected with events and corresponding possible location

Window number	Root cause
223	Station5
258	Station1
263	Station2
269	Station3
288	Station5
348	Station5
485	Station2
536	Station5
537	Station5

It can be seen from Table 3 that most of the events are detected in the first dynamic latent variable, which agrees with the DiCCA objective that the most predictable dynamic latent variable is extracted first.

5. CONCLUSIONS

In this paper, a DiCCA based discrete Fourier transformation is proposed to detect the events in the PMU data and identify the possible locations of the events in a power system. DiCCA first extracts a set of lower dimensional dynamic latent variables with dominant predictability from the original variables. Then the discrete Fourier transformation is applied to each of the extracted dynamic latent variable to detect events of low frequency oscillations. The advantage of this method is that the number of discrete Fourier transformations required is fewer than the number of original variables. In addition, the contributions of each PMU station to each of the extracted dynamic latent variable can be calculated, and the station with the largest contribution can be identified as the possible location of the events. Both of these advantages cannot be achieved by the methods designed for single RPAD pair, such as the direct discrete Fourier transformation method and matrix-pencil method. The case study on real PMU data demonstrates the effectiveness of the proposed method.



(a) w_1 (b) w_2 (c) w_3

(d) w_4 (e) w_5

Fig. 2. Plots of weight vectors $w_1 \sim w_5$

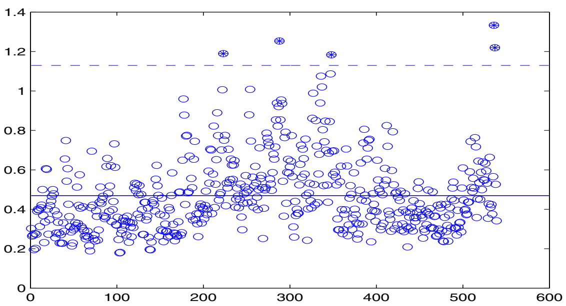


Fig. 3. Peaks of DFT in the range $0 \sim 2$Hz for every 10-second window for $DLV1$, solid line shows the mean of the peaks and dash line shows the 3.5 standard deviations above the mean

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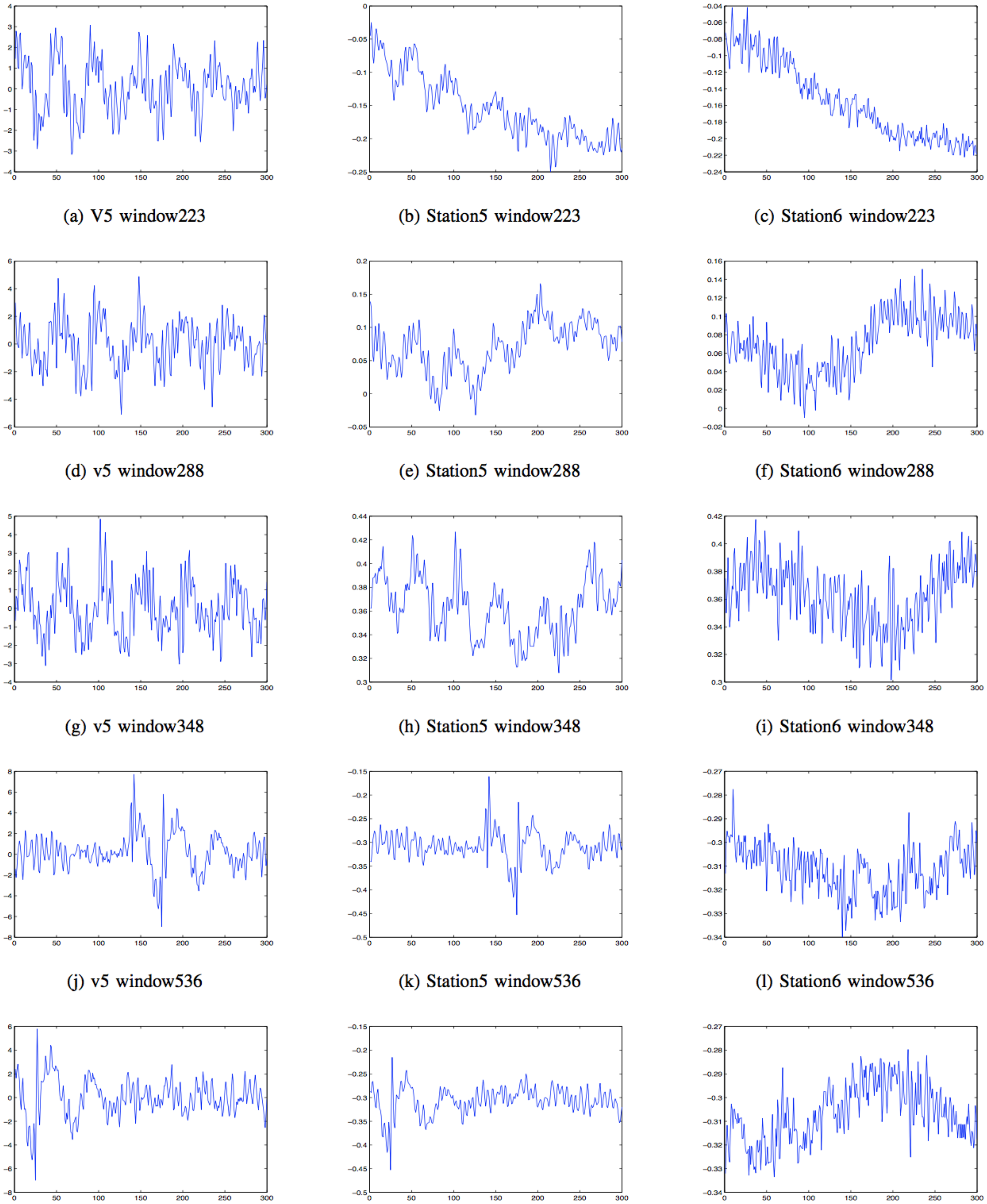

(a) V5 window223 (b) Station5 window223 (c) Station6 window223

(d) v5 window288 (e) Station5 window288 (f) Station6 window288

(g) v5 window348 (h) Station5 window348 (i) Station6 window348

(j) v5 window536 (k) Station5 window536 (l) Station6 window536

(m) v5 window537 (n) Station5 window537 (o) Station6 window537

Fig. 4. Plots of $V5$ and related differentiated phase angles at Station 5 and Station 6