Adaptive Blind Equalization for Automatic Partial Discharge Signal Processing and Pattern Classification

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Abstract- Partial discharge (PD) monitoring can reveal various types of insulation defects and provide an effective means for condition assessment of high voltage (HV) equipment. One of the challenging tasks of PD monitoring is to effectively extract PD signals from acquired signals, which are susceptible to extensive noise. The extracted PD signals can then be further processed for identifying the insulation defects that generate the discharges, i.e. PD pattern classification. This paper proposes an eigenvector algorithm (EVA)-based blind equalization (BE) for PD signal de-noising. An original noise-corrupted PD signal is processed by EVA to generate a series of equalized signals. By using kurtosis as a selection criterion, an optimal equalized signal that recovers PD impulses can be obtained. Pulse sequence of the optimal equalized signal can be used for PD pattern classification. To verify the effectiveness of the proposed de-noising method, extensive laboratory experiments were conducted. The results show that the proposed method is capable of extracting PD signals from original signals, which are overwhelmed by severe background noise. Moreover, the extracted signals preserve pulse sequence patterns, which are distinctive for different insulation defects and consistent without affected by the types of PD sensors and data acquisition systems.

I. INTRODUCTION

High voltage (HV) equipment is an essential component for power generation and transmission/distribution networks. To prevent unexpected breakdowns of HV equipment due to insulation failures, partial discharge (PD) measurement provides a convenient means for on-line insulation assessment. However, the acquired PD signals can be easily overwhelmed by severe background noise during measurements [1, 2].

To de-noise the acquired noise-corrupted PD signals before making more reliable insulation assessments, a number of de-noising techniques have been developed in the past [1-4]. Among these techniques, wavelet transform (WT) has attained a higher attention on PD de-noising [1, 2]. Through the signal decomposition by using wavelet functions, a signal can be decomposed into a range of coefficients with different frequency scales. De-noising can be achieved by applying thresholds to the coefficients and selecting coefficients corresponding to PD signals. However, challenges still pose on selecting wavelet functions. Improper wavelet functions can totally alter the de-noising performance [5]. Notch filter is also used for de-noising on PD signals contaminated by cyclic noise [4]. However, forgetting factor and bandwidth are

required to be set before de-noising [4, 6]. Thus, notch filter is not an adaptive approach for on-line PD measurement, in which the frequency ranges of cyclic noise are varying.

A new approach, Eigen-decomposition, was recently proposed to extract PD signals from cyclic and random noise [3]. It decomposes a signal and then distinguishes PD signals from cyclic and random noise based on the eigenvalues corresponding to the decomposed signals. Although the results show that cyclic and random noise can be removed, the requirement of manual selection makes this approach non-adaptive.

After PD signal de-noising, phase-resolved PD (PRPD) can be used for PD pattern classification [7]. PRPD depicts amplitudes and numbers of PD impulses with reference to a power cycle. It is assumed that a unique PRPD pattern is associated with a particular insulation defect. However, this assumption may not be always held since a PD pattern can be affected by resolution and bandwidth of data acquisition systems as well as different types of PD sensors [8].

This paper proposes an adaptive PD signal de-noising method to remove cyclic noise by using eigenvector algorithm (EVA)-based blind equalization (BE). This method adopts PD pulse sequence obtained from the de-noised signals for PD pattern classification. The EVA-based BE generates a series of equalized signals aiming at recovering a PD signal from a noise-corrupted signal. By using kurtosis as a selection criterion, an optimal equalized signal (i.e. de-noised signal) can be obtained to construct pulse sequence for PD pattern classification. The proposed method is verified by using PD signals acquired by inductive and capacitive PD sensors with different data acquisition systems for various experimental PD models.

The organization of this paper is as follows. Section II provides the theoretical background of EVA-based BE. Section III presents the experimental setup. Section IV introduces the proposed method. Section V discusses the results obtained by using the proposed method. Section VI concludes the paper.

II. BRIEF REVIEW OF EIGENVECTOR ALGORITHM (EVA) FOR BLIND EQUALIZATION (BE)

Blind equalization (BE) is developed for retrieving a source signal $s(k)$ from a received signal $j(k)$ by adjusting the coefficients of equalizer $e(k)$ as shown in Fig. 1a [9], which uses a single-input single-output (SISO) BE system as an

(b) EVA system

(a) SISO BE system

Fig. 1. SISO and EVA BE systems [9]

example. The retrieved signal is called equalized signal $x(k)$. By considering only some statistical parameters of the source signal, the equalizer's coefficients can be adjusted based on the received signal [10]. For accurately recovering the source signal, a combined response of the system $u(k)$ embraces only one component with unit magnitude as [11]:

$$u(k) = b(k) * e(k) = \delta(k - k_0) \quad (1)$$

where $*$ is convolution operator, $\delta(k)$ is Dirac delta function, and k_0 is time delay constant.

In [11], BE is defined by maximizing the absolute 4th-order cumulant of the equalized signal as:

$$\max |c_4^x(0,0,0)| \quad \text{s.t. } r_{xx}(0) = r_{ss}(0) \quad (2)$$

where $c_4^x(0,0,0) = E[x^4(k)] - 3\{E[x^2(k)]\}^2$ and r denotes auto-correlation. Since this approach requires a large amount of received signals for equalization process, the operating time become longer if least mean squares (LMS) method is used (LMS is used to determine optimum solutions of equalization) [10]. Another drawback of this approach is the lack of convergence rate, which is the proportion of equalization's improvement and data size's increment.

To improve the performance of the approach proposed in [11], EVA was designed by adding a reference equalizer paralleling to the linear equalizer as shown in Fig. 1b [9]. With the equalized signals generated by the reference equalizer, this configuration seeks an optimal equalized signal by an iteration process. Also, instead of using the maximum absolute 4th-order cumulant in [11], EVA calculates the maximum 4th-order cross-cumulant as:

$$\max |c_4^{xy}(0,0,0)| \quad \text{s.t. } r_{xx}(0) = \sigma_s^2 \quad (3)$$

Since $x(k) = j(k) * e(k)$, (3) becomes:

$$\max |e^* C_4^{yj} e| \quad \text{s.t. } e^* R_{jj} e = \sigma_s^2 \quad (4)$$

where $*$ is conjugate transpose function, C is Hermitian cross-cumulant matrix, and R is auto-correlation matrix. Solving the optimization problem in (4) leads to the expression of a generalized eigenvector problem as:

$$C_4^{yj} e_{EVA} = \lambda R_{jj} e_{EVA} \quad (5)$$

where λ is the maximum eigenvalue for selecting the eigenvector e_{EVA} .

EVA is implemented as a procedure for updating reference equalizer. Assuming an initial iteration index $i = 0$ and n is

equalizer length, EVA is executed by the following iteration process:

1. Set the reference equalizer $f^{(0)}(k) = \delta(k - \lfloor n/2 \rfloor)$, where $\lfloor \cdot \rfloor$ is floor function, and calculate auto-correlation matrix R_{jj} .
2. Determine the equalized signal $y(k) = j(k) * f^{(i)}(k)$ and find the cross-cumulant matrix C_4^{yj} .
3. Substitute the results of R_{jj} and C_4^{yj} in (5) and find $e_{EVA}^{(i)}(k)$, which corresponds to the maximum eigenvalue λ .
4. Let $f^{(i)}(k) = e_{EVA}^{(i)}(k)$ and $i = i + 1$. Go to Step 2 until i reaches the maximum iteration number.

III. EXPERIMENTAL SETUP AND PD MODELS

Two different types of PD measurement setups were employed in this paper to acquire PD signals (Fig. 2). Inductive PD measurement consists of two current transformers (CTs) to pick up induced PD signals. CT1 and CT2 have bandwidth of 500 kHz - 50 MHz and 350 kHz - 35 MHz, respectively. The PD signals acquired from both CTs were recorded by digital oscilloscope with maximum sampling rate of 1 GHz. The capacitive measurement includes a coupling capacitor and measuring impedance. The PD signals were recorded through a commercial system complying with IEC60270 [12].

Fig. 2. Experimental setup

To simulate various insulation defects, four experimental PD models were constructed. These models are corona, discharge in transformer oil, surface discharge, and internal discharge [9].

IV. THE PROPOSED PD SIGNAL DE-NOISING METHOD

The PD signal de-noising method proposed in this paper is to extract PD signals from the acquired signals, which are contaminated by cyclic noise. The extracted signals are then used for pulse sequence analysis. The flow chart of the proposed method is shown in Fig. 3.

Firstly, the acquired noise-corrupted PD signal is processed by EVA. There is a wide range of cyclic noise generated from communication systems, AC power sources, and radio transmissions with the frequency range up to 2 GHz [2]. In this paper, the cyclic noise is simulated by adding 10 random cyclic signals with different amplitudes and frequencies up to 2 GHz. EVA generates a number of equalized signals in the iteration process. Here, ten iterations are used to produce ten equalized signals to reveal the embedded PD signals. Then, kurtosis is calculated on each equalized signal. Since some equalized signals may not be able to recover PD impulses, an optimal equalized signal with the maximum kurtosis is used for recovering PD impulses while keeping noise minimized. Thus, the above optimal equalized signal is treated as a de-noised signal. Finally, pulse sequence diagram is obtained from the optimal equalized signal and subsequently adopted for PD pattern classification.

Fig. 3. Flowchart of the proposed method

V. VALIDATION OF THE PROPOSED METHOD

As mentioned in Section IV, an optimal equalized signal from EVA to reveal PD signals is selected by using kurtosis. Fig. 4 shows four equalized signals generated by EVA on a simulative noise-corrupted signal. It can be seen that equalized signals 1 and 2 are still overwhelmed by noise. Although equalized signal 3 is able to recover PD signals, some noise is still present in the signal. On the other hand, equalized signal 4 retrieves all the PD signals with correct pulse sequence and removes the severe cyclic noise. If considering kurtosis value in each equalized signal, equalized signals 1 to 4 have the values of 5.8, 5.4, 823, and 5671, respectively. The largest kurtosis is associated with equalized signal 4, which thus can be selected as an optimal equalized signal.

Fig. 4. Results of equalized signals for a simulative PD signal

Fig. 5. Results of discharge in transformer oil on (a1-e1) CT1 and (a2-e2) capacitive measurement

To verify the proposed method, PD signals acquired from experimental PD models were used for analysis. Fig. 5 shows de-noising results of the proposed method for discharge in transformer oil acquired from CT1 and capacitive measurement systems. The original signals acquired after noise gating and corresponding noise-corrupted signals are

shown in Fig. 5a and b respectively. After applying the proposed EVA method, an optimal equalized signal (or de-noised signal) can be selected in each noise-corrupted signal as shown in Fig. 5c. These optimal equalized signals can retain all the PD impulses with correct pulse sequence, while keeping the noise minimized. In Fig. 5d, PRPD diagrams constructed from original signals are plotted.

The pulse sequence diagrams are constructed from the corresponding optimal equalized signals (Fig. 5e). To construct the pulse sequence diagrams, each power cycle are divided into 360 phase angles. If PD impulses exist in a phase angle, one small circle is assigned to indicate the existence of PD impulses. The pulse sequence diagrams are then formed by gathering the small circles in all power cycles together into one cycle. From Fig. 5, it can be noticed that the PRPD patterns are different by using two different types of PD sensors and data acquisition systems. The inconsistency of PRPD patterns can incur misinterpretation in PD pattern classification. In contrast, pulse sequence provides consistent patterns between the two signals.

Fig. 6 shows the results of PRPD and pulse sequence for internal discharge acquired by CT1 and CT2. Similar to the results in Fig. 5, PRPD patterns are different when different CTs are used. However, the pulse sequence patterns are quite similar. Consistent pulse sequence patterns can also be observed from surface discharge and corona (Fig. 7) with the PD signals acquired from CT1 and CT2.

Fig. 6. PRPD and pulse sequence of internal discharge on CT1 and CT2

Fig. 7. Pulse sequence of surface discharge and corona on CT1 and CT2

VI. CONCLUSIONS

This paper proposes a PD signal de-noising method by using eigenvector algorithm-based blind equalization. After de-noising, pulse sequence diagrams are obtained from the de-noised signals. To verify the proposed method, PD signals were acquired from a number of experimental PD models by using both inductive and capacitive PD sensors and different data acquisition systems. Results demonstrate that the proposed method is able to eliminate severe cyclic noise with a wide range of frequency band. Also, the constructed pulse sequence diagrams using the de-noised signals can attain higher consistency for PD pattern classification even different PD sensors and data acquisition systems are used.

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