Oscillation Recognition Using a Geometric Feature Extraction Process Based on Periodic Time-Series Approximation

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ABSTRACT Oscillations may cause both economic and technical problems such as a reduction in overall system reliability. Therefore, detecting and preventing oscillatory behavior that affects power systems is important. This paper proposes an oscillation recognition method that includes monitoring and extracting features in a recursive and sequential manner in a time-series measurement in power systems. We propose a geometric feature extraction process for recognizing oscillations by constructing an average system and Poincaré map for time-series measurement. The proposed process provides the features of a system’s damping and frequency of oscillation, and the developed monitoring systems are based on nonlinear dynamics. The circulating oscillatory behavior is represented on a finite-integer-delay embedded time-series plane, extracted by a Poincaré map construction, and examined directly along the trajectory to monitor the features of the oscillation according to damping and frequency. Oscillatory behavior recognition is tested on IEEE’s second benchmark system for subsynchronous resonance to verify the fast extraction of oscillation components. In addition, a case study for Korean power systems with a high penetration of renewable energy and application on actual measurement data is carried out to demonstrate the practical application of the process.

INDEX TERMS Approximation method, oscillation monitoring, power system measurement, subsynchronous oscillation, time-series analysis.

NOMENCLATURE

LIST OF SYMBOLS – MATHEMATICAL DEFINITIONS

\[ O(\varepsilon) \] Periodic averaging approximation difference
\[ \varepsilon \] An arbitrary small number
\[ D_0 \] Compact set defined in real coordinate subspace
\[ f(\cdot) \] Nominal system
\[ f_m(\cdot) \] Approximated system by periodic average
\[ P_k(\cdot) \] Poincaré map for system with periodic solution
\[ R^n \] Real coordinate space of n dimensions
\[ T \] Period of solution in time \( t \)

LIST OF SYMBOLS – TIME-SERIES REPRESENTATION

\[ \Delta \] Finite integer delay specified as a quarter of unit period sample \( K \)
\[ \delta(k) \] Finite integer delay (FID)
\[ \hat{\delta}_i \] Estimated system damping
\[ \hat{f}(k) \] Estimated mode frequency
\[ \hat{r}_i(k) \] Radius of trajectory
\[ \phi(k) \] Time series measurement data
\[ f_m(\cdot) \] Two dimensional embedded system via periodic delay in time-Series
\[ m_{n,W}^{(i)} \] Slope of the trajectory for \( i \)th interval for interval length \( W \), at measurement location \( n \)
\[ t_k^* \] Time tagging value for selected points at Poincaré section

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I. INTRODUCTION

Oscillations in power systems represent the periodic exchange of unintended energy between different components of the power grid. They are characterized by frequency, damping, amplitude, and phase. Analyzing the features of oscillations is important as oscillations can cause problems ranging from safety concerns and decreased power quality to potential equipment damage and system instability, which may lead to voltage collapse of the system [1]–[3]. Recently, power systems have been equipped with phasor measurement unit (PMU) devices and wide-area monitoring systems to provide information on a system’s oscillatory behavior. A few events or analyses of conditions for measured data with regard to oscillatory behavior in power systems have been reported [3], [4]. In many cases, oscillation monitoring is focused on low-frequency oscillation (LFO), as PMUs can only deliver information at 30, 60, or 120 samples per second, or 8.33–33 ms per point. This performance dependence of PMUs could still not detect many important phenomena in power systems, specifically fast responses such as subsynchronous oscillations (SSOs). Therefore, in this study, the application of oscillation detection is assumed to not be limited to PMU data, but includes very high-sampling measuring devices such as digital fault recorders (DFRs) or individual inverter data [2].

Previous research on power system oscillation analysis was primarily based on model-based eigenanalysis. However, several recent works focus on data-driven methods for monitoring oscillation modes by power-system measurements. The Fourier transform (FT) is the most direct method to represent time-domain data as frequency-domain exponent but is limited for spectrum analysis. Recently, FT has been applied to other methods for accurate identification of power system modes [5], [6]. Hilbert-based approaches are used for practical measurement data combined with empirical-mode decomposition [7]–[9], and the results have been compared with Prony methods [10]. Meanwhile, the Prony method has been compared with other methods for identification of dominant modes, such as the continuous wavelet transform (CWT) [11], [12] or Kalman filter [13], to show its usefulness or improvement. The Prony method itself has been improved recently; its robustness to data outliers has been enhanced [14]. These dominant-mode-identification methods are measurement-based approaches, but they require a specific interval of time windows. In the operation center at the Bonneville Power Administration (BPA), a simple root-mean-square (RMS)-based energy filter was implemented to detect oscillations in multiple frequency bands [15]. BPA’s method is rather intuitive for the four types of natural oscillations, but forced oscillations, which can be observed in every frequency band, are difficult to identify. However, if the conditions of the measurement devices are sufficient to observe oscillatory behavior addressed in [16], time-series techniques, such as the maximum Lyapunov exponent for nearly real-time oscillation detection, are available [17].

The main problem of oscillation recognition in this paper is defined to monitor and extract features recursively and sequentially as a time-series approach in power systems. Additionally, this problem is estimating the magnitude, system damping, and mode frequency. The proposed process is motivated by analytic methods for nonlinear dynamics of distinctive phenomena as oscillations [18], [19]. As the field of sensors or measurement devices grows, performance is advanced for practical time-series applications to observe oscillations such as subsynchronous resonance (SSR) phenomena in power systems. In this paper, a time-series process for oscillation recognition using periodic approximation is proposed by constructing data into a geometric manner. This approach enables the reduction of time-consuming computation without manipulating matrices by dividing the signal into several segments.

This paper begins with the introduction of the general approximation approach of an average system and Poincaré map in Section II. The proposed process is then developed for the time-series considering mathematical properties. In Section III, both numerical and geographical results are discussed for the proposed process for the IEEE second benchmark system for SSR computation and a case study in Korean power systems with highly penetrated renewable energy. Moreover, the application of the proposed process is applied to measurement data for actual oscillation incident in Korean power systems. The results with regard to data acquisition and delay are discussed in Section IV, after which the paper is concluded.

II. GEOMETRICAL REPRESENTATION OF OSCILLATION PHENOMENA

This section introduces the relationship between an average system and Poincaré map for a periodic solution for arbitrary systems with the response of oscillatory behavior. Subsequently, the proposed geometric feature extraction (GFE) process as a time-series approach is carefully derived from the definition.

A. MATHEMATICAL MOTIVATION OF OSCILLATORY BEHAVIOR

This paper was motivated by the periodic perturbation and system averaging method introduced in [28]. To derive nonlinear systems mathematically, we adopt a small parameter, $\epsilon$, and periodic averaging approximation difference, $O(\epsilon)$, which will be redefined as a radius of trajectory (RoT) afterward. Note that this $\epsilon$ is constant for mathematical derivation. However, in practical problems, this value cannot be strictly constant but varies with time in power systems.

1) AVERAGE SYSTEM AS AN APPROXIMATION FOR EQUILIBRIUM OF PERIODIC SOLUTION

Consider a power system experiencing an oscillatory behavior for a positive $\epsilon$ as shown in Fig. 1. Therefore, the system
can be represented as

\[ \dot{x} = \varepsilon f(t, x, \varepsilon). \]  

If the system is physically feasible, \( f \) and its partial derivatives with respect to \( (t, x, \varepsilon) \) are continuous and bounded for \( (t, x, \varepsilon) \in [0, \infty) \times D_0 \times [0, \varepsilon_0] \), for every compact set \( D \subset D_0 \), where \( D \subset \mathbb{R}^n \) is a domain. Moreover, \( f(t, x, \varepsilon) \) is \( T \)-periodic in \( t \) for a positive \( \varepsilon \). Therefore, the average system can be defined to approximate the behavior of the nonautonomous system (1).

\[ \dot{x} = \varepsilon f_{av}(x), \]  

where,

\[ f_{av}(x) = \frac{1}{T} \int_0^T f(t, x, 0) \, dt. \]  

Therefore, the oscillatory behavior can be decomposed into the function \( u \), which is a zero mean and is \( T \)-periodic in \( t \). By adopting a time variable change as \( t = s/\varepsilon \) and state variable change as \( x = y + \varepsilon \int_0^s f(t, x, 0) - f_{av}(x) \, dt \), the system yields the following:

\[ \dot{y} = \varepsilon f_{av}(y) + \varepsilon^2 q(s/\varepsilon, y, \varepsilon), \]  

Or

\[ \frac{dy}{ds} = f_{av}(y) + \varepsilon q(s/\varepsilon, y, \varepsilon), \]  

where the function \( q(s/\varepsilon, y, \varepsilon) \) is \( \varepsilon T \)-periodic in \( s \) time scale and period \( T \) for \( t \) time scale. Therefore, system (1) can be represented as an autonomous system with a periodic perturbation by averaging by the approximation of the periodic behavior.

In [28], theorems were summarized for the approximation \( O(\varepsilon) \), with some conditions for \( x(0, \varepsilon) - x_{av}(0) = O(\varepsilon) \) applies for \( x(t, \varepsilon) - x_{av}(\varepsilon t) = O(\varepsilon) \) on the region of attraction and some or all time intervals \( t \). Therefore, in a time-series approach, moving the \( T \)-period average of measurement data as an approximation of equilibrium point can provide information associated with the mapping concept in periodic perturbation discussed in the following section.

2) POINCARÉ MAP OF A PERIODIC SOLUTION

Simplifying (5), consider the periodically perturbed system as

\[ \dot{x} = f(x) + \varepsilon g(t; x, \varepsilon). \]  

Under the same physically feasible conditional statement, the aforementioned average system \( \dot{x} = f(x) \) is stable and the perturbation \( g \) is \( T \)-periodic and bounded at the neighborhood of \( O(\varepsilon) \). Let the solution of (6) be given as \( x = \phi(t; f, 0, x_0, \varepsilon) \), we can then define a map \( P_\varepsilon \) as

\[ P_\varepsilon(x) = \phi(T; 0, x, \varepsilon), \]

where the state of the system at time \( T \) with the initial state at time zero is \( x \). Subsequently, the solution is \( T \)-periodic if and only if the equation \( x = P_\varepsilon(x) \) has a solution. Additionally, this solution is unique in the boundary \( ||x - 0|| < k ||\varepsilon|| \) if the equilibrium point is \( x = 0 \). This map is simply called the Poincaré map of the \((N + 1)\)-dimensional autonomous system.

The solution trajectory of (6) should satisfy the geometrical condition that the trajectory intersects the Poincaré map in transversally the same direction to ensure the uniqueness of the equation [19]. Furthermore, this paper extends to the time-series approach from the mathematical concept for the periodic solutions for a constant \( \varepsilon \) and to consider quasi-periodic situations such as varying \( \varepsilon(t) \).

B. GFE PROCESS IMPLEMENTATION USING A PERIODIC TIME-SERIES APPROXIMATION

This section introduces the proposed geometric feature extraction process based on a nonlinear dynamics theorem with regard to the periodic solution discussed above. Time-series measurement values, which are one-dimensional vectors, cannot be used to form the Poincaré map where the dimension is \((N - 1)\) of a nominal system dimension \( N \). Therefore, the new problem can be formed as a time-varying delay difference equation given by [29]

\[ x(k + 1) = x(k) + \varepsilon f_m(x, k), \]

where \( \phi(k) \) stands for the measured time-series for system \( f_m(\cdot) \). Additionally, \( \delta(k) \) is a finite integer delay (FID) value such that \( \delta(k) \in [0, \Delta], \Delta > 0, \) for a sufficiently small \( \varepsilon \).

1) STEP 1: EMBEDDING TIME-SERIES TO A 2-D SYSTEM VIA PERIODIC DELAY

In oscillatory cases, the Poincaré map does not consider the linearly coupled abscissa and ordinate, but extracts the desired geometric property of the phenomena. This unintended coupling error can be avoided by choosing an appropriate FID for \( \Delta \). Thus, the solution or trajectory for the
time-series plane is best represented as the FID of \( \delta(k) = K/4 \) when the time-series is an approximately \( K \)-periodic in \( k \).

However, in the initial stage, the period \( K \) is not given for the time-series measurement, unless applying the Fourier transformation. Therefore, one can first set the appropriate initial FID over 5 samples to construct a 2-D system as described in Fig. 2. The signal was generated as 1 Hz of a fundamental signal composed of two components 10%, 3 Hz and 5%, 0.4 Hz amplitude and frequency, respectively. Subsequently, if at least two Poincaré sets are acquired, the delay can be updated for accurate operation of the proposed process, which will be discussed in a later section.

2) STEP 2: APPROXIMATION OF PERIODIC AVERAGE SOLUTION
For an approximate \( K \)-periodic time-series, the measurement can be averaged by a window size of \( K \), so that the center of the trajectory is required to associate with the Poincaré section. Therefore, the average solution for (8) is given by

\[
x_{av}(k) = \begin{cases} 
\phi(k), & n \in [k_0 - \Delta, k_0] \\
\frac{1}{K} \sum_{i=0}^{K-1} x(i+k), & k > k_0,
\end{cases}
\]

where the output for the average time-series is naturally given before \( k_0 \) and, subsequently, the \( K \)-period moving average is applied.

3) STEP 3: POINCARÉ MAP RECONSTRUCTION SCHEME
Several conditions affect the construction of a Poincaré section at the embedded time-series phase portrait for data \( x(k) \) and delayed data \( x(k - \delta(k)) \) for the delay of sample number \( \delta(k) \) [27].

First, we must consider the direction of the trajectories. To find a set of points of trajectories that intersect transversally to the Poincaré surface, we must define the slope of trajectory flow \( m_{n,W}^{(i)} \) by linear regression as

\[
m_{n,W}^{(i)} = \frac{\sum_{k=i}^{i+W} (x(k) - x_{av}(k)) (x(k - \Delta) - x_{av}(k))}{\sum_{k=i}^{i+W} (x(k) - x_{av}(k))^2},
\]

where the average term for both the measured and delayed axes is approximately the same as \( x_{av}(k) \approx x_{av}(k - \Delta) \) and \( W \) is the size of the window for short-term linear regression. Given the direction of flow as a slope of trajectory, setting the turning-point conditions as a change of sign is natural as Fig. 3.

Second, one must consider the position of the map. The trajectory points that intersect transversally to the Poincaré surface and cross in the same direction should satisfy the boundary condition. This time-series approach can be roughly accepted on the basis of the corollary of the Bendixon criterion that describes the inside of any periodic orbit: at least one equilibrium point must exist [28].

Finally, even if the direction and position are satisfied, some noises cannot be filtered, and this may yield an inaccurate value for the RoT. Therefore, from the continuity considered at the beginning stage of the mathematical description, the consistency of the trajectory should be considered by rolling it back to the direction checking part. Therefore, the set of the Poincaré map should have the same turning point direction and must consistently form a downwards and upward trend.

4) STEP 4: GEOMETRICAL FEATURE EXTRACTION
For every Poincaré map reconstruction scheme, time can be tagged as \( t_k \), for each of the selected points. Therefore, the frequency estimation can be defined as

\[
\hat{f}(k) = \frac{1}{t_{k+1} - t_k}.\]

FIGURE 2. A concept of determining the finite integer delay and constructing a 2-D system via time-series measurement.

FIGURE 3. Poincaré map reconstruction scheme for periodic response of the system.
For other geometrical features, the RoT $r_k$ is calculated between the estimated equilibrium $x_{av}$ and the Poincaré set of $(x^*(k), x^*(k - \Delta))$ as

$$r_k = \sqrt{(x_{av} - x^*(k))^2 + (x_{av} - x^*(k - \Delta))^2}. \quad (12)$$

By using the geometrically extracted information from the RoT, we can create a nonlinear regression model to extrapolate the featured data for system damping. The regression model can be selected as

$$\hat{r}_i(k) = \hat{\alpha}_i \cdot e^{(\hat{\sigma}_i \cdot k + \hat{\phi}_i)}, \quad (13)$$

Or

$$\log \hat{r}_i(k) = \hat{\alpha}_i k + (\log \hat{\alpha}_i + \hat{\phi}_i) = \hat{\sigma}_i k + \hat{\beta}_i, \quad (14)$$

where $\hat{\alpha}_i$ is related to the initially estimated magnitude, or the offset of the RoT, which is closely related to the magnitude of oscillation in the system. The shifting element $\hat{\phi}_i$ is adjusted to make the result of the exponential regression more realistic. From (13) and (14), the estimated system damping $\hat{\sigma}_i$, which is the key parameter to identify the oscillation, can be directly calculated from the over-determined form via the accumulated RoT and time tagging value.

In this paper, a simple linear regression in a log scale is carried out to extract the system-damping information. The nonlinear regression process is recursive and the RoT is acquired for every time step.

5) STRUCTURE FOR IMPLEMENTATION OF GFE PROCESS

Fig. 4 shows a flow chart for GFE process. The whole process consists of the aforementioned steps to provide an output of RoT, system damping, and frequency. After the type of data is defined, an initial FID setting value for frequency is required to construct state space. Then the updated FID using estimated frequency can be applied, recursively. Furthermore, the correction scheme is needed for practical application, which discussed in the later section.

C. COMPARISON OF TIME-SERIES METHODS FOR OSCILLATION ANALYSIS

As per Table 1, the GFE process might be slower than the previous approach but it considers detailed mathematical concepts.

III. APPLICATION OF THE GFE PROCESS TO POWER SYSTEM MEASUREMENT DATA

A. CASE I: OSCILLATION STUDY WITH NON-ZERO DAMPING

To further illustrate the usefulness of the method, we consider both data from simulations based on MATLAB Simulink and PSSE Simulation for planning data in a Korean power system.

1) IEEE SECOND BENCHMARK SYSTEM OF SSR COMPUTATION EXAMPLE

In this section, we apply the proposed GFE process to identify and analyze SSR phenomena. Fig. 5 shows the test system configuration for the SSR study and Table 2 shows the parameters of the corresponding system. The conditions used in [17] have been applied in this paper.

SSOs are in the 10–50-Hz range; thus, a much higher sampling rate is required to identify and analyze these oscillations. The sampling condition was selected as 48 points per cycle and 10 as the reporting rate factor. Fig. 6 shows
the voltage measured in the bus fault location, where the growing oscillation is observed for approximately 20 s and a new periodic solution is formed after that. Fig. 7a shows 10 s of the time-series representation plane of the voltage measured at the fault location. Along the circular trajectory, the selected points within the Poincaré map are chosen and marked as black circles on the plane. For detailed figure, the RoT, the distance between the Poincaré section point $x^*(k)$ and approximated equilibrium point $x_{av}(k)$ is dramatically reduced so that the two points get closer. Fig. 7b shows the RoT that is equivalent to the Euclidean distance between the estimated equilibrium $x_{av}$ and selected points $x^*(k)$ of the trajectory. The Euclidian distance has been calculated for every unit cycle of oscillation in Fig. 7b using the estimated set of Poincaré map. The spike on the figure can imply that the system is experiencing a short-term transient.

![FIGURE 5. Schematic diagram for SSR second benchmark study example.](image)

![FIGURE 6. Voltage measured at the fault location for SSR example.](image)

| Parameter Description                  | Value       |
|---------------------------------------|-------------|
| Generator inertia coefficient (s)     | 0.8788      |
| LP inertia coefficient (s)             | 1.5498      |
| HP inertia coefficient (s)             | 0.24894     |
| Generator-LP Stiffness (pu/ rad)      | 83.47       |
| LP-HP Stiffness (pu/ rad)              | 42.702      |
| Synchronous reactance in d-axis $X_d$ (pu) | 1.65        |
| Transient reactance in d-axis $X'_d$ (pu) | 0.25        |
| Sub-transient reactance in d-axis $X'_d$ (pu) | 0.2        |
| Synchronous reactance in q-axis $X_q$ (pu) | 1.59        |
| Transient reactance in q-axis $X'_q$ (pu) | 0.46        |
| Sub-transient reactance in q-axis $X'_q$ (pu) | 0.2        |
| Generator leakage reactance $X_L$ (pu) | 0.14        |
| Transformer impedance $Z_{tr}$ (pu)   | 0.0006+j0.12 |
| Transmission line impedance 1 $Z_{L1}$ (pu) | 0.0074+j0.08 |
| Transmission line impedance 2 $Z_{L2}$ (pu) | 0.0067+j0.0739 |
| Series capacitance $X_C$ (pu)          | -j0.084     |

![FIGURE 7. Poincaré map and RoT calculation for SSR study.](image)

Fig. 8a is the system damping value estimated using the RoT in Fig. 7b. The damping has been estimated initially at 0.52 s, so there are 0.4 s (approximately 10 periods of the mode) of a delay than the first RoT value and the value is -4.4 1/s. The damping then increases sharply to 0.6 1/s at 0.72 s. After the transient completes at 3 s, the value becomes steady at approximately 0.2 1/s. Furthermore, in Fig. 8b, the estimated frequency is between 24.2 and 25.3 Hz with an average of 24.77 Hz. The first frequency has a 0.07-s delay (almost two periods) compared with the RoT calculation. Prony’s method is applied; the damping of the dominant mode is 0.2104 and its frequency is 24.77 Hz. The frequency is exactly the same and the damping is slightly more conservative.

![FIGURE 8. System damping value estimated using the RoT in Fig. 7b.](image)

Fig. 9 corresponds to the SSR observed for 10 s by using the proposed index for various compensation levels. From 43.5 to 62% of the compensation level, the system is unstable due to the SSR phenomenon. Compared with the equivalent impedance, high resistance or negative reactance is observed in the corresponding range.

![FIGURE 9. System damping value estimated using the RoT in Fig. 7b.](image)

In [17], the relationship between system strength and MLE is demonstrated by changing $Z_{T}$ and $Z_{L2}$. The results can be summarized as follows: the effect of resonance is larger if the distance between the generator and transmission...
line is sufficiently close at a small transformer impedance $Z_{Tr}$, and the short circuit ratio is higher. A similar result can be obtained using the estimated damping of the GFE process, while the series capacitor scanning results are the same.

B. CASE II: OSCILLATION STUDY WITH ZERO DAMPING

1) OSCILLATION FOR KOREA POWER SYSTEMS WITH HIGH PENETRATION OF RENEWABLE ENERGY

Fig. 10 shows a configuration for the oscillation study for the southwest side of Korean power systems. The wind plant was modeled as a WECC Type 4 (fully rated converter) generator, where the voltage error dead-band lower and upper threshold value for a generic renewable electrical control model was set as $\pm 0.05$. Additionally, the electrical control model for a large-scale PV was used for photo-voltaic (PV) modeling and the dead band was set as $\pm 0.05$, the same as the wind plant. According to the grid code, the power factors of the wind plant and PV generator was set to $\pm 0.95$ and 1.00 in the machine data, respectively. Additionally, the results for detecting the oscillations for each case are discussed, applying the GFE process.

2) PRELIMINARY STUDY IN HIGH PENETRATION OF RENEWABLE ENERGY

In this natural oscillation scenario, the oscillation occurs due to renewable energy resources. Specifically, after the three-phase bus fault was cleared at bus 6, after the fault at the same location, the oscillation was observed as Fig. 11, throughout the whole interested area by a frequency...
of 3.75 Hz. In Fig. 11, stage A was the transient interval, where the time range was from 1.1 to 1.25 s. Additionally, stage B was two periods of oscillation, the first and second being up to 1.53 and 1.8 s, respectively.

The oscillation was directly caused by the ±0.05 Q/V dead-band at the current controller which simultaneously exchanged 330 MW of power between generators 1 and 2. Therefore, the source of this scenario was renewable energy connected to bus 1. By the Prony analysis, damping was -0.025 % and the mode frequency 3.74 Hz. Additionally, the CWT produced a similar level as 0.46 % damping and 3.65 Hz. Therefore, the oscillation was a sustained natural oscillation.

3) EXAMINATION OF OSCILLATIONS USING THE GFE PROCESS

For all bus voltages acquired in the area of interest, oscillation features can be extracted geometrically. From the preliminary study using the existing time-series approach, the damping coefficient was approximately zero; therefore, the effective area for oscillation can be shrunk into 33 buses. In Table 4, buses have been classified by locations for a specific range of RoT and approximate zero damping. From areas 1 to 3, the magnitude of oscillation decreased when the electrical distance was further from the source. Additionally, the estimated system damping was approximately zero, which is a true value according to the results of existing methods—Prony, CWT, etc. The other buses had small magnitudes of oscillation and the estimated damping exhibited detrending or non-zero values.

Fig. 12 shows the GFE result when the voltage was measured at buses 1, 8, and 21, followed by the geometrically extracted quantities of the three significant results of the RoT, damping, and frequency. In Fig. 12a, a sustained oscillatory behavior was observed after 1.7 s, such that the GFE result was calculated within stage B, which was two periods after stage A, and was a transient interval. In Fig. 12b, the fluctuating range of the system damping was −0.69 to 0.36 % for bus 1, −0.48 to 1.04 % for bus 8, and −0.82 to 0.83 % for bus 21. These values were calculated in the confidence range approximately a second after stages A and B, where the estimated damping by Prony and CWT methods corresponded to the range within these values. In Fig. 12c, the frequency was calculated as 3.75 Hz, which was quite similar to that of existing methods and the result was obtained earlier than the RoT values in Fig. 12a.
to a singular matrix when constructing the system damping ± \text{RoT}. The estimated damping in Fig. 15b, fluctuated within gradually increased for 217 s before the increase in oscillation with growing features.

\[ \text{show how fast and to exactly recognize if this was a 1.3 Hz} \]

At this earlier stage of the incident, we applied GFE to process 2) EXAMINATION OF OSCILLATION USING THE GFE

\[ \text{and the system secures damping of 8.77 \%.} \]

\[ \text{decreased to 800 MW, the mode frequency becomes 0.604 Hz} \]

\[ \text{corresponding generators and the system configuration.} \]

\[ \text{1) OSCILLATORY EVENT DESCRIPTION BY MEASUREMENTS} \]

\[ \text{This event occurred due to a falsely set parameter of the excitation system without the operation of the power system stabilizer (PSS) for generators T\#8 and T\#9. Operators increased the output of T\#9 in the first 1.5 h, which caused local mode oscillation. Subsequently, a 1.3 Hz local mode oscillation was observed as a growing oscillation and its magnitude was 200 MW peak-to-peak maximum, which sustained for a few hours before the oscillation naturally damped out. The operators decreased the corresponding generator output to 800 MW. After that, the operators prepared a plan to prevent this event by turning generator T\#9’s PSS to active, and changing the parameter of the automatic voltage regulator (AVR).} \]

\[ \text{The preliminary small signal stability analysis revealed that the system mode had a frequency of 1.554 Hz and damping of 0.62 \%. Subsequently, if the generator output is decreased to 800 MW, the mode frequency becomes 0.604 Hz and the system secures damping of 8.77 \%.} \]

\[ \text{2) EXAMINATION OF OSCILLATION USING THE GFE PROCESS} \]

\[ \text{At this earlier stage of the incident, we applied GFE to show how fast and to exactly recognize if this was a 1.3 Hz oscillation with growing features.} \]

\[ \text{As the RoT result in Fig. 15a shows, the generator output gradually increased for 217 s before the increase in RoT. The estimated damping in Fig. 15b, fluctuated within ± 0.25 l/s at those time intervals. This fluctuation was due to a singular matrix when constructing the system damping} \]

\[ \hat{\sigma}_i. \text{Therefore, after the correction was made to filter out non-oscillatory behavior, the damping should have been zero as shown in Fig. 15b. The criteria for the cut-out value for RoT was set to 0.005, which is slightly higher than the maximum value of 0.0041 for the non-oscillatory interval at Fig. 15a. If the cut-out value for RoT is set high, oscillation recognition time will be delayed. On the contrary, low cut-out value might yield misjudgment of damping or frequency due to noises. The minimum reciprocal condition number was set to 3.5e−16, as the profile of reciprocal condition number before 220 s is below 3.5e − 16. The minimum reciprocal condition number is required to filter out badly conditioned or nearly singular matrix for damping estimation. And the smoothing method was applied as the mean of three neighborhood samples. Frequency fluctuated up to 20 Hz until 220.4 s due to low signal-to-noise ratio; hence, the Poincaré map could not be constructed. Therefore, the similar correction scheme with damping estimation was applied for frequency calculation.} \]

\[ \text{As the RoT increased, the signal was larger than the noise or other insignificant components, the damping was estimated near 0.2 (1/s), and the damping became approximately zero as shown in Fig. 15b. Additionally, the frequency secured a steady value of 1.3 Hz after 220.4 s as shown in Fig. 15c.} \]

\[ \text{When the CWT was applied, the spectral amplitude, a decomposed time section of 1.297 Hz exhibited almost a similar value of the RoT time spectrum.} \]

\[ \text{C. PRACTICAL APPROACH OF THE GFE PROCESS FOR ACTUAL INCIDENT IN KOREAN POWER SYSTEMS} \]

\[ \text{Finally, we conducted a practical approach of the GFE for actual events that occurred at the Korean power systems on August 31, 2016. Fig. 13 and 14 show the measured MWs at the Generator area configuration of the west side of the Korean power system.} \]

\[ \text{FIGURE 13. Generator area configuration of the west side of the Korean power system.} \]

\[ \text{D. DISCUSSION} \]

\[ \text{A. DATA ACQUISITION AND SAMPLING CONDITION} \]

\[ \text{As the fundamental principle of synchronized measuring devices, frequency-divided spectral leakage can be observed for the power system oscillation due to a fixed sampling frequency and fixed size of the time window [23]–[26]. This means that whenever the sampled instantaneous values are reported as phasor or direct-quadrature-zero (dq0) quantities for a reported sampling frequency } F_s \text{, other components exist apart from the stationary points. According to sampling theory, a sampling frequency twice as high as the maximum oscillation frequency } F_o \text{ for the time window of interest is necessary, to prevent information loss due to spectral aliasing. However, to construct the proposed plane base on the FID, the time lag is preferably set as a quarter of oscillation period as } \delta (k) = K/4 = nint (T/4 \Delta t), \text{ so the sampling frequency must be at least four times the mode of interest observed in the system [27].} \]

\[ \text{1) SELECTION OF MEASUREMENT DATA TO APPLY THE GFE PROCESS} \]

\[ \text{The simulation discussed firstly for SSR and then for renewable energy mostly used voltage measurement at individual buses. However, in the third practical case, we used current measurement data, such that the voltage measured in the generator did not change sufficiently, to let the regression process yield to a singular issue. Therefore, using voltage} \]
measurement was preferable when applying the GFE process. However, for the specific elements that controlled voltage such as a generator or flexible AC transmission system (FACTS), a current measurement for the GFE application was allowed.

2) THE EFFECTS OF MEASUREMENT ERRORS
The proposed GFE process has measurement error-tolerant features. Among the measurement errors, there could be noise due to sensors, or loss of data due to communication failure.

First of all, the Poincaré map reconstruction scheme includes checking direction and consistency via the slope of the trajectory. And this slope is calculated by the short-term linear regression method as shown in Fig. 3, which makes the process to neglect some of the noises. Next, if there are temporary loss of data during communication failure, Poincaré map cannot be constructed because the trajectory does not guarantee consistency.

So, this selective feature of the GFE process can keep the output of RoT, damping, and frequency solidly associated with the correction scheme.

B. EVALUATION OF COMPUTATIONAL DELAY IN THE GFE PROCESS
For the result of the Korean power system, stage A or transient interval was 160 ms but can be considered up to one period,
or 270 ms. Additionally, adding 2-D FID embedding delay of a quarter of period (68 ms) and a Poincaré map reconstruction delay from 5 to 7 sampling (83–117 ms), the delay for RoT calculation time added up to 450 ms. Furthermore, when the damping estimation was considered, which is over five periods or 1,333 ms, the conservative total delay time became 1,783 ms.

The mode frequency may be varied due to different oscillation sources in the power systems. The mode oscillation ranges from 0.01 to 50.0 Hz are well described in [3]. In Table 5, the delay for each stage is compared by each of the different mode frequency ranges to show that the proposed GFE process required less time as the system has a higher component of mode frequencies.

### V. CONCLUSION

This paper proposes a geometrical feature extraction process based on the periodic time-series approximation to recognize oscillatory behavior in power systems. The oscillatory behavior is deeply related to a nonlinear property that was derived in a mathematical definition. Subsequently, the proposed GFE process was developed in time-series data by curve-fitting in the frequency domain. Specifically, for IEEE second benchmark system by varying compensation level, the system damping trend and CWT. Specifically, for IEEE second benchmark system and the high-renewable-considering theoretical conditions and was applied to the GFE process required less time as the system has a higher component of mode frequencies.

- Pre- or post-processes are unnecessary. Only additional correction schemes can be applied to make an exception condition for measurement error or non-periodic intervals.
- System oscillation can be recursively calculated by using stand-alone measurements such as individual voltage or current data with error-tolerant features.

The time-series process originated from nonlinear system analysis can be used for online monitoring of arbitrary features of oscillations. Furthermore, this proposed process can be an extended framework associated with artificial intelligence technologies such that causes of oscillations can be classified using geometric features.

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