Study of time-frequency analysis methods of TWACS outbound signal

Ying Wei

Abstract—In this paper, some time-frequency analysis methods were studied to get the detailed characteristics of two-way automatic communication system (TWACS) outbound signal sampled from industry power network with high disturbance. Compared with traditional time-domain detecting algorithm, time-frequency analysis methods, including short-time Fourier transform (STFT), Wigner distribution (WD) and complex wavelet transform (CWT), could extract the characteristics from time-domain and frequency-domain of the signal analyzed, which significantly improves the detecting accuracy of modulated signal with strong noise. Principle and algorithm of each time-frequency analysis method were stated. Then these methods were employed to analyze the outbound signal of TWACS sampled from industry power network. Simulation results and theoretical analysis demonstrated that complex wavelet seemed the best time-frequency analysis method of detecting the outbound signal of TWACS with the advantages of high accuracy and low calculated quantity.

Index Terms--two-way automatic communication system (TWACS); time-frequency analysis; Short-time Fourier Transform (STFT); Winger Distribution (WD); complex wavelet transform (CWT)

I. INTRODUCTION

Two-way automatic communication system (TWACS) is a new communication system based on the distribution power network [1-4]. Compared with other power line communication technology, TWACS has several advantages such as low cost, long transmission distances, high anti-disturbance capability and so on. In 1994, the system was firstly used to read water meter remotely in America and now is being employed to read electric meter remotely in some areas of China. The system also could be used in load control, load research, demand monitor, cap bank switching, outage record, tamper detection and so on.

So-called two-way means that the system has two communication channels, namely outbound channel and inbound channel. Outbound channel is the transmission way from substation to the end user and inbound channel is inversely. The structure of this system is showed as Fig. 1.

This work was supported in part by NSFC under grant 61176020 and 50903028.
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ISBN: 978-0-9803267-4-1
system, the receiver should have the capability to synchronize itself to the system through decoding the message at the right moment. As soon as the remote transponder unit (RTU) connected to the electric utility system, the decoder uses the following algorithm to detect the presence of signals.

\[ S_1 = (T_i - T_{i+1}) + (T_{i+2} - T_{i+3}) \]
\[ S_2 = (T_{i+1} - T_{i+2}) + (T_{i+3} - T_{i+4}) \] (1)

When no signal is present, \( S_1, S_2 \ldots \) etc. are either very small or equal to zero. If an ideal noise-free situation containing one signal only is assumed, the application of the algorithm mentioned above will give rise to the following results: 0, 0, -δ, +2δ, +2δ, -δ, -δ, 0, 0.

The sequence of half cycles producing the above pattern is shown in Fig. 4.

At the end of the second +2δ, which is associated with the \( H \)-th half cycle, a conclusion can be made that a signal has indeed been received. Ideally, another signal can be injected at \( I \) and another complete signal will occupy \( I, J \) and \( K \). However, the network perturbation due to modulation during \( F, G \) and \( H \) may persist long enough to get into half cycle \( I \). It was determined that the start of the next signal should be in \( J \). Hence, each signal is contained in four consecutive half cycles such as \( F, G, H \) and \( I \). A structured pre-message common to every RTU, called "preamble", was designed to enable the RTU to determine the correct start of group of four consecutive half cycles containing the signal. Once synchronization with the correct start is accomplished, the decoding of the message is simplified.

The characteristics of outbound was extracted in time domain so the algorithm is called "detecting differential in time-domain" [3]. This algorithm has achieved satisfactory effect in usual transmission situations. However, the power distribution network is used for electric power distribution and transmission, thus, the power transmission links such as electric power circuit environment and intermediate equipment of the distribution network might be not the ideal medium for information transmission. Therefore, the algorithm of the detecting differential in time domain is often utilized in civil power grid with lower interference. In the environment of industrial power grid with high power load, active equipments which often switch and change, and induce high interference and noise. The modulated signal of TWACS couldn’t be detected by the algorithm of detecting differential in domain, especially when the jamming signal appears around zero-cross area where the useful modulated signals should be. So in this paper three kinds of time-frequency analysis methods which could extract the time-domain and frequency-domain characteristics of modulated signals of TWACS were investigated and discussed. These time-frequency analysis methods were used to detect the real signals of TWACS from the industrial fields and sound effect has been achieved.

II. TIME-FREQUENCY DOMAIN ANALYSIS METHODS

A. Short-time Fourier Transform

The STFT method assumes that the signal \( f(t) \) is quasi-stationary, and analyzes the signal by taking the FT of the windowed signal. For a signal \( f(t) \), its STFT is defined as

\[ F(b,\omega) = \int_{-\infty}^{\infty} f(x) g(x-b)e^{-j\omega x}dx \] (2)

where \( g(t) \) is the sliding analysis window. Windowing the signal leads to a tradeoff in time resolution versus frequency resolution. Good time resolution requires short duration windows, whereas good frequency resolution requires long duration windows. Here \( F(b,\omega) \) reflects the relative composition of the signal \( f(x) \) on time \( b \) and frequency \( \omega \). For the time-frequency properties, this method could be used to analyze TWACS outbound signal.

The analysis process is showed as follows:

(i) Sampling process: Data obtained from industrial power grids by sampling frequency speed \( f_s = 5000 \text{ Hz} \) were gathered, corresponding to 100 points per cycle, because the frequency of the power signal equals to 50 Hz. For the sake of four consecutive half cycles defining one single bit, then sampling data of two neighboring period voltage waveform were left. That is, 200 points sampling data would be analyzed.

(ii) Differential process: This process aimed to reduce the effect caused by random noise of stationary feature. It was presumed that the random noise affected each period of the power signal equally. For every two neighboring power frequency voltage waveform presented one single bit, subtraction of former 100 points and next 100 points could decrease the effect of random noise.

(iii) Preprocessing process: All the sampling data subtracted the mean value of data, which could remove DC component from these data (see Fig. 5-2).

(iv) Short-time Fourier transform: Hamming window was chosen for the short-time Fourier transform of these 100 points data. Here hamming window has the length of 32-point and the shift rate of every 4-point. Furthermore, the frequency resolution would depend on the sampling frequency and the length of window chosen. Therefore, in this example the frequency resolution was 5000/32 Hz.

(v) Calculating eigenfunction process: According to the discrete eigenfunction (showed as equation (3)), results were calculated and showed in Fig. 5-3.

\[ S(i) = \frac{1}{m_2 - m_1 + 1} \sum_{k=m_1}^{m_2} P(i,k) \] (3)
From Fig. 6, such results could be achieved that the energy of the signal analyzed in the frequency band between 200 Hz and 600 Hz varied consistently with the position and energy changes of TWACS modulated signal. So the waveform of eigenfunction could be divided into 3 time areas: the first was from window 1 to 6; the second area was from window 7 to 12; window 13 to 18 of course was the last area. Then the average energy for each area was calculated as 0.1144, 0.2798 and 0.1179. The energy in the modulated area was obviously higher than areas where there was no modulation signal. Thus, an energy threshold which equaled to 0.2 could be defined to judge whether there was a modulated signal.

**B. Wigner Distribution**

Wagner distribution (WD) is a method used widely in the time-frequency domain analysis, which has significant advantages of high resolution, the energy concentration and tracking instantaneous frequency. However, when implemented to analyze the signal of compositions with multiple different frequency components, WD analysis will cause serious interference, which makes the physical interpretation of spectrum difficult.

In order to improve the time-frequency characteristics of the signal analyzed, two-dimensional spectrum function \( P(t, \omega) \) was achieved by Cohen from the physical meaning and the math expression of the instantaneous energy spectrum.

\[
P(t, \omega) = \frac{1}{4\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} M(\theta, \tau) e^{-j\omega \tau} d\tau d\theta
\]  

(4)

where

\[
M(\theta, \tau) = A(\theta, \tau) \cdot \phi(\theta, \tau)
\]

(5)

is the eigenfunction,

\[
A(\theta, \tau) = \int f(\mu + \frac{\tau}{2}) f^*(\mu - \frac{\tau}{2}) e^{j\omega \mu} d\mu
\]

(6)

is the ambiguity function and \( \phi(\theta, \tau) \) is called kernel function. Different constraint conditions of the kernel functions cause different spectral functions' properties.

Some studies showed that Choi-Williams spectrum where the kernel function is

\[
\phi(\theta, \tau) = e^{\left(-\frac{\theta^2}{2\sigma^2}\right)}
\]

(7)

can control the cross-terms by the choice of the constant \( \sigma \).

Fig.6. Waveform of eigenfunction for WD

Choi-Williams spectrum analysis would be used to analyze data collection same as used in short-time Fourier (see Fig.6). The waveform of eigenfunction could be also divided into 3 time areas: from the 1st point to the 44th point, from the 45th point to the 55th point and from the 56th point to the 100th point. The average energy of first area was 0.0124, of the second area was 0.0396 and of the last area was 0.0127. Thus, the energy in the area including modulation signal accounted for 61.20% of the total energy of all the areas, which reflected the change trend of energy before and after modulating.

In order to explain the problem more accurate, 20 sets of data were sampled from the industrial power grid, 10 sets of which were signals without modulation and the other 10 sets of which were signals with modulation. The results achieved from Choi-Williams spectrum analysis method were listed in Table 1, which showed that the energy in the area including modulation signal accounted for 61.20% of the total energy of all the areas, which reflected the change trend of energy before and after modulating.

In order to explain the problem more accurate, 20 sets of data were sampled from the industrial power grid, 10 sets of which were signals without modulation and the other 10 sets of which were signals with modulation. The results achieved from Choi-Williams spectrum analysis method were listed in Table 1, which showed that the energy in the area including modulation signal accounted for about 60% of the total energy and the energy in the area without modulation signal accounted for less than 30% of total energy.
C. Complex Wavelet Analysis

In recent years, wavelet transform with good time-frequency localization properties are widely used in the detection of power quality, but many literatures use real wavelet. However, because the disturbances impact not only amplitude but also phase, for the real wavelet which can only extract the signal amplitude-frequency characteristics and that can not reflect signal phase-frequency characteristics, its detection accuracy will be reduced. For complex wavelet can extract signal amplitude-frequency characteristics and also phase-frequency characteristic, it has wider applications than traditional real wavelet.

For the function or signal \( f(t) \), its wavelet transform is defined as following:

\[
W_f(a,b) = \int_{-\infty}^{\infty} f(t) \Psi_{(a,b)}(t) \, dt = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) \Psi(t) \frac{e^{-i\frac{2\pi b}{a}t}}{a} \, dt
\]  

Here \( \Psi_{(a,b)}(t) \) was called wavelet function induced by mother wavelet \( \Psi(t) \). The different characteristics of wavelet function caused different influences on the analysis results: single amplitude spectrum may be hard to meet the requirements of abundant information, while phase spectrum of complex wavelet transform contained rich information, which was useful to analyze and locate the abrupt signal. Thus, the complex wavelet transform was employed to analyze the TWACS modulation signal. Generally, there are many kinds of complex wavelet transform. Considered the ability to verify the information and the requirement of real-time recursion algorithm, such complex wavelet transform where

\[
\Psi(t) = \left( \frac{6\sigma^2}{5} - \frac{6\sigma^2 t^2}{5} + \sigma^3 \right) e^{-\sigma^2} e^{i\omega t} u(t)
\]  

was employed in this work.

Sampled data which were used in two methods above was now analyzed by complex wavelet transform. It could be noteworthy that complex wavelet transform was used on the basis of the source data without subtraction. Subtraction was committed after the transform. Fig. 7 showed that the modulated information could not be detected through amplitude spectrum after complex wavelet transform. Even with the subtraction, the feature of modulated information seemed hard to extract. In Fig. 4, the waveform of phase spectrum showed that obvious feature information appeared in the area of 150-th point where the modulation signal was posed in the time domain. Thus, phase spectral information with subtraction could be used to extract the feature. Sum of phase from the 45th to 55th point (near cross-zero area) was calculated as the feature of modulate signal. This method was used to investigate 20 sets of data, 10 sets of which were signals with modulated information and the other 10 sets of which were signals without modulated information. For clarity, the analysis results were listed in table 2. If the signal was with modulated information, the sum of phase was about 6 or so. On the contrary, if the signal was without modulated information, the sum of phase was about zero or so. The position of the modulated signal also could be judged by the polarity of the results. That is, if the result was positive, the modulated signal represented bit “1”, and if the result was negative, the modulated signal represented bit “0”.

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Table 1 Analysis results

Fig. 7. Waveform of amplitude spectrum

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<td>20</td>
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Table 2 Analysis results
D. Results

Through three kinds of time-frequency analysis methods mentioned above, such results could be achieved that the short-time Fourier transform analysis method had some disadvantages. First, the computing size was comparatively huge. Because STFT needed to calculate window Fourier transform several times which depended on the length of the data. Second, information content was limited. Although the computing size was increased, the length of the characteristic function curve only depended on the length of the window function employed in the STFT, which caused feature information less. Third, size of the window function was fixed. That means once the window function and its length were selected, its time-frequency resolution was fixed, which caused the STFT not be able to track the frequency changes of the signal analyzed. Last, detecting results was very limited. Once the signal was poisoned by strong noise, it was hard to detect the useful information of modulated signal by this method.

Compared with STFT, WD spectrum analysis had better energy aggregation and could detect accurate starting time of the modulated signal. Analysis results listed above were carried out on the situation of serious distortion on the grid and weak energy of modulated signal. The results would be better in the normal situation. WD spectrum had the meaning of the signal energy, therefore, the feature extracted from WD spectrum could only judge whether the modulated signal existed but not the type of modulated signal. In other words, modulated signal presented bit “1” or bit “0” could not be determined by WD spectrum.

Forward recursive algorithm could be used to calculate complex wavelet transform, so it could reach the high calculating speed. Complex wavelet transform extract phase characteristics, thus it could not only detect the existence of the modulated signal, but also judge the type of modulated signal.

III. Conclusion

(i) For TWACS transmitted on the industrial power network, time-frequency analysis methods mentioned above could achieved better detecting results than traditional time-domain detecting algorithm.

(ii) Among these time-frequency analysis methods, complex wavelet transform was sensitive to the phase spectral information, which was beneficial to extract the information of modulated signal. This method could not only detect the existence of the modulated signal, but also judge the type of modulated signal.

IV. PUBLICATION POLICY

The submitting author is responsible for obtaining agreement of all coauthors and any consent required from sponsors before submitting a paper.

REFERENCES