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Signal clustering of power disturbance by using chaos synchronization

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ABSTRACT

This study develops and applies a chaos synchronization-based detection method for an engineering application of monitoring power quality disturbance. The new method can detect minor dynamic changes in signals. Likewise, prominent characteristics of system signal disturbance can be extracted by this technique. The method is then combined with the extension recognition algorithm to accurately apply to signal clustering of power disturbance. According to extensive computer simulation results and a comparison among three typical chaotic systems, it is confirmed that the proposed method is well applicable using various chaotic systems, mostly with very high accuracies. As compared with other traditional methods, the new method is shown to have higher accuracy, faster computing speed and better expandability. It is foreseen that if the method can be implemented by system-on-chip in the near future, it will find many real engineering applications such as hand-held power quality analyzers and auxiliary means for on-line real-time detection, among others.

Introduction

From the definition of IEEE Standard Dictionary of Electrical and Electronics Terms, power quality refers to "the concept of powering and grounding sensitive electronic equipment in a manner suitable for the equipment." It is widely defined as "the degree of satisfaction of users with the power supply quality of power companies."

In recent years, as a variety of precision equipment are used in the applications of electronic equipment and distributed power sources in the high-tech industry, the requirement for power quality has become increasingly desirable [1]. Noticeably, the causes for power quality events include natural disasters, human factors, external object contact, equipment deterioration, and circuit specifications [2]. In a power system, due to nonlinear loads (e.g., commutation equipment and welders), the electric energy converters in the equipment create a large amount of non-fundamental frequency current flows into the power system, causing current harmonics [3]. The above factors can cause voltage sags, swells, and interruptions or harmonics of power systems. Therefore, the state of a power system should be online measured by a monitoring instrument, thereby improving the power supply quality.

A power engineer needs to recognize and classify the detected power system signals when monitoring and analyzing the power quality problem, so as to attain the goal for accurate diagnosis and analysis [4]. An existing problem is, as has been commonly observed, that most if not all present instruments for monitoring power systems identify the states of the power system signals according to long-term voltage measurements, such as the root-mean-square (RMS) value of voltage in unit time as well as the variance of the value in unit time, or to detect whether there is voltage sag or power harmonics according to the changes in voltage peaks and frequencies.

In order to analyze various power quality problems accurately, multiple electric power characteristics should be measured, but then the analysis becomes very time consuming [5,6]. Previous studies [7] use the Fourier Transform to analyze the frequency contents as the basis of classifying frequencies. The current needs to remain for a period of time, and then the conversion takes an even longer time. Since the information of time disappears after the Fourier Transform is taken, the aforementioned studies suggest to use the Short-Time Fourier Transform. Although the relevance between time and frequency domains can be expressed after Short-Time Fourier Transform [8], the window of Short-Time Fourier Transform has a fixed width. In other words, when the time domain requires higher resolution, the resolution of the frequency will be reduced. Therefore, it is not an ideal method for analyzing instantaneous electric power signals, and moreover it cannot detect the electric power signals with significant noise. As a result, Fourier Transform has relatively lower detection accuracy. In order to overcome this defect, several studies use the Wavelet Transform

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[9] to analyze power system signals, which suggest approximate the window width between frequency domain and time domain to provide higher time-domain resolution for the high frequency part of a signal, and to provide higher frequency-domain resolution for its lower frequency part. Therefore, in the transient period of a power system, Wavelet Transform has improved the defect of Fourier Transform, so that more prominent characteristics may be extracted by Wavelet Transform as the input characteristics used by many artificial intelligence algorithms such as Neural Network Algorithm (NNA) [10], Fuzzy Theoretic (FT) scheme [11], and Genetic Algorithm (GA) [12]. However, the number of characteristics extracted by Wavelet Transform is obviously larger, and likewise the noise interference in the power system cannot be recognized clearly, thus the power quality monitor accuracy is reduced.

Some other studies use classification schemes, such as *K*-means clustering algorithm [13], *C*-means clustering algorithm [14], and Support Vector Machine (SVM) [15]. The *K*-means and *C*-means clustering algorithms are both mean-square-error clustering schemes, and their cluster numbers are determined randomly. If the cluster numbers are selected correctly, they can yield very good recognition results. On the contrary, if the cluster numbers are allocated incorrectly, the recognition rates will decrease significantly. Since this method adopts random allocation, there may be electric power signal classification errors, so that the recognition accuracy may be affected. The SVM is a new sorting algorithm based on statistics. It divides the input signals into two different sets by a hyperplane in space. The combination of multi-SVM is obtained in multi-signal states, but the optimal classification must be calculated. Therefore, some optimization algorithms are used, such as particle swarm optimization [16], GA [17], and annealing algorithm [18], to determine appropriate parameter values, which improve the classification to yield better results.

On the other hand, chaos theory has been applied in different fields in recent years, in particular with chaos detection [19]. A subtle change in an electric power signal can be detected based on chaos theory, where power system signals are used to validate the accuracy of chaos-based methods. Recent studies have remedied some defects in chaos-based methods, as reported in [20].

Moreover, chaos synchronization has been used to detect power quality changes, where electric power signals are classified by, for example, the Particle Swarm Optimization Probabilistic Neural Network (PSO-PNN), which was used for detection through chaos synchronization [21]. The signal response to each type of power qualities is observed from the underlying chaos waveform. However, in this method, complex classification needs to be carried out before detection, so the detection needs a longer time. Moreover, power systems with noise have not been discussed in the literature before. From the same approach, this study simplifies the method in [20] for detection, which can now significantly shorten the detection time and also well handle electric power signals with noise.

More precisely, this study remedies the defects found in various methods proposed in previous investigations, by using chaos synchronization-based technique to extract fewer characteristics from power system signals in a shorter time. Noise interference in the power system can be easily identified by using chaotic characteristics. The dynamic trajectories in the chaos synchronization are extracted from the power system by using this method. The error trajectories are then used to avoid using the general power system characteristics such as voltage, current, and power, which are more costly to obtain and to use.

This study implements power system detection mechanism, hoping to reduce both the characteristic number of extracted waveform and the computing time. The extension recognition method will be used to analyze the state of the power system disturbance, so as to maintain the accuracy of identification and shorten the detection time.

The proposed method is then verified and validated by extensive numerical simulations on a power system setting, using some typical chaotic systems as examples, demonstrating its effectiveness for potential engineering applications.

Architecture of power quality monitoring and analysis

Power disturbance in general may be classified as voltage disturbance and current disturbance, which provide voltage and current deviations from the ideal sine waves, which have potential impacts on power grids or electrical equipment. It is usually resulted from human factors, natural disasters and power system characteristics. Common electric power signals are listed in Table 1 [22–25].

All of the present measuring instruments identify whether there is voltage sag, swell or power interruption, through long-term voltage monitoring, calculating the voltage RMS value in unit time, and observing the variation of the value in unit time. They may also identify whether there is voltage flicker or power harmonics according to the changes in voltage peaks and frequencies. In order to analyze various power quality problems accurately, multiple electric power characteristics should be measured. It has been observed that there may be misrecognition when the electric power system is subject to noise interference.

Given the above background, this study is motivated to try utilizing the dynamic trajectories of a chaotic system to convert the power quality disturbance waveform, so as to extract fewer characteristics in shorter time, and to increase the accuracy of detection based on the sensitive characteristics of chaos.

Specifically, this study designs a chaotic synchronization detector to convert the input signal waveform, and extract prominent characteristics from the waveform. The extension theory in pattern recognition will then be used to identify the type of the power disturbance signals. The overall scheme is shown in Fig. 1.

The proposed detection method

The proposed chaos synchronization-based method uses the sensitive characteristic of chaotic dynamic trajectories to identify the disturbance waveform of a power system accurately and rapidly, such as normal voltages, voltage swells, voltage sags, voltage interruptions and voltage harmonics. It is well known that if there is noise in the disturbance waveform, most traditional methods generally cannot recognize the correct characteristics accurately. One contribution is that the chaos synchronization-based technique can overcome this main defect of most traditional methods, and can also increase the accuracy level of power quality analysis significantly.

Chaos synchronization detection method

The modern chaos theory was initiated by meteorologist Edward N. Lorenz in 1963 [26]. For any subtle change in initial condition of a chaotic system, the system state changes significantly after a long period of time. In addition, when two chaotic systems with slightly different parameters have the same initial conditions, there will also be significant differences between the two states after a long period of time. Therefore, the notion of chaos synchronization was proposed in 1990 [27] to carefully study how to synchronize two chaotic system trajectories. Fig. 2 is a schematic diagram of two chaotic states achieving synchronization.

In a general setting, the two chaotic systems are called Master System and Slave System, respectively. When the master and slave

Table 1
Common electric power signals.

Category		Duration	Voltage magnitude and spectral content
Sag	Instantaneous	0.5–30 cycle	0.1–0.9 pu
	Momentary	30 cycles – 3 s.	0.1–0.9 pu
	Temporary	3 s. – 1 min	0.1–0.9 pu
Swell	Instantaneous	0.5–30 cycle	1.1–1.8 pu
	Momentary	30 cycles – 3 s.	1.1–1.4 pu
	Temporary	3 s. – 1 min	1.1–1.2 pu
Interruption	Momentary	0.5 cycles – 3 s.	<0.1 pu
	Temporary	3 s. – 1 min	<0.1 pu
Harmonics		Steady state	0–20% (0–100th harmonic)

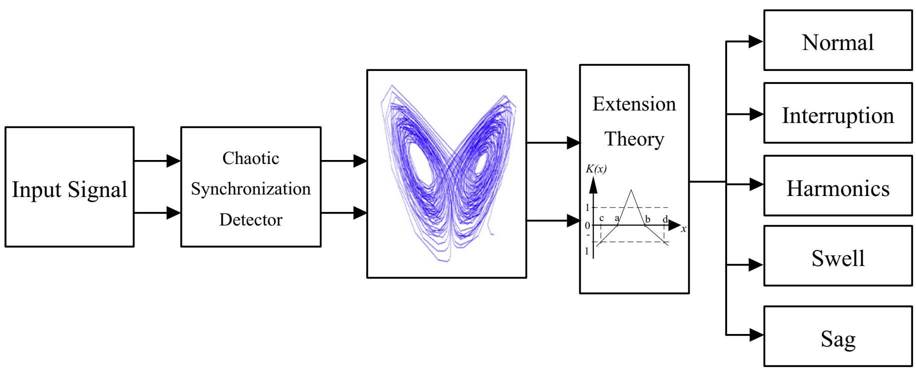

Fig. 1. The proposed power quality detection system.

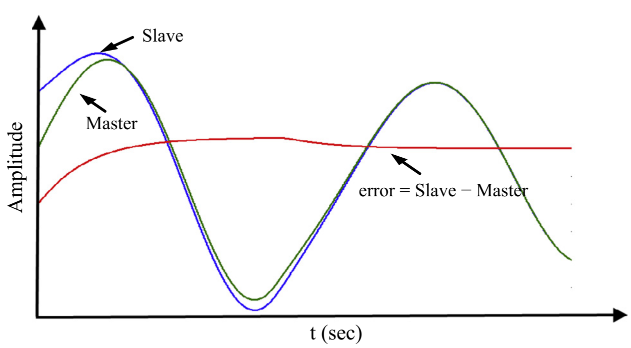

Fig. 2. Schematic diagram of two chaotic states achieving synchronization.

systems have different initial values, the dynamic trajectories of the two are very different in a long run. In [27], a controller was applied to the back end of the slave system, deriving it to track the state of the master system so as to achieve synchronization, as described by Eq. (1):

$$\lim_{t\to\infty}\|X_{Slave,i}(t) - X_{Master,i}(t)\| \to 0, \quad i = 1,2,\ldots,n \tag{1}$$

This approach was used to detect power system signals lately. The master and slave chaotic systems are expressed by Eqs. (2) and (3), respectively:

Master:

$$\begin{cases} \dot{x}_1 = F_1(x_1,x_2,x_3,\ldots,x_n) \\ \dot{x}_2 = F_2(x_1,x_2,x_3,\ldots,x_n) \\ \vdots \\ \dot{x}_n = F_n(x_1,x_2,x_3,\ldots,x_n) \end{cases} \tag{2}$$

Slave:

$$\begin{cases} \dot{y}_1 = F_1(y_1,y_2,y_3,\ldots,y_n) + u_1 \\ \dot{y}_2 = F_2(y_1,y_2,y_3,\ldots,y_n) + u_2 \\ \vdots \\ y_n = F_n(y_1,y_2,y_3,\ldots,y_n) + u_3 \end{cases} \tag{3}$$

where F_i (i = 1,2,…,n) is a nonlinear function, Eqs. (4), (5) form an error state as Eq. (8) and a dynamic error as Eq. (6):

$$e_1 = y_1 - x_1, \quad e_2 = y_2 - x_2, \ldots, e_n = y_n - x_n \tag{4}$$

$$\begin{cases} \dot{e}_1 = F_1(x_1,x_2,x_3,\ldots,x_n) - F_1(y_1,y_2,y_3,\ldots,y_n) + u_1 \\ \quad = G_1(e_1,e_2,\ldots,e_n) + u_1(e_1,e_2,\ldots,e_n) \\ \dot{e}_2 = F_2(x_1,x_2,x_3,\ldots,x_n) - F_2(y_1,y_2,y_3,\ldots,y_n) + u_2 \\ \quad = G_2(e_1,e_2,\ldots,e_n) + u_2(e_1,e_2,\ldots,e_n) \\ \vdots \\ \dot{e}_n = F_n(x_1,x_2,x_3,\ldots,x_n) - F_n(y_1,y_2,y_3,\ldots,y_n) + u_n \\ \quad = G_n(e_1,e_2,\ldots,e_n) + u_n(e_1,e_2,\ldots,e_n) \end{cases} \tag{5}$$

where G_i(i = 1, 2, ..., n) is a nonlinear function, and the dynamic error equation is also a chaotic system. In order to improve the diagnostic rate and reduce the false possibilities by the extension theory for fault diagnosis, the chaotic synchronization error dynamics were used to pre-process the signal that is to be diagnosed.

Here, a chaotic dynamic trajectory is used to study various system operating states, such as periodic, aperiodic and random states, in the time domain, thereby identifying the power quality disturbance state. The multiple dynamic errors are expressed as in Eq. (6):

$$\begin{cases} \dot{e}_1[j] = \dot{y}_1[j] - \dot{x}_1[j] \\ \dot{e}_2[j] = \dot{y}_2[j+1] - \dot{x}_2[j+1] \\ \vdots \quad \vdots \quad \vdots \\ \dot{e}_n[j] = \dot{y}_n[j+n-1] - \dot{x}_n[j+n-1] \end{cases}, \quad j = 1,2,3,\ldots,j-n \tag{6}$$

where x_i (i = 1,2,3) is a normal signal of the power system and y_i (i = 1,2,3) is the actual system signal to be measured, which is injected into the chaotic dynamic error Eq. (4) to obtain an output waveform. Prominent characteristics are then extracted from the output waveform, and the state of the power system signal is finally identified by using the extension theory (to be detailed below).

As a test framework, this study uses two Lorenz chaotic systems [28][29], one as the master system and the other as the slave system, expressed as in Eqs. (7), (8). The dynamic error state equation is worked out and expressed in the matrix form as shown in Eq. (9).

$$\text{Master}:\begin{cases}\dot{x}_1=\alpha(x_2-x_1)\\ \dot{x}_2=\beta x_1-x_1x_3-x_2\\ \dot{x}_3=x_1x_2-\gamma x_3\end{cases} \tag{7}$$

$$\text{Slave}:\begin{cases}\dot{y}_1=\alpha(y_2-y_1)+u_1\\ \dot{y}_2=\beta y_1-y_1y_3-y_2+u_2\\ \dot{y}_3=y_1y_2-\gamma y_3+u_3\end{cases} \tag{8}$$

$$\begin{bmatrix}\dot{e}_1\\ \dot{e}_2\\ \dot{e}_3\end{bmatrix}=\begin{bmatrix}-\alpha & \alpha & 0\\ \beta & -1 & 0\\ 0 & 0 & -\gamma\end{bmatrix}\begin{bmatrix}e_1\\ e_2\\ e_3\end{bmatrix}+\begin{bmatrix}0\\ -y_1y_3+x_1x_3\\ y_1y_2-x_1x_2\end{bmatrix}+\begin{bmatrix}u_1\\ u_2\\ u_3\end{bmatrix} \tag{9}$$

where α, β and γ are positive constants. The eigenvalues are obtained from Eq. (9), as Eq. (10):

$$\begin{aligned}\lambda_1&=-\tfrac{\alpha+1}{2}+\tfrac{1}{2}\sqrt{(\alpha+1)^2-4\alpha(1-\beta)}\\ \lambda_2&=-\tfrac{\alpha+1}{2}-\tfrac{1}{2}\sqrt{(\alpha+1)^2-4\alpha(1-\beta)}\\ \lambda_3&=-\gamma\end{aligned} \tag{10}$$

If the real parts of the eigenvalues are negative, the state of system (9) is stable [30], so the $e2$ upper half waveform can be extracted from the output waveform, which can be divided into 3 characteristics according to the $e1$ value, expressed as Eq. (11):

$$c_k=\frac{1}{n}\sum_{i=1}^{n}e_{2k,i},\quad k=1,2,3 \tag{11}$$

where c_1, c_2 and c_3 are the characteristics used in this study, $e_{21,i}$, $e_{22,i}$, $e_{23,i}$ (i = 1,2,...,n) represent the chaotic dynamic error values in three different error intervals, respectively, when $e_2 > 0$.

According to various state waveforms of the power quality signals including normal, voltage swell, voltage sag, interruption and harmonics signals, the matter-element model in the extension theory is built to identify the output signals of the power system. This study uses the average value calculated by Eq. (11) as the characteristic values for such identification.

Outline of the extension theory

In signal processing, artificial intelligence algorithms are often used for signal analysis and classification. Extension theory not only can be applied to signal fault diagnosis but also can achieve better effectiveness than neural networks. It is very convenient to use without the need of learning from samples. It only needs to set the classical domain and the joint field. The extension theory provides a law and a method to study the extensibility of an object, and uses quantification and qualification analyses to solve contradictory problems from these two perspectives [31,32]. The two major pillars of the extension theory are matter-element theory and extension set. These two concepts are used to quantify objects and to implement planning based on the correlativity, aiming to describe the information about the object.

According to this theory, the range of a fuzzy set is extended from [0, 1] to $(-\infty,\infty)$. The schematic diagram of a fuzzy set and its extension set is shown in Fig. 3 [31].

The matter-element theory and extension set are briefly described below.

Matter-element theory

The aim of matter-element theory is to study the matter-element extensibility and matter-element transformation as well as the properties of the matter-element transformation. For a variety of objects or phenomena, to specify the differences among them, the so-called characteristic mode is used for distinction. If the form, attitude and pattern forming objects are different, and if the differences are expressed as mathematical magnitudes in the form of the matrix Eq. (12) [32]

$$R=(\mathrm{N},\mathrm{c},\mathrm{u}) \tag{12}$$

where N represents the matter; c is the characteristic of the matter-element, and u is N's measure of the characteristics c, in which u can be a value or an interval. Here, R = (N, C, U) is a multi- dimensional matter-element, $C=[c_1c_2\ldots c_n]^T$ is a characteristic vector, and $U=[u_1u_2\ldots u_n]^T$ is the corresponding magnitude vector.

If the characteristic magnitude is a range, then this range is called a classical domain, contained in the joint field, with intervals $F_0=\langle a,b\rangle$, $F=\langle c,d\rangle$, and $F_0\in F$, where a and b are the upper and lower limits of the classical domain, respectively, c and d are the upper and lower limits of the joint field, respectively.

Extension set

The core of the extension theory includes the extension set and the extension correlation function, which extends the fuzzy set from [0, 1] to $(-\infty,\infty)$, and expresses the correlation function as the particularity of the object. The extension set extends the range of a set to all real numbers, $(-\infty,\infty)$, representing the degree of a characteristic. Then, the extension set is defined as follows [33]:

If Ω is the domain, and for any element ω in Ω, $\omega\in\Omega$, there is a corresponding real number, $K(\omega)\in(-\infty,\infty)$, then the extension set is defined as

$$\Pi=\{(\omega,y)|\quad \omega\in\Omega,\quad y=K(\omega)\in(-\infty,\infty)\} \tag{13}$$

where $y=K(\omega)$ is the correlation function of the extension set Ω, and $K(\omega)$ is the correlation grade of ω on the extension set denoted by A, with range $(-\infty,\infty)$. The extension set Π in domain Ω is expressed as

$$\Pi=\Pi^{+}\cup\Pi^{0}\cup\Pi^{-} \tag{14}$$

where

$$\Pi^{+}=\{(\omega,y)|\quad \omega\in\Omega\quad ,y=K(\omega)>0\} \tag{15}$$

$$\Pi^{0}=\{(\omega,y)|\quad \omega\in\Omega\quad ,\quad y=K(\omega)=0\} \tag{16}$$

$$\Pi^{-}=\{(\omega,y)|\quad \omega\in\Omega,\quad y=K(\omega)<0\} \tag{17}$$

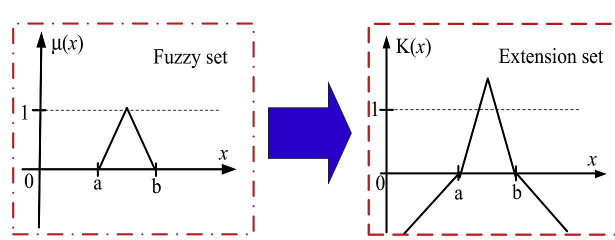

Fig. 3. Schematic diagram of a fuzzy set and its extension set.

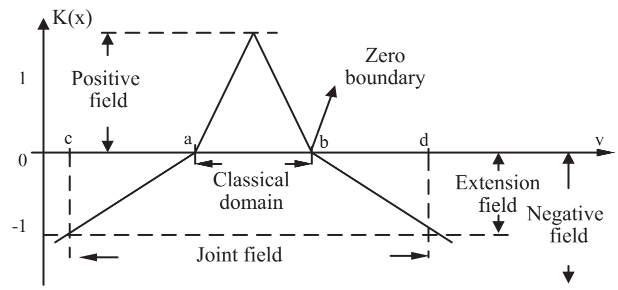

Fig. 4. Schematic diagram of the extension correlation function.

where Π^0, Π^+ and Π^- are the zero boundary, positive field and negative field in the extension set, respectively. The extended membership function is shown in Fig. 4.

Simulation results and discussion

This study establishes data as per IEEE Std 1159–1995, and uses Matlab to simulate the power quality problems, including power interruption, voltage sag, voltage swell and power harmonics, as illustrated by Fig. 5. More details about the common electric power signals with IEEE Std 1159–1995 have been added into Table 1.

Fig. 6 shows the simulated white Gaussian noise waveform of a power system input signal with external noise interference. The power system disturbing signal with noise waveform is shown in Fig. 7.

At present, general power quality measuring instruments can capture the effective values of the voltage, but only the problems resulted from voltage amplitude variation can be identified. The harmonics, frequency variation and external noise interference cannot be detected specifically. Therefore, this study uses chaotic characteristics, as discussed above, so that when a power system signal has any subtle change or noise effect, prominent characteristic differences can be observed in the chaotic waveform.

Specifically, this study uses the dynamic error equation of the Lorenz chaotic system as an example. The chaotic waveform conversion was carried out for both the normal electric power waveform and the disturbed electric power waveform. A trajectory of the chaotic motion was extracted as the input for the extension-based dynamic identification method. The waveforms after chaotic trajectory conversion are shown in Figs. 8–11. The corresponding chaotic waveforms with 5% noise are shown in Figs. 12–15.

Figs. 8–11 show that the chaotic waveforms are around the center point (0,0). It is known that the chaotic trajectory attracts this signal towards the center point (0,0), so it will not deviate from it, which also generates a chaos-like signal. According to the comparison between the chaotic waveform of the normal signal in

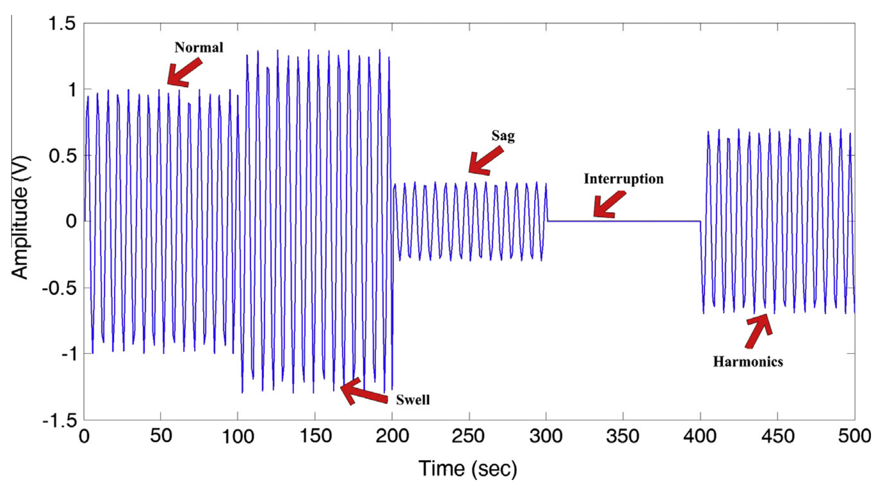

Fig. 5. Various power disturbance signals.

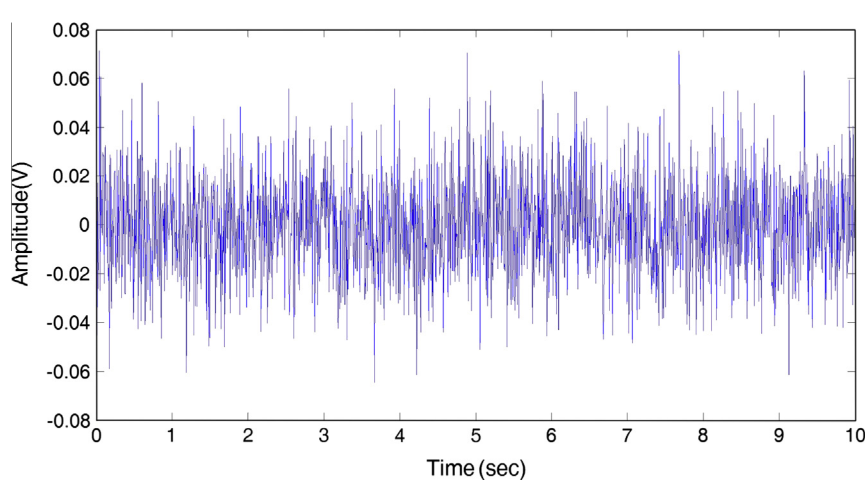

Fig. 6. White Gaussian noise waveform.

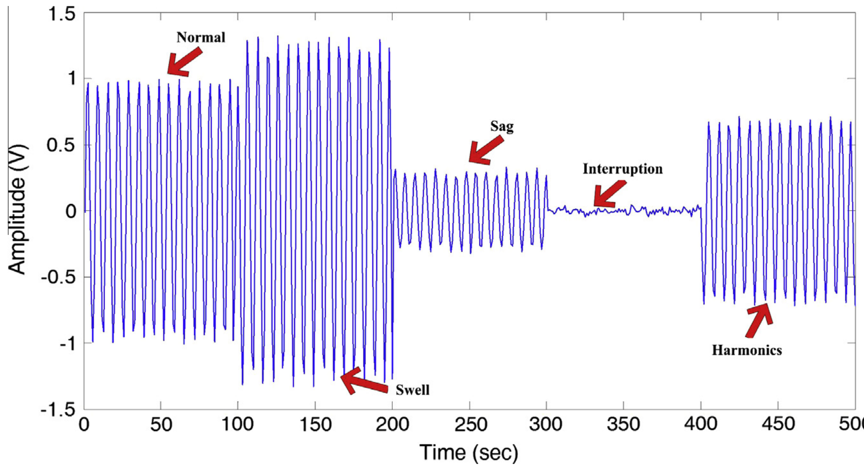

Fig. 7. Various power disturbance signals with noise.

Fig. 8 and the sag waveform in Fig. 9, the attractors in Fig. 9 are closer to the center point (0,0) than that in Fig. 8. This indicates that the attraction of the center point is stronger in the former case. In comparison to Figs. 10 and 11, where the attractors are farther from the center point, indicating that the attraction of the center point is weaker there.

On the other hand, according to the chaotic waveforms with noise in Figs. 12–15, besides the strengths of the chaotic attractors, they are also denser. On the contrary, the chaotic waveforms without noise are relatively more uniform. For this reason, the present study uses the characteristics of the chaotic attractors to detect possible external noise interference to the chaotic motion trajectories. The characteristics of various electric power signals are then extracted from the chaotic motion trajectories, and the extension theory is then used to identify to which electric power signal state the waveform of the power system output signal belongs. It helps

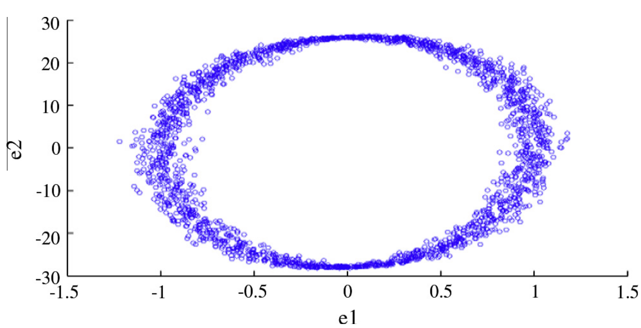

Fig. 8. Chaotic scattering under normal voltage of the power system.

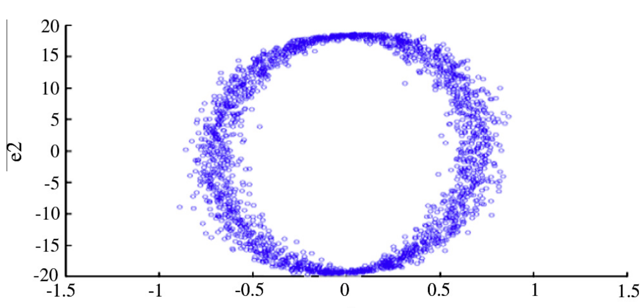

Fig. 9. Chaos scatter under voltage sag of the power system.

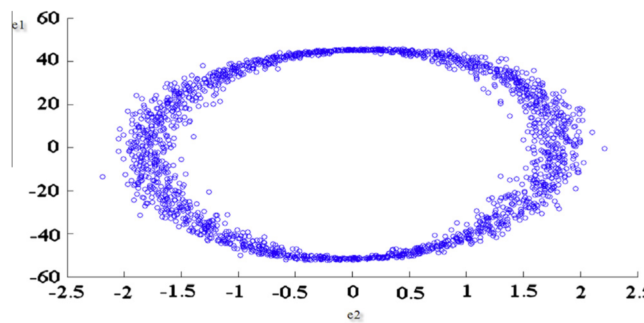

Fig. 10. Chaos scatter under voltage swell of the power system.

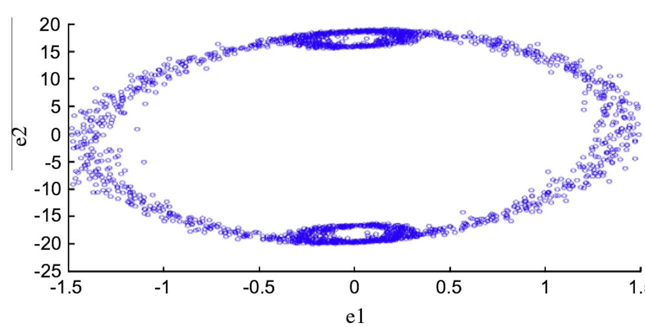

Fig. 11. Chaos scatter under voltage harmonics of the power system.

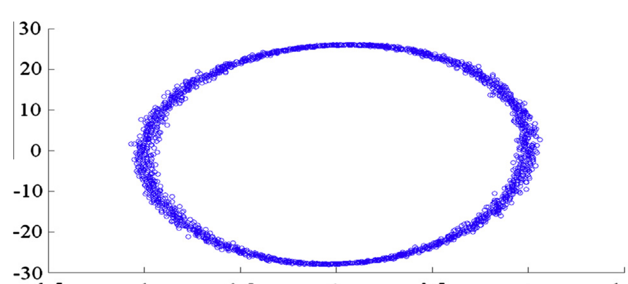

Fig. 12. Chaos scatter of normal voltage with 5% noise.

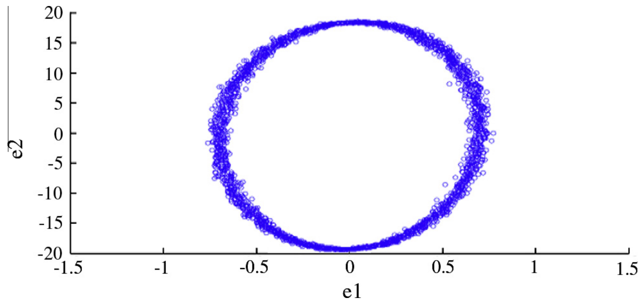

Fig. 13. Chaos scatter of voltage sag with 5% noise.

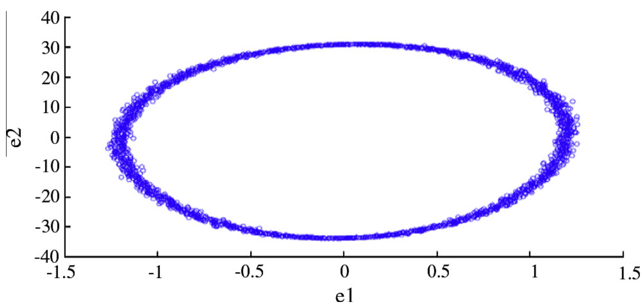

Fig. 14. Chaos scatter of voltage swell with 5% noise.

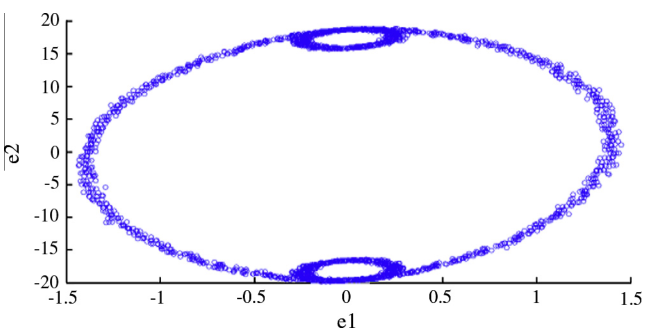

Fig. 15. Chaos scatter of voltage harmonics with 5 noises Table 1.

the power engineers to detect and improve the power quality in interest.

According to the comparison among various chaotic trajectory waveforms shown above, one can observe that the chaotic characteristics make the waveforms to circle around the origin, and to make both the horizontal and vertical waveforms gradually become symmetrical. Based on this observation, the present study only selects the equalization point values of the upper half wave e_2 of e_1 within intervals [−1.5,−0.5], [−0.5,0.5] and [0.5,1.5], as the extracted characteristic values. Table 2 shows the matter-element model of the signal type.

Finally, a matter-element module is built, and the weights of various characteristics are set as 1/3. The signal is injected and the disturbed state of the electric power signal is detected accurately through the proposed extension-based recognition process. The results are further discussed below.

According to the matter-element module in Table 2 and the identification results, this study detected 100 groups of signals with noise, and then disregarded noise to inspect the pure power quality. Besides the Lorenz system, this method was also tested using two other different chaotic systems, a new Lorenz system [34] and a Sprott system [35], for comparison, as shown in Eqs. (18), (19). The purpose here is to verify that the proposed method is not only limited to a special kind of chaotic systems. The identification accuracies using different chaotic systems are summarized and compared in Table 3.

Table 2
Extension matter-element model for voltage signals in various states.

$$\begin{bmatrix} \text{Normal} & c_1 & \langle 12,13\rangle \\ & c_2 & \langle 24,25\rangle \\ & c_3 & \langle 13,14\rangle \end{bmatrix} \qquad \begin{bmatrix} Sag & c_1 & \langle 1,11\rangle \\ & c_2 & \langle 1,23.5\rangle \\ & c_3 & \langle 1,12.5\rangle \end{bmatrix}$$

$$\begin{bmatrix} Swell & c_1 & \langle 14,30\rangle \\ & c_2 & \langle 24.5,40\rangle \\ & c_3 & \langle 15,30\rangle \end{bmatrix} \qquad \begin{bmatrix} Int. & c_1 & \langle 0,0.99\rangle \\ & c_2 & \langle 0,0.99\rangle \\ & c_3 & \langle 0,0.99\rangle \end{bmatrix}$$

$$\begin{bmatrix} Har. & c_1 & \langle 10,14\rangle \\ & c_2 & \langle 10,17\rangle \\ & c_3 & \langle 12,15\rangle \end{bmatrix} \qquad \begin{bmatrix} \text{Joint Field} & c_1 & \langle 0,45\rangle \\ & c_2 & \langle 0,45\rangle \\ & c_3 & \langle 0,45\rangle \end{bmatrix}$$

$$\text{New Lorenz system}: \begin{cases} \dot{x}_1 = ax_1 - bx_2x_3 \\ \dot{x}_2 = -cx_2 + ex_3 + x_1x_3 \\ \dot{x}_3 = -fx_3 + x_1x_2 \end{cases} \tag{18}$$

$$\text{Sportt system} \begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 \\ \dot{x}_3 = -\alpha x_1 - x_2 - \beta x_3 + 2sign(x_1) \end{cases} \tag{19}$$

The parameters a, b, c, e, f, α and β in Eqs. (18), (19) are positive constants, and the values were determined by calculating the associated eigenvalues of the corresponding chaos equations [31]. The sign (.) in Eq. (19) is defined as in Eq. (20).

$$sign(x_1) = \begin{cases} 1, & x_1 > 0 \\ -1, & x_1 < 0 \end{cases} \tag{20}$$

The error states of all chaotic systems are calculated by using the proposed method. The same characteristic is extracted and the voltage signals of different power systems are classified by

Table 3
Comparison of detection accuracies of the three simulated chaotic systems.

Signal		Chaotic system		
		Lorenz	New Lorenz	Sprott
Normal	With noise	97%	95%	95%
	Without noise	98%	96%	95%
Sag	With noise	95%	97%	96%
	Without noise	96%	96%	97%
Swell	With noise	96%	96%	96%
	Without noise	97%	97%	96%
Interruption	With noise	98%	98%	96%
	Without noise	97%	98%	96%
Harmonics	With noise	96%	95%	95%
	Without noise	97%	96%	95%
Total average	With noise	96.4%	96.2%	95.6%
	Without noise	97%	96.6	95.8%

Table 4
Comparison of traditional methods against the method proposed in this paper.

Test method	Diagnosis rate (%)
K-means clustering (Wavelet transform)	59.2
Fuzzy *C*-means clustering (Wavelet transform)	61.2
Extension theory (Wavelet transform)	85.4
Extension genetic algorithm (Wavelet transform)	91.7
Extension theory (Lorenz chaotic system)	97
Extension theory (Liu chaotic system)	97.4
Extension theory (new lorenz chaotic system)	96.6
Extension theory (Sportt chaotic system)	95.8

using the extension theory, as discussed above. The accuracies (successful percentages) of the proposed detection method are summarized in Table 3 for comparison.

According to Table 3, the accuracies are all higher than 95% for the three chaotic systems used, especially for the Lorenz system. This demonstrates that the method proposed in this paper is indeed very effective, therefore can be applied to various signal detections.

The proposed method is now compared to the traditional methods in Table 4. As can be seen, the new method is better than all other methods in terms of accuracy, not to mention that it is also faster.

Conclusions

This study has developed a signal detection method based on chaos synchronization, which can effectively extract prominent characteristics and to build a matter-element model. Extension theory from pattern recognition was used for the detection. Extensive computer simulations using the Matlab tool were performed for various signal detection problems due to electric power system disturbance.

The following are concluding remarks:

1) In this study, the averaged accuracy in the case of no noise is 96% and in the case of 5% noise is 95%, demonstrating that the proposed detection method is very effective for detecting power quality.
2) The proposed detection method has higher accuracy than all traditional methods developed in previous studies. Some main defects in traditional methods have been resolved. General power quality analyzers cannot identify power harmonics and electric power signals with noise interference. However, when the proposed chaos synchronization-based detection is adopted, the extracted characteristics are very prominent; therefore, it is more likely to be able to detect power harmonics and power disturbance in the case with noise disturbance.
3) This new method is very simple and has high accuracy. The new method does not require extracting the power system characteristics, such as voltage, current, and power. It is desirable to extract the dynamic error trajectories after chaos synchronization, so as to obtain distinguished characteristics for further identification using the extension theory for pattern recognition.
4) Since the proposed method has a very simple structure, its computation is very fast, with high accuracy and good expandability. If furthermore the developed scheme can be implemented in embedded system chips in the near future, it will be very useful for miniaturization of hand-held power quality analyzers and detection devices.

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References

[1] Dugan RC. Electrical Power Systems Quality, 2nd ed., In: IEEE Recommended Practices for Monitoring Electric Power Quality ANSI/IEEE Std. McGraw-Hill Inc; 2002: 1159–1995.
[2] Liu YQ, Wu GP, Hua HS, Wang L. Research for the effects of high-speed electrified railway traction load on power quality. Electric Utility Deregulation and Restructuring Power Technol 2011:569–73.
[3] Arrillaga J, Bradley DA, Bodger PS. Power System Harmonics. Wiley; 1985.
[4] Gilbert DM, Morrison IF. A statistical method for the detection of power system faults. Int J Electr Power Energy Syst 1997;19(4):269–75.
[5] Yilmaz SA, Alkan A, Asyali MH. Applications of parametric spectral estimation methods on detection of power system harmonics. Electr Power Syst 2008;78(4):683–93.
[6] Chen LJ. Study of partial discharge measurement in power equipment using acoustic technique and wavelet transform. IEEE Trans Power Deliv 2007;22(3):1575–80.
[7] Santoso S et al. Characterization of distribution power quality events with Fourier and wavelet transforms. IEEE Trans Power Deliv 2000;15(1):247–54.
[8] Pei SC, Yeh MH, Luo TL. Fractional Fourier series expansion for finite signals and dual extension to discrete-time fractional Fourier transform. IEEE Trans Sig Proces 1999;47(10):2883–8.
[9] Yilmaz AS, Subasi A, Bayrak M, Karsli VM, Ercelebi E. Application of lifting based wavelet transforms to characterize power quality events. Electr Power Syst Res 2008;48(1):683–93.
[10] Santoso S, Powers EJ, Grady WM, Hofmann P. Power quality assessment via wavelet transform analysis. IEEE Trans Power Deliv 1996;11(2):924–30.
[11] Saroj KM, Ashok KP. Fuzzy classifiers for power quality events analysis original research article. Electr Power Syst Res 2010;80(1):71–6.
[12] Wang MH, Tseng YF. A novel analytic method of power quality using extension genetic algorithm and wavelet transform. Exp Syst Appl 2011;38(10):12491–6.
[13] Mora-Flórez J, Cormane-Angarita J, Ordóñez-Plata G. K-means algorithm and mixture distributions for locating faults in power systems. Electr Power Syst Res 2009;79(5):714–21.
[14] Sudha KR, Raju YB, Sekhar AC. Fuzzy C-Means clustering for robust decentralized load frequency control of interconnected power system with Generation Rate Constraint. Int J Electr Power Energy Syst 2012;37(1):58–66.
[15] Hu GS, Xie J, Zhu FF. Classification of power quality disturbances using wavelet and fuzzy support vector machines. Int Conf Machine Learn Cybernet 2005;7:3981–5.
[16] Ardjani F, Sadouni K. Optimization of SVM multiclass by particle swarm (PSO-SVM). Int J Modern Edu Comput Sci 2010:32–8.
[17] Zhang H, Chen QY, Xiang ML, Ma CY, Huang Q, Yang SY. In silico prediction of mitochondrial toxicity by using GA–CG–SVM approach. Toxicol in Vitro 2009;23(1):134–40.
[18] Sartakhti JS, Zangooei MH, Mozafari K. Hepatitis disease diagnosis using a novel hybrid method based on support vector machine and simulated annealing (SVM-SA). Comput Methods Prog Biomed 2011. [available online].
[19] Su HS, Zhao F. Chaos detection method for power quality disturbance. Intell Control Automation 2006;1:5003–7.
[20] Huang CH, Lin CH, Kuo C. Chaos synchronization-based detector for power-quality disturbances classification in a power system. IEEE Trans Power Deliv 2011;26(2).
[21] Yalcin ME, Suykens JAK, Vandewalle J. Master slave synchronization of Lur'e systems with time-delay. Int J Bifurcation Chaos 2001;11(6):1707–22.
[22] Dash PK. Power quality analysis using S-transform. IEEE Trans Power Deliv 2003;18(2):406–11.
[23] Kwang TC, Kumaran V, Siam FM, Busrah AM. Power quality event characterization. In: The 4th IET conference on power electronics 2008;543–547.
[24] Bhattacharyya S. Consequences of poor power quality: an overview. In: The 42nd international universities power engineering conference 2007; 651–656.
[25] Abdullah AR. Detection and classification of power quality disturbances using time-frequency analysis technique. In: The 5th student conference on research and development 2007; 1–6.
[26] Lorenz EN. Deterministic nonperiodic flows. J Atmos Sci 1963;20:130–41.
[27] Pikovsky A, Rosenblum M, Kurths J. Synchronization: A Universal Concept in Nonlinear Science. Cambridge, UK: Cambridge University Press; 2000.
[28] Lu J, Chen G. A new chaotic attractor coined. Int J Bifurcation Chaos 2002;12(3):659–61.
[29] Willsey MS, Cuomo KM, Oppenheim AV. Selecting the Lorenz parameters for wideband radar waveform generation. Int J Bifurcation Chaos 2010;21(9):1–12.

[30] Huang CH, Lin CH, Kuo CL. Chaos synchronization based detector for power quality disturbances classification in a power system. IEEE Trans Power Deliv 2011;26(2):944–53.
[31] Wang MH. Application of extension theory to vibration fault diagnosis of generator set. Proc Generation Trans Distribution 2004;151(4):503–8.
[32] Wang MH, Ho CY. Application of extension theory to PD pattern recognition of high voltage current transformers. IEEE Trans Power Deliv 2005;20(3):1939–46.
[33] Wang MH. Extension neural network-type 2 and its applications. IEEE Trans Neural Networks 2005;16(6):1352–61.
[34] Dong E, Feng L, Chen ZP, Chen ZQ. A new three-dimensional autonomous chaotic system with a pair of diagonal double-wing attractor and its circuit realization. In: Int. Workshop on Chaos-Fractals Theories and Applications 2009; 267–271.
[35] Sprott JC. Some simple chaotic flows. Phys. Rev. E 1994;50:R647–650.