

Application of Joint Time-Frequency Analysis on PD Signal Based on Improved EEMD and Cohen's Class

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Abstract. The feature extraction and pattern recognition of partial discharge signal are key steps of equipment condition assessment and fault diagnosis. Time-frequency analysis on PD pulse can make up for deficiencies of traditional phase statistical method by extracting more comprehensive and effective information from waveform. Cohen's class distribution is a commonly used time-frequency analysis method except for influence of cross interference terms. This paper presents a method of joint time-frequency analysis on PD pulse signal based on EEMD and Cohen's class. The end effect of EEMD is studied and an extending technology based on SVR-regression fitting method is proposed as well. The exponential attenuation oscillating function added with Gaussian white noise and narrow band interference is used to simulate the high frequency current PD signal of power equipment. The results show that this method can accurately identify the characteristic PD pulse. This method can not only guarantee the time-frequency concentration of effective signal, but also inhibit the influence of IMFs' cross interference terms. Finally, we prove the effectiveness and practicality of this method by applying it on PD signal field measured in substation.

Introduction

Feature extraction of partial discharge waveform and the pattern recognition technology are the keys to partial discharge detection^[1-4]. Although the phase statistical method based on atlas analysis has achieved certain efficiency in practical applications, this method fails to make full use of the effective information of time domain, frequency domain waveform, the timeliness of spectrum and so on. What is worse, it's likely to cause false positives or false negatives^[1-2]. Since the partial discharge signal is a typical non-stationary random signal, we can more comprehensive acquire the signal's waveform information by using the time-frequency analysis methods. This method can be an auxiliary method of traditional phase statistical method. It has a great significance to the judgment of discharge type and severity.

Currently the commonly used time frequency analysis methods mainly include linear time-frequency analysis such as Short Time Transform(STFT)、Gabor Transform、Wavelet Transform, etc. The quadratic time-frequency analysis orient Cohen's class distribution and adaptive frequency analysis^[5-7]. Cohen's class distribution can be seen as the distribution of signal energy in time domain and frequency domain with a clear physical meaning, and it can take into account the panorama and localized characteristics of time domain and frequency domain except the problem of cross-term interference^[4-7].

Empirical Mode Decomposition (EMD) is a key step of Hilbert-Huang Transform^[8-10]. It has the advantage of fully adaptive, but the algorithm itself has the problem of modal aliasing and end effect. Wu. Z et al.^[11] proposed Ensemble Empirical Mode Decomposition (EEMD) based on EMD by adding Gaussian white noise auxiliary. EEMD can effectively suppress Modal aliasing problem^[11-12]. Data extension based on forecast of time domain sequence is a commonly used method of inhibiting end effect. Support Vector Machine for Regression (SVR) is a kind of high-dimensional space nonlinear regression algorithm based on SVM. It can better predict the data sequence^[13-14].

This paper presents a method of joint time-frequency analysis on PD pulse signal based on EEMD and Cohen's class and utilizes SVR to suppress the end effect. Firstly, SVR is used to extend the original time-domain PD signal, and then the signal is decomposed into several Intrinsic Mode Function (IMF). Secondly, intercept valid signal segment by extension rules. Finally, the characteristics IMFs are analyzed by the Cohen's class distribution and superimposed respectively. Apply the proposed method to time-frequency analysis of simulate PD signal, and the results show that this method can accurately identify the characteristic PD pulse. This method can not only guarantee the time-frequency concentration of effective signal, but also inhibit the influence of IMFs' cross interference terms. We prove the effectiveness and practicality of this method by applying it on PD signal field measured in a substation.

The basic theory and improvement of EEMD

The basic theory of EEMD

Assume that $x(t)$ is a real non-stationary signal with a finite energy. It is necessary to convert the signal into a complex signal form. Its analytic signal is defined as follows:

$$z(t) = x(t) + jH[x(t)]. \quad (1)$$

The equivalent complex signal form:

$$z(t) = A(t)e^{jf(t)}. \quad (2)$$

where

$$A(t) = \sqrt{x^2(t) + H^2[x(t)]}; \quad (3)$$

$$f(t) = \arctan(H[x(t)]/x(t)); \quad (4)$$

$$H[x(t)] = \frac{1}{p} \int_{-\infty}^{\infty} \frac{x(t)}{t-t} dt. \quad (5)$$

$A(t)$ is the instantaneous amplitude of $z(t)$. $f(t)$ is the instantaneous phase of $z(t)$ and $H[x(t)]$ is the Hilbert Transform.

The instantaneous frequency is defined as the time derivative of the phase function:

$$f(t) = \frac{1}{2p} \frac{df(t)}{dt}. \quad (6)$$

Eq.1 shows that analytic signal not only can ensure information integrity but exclude the negative frequency components of real signal.

The EMD method decomposes the signal into n IMFs according to their characteristics whose center frequency are progressively reduced:

$$x(t) = \sum_{i=1}^n c_i(t) + r_n(t). \quad (7)$$

where, $c_i(t)$ is IMF and $r_n(t)$ is the residual function. Since the IMFs have a single frequency at each moment, so that the instantaneous frequency has a clear physical meaning.

IMFs subject to the following two conditions:

- 1) Within the whole data, the number of extreme points and the zero crossings must be equal or differ by no more than one;
- 2) At any time, the upper and lower envelope are locally symmetrical to time line.

The sieving control of EMD is usually realized by limiting standard deviation^[8-10]. However, the selection of sieving thresholds has great influence on the results. Sieving stop condition proposed by French scholar Gabriel Riling is used. Define function

$$a(t) = \frac{e_{\max} + e_{\min}}{e_{\max} - e_{\min}}. \quad (8)$$

Where e_{\max} , e_{\min} are the envelope of original signal. Set three thresholds q_1 , q_2 , a . Terminate screening when the ratio of value in $a(t)$ less than q_1 reach a and there are no value greater than

q_2 . Default $q_1=0.05$ 、 $q_2=0.5$ 、 $a=0.95$. Compared with the standard deviation method, this method can effectively avoid excessive screening and can better preserve the signal mean characteristics.

Wu. Z et al.^[11] added Gaussian white noise to EMD so that signals of different frequencies are automatically projected onto the corresponding frequency scale of uniform space established by the white noise. EEMD method makes the problem of modal aliasing effectively suppressed.

EEMD decomposition process is as follows :

- 1) Add Gaussian white noise to $x(t)$:

$$s_j(t) = x(t) + w_j(t) \quad , \quad j=1, \mathbf{L}, m \quad ; \quad w_j(t) \sim N(0, \sigma^2) \quad (9)$$

- 2) Decompose $s_j(t)$ to n IMFs and one residual function according to the standard method of EMD;
- 3) Repeat steps 1) and 2) m times, each time add independent white noise sequence $w_j(t)$. Finally get m group decomposition:

$$\begin{aligned} & \{c_{11}(t), c_{21}(t), \mathbf{L} c_{n1}(t), r_{n1}(t)\} \quad , \quad \dots \\ & \{c_{1j}(t), c_{2j}(t), \mathbf{L} c_{nj}(t), r_{nj}(t)\} \quad , \quad \dots \quad , \\ & \{c_{1m}(t), c_{2m}(t), \mathbf{L} c_{nm}(t), r_{nm}(t)\} \end{aligned} \quad (10)$$

- 4) Respectively, take the m IMFs' and the residual item' average as the final decomposition results:

$$c_i^*(t) = \frac{1}{m} \sum_{j=1}^m c_{ij}(t) \quad ; \quad (11)$$

$$r_n^*(t) = \frac{1}{m} \sum_{j=1}^m r_{nj}(t) \quad . \quad (12)$$

Finally $x(t) = \sum_{i=1}^n c_i^*(t) + r_n^*(t)$, where $c_i^*(t)$ is the IMF and $r_n^*(t)$ is the residual function.

EEMD end effect inhibiting by SVR

Extension method is generally used to suppress the end effect of EEMD. SVR is proposed by introduced insensitive loss function e to SVM. This method makes the samples from low-dimensional feature space to a high-dimensional space (Hilbert space) by kernel nonlinear mapping^[13-14]. And then looking for an optimal classification surface so that the error of all training samples to the optimal classification surface is minimized^[15]. SVR has the advantage of little calculation, high precision regression when solving the problem of nonlinear classification, regression and other issues in high-dimensional space by using linear learning methods.

Assume $\{(x_i, y_i), i=1, 2, \mathbf{L}, l, x_i \in R^d, y_i \in R\}$ is the training sample sets. Hilbert space linear regression functions is

$$f(x) = \omega \bullet \Phi(x) + b \quad . \quad (13)$$

Where $F(x)$ is the nonlinear mapping function, ω is the weight coefficient, b is the threshold. The problem is transformed into the following optimization problems of weight coefficient ω and threshold b :

$$\min \left\{ \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^l (x_i + x_i^*) \right\} \quad ; \quad (14)$$

$$s.t. \begin{cases} y_i - \omega \bullet \Phi(x_i) - b \leq e + x_i \quad ; \\ -y_i + \omega \bullet \Phi(x_i) + b \leq e + x_i^* \quad ; \\ x_i \geq 0, x_i^* \geq 0, i=1, 2, \mathbf{L}, l. \end{cases} \quad (15)$$

Where e is the parameters of insensitive loss function. The smaller the e is, the higher the regression accuracy will be; x_i 、 x_i^* is the slack variable; C is the penalty factor. The higher C is, the higher fitting accuracy will be with a lower generalization ability. We obtain the dual form of Eqs.(14) and (15) by introducing LaGrange function :

$$\max_{a, a^*} \left[-\frac{1}{2} \sum_{i,j=1}^l (a_i - a_i^*)(a_j - a_j^*) K(\mathbf{x}_i, \mathbf{x}_j) - \sum_{i=1}^l (a_i + a_i^*) e + \sum_{i=1}^l (a_i - a_i^*) y_i \right]; \quad (16)$$

$$st. \begin{cases} \sum_{i=1}^l (a_i - a_i^*) = 0 \\ 0 \leq a_i \leq C; \\ 0 \leq a_i^* \leq C. \end{cases} \quad (17)$$

Where, $K(\mathbf{x}_i, \mathbf{x}_j) = F(\mathbf{x}_i) \bullet F(\mathbf{x}_j)$ is called kernel function. This article choose the Radial Basis Function (RBF).

We can get the optimal solution by solving Eq. (16)

$$\omega^* = \sum_{i=1}^l (a_i - a_i^*) F(\mathbf{x}_i) \text{ and } b^*. \quad (18)$$

The Regression function:

$$\begin{aligned} f(\mathbf{x}) &= \omega^* \Phi(\mathbf{x}) + b^* = \sum_{i=1}^l (a_i - a_i^*) \Phi(\mathbf{x}_i) \Phi(\mathbf{x}) + b^* \\ &= \sum_{i=1}^l (a_i - a_i^*) K(\mathbf{x}_i, \mathbf{x}) + b^* \end{aligned} \quad (19)$$

Extend the signals' endpoints by SVR and take the extension to the right for example. Specific steps are as follows:

- 1) Suppose the time domain sequence $\{x(i)\}_{i=1}^N$ and normalize. Where N is the number of sampling points; the number of training samples is L , the upper limit of extension points is N_l ; the training set generated is $T = \{(\mathbf{p}_j, t_j)\}_{j=1}^L$; $\mathbf{p}_j = [x(j), \mathbf{L}, x(N-L+j-1)]^T$ is the input vectors; $t_j = x(N-L+j)$ are training set output. The training set only takes the right 1/3 of the original signal data to control the operation speed under the premise of fitting precision (the same to the left);
- 2) Select the optimal parameters of RBF kernel function by the cross validation method: penalty factor C , the kernel function of the variance g of RBF and set e ;
- 3) Construct regression model using the Eq. (19) and project. $\mathbf{p}_{L+1} = [x(L+1), \mathbf{L}, x(N)]^T$ is the test set input, the forecast output is $t_{L+1} = x(N+1)$. Anti-normalize it and we will get the first boundary point extended. Add t_{L+1} to the right side of $\{x(i)\}_{i=1}^N$ to get the $\{x(i)\}_{i=1}^{N+1}$ and let $N = N+1$;
- 4) Repeat step 3) until we can detect k maximum value and minimum values newly generated in the right end or reach the upper limit of extension N_l ;
- 5) Similarly, extend the data to the left so that we can form a new signal sequence $x^*(t)$;
- 6) Decompose $x^*(t)$ by EEMD analyzed in section 1.1;
- 7) We will get the final decomposition results after truncating IMFs and R according to the extension rules.

Joint time-frequency analysis based on Improved EEMD and Cohen's Class

Cohen's class time-frequency distribution and cross-term problems

Define the ambiguity function of the analytic signal:

$$A_z(t, v) = \int_{-\infty}^{\infty} z\left(t + \frac{t}{2}\right) z^*\left(t - \frac{t}{2}\right) e^{j2\pi vt} dt. \quad (20)$$

Fuzzy function is the inverse transform of instantaneous correlation function. It describes the correlation of $t-v$ plane (delay - offset plane). Cohen's class time-frequency distribution is the two-dimensional Fourier transform of kernel weighted fuzzy function actually:

$$C_z(t, f) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} A_z(t, v) f(t, v) e^{-j2\pi(v+ft)} dv dt . \quad (21)$$

Where $f(t, v)$ is the kernel function . The distribution is WVD actually when $f(t, v) = 1$. WVD has a higher resolution, but more serious cross-term interference as well when the signal has multi-frequency components.

Joint time-frequency analysis based on improved EEMD and Cohen's class

This paper presents a method of joint time-frequency analysis on PD pulse signal based on improved EEMD and Cohen's class. Firstly, the original PD time-domain signal is divided into a number of IMF component by using the improved EEMD method proposed in section 1.2 and then filter the characteristics IMFs according to the energy and waveform features. Finally, make frequency analysis on characteristics IMFs based on Cohen's and superimposed. i.e.

$$C^x(t, f) = \sum_{i=1}^{n_i} C_i^c(t, f) \quad (22)$$

Where $C_i^c(t, f)$ is the Cohen's distribution on IMFs selected, and n_i is the number of characteristics IMFs. Since crossing between each frequency band of the IMFs is small, making Cohen's distribution and superimposing can effectively reduce the total cross-interference term. Comprehensive comparison of various Cohen's class time - frequency distribution shows that CWD distribution analysis have better results in the cross-interference term suppression and resolution of time and frequency domain^[20].

Analysis of simulation PD signals

Simulate the high-frequency current PD signal of electrical equipment using single exponential decay oscillating function(SEAOW)and double exponential decay oscillating function(DEAOW) :

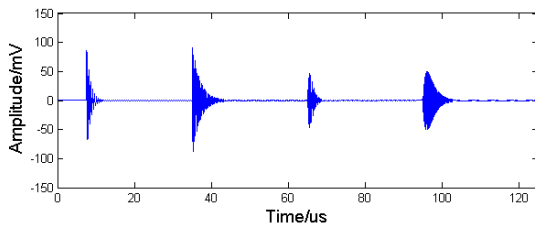
$$f_1(t) = Ae^{-\frac{t}{\tau}} \sin(2\pi f_c t) ; \quad f_2(t) = A(e^{-\frac{1.3t}{\tau}} - e^{-\frac{2.2t}{\tau}}) \sin(2\pi f_c t) \quad (23)$$

Where A is the amplitude of PD signal, t is the attenuation coefficient, f_c is the center oscillation frequency. The simulation parameters shows in Tab.1 and the Fig.1 (a) shows the simulation results.

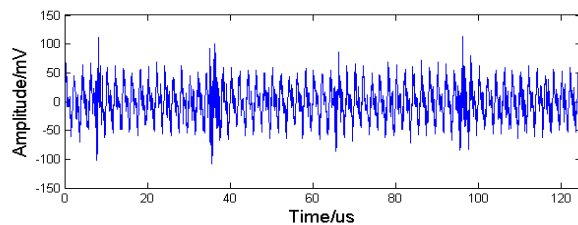
Gaussian white noise which the noise ratio is -5dB is added to the signal in Fig.1(a). And then overlap two sinusoidal simulate narrow band interference with the amplitude of 20mV, frequency of 1MHz and the amplitude of 30mV, frequency of 0.5MHz respectively. The results shown in Fig.1 (b).

Tab.1 the simulation parameters of PD signal

model	A /mV	t / μs	f_c /MHz
SEAOW	100	1	2
SEAOW	100	2	3
DEAOW	250	1	2.5
DEAOW	275	2	4



(a) Simulation PD signals



(b) Simulation PD signals with noises

Fig.1 Simulation PD signals with and without noises

Apply the EEMD decomposition method to the signal in Fig.1 (b) and the Gaussian white noise's standard deviation is 0.2 , M takes 100 times. The results shown in Fig. 2. Observe the IMFs and the residual function R can be found that the end warp phenomenon become clear with the increase of decomposition layers. The residual energy is the larger items about 3mV.

Apply the EEMD improved by SVR described in section 1.2. SVR optimal parameters selected by SVR: $C = 5.658$, $g = 0.0028$ and set $e = 0.01$. Re-decomposition results shown in Fig.3 (only shows

IMF6-IMF9 and R). The contrast of Fig. 2 and Fig.3 shows that end warp phenomenon is significantly weakened. The average magnitude of the residual function R significantly decreased, almost negligible. The improved EEMD decomposition method makes the end effect effectively suppressed.

Analysis shows that the number of extension k is directly related to the final result. If k is too small, the endpoint problems are not effectively improved. However, the prediction accuracy of SVR will gradually reduce as the k value increases. Comprehensive comparison indicates that it is ideal when $k=3$.

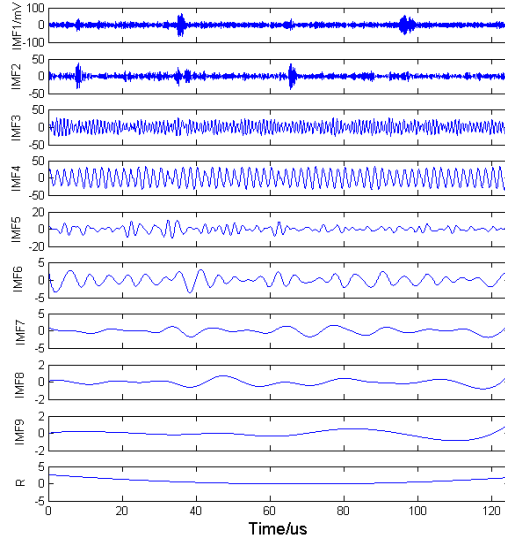


Fig.2 EEMD decomposition of simulation PD signal

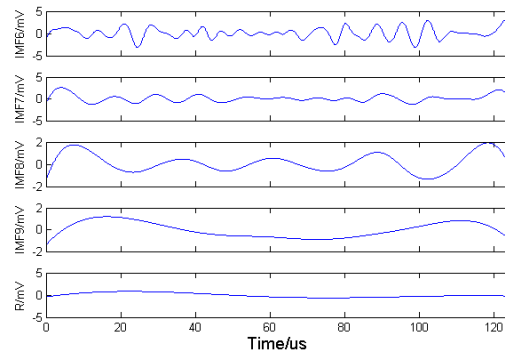


Fig.3 Improved EEMD decomposition Of simulation PD signal

Compare the result decomposed by improved EEMD and the original signal in Fig.1 (a). IMF1 and IMF2 contain the major energy and waveform characteristics of the test signal and mix with a small amount of residual white noise; IMF3 and IMF4 centralize narrow band interference signal; IMF5-IMF9 are mainly small amplitude low-frequency components which can be considered as the "false components" of decomposition. So select IMF1 and IMF2 as the characteristic IMFs. Joint time-frequency distribution based on improved EEMD and CWD are Respectively used to analyze the signal of Fig.1(b) and the results show in Fig.4 and Fig.5. Fig.4 indicates that although the narrow-band interference can be identified by CWD directly, the characteristics of time-frequency is ambiguity as the presence of serious cross-term interference. On the other hand, the proposed method significantly improves the signal frequency resolution of PD pulse, and cross-interference term is completely removed.

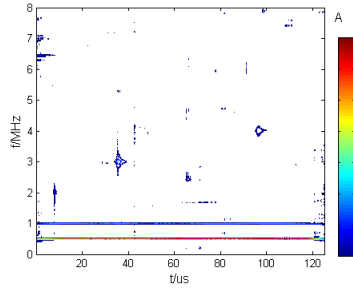


Fig.4

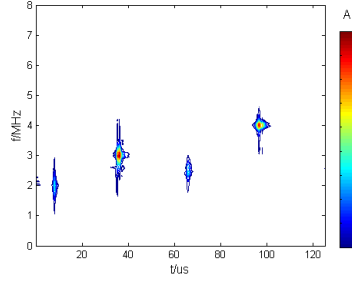


Fig.5

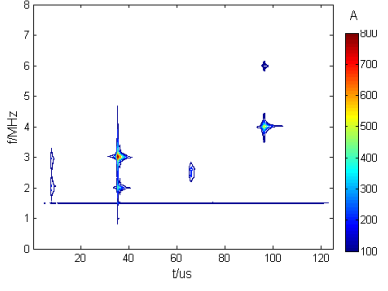


Fig.6

Fig.4 CWD distribution of simulation PD signal

Fig.5 Joint time-frequency analysis on PD signal based on improved EEMD and CWD distribution

Fig.6 Joint time-frequency analysis on PD signal based on wavelet decomposition and CWD distribution

Wavelet decomposition is a commonly used multi-scale signal analysis method. We can obtain good local characteristics both in t time domain and the frequency's if the wavelet basis is selected appropriate. Joint time-frequency analysis based on wavelet decomposition and CWD is used to comparative analyze. Select the db3 wavelet to decompose the simulation signal into 5 layer. d_2 And d_3 are selected to CWD and superimpose. The results show in Fig.6.

Fig.6 indicates that the joint analysis based on CWD and wavelet decomposition can effectively suppress cross interference term as well when the signal component is less. But whether the resolution of time domain or frequency are significantly lower than the proposed method. What's more, the choice of wavelet decomposition has great impact on results, compared with the adaptive advantage of the proposed method.

Analysis of the signals field measured in substation

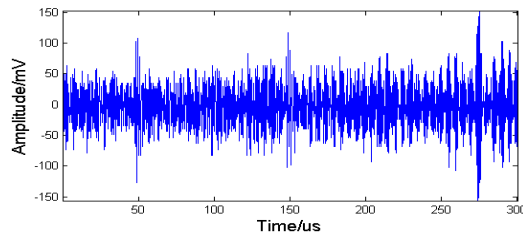


Fig.7 The field measured frequency current signal in a substation

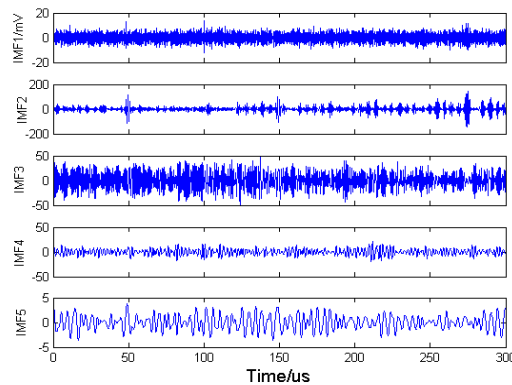


Fig.8 Improved EEMD decomposition Of the field measured PD signal

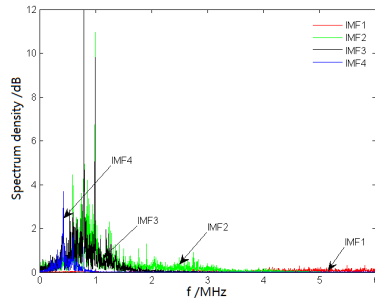


Fig.9

Fig.9 The spectrum analysis of IMFs

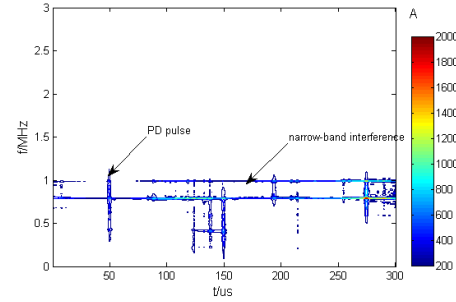


Fig.10

Fig.10 Joint time-frequency analysis on field measured PD signal based on improved EEMD and CWD

A piece of abnormal PD signals field measured by partial discharge monitoring system of a 35kV cable in a Shanghai substation. The detection method is the high-frequency current. Its time-domain waveform shown in Fig.7. The results analyzed by improved EEMD show in Fig.8. Fig.9 is the spectrum analysis results of each IMF. From Fig.8 and Fig.9 we can learn that noise is mainly white noise and narrow band interference. White noise is mainly concentrated in IMF1. IMF4 and IMF5 are mainly narrow band interference signal. PD pulse signal are mainly in IMF2 and IMF3 in. Therefore IMF2 and IMF3 are chosen as characteristic IMFs and completed the follow-up analysis. The results are shown in Fig. 10.

Analyze Fig.10 we can see that the PD signal field measured is mixed with two narrow band interference with the frequency of 0.8MHz and 1MHz (consistent with the frequency of two radio stations). Obviously identify 6 PD pulses with high temporal resolution. respectively. The occurrence times are 50 ms、125 ms、140 ms、150 ms、295 ms and 275 ms. The frequency domain resolution is relatively low, but easier to determine that the main frequencies are 0.4MHz and 0.8MHz. Therefore when the proposed method is applied to field measured PD signal, the result has a better time and frequency resolution.

Conclusions

- 1) EEMD can effectively separate each frequency component self-adaptively. However the phenomenon of endpoint warped is seriously.
- 2) EMD end effect can be effectively suppressed based on SVR extension method. The selection of the number of extension extreme points should be taken into account many factors comprehensively .
- 3) Comparing the analysis results of partial discharge signals respectively based on improved EEMD and wavelet decomposition combined with Cohen's class, the former not only can effectively suppress cross-term interference, but also have a higher time-frequency resolution.

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References

- [1] Koo J Y, Jung S Y, Rvu C H, et al. Identification of insulation defects in gas-insulated switchgear by chaotic analysis of partial discharge[J]. IET Science, Measurement & Technology, 2010, 4(3): 115-124.
- [2] HUANG Liang, TANG Ju, LING Chao, ZHANG Xiaoxing. Pattern Recognition for Partial Discharge Based on Multi-feature Fusion Technology[J]. High Voltage Engineering, 2015, 41(3):947-955.

- [3] DING Dengwei, TANG Cheng, GAO Wensheng. Frequency Attributes and Propagation Properties of Typical Partial Discharge in GIS[J]. High Voltage Engineering, 2014, 40(10): 3243-3251.
- [4] WANG Hui, HUANG Chengjun, YAO Linpeng, et al. Application of Reassigned Cohen Class Time-frequency Distribution to the Analysis of Acoustic Emission Partial Discharge Signal for GIS[J]. High Voltage Engineering, 2010 (11): 2724-2730.
- [5] WANG Meng, TAN Kexiong. Time-Frequency Distribution Method for Extracting Features of Partial Discharge Pulse Shape[J]. Journal of Electrician Technique, 2002, 17(2): 76-79.
- [6] MA Linli. Adaptive Time-Frequency Analysis for Non-Stationary Signals[D]. Xidian University, 2012.
- [7] GE Zhongxue, CHEN Zhongsheng. Matlab Time-frequency Analysis Technology and Its Application[M]. Posts & Telecom Press, 2006.
- [8] Huang N E, Shen Z, Long S R, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis[J]. Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences, 1998, 454(1971): 903-995.
- [9] Herold C, Leibfried T. Advanced signal processing and modeling for partial discharge diagnosis on mixed power cable systems[J]. Dielectrics and Electrical Insulation, IEEE Transactions on, 2013, 20(3): 791-800.
- [10] Chan J C, Ma H, Saha T K, et al. Self-adaptive partial discharge signal de-noising based on ensemble empirical mode decomposition and automatic morphological thresholding[J]. Dielectrics and Electrical Insulation, IEEE Transactions on, 2014, 21(1): 294-303.
- [11] Wu Z, Huang N E. Ensemble empirical mode decomposition: a noise-assisted data analysis method[J]. Advances in adaptive data analysis, 2009, 1(01): 1-41.
- [12] Lei Y, He Z, Zi Y. EEMD method and WNN for fault diagnosis of locomotive roller bearings[J]. Expert Systems with Applications, 2011, 38(6): 7334-7341.
- [13] ZHENG Hanbo, WANG Wei, LI Xiaogang. Fault Diagnosis Method of Power Transformers Using Multi-class LS-SVM and Improved PSO[J]. High Voltage Engineering, 2014, 40(11): 3424-3429.
- [14] Chuang C C, Su S F, Jeng J T, et al. Robust support vector regression networks for function approximation with outliers[J]. Neural Networks, IEEE Transactions on, 2002, 13(6): 1322-1330.