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Application of Huber-Similarity Measure on PD Detection

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Abstract: Extraction of Partial Discharges (PD) is a key step in diagnosis and evaluation of the power system equipment condition. In field testing, besides high frequency noise and disturbance, Power Frequency (P.F.) harmonics also couple with PD measurement sensors. In order to deal with both types of noises and disturbances, in this paper, a new PD signal extraction algorithm is presented, which is based on a combination of Huber Function, Discrete Cosine Transform (DCT), ℓ_1 and ℓ_2 norms. This new method, which is introduced as Huber Similarity Measure for Partial Discharge (HSMPD), was evaluated through experimental laboratory constructed PD models. Results show this proposed algorithm successfully extracted PD signals in the presence of baseline and high frequency noises and disturbances. HSMPD can be employed as a backbone in intelligent diagnosis systems for improving the accuracy of PD condition monitoring equipment.

Keywords: Condition monitoring, Huber function, Partial discharge, Signal detection.

1 Introduction

Advances in technology made on-line condition monitoring of power apparatus reliable and cost–effective, which ensure the health and safe operation of electrical equipment [1], optimize facility operations [2], and help keep companies competitive in the market [3]. PD monitoring is one of the best methods for assessment the condition of electrical insulation inside power apparatus [4, 5]; and the integrity and design deficiencies of the insulation can be evaluated from PD characteristics such as its phase of occurrence, amplitude [6] and waveform [7, 8]. However, the problem of PD signal extraction in online monitoring systems remains a challenging task because of significant interference strong coupling, such as P.F. baseline, and the existence of high frequency noise and disturbances in substation environment [9, 10].

A few number of investigations have been carried in the field of PD extraction, their main tool is wavelet analysis [11 – 13]. Wavelet is an effective

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tool for de-noising applications [14, 15]; however, it faces difficulty regarding separating low frequency baselines as noise [16]. This is a problem when field measurement is performed by antenna and strong P.F. noise and disturbance couples with high frequency measurement.

Reviewing pattern recognition techniques shows that similarity measure can be used as a tool for comparing different objects and identifying similar ones [17]. This technique has been applied in different areas such as image guided surgery [18], computer vision [19] and remote sensing [20]. This encouraged the authors to employ similarity measure for finding similar PD waveforms in PD database. On the other hand, this means PD activities in a P.F. window can be detected. To overcome the problem of extracting PD signals in the presence of baseline noise and disturbance, in this paper, a similarity measure index called Huber-function [21] is defined which is sensitive to low frequency components as well as high frequency contents of signals. This helps the process of separating original PD activity from recorded data.

The structure of paper is as follows: Huber-similarity-methodology is explained in the next section; then, in order to evaluate the efficacy of proposed method, a laboratory test is performed, 3 PD model to produce “surface discharge”, “corona” and “discharges in oil” are built; captured PD data are applied on the proposed method and results are discussed.

2 Methodology

In order to find the location of the PD signal, the approach is to match the following equation on the recorded PD signal window:

$$Y = P + N + \eta\,, \tag{1}$$

where P is the reference PD signal and Y is the recorded PD signal, N is a zero mean white Gaussian noise; and η is a baseline distortion such as the fundamental and harmonics of P.F. induced voltage. We define a feature space in which η and N has known statistical representation. The similarity measure in this paper is based on the Maximum a Posteriori (MP) and M estimator. Because of smooth behavior, baseline distortion has a sparse representation in a transform domain such as Discrete Cosine Transform (DCT). It means that the baseline distortion has a strong peak at the origin and the long tail, and can be modeled by a Laplace distribution [22]:

$$p_L(e) = \frac{1}{2\lambda} e^{\frac{-|e|}{\lambda}}\,. \tag{2}$$

This Laplacian distribution models the long tail better than Gaussian. In this paper, MP method is used for defining the new similarity measure; in other words, the goal is to maximize the following probability:

$$p\left(T \middle| y_t, p_t\right) \propto p\left(y_t, p_t \middle| T\right) p\left(T\right), \tag{3}$$

where y_t and p_t are random variables of the transform representations of the original and noisy PD signals. MP is used to maximize this probability. It is assumed that the transform domain is unitary. Hence, with respect to Independent Identically Distributed (I.I.D) assumption of Gaussian noise and disturbance, the distribution of the time domain and transformed noise and disturbances are identical. With this assumption, the log likelihood function is:

$$MP_G : \log p\left(y_t, p_t \middle| T\right) = \frac{-1}{\sigma} \sum_{i=1}^{n} \left(y_{ti} - p_{ti}\right)^2 , \tag{4}$$

where y_{ti} and p_{ti} are the i th coefficient of the transform representation of the original and noisy PD signals respectively; and n is the number of samples per recording window.

Equation (4) shows that norm ℓ_2 (Sum of Squared Difference) is also an optimal similarity measure in the presence of Gaussian noise and disturbance in MP view. Using Laplacian model for η , the following log likelihood function is obtained:

$$MP_L : \log p\left(y_t, p_t \middle| T\right) = \frac{-1}{\lambda} \sum_{i=1}^{n} \left| y_{ti} - p_{ti} \right| . \tag{5}$$

It can be seen that norm ℓ_1 is an optimal similarity measure in MP view. This discussion shows that both ℓ_2 and ℓ_1 norms of the original and noisy PD signals in transform domain are optimal similarity measures in the presence of Gaussian noise and disturbance and baseline distortion, respectively. When both noises and disturbances exist in field while PD data are recorded, it is suggested to define a new similarity measure based on a combination of ℓ_2 and ℓ_1 norms in order to localize PD events. it is assumed that amplitude of Gaussian noise and disturbance is less than that of baseline distortion in transform domain. Considering this assumption, a similarity measure can be defined: it is a combination of ℓ_2 and ℓ_1 norms where its behaviour is ℓ_2 norm near origin and is proportional to ℓ_1 norm far away from the origin. To achieve this, a similarity measure based on Huber function [20] which is a combination of ℓ_2 and ℓ_1 norms is proposed; in this paper it is named Huber Similarity Measure for Partial Discharge (HSMPD):

$$HSMPD\left(Y, P\right) = \sum_{i=1}^{n} \zeta\left(y_{ti} - p_{ti}\right), \tag{6}$$

where

$$\zeta_H(t) = \begin{cases} \frac{1}{2}t^2, & |t| \le \alpha; \\ \alpha|t| - \frac{\alpha^2}{2}, & |t| \ge \alpha; \end{cases} \tag{7}$$

is the Huber function for $\alpha > 0$, and α is the contamination degree of outlier. Here, α is set to 1.34σ where σ^2 is the variance of Gaussian noise and disturbance; the noise and disturbance variance σ^2 is estimated from the wavelet coefficients of noisy image by the robust median estimator of

$$\sigma = \frac{median(|w_i|)}{0.6745},$$

which is used from the finest scale wavelet coefficients [23]. The location of PD signal in P.F. window is obtained by minimizing the HSMPD. PD location algorithm is:

$$D_{PD} = [y_{ti} - p_{ti}] = T(Y - P), \tag{8}$$

$$HSMPD(Y,P) = \sum \zeta_H(y_{ti} - p_{ti}), \tag{9}$$

$$PD_{loc} = \arg\min(HSMPD(Y,P)), \tag{10}$$

where T is DCT transform and PD_{loc} is the location of PD activity in P.F. database.

3 Application of HSMPD on PD Model

In this section, details of the three PD models are presented. Fig. 1 shows the flowchart of HSMPD for PD extraction. In High Voltage (HV) Lab, 3 PD models called "Corona", "Surface Discharge" and "Discharges in Oil" are built, a Digital Storage Oscilloscope (DSO) records the data. HV test is carried out and HSMPD is applied to signals produced by these test objects.

3.1 Results of HSMPD on Corona Model

This PD Model was fabricated by using a needle of 170 mm-tip-radius as the HV electrode in a distance of 10 mm to a plane electrode with diameter of 22 cm. HV is applied to this test object and increased up to 6kV; PD activities are appeared in DSO. Fig. 2 shows an example of HSMPD method applied on recorded PD data. Localized PD signals are shown by red dots. One of the extracted PD signals is illustrated in box view of this figure.

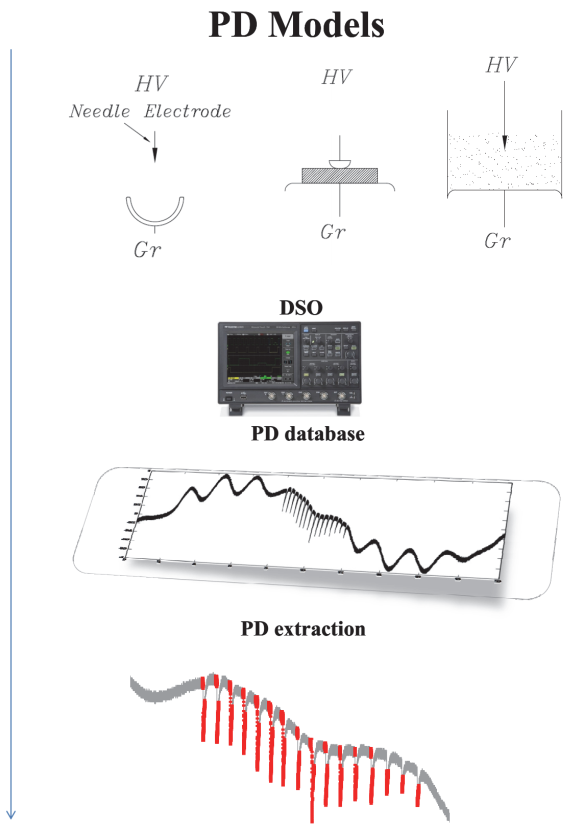

Fig. 1 – *Flowchart of the HSMPD method.*

3.2 Results of HSMPD on Surface Discharge Model

This model is built by putting a plexy-glass of 3.7 mm thickness and diameter of 22 cm between HV and ground electrode. HV is applied to this model and PD signals are captured by DSO. Fig. 3 shows an example of HSMPD method applied on recorded PD data. PD signals occur at Global minimum of HSMPD as shown in the box view. Localized PD signals are shown by red dots.

3.3 Results of HSMPD on Discharges in Oil Model

Needle-plane electrode configuration is used to construct this model. Distance between needle and plane electrode is 10 cm, diameter of plane electrode is 25 cm. Voltage is increased up to 22 kV. Fig. 4 shows an example of HSMPD method applied on recorded PD data. Localized PD signals are shown by red dots. As can be seen from these figures, HSMPD successfully found the location of PD signals.

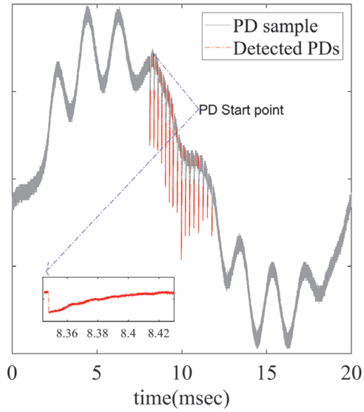

Fig. 2 – *Application of HSMPD on a PD-Record Sample for Corona Model.*

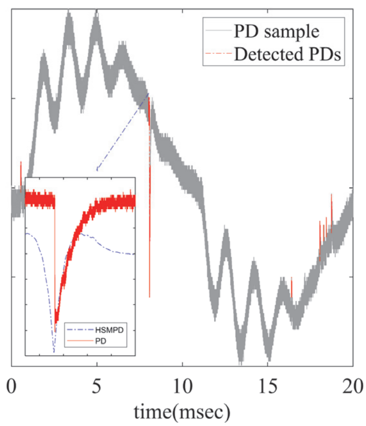

Fig. 3 – *Application of HSMPD on a PD-Record Sample for Surface discharge Model*

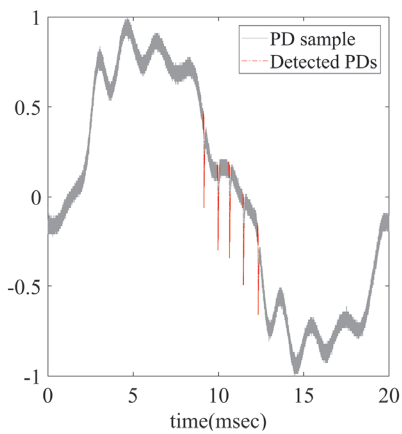

Fig. 4 – *Application of HSMPD on a PD-Record Sample for Oil Discharge Model.*

4 Noise and Disturbance Robustness Examination

In this section, HSMPD is applied on contaminated PD data wherein an artificial zero mean white Gaussian noise has been added. SNR of PD signals has been reduced to a value in which detection error happens. Fig. 5 shows an example of adding noise and disturbance to original PD data. In order to evaluate the performance of proposed method for each SNR level, the error measure ε of PD detection is calculated by comparing the detection results of original and contaminated PDs. The scenario of noise-addition is repeated multiple times for each PD-record;

$$\varepsilon = 1 - \frac{1}{k}\sum_i \sum_j \frac{N_{corr,i,j}}{N_{org,i} + N_{wr,i,j}}, \tag{11}$$

where, k is the number or iteration, $N_{corr,i,j}$ and $N_{wr,i,j}$ is number of correct detected and wrong detected PDs in jth iteration of ith PD-record for each PD model respectively; $N_{org,i}$ is total number of detected PDs obtained from ith original PD data set.

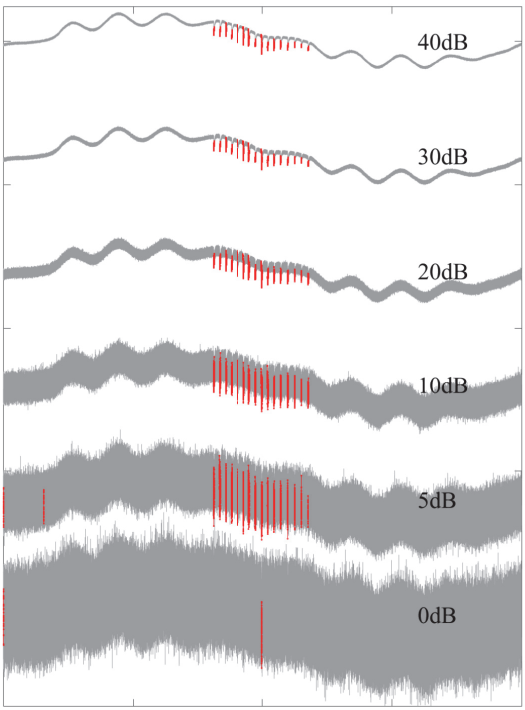

Fig. 5 – *An example for the effect of adding Noise and disturbance to a sample of Corona Model PD data.*

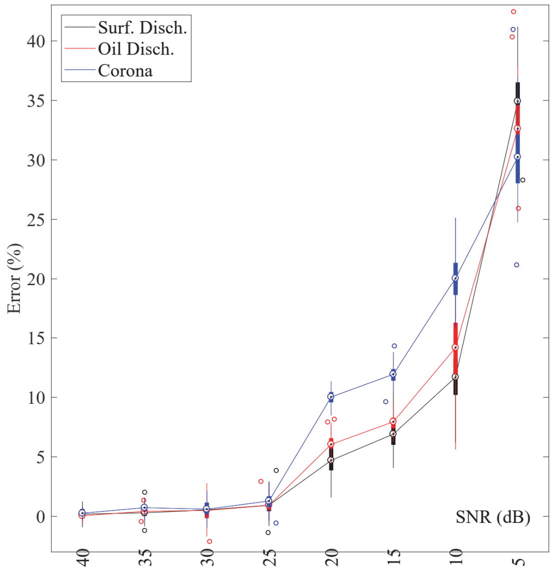

Fig. 6 – *HSMPD-Error measure for PD detection.*

The error measures for PD detection as a function of SNR are shown in Fig. 6; k is set to 100 iteration. From these results, we observe that PD detection Error is rising when SNR reduces to 5dB.

5 Conclusion

In this paper, a new method of PD detection based on the Huber similarity measure has been proposed. The main contribution of this paper is to demonstrate that P.F. harmonic distortion has a sparse representation in DCT transform domain. In fact, in this paper, PD detection is performed by measuring the similarity between a reference PD signal and a PD database.

In this work, by using Maximum a Posteriori concept, we deal with Gaussian noise and disturbance and baseline-power-frequency harmonic-distortions by obtaining ℓ_2 and ℓ_1 norms separately. In the proposed HSMPD method, Huber Function, as a new similarity index in this field, is applied on the combination of ℓ_2 and ℓ_1 norms. Results of application of HSMPD on artificial PD models are visualized, Figs. 2 – 4. From these figures, it is obvious that HSMPD has successfully extracted PD signals.

The HSMPD algorithm has been investigated in different Gaussian noise and disturbance levels and results are illustrated in Fig. 5. From this figure, it can be concluded that HSMPD error measure is rising when SNR is up to 5dB, which is a trade-off between Gaussian and baseline noise and disturbance detection methods. In order to show the effectiveness of our feature based proposed method, the results are compared with the wavelet method which is directly applied on PD record data. Daubechies family wavelets are used in this work. In order to deal with baseline distortion, low frequency content of PD data, η is suppressed as follows:

$$\widehat{Y} = W\left[P + N + \eta\right] \xrightarrow{\text{Strict Denoising}} \widehat{\eta} = W^{-1}DW\left[Y\right]. \tag{12}$$

Strict de-noising in this work acts like minimum-phase lowpass filtering. Now, noisy PD activity can be derived:

$$\overline{P + N} = Y - W^{-1}DW\left[Y\right], \tag{13}$$

where W is the wavelet transform and D is the projection matrix. Considerable part of P is missing when η is suppressed; this will decrease the efficiency of wavelet in the case of PD extraction. For reconstruction of PD data, the decomposition level chosen is 8. Fig. 7 shows an example of wavelet method. Results for different Gaussian noise and disturbance levels are shown in Fig. 7. The wavelet method loses efficiency when SNR reduces to 25dB; this is because of missing part of P in de-noising of PD data. Results of Figs. 6 and and 8 show that HSMPD is more efficient in comparison with the wavelet thresholding method for PD extraction when baseline noise and disturbance exists. HSMPD can be used as a backbone in expert PD monitoring systems.

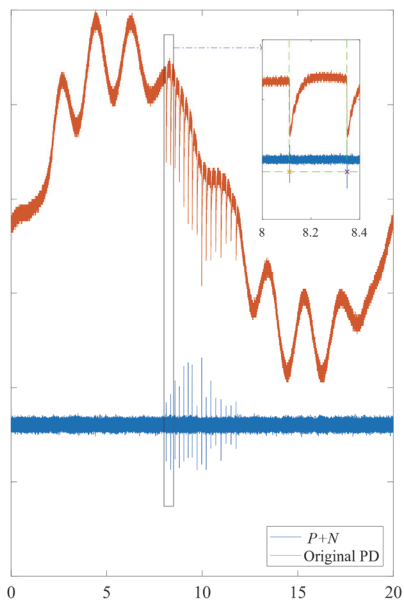

Fig. 7 – *Wavelet Threshold Method for PD extraction.*

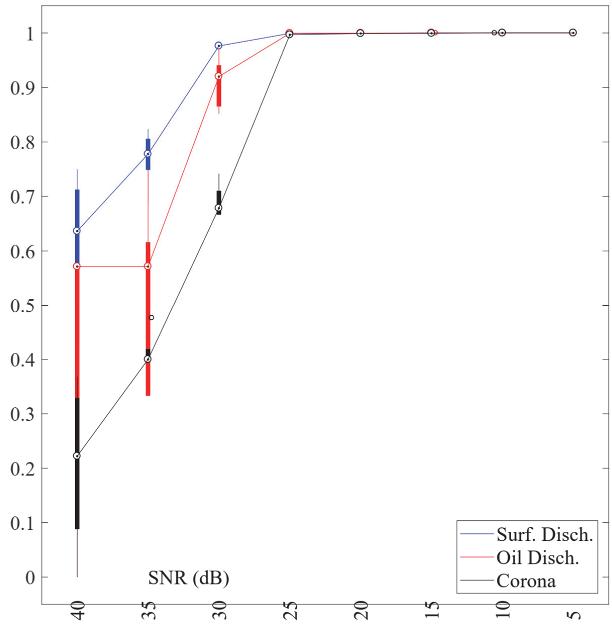

Fig. 8 – *Wavelet Threshold Method for PD extraction.*

Future research will focus on the investigation of using other similarity algorithms in PD extraction.

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