Identification and Localization of Partial Discharge in Transformer Insulation Adopting Cross Recurrence Plot Analysis of Acoustic Signals Detected using Fiber Bragg Gratings

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ABSTRACT

In this paper, we propose the use of a Cross Recurrence (CR) Plot Analysis based technique applied on signals captured using fiber Bragg grating sensors to improve the accuracy of detection and localization of partial discharges. With the help of detailed simulations, the performance of the proposed technique in estimating the Time Difference of Arrival (TDOA) is evaluated. A novel technique of extracting the frequency from CR plots is also proposed and frequencies of single as well as multiple-tones signals are extracted successfully. Controlled experiments are conducted to verify the technique and the estimates of location are found to be within an error of less than a centimeter.

Index Terms — Cross Recurrence Plot Analysis, Partial Discharge, Fiber Bragg Gratings, Power Transformers, Acoustic Emission sensing

1 INTRODUCTION

The primary goal of any power distribution network is to guarantee uninterrupted power supply to the consumer. One of the critical components in such a power distribution network is the power transformer. However, they are susceptible to breakdown primarily due to improper insulation design or poor quality of insulation structure or casing [1]. As such, condition monitoring of transformer insulation forms an integral step in ensuring consistent operation of the power equipment.

The transformer insulation normally undergoes accelerated ageing due to electrical, thermal and mechanical stresses during operation. It is essential to monitor these degradations before it leads to a catastrophic failure [2]. Partial discharges (PD), which consists of highly localized electric discharges occurring in the insulation serve as early indicators of such insulation degradation [3].

Partial discharge detection has been demonstrated through several techniques including in-line current transients, electromagnetic (UHF) detection, and acoustic emission (AE) monitoring [3]–[5]. Among these, the latter is attractive as it offers the possibility of on-line detection and discharge localization [6]. However, the precise identification of the location of discharge is challenging as the acoustic signals generated are feeble and suffer considerable amount of attenuation before they reach the sensor. Further, it is also essential that the sensor system should be able to minimize the rate of false alarms [7].

Piezoelectric based sensors (PZTs) mounted on the external surfaces of the transformer tank have been used conventionally used for detecting acoustic emissions from discharges [8]. However such sensors are susceptible to electromagnetic interference (EMI) in the substation operating zone. In contrast, fiber optic based acoustic emission sensors have negligible EMI, are compact, light weight and can be installed in a minimally invasive manner [9]. Specifically, a class of fiber optic sensors based on fiber Bragg gratings (FBG) have been found to be well suited for the above application owing to their robust transduction mechanism wherein the acoustic signals are converted to optical wavelength modulation [10]. One of the key challenges in using FBG based sensors for sensing acoustic emissions generated from partial discharges is to identify an efficient technique to extract the wavelength-modulated information. In other words, a highly sensitive FBG interrogation technique is necessary to capture the ultra-low acoustic signals emitted during a discharge event.

In this context, an attempt has been made to detect the AE signals and to localize the discharges by adapting the Cross Recurrence Plot Analysis (CRPA) technique [11]. The technique is found to work well on low SNR signals detected by multiple sensors placed across the tank and also in reducing the number of false alarms.

2 BACKGROUND

2.1 FIBER OPTIC SENSORS FOR PD DETECTION

A variety of fiber optic sensor configurations have been
used to detect acoustic waves generated by PD, which produce either phase modulation or wavelength modulation. One of the earliest demonstrations of PD detection was using a Michelson interferometric configuration to detect phase modulation due to the acoustic waves [12]. Yu et.al. used an extrinsic Fabry Perot interferometer (EFPI) consisting of an air cavity between a diaphragm and the fiber tip [13]. The angular dependence of such EFPI sensor was investigated by Song et.al with the objective of determining the direction of the acoustic waves [14]. A Mach-Zehnder interferometric configuration reported by Boffi et.al. achieves a sensitivity of 0.4 mrad/PC with a resolution of 50 PC using a 5 cm diameter coil of 10 m long fiber [15]. Sanahuja et.al. reported a sensitivity of 0.5 rad/Pa using a similar interferometric configuration and a He-Ne laser [16]. A recent work by Posada Roman et.al. achieved sensitivity of 1.3 Pa by using a 17 m long sensing fiber in a Mach-Zehnder interferometric configuration [17]. However, such approaches make the sensor bulky and are susceptible to fringe fading problems due to random polarization fluctuations.

On the other hand, fiber Bragg grating sensors are compact and are amenable to array sensing, which can be a great advantage while determining the location of PD. In contrast to the phase encoded schemes presented above, FBGs are quite rugged as they encode sensing information in wavelength which is impervious to noise. An overview of the use of FBGs in detecting acoustic waves can be found in [18], Lima et.al. demonstrated configurations for detecting PD using mandrel-based FBG and FPI sensors with resolutions of 320 Pa and 140 Pa at a frequency of 60 kHz [19], [20]. However, for real-time testing purposes, the sensitivity needs to be improved and there have been much better results reported for FBG sensors, although not for PD detection. The sensitivity enhancement has been achieved by various groups through either modified FBG sensor configuration or through specially designed interrogation systems [21]–[23].

### 2.2 FBG BASED ACOUSTIC EMISSION SENSING AND DYNAMIC INTERROGATION

A fiber Bragg grating (FBG) is a periodic perturbation in the refractive index of the core of an optical fiber extending over a limited length, typically a few micrometers. The FBG acts like a narrowband optical filter, reflecting a narrow band of wavelengths around a center wavelength called the Bragg wavelength from the incident broadband optical signal [10].

A schematic diagram of a typical FBG based sensor is shown in Figure 1. The FBG sensor connected to port 2 of the circulator is illuminated using a broadband optical source. The optical signal reflected from the grating is captured by a spectrum analyzer that is connected to port 3 of the circulator. The spectrum analyzer tracks the wavelength shift, which may be correlated to the amount of strain or temperature experienced by the FBG using suitable calibration.

One of the prominent challenges in the use of FBG based sensors for sensing dynamic signals like acoustic emissions is the efficient conversion of wavelength encoded signals to useful information. Some of the techniques proposed by various sensing groups in this regard include the use of tunable narrow band lasers [24], edge filters [25], [26], arrayed waveguide gratings [27] and interferometric methods [28]–[30]. In the present study, we have used the tunable laser based interrogation of FBG for detection of acoustic signals generated due to PD.

![Figure 1. Schematic representation of a typical FBG based sensor system.](image)

#### 2.3 CROSS RECURRENCE PLOT ANALYSIS

Cross Recurrence Plot Analysis (CRPA) is based on the recurrence of the phase trajectory of signals [31]. Suppose that the measured signal $x$ is a discrete time series of length $N_t$ with a sampling interval $\Delta t$. First the phase space has to be reconstructed for which the time-delay embedding method is used, and it can be written as:

$$x_m(t) = [x(i), x(i + \tau), \ldots, x(i + (m-1)\tau)]$$

where $m$ is the embedding dimension of the phase space, $\tau$ represents a delay, $i = [1,2,\ldots,N = N_t-(m-1)\tau]$ represents the sample index. A similar approach is adopted for the other measured signal $y$ and can be expressed as:

$$y_m(t) = [y(i), y(i + \tau), \ldots, y(i + (m-1)\tau)]$$

The phase space defined above is extended to result in matrices $x(t)$ and $y(t)$ of the order $N^2 \times m$. The degree of similarity between the two vectors of the phase space trajectory is measured. This leads to the similarity matrix $d$ defined as:

$$d(i, j) = \text{Sim}(x(t), y(t))$$

where $\text{Sim}$ is a function chosen to study the likeness of the phase space vectors. The CRPA matrix is then obtained through the comparison of each of the coefficient of the similarity matrix with a suitable threshold. It is defined as:

$$\text{CRPA}(i, j) = \Theta(d(i, j) - \varepsilon)$$

where $\Theta$ is the Heaviside function and $\varepsilon$ is an appropriately chosen threshold. Note that the size of CRPA matrix is appropriately reshaped to $N \times N$.

Depending on the signatures recurring in the two signals, the CRPA matrix exhibits certain patterns. It is important to quantify these patterns using appropriate metrics [11]. Three different Recurrence Quantification Analysis (RQA) measures have been proposed, namely t-recurrence rate (RR), sum of
similarity (SS) and normalized sum of similarity (NS) as given below:

\[
RR(t) = \begin{cases} 
\frac{1}{N(t)} \sum_{i=1}^{N(t)} CRPA(i-t,i) & (t < 0) \\
\frac{1}{N(t)} \sum_{i=1}^{N(t)} CRPA(i,i+t) & (t \geq 0)
\end{cases} 
\]

(5)

\[
SS(t) = \begin{cases} 
\frac{1}{N(t)} \sum_{i=1}^{N(t)} CRPA(i-t,i) \otimes d(i-t,i) & (t < 0) \\
\sum_{i=1}^{N(t)} CRPA(i,i+t) \otimes d(i,i+t) & (t \geq 0)
\end{cases} 
\]

(6)

\[
NS(t) = \begin{cases} 
\frac{1}{N(t)} \sum_{i=1}^{N(t)} CRPA(i-t,i) \otimes d(i-t,i) & (t < 0) \\
\sum_{i=1}^{N(t)} CRPA(i,i+t) \otimes d(i,i+t) & (t \geq 0)
\end{cases} 
\]

(7)

The TDOA is estimated from these measures as:

\[
\text{TDOA} = t \text{ such that } \text{argmax}(RQA(t))
\]

(8)

where \(RQA(t) = RR(t), SS(t) \text{ or } NS(t)\)

The signals acquired through FBG sensors are typically of low SNR values. In such scenario, a CRPA is quite useful to not only detect the occurrence of partial discharges but also help to localize these discharges.

3 THEORETICAL STUDIES OF CRPA FOR MONITORING PARTIAL DISCHARGES

In order to establish the capability of CRP analysis for estimation of TDOA at low levels of SNR, appropriate simulations were carried out. The performance of different RQA measures were compared with the objective of identifying the best measure for monitoring the acoustic signals due to partial discharge using FBG sensors. The quantification of the optimum threshold settings for the CRPA matrix and the performance of the algorithm for signals with unequal SNR were also investigated through simulations.

For our simulations, we chose an acoustic signal consisting of 100 samples with sampling time of 0.5 µs to represent a sinusoidal signal at 200 kHz and added 100 samples at each side of the above sequence. This signal was mixed with additive white Gaussian noise of a specified standard deviation to generate 300 samples of data as shown in Fig. 2(a). Similarly, another signal (Signal 2) was generated with similar acoustic signature but another set of additive white Gaussian noise samples. The two signals were delayed with respect to each other to represent three different TDOA values in our simulations: 0 µs, 35 µs and -35 µs. Figure 2 shows the three pairs of signals at SNR of 10 dB and their corresponding CR plots.

In order to estimate the TDOA value from the CR plots, three different RQA measures described in the previous section were considered for the study. The CR plots were obtained for signals as a function of different SNR and the corresponding TDOA values were estimated. It is observed from Fig. 3 that both the SS and NS metrics gave more accurate estimates of TDOA compared to the RR metric. This is quite expected since the RR measure relies only on the binary values of CR plot to predict the estimate and fails to consider the relative amplitudes of the individual entries in the similarity matrix.

The performance of the above RQA metrics in estimating TDOA for signals having SNR less than 0 dB were also attempted through simulations. In such cases, the signal would be completely masked by the noise. Figure 3 reveals that the SS measure can give accurate results of TDOA estimate for signals with SNR as low as -5 dB. It may also be noted that for the SS and NS metrics, the delay estimate moves closer to zero for non-zero values of TDOA as the SNR is reduced to -10 dB. This may be explained as follows: for lower values of SNR, the CRPA matrix would contain noisy data across the entire matrix. In such a scenario, the main diagonal which corresponds to zero TDOA value would be the dominant estimate. Overall, it is clear that the SS measure provides as good or better results compared to other measures and hence it is chosen for further simulation studies elaborated below.

Further simulation studies were focused on determining the optimum threshold setting for the formulation of the CRPA matrix. As discussed previously, a suitable threshold is applied to the similarity matrix \(d(i,j)\) defined in Equation (3) to obtain the CRPA matrix. The threshold levels chosen for the study were \(1\sigma, 2\sigma\) and \(3\sigma\) where \(\sigma\) denotes the standard deviation of the data samples presenting to the CRP analysis. Figure 4 shows the results of TDOA estimation using the SS metric for various levels of the threshold. Since the error in TDOA estimate based on SS metric for various levels of thresholds is
not much different (<5 µs), a threshold setting of 1σ was chosen for all further simulations.

In a multi-sensor environment, the signals detected by the different sensors will not have the same SNR. Hence it is important to evaluate the performance of the algorithm for different values of SNR of detected signals. The results of the simulations performed in this regard are presented in Figure 5. The maximum error obtained for the case when the SNR of the signals are -3 dB and -10 dB respectively is around 7 µs, corresponding to physical distance of less than a centimeter. Thus, the SS metric with 1σ threshold for the CRPA matrix is found to be robust against low SNR conditions.

A further exploration of the CRPA matrix was aimed at extracting the frequency information from a CR plot. Figure 6(a) shows a sample CR plot with zero delay between the signal pair. The irregular black patches which are present throughout the area correspond to a noisy data. Clearly, it is quite difficult to detect any acoustic signature within such data. In such a scenario, consider the histogram taken by considering bins along the backward diagonal as shown in Figure 6(b). Each of the diagonal is assigned a time index based on the sampling rate with the main diagonals corresponding to zero. In order to detect any acoustic
signature, Fourier transform of this histogram is evaluated. As shown in Fig. 6(c), there is a clear acoustic tone at 200 kHz present in the histogram data which was not apparent in the conventional CRPA data.

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Figure 6. (a) A sample CRPA plot (b) Histogram plot of the data along the backward diagonal of CR matrix, (c) Corresponding frequency spectrum estimated from the histogram clearly showing the presence of an acoustic signal at 200 kHz.

A novel technique of estimating the frequency of the signal from a cross recurrence plot is presented in this paper, although it was tested on a single tone signal. Typical partial discharge signals are broadband extending over a few hundred kHz [6]. Figure 7 shows the frequency estimation results obtained for a situation where there are two such components in the signal. As discussed earlier, the CR matrix is quite noisy for the low SNR case. However, upon performing the histogram analysis along the backward diagonal data we are able to unearth the signals from the noisy background. As seen from Fig. 7(c), the estimation was successful in picking up the respective frequency components.

4 RESULTS AND DISCUSSION

An experimental setup was devised to verify the capability of the proposed technique in detecting and localizing practical acoustic signals. A schematic representation of the experimental setup is shown in Figure 8. To model the transformer tank, a MS tank of size 1 ft x 1 ft x 1 ft was used which was filled with water since water has similar acoustic properties as transformer oil. An underwater acoustic transducer driven by a pulser/receiver unit was used to generate acoustic bursts to simulate the PD-induced acoustic signals. Two FBG sensors were placed on either side of the source to capture these acoustic bursts. The sensors are interrogated with the help of a tunable laser source which is tuned to the reflection slope of the FBG. The signals reflected from the sensors are captured using an in-house designed dynamic interrogator board. A photograph of the experimental setup is shown in Figure 9. The relative positions of the sensors and the source was varied to simulate the effects of multiple locations.

Figure 8. Schematic representation of the experimental setup

Figure 9. Photograph of the experimental tank showing the source and sensors

In our experiment, we fixed the location of Sensor 1 at 10 cm away from the acoustic source and varied the position of Sensor 2. The acoustic signals from both the sensors were captured using the dynamic interrogator. A sample data trace captured from both sensors when Sensor 1 and Sensor 2 are 10 cm and 6 cm away from the source respectively is shown in Figure 10. To further improve the SNR of the signal, the raw
data was filtered using adaptive line enhancement (ALE) technique previously reported for FBG-based detection of acoustic signals [32].

![Figure 10](image1.png)

Figure 10. AE signal acquired by FBG sensor with SNR -7.6 dB and -13.8 dB respectively (a) Raw trace (b) ALE-filtered trace

The CRP analysis was applied on the ALE-filtered time domain signals obtained from both the sensors. As discussed in the previous section, the TDOA is estimated using the SS-metric. The TDOA value is then converted to a distance estimate by scaling it with the velocity of acoustic waves in water (1482 m/s). The repeatability of the experimental results is verified by performing five consecutive trials at the same distance setting as shown in Figure 11 (a). It may be observed that for locations at which Sensor 2 is more than 6 cm away from the source, the error in the TDOA estimate is well within 1 cm. However, larger errors are observed for distances less than 6 cm. This is attributed to the near field effect over a distance of $2D^2/\lambda$ ($D$ : Diameter of the acoustic source, $\lambda$: acoustic wavelength), which corresponds to 5.4 cm at the excitation frequency of 200 kHz. This observation emphasizes the fact that such acoustic measurements need to be performed in far-field to get accurate results.

To support the above claim of near field errors, the mean error and standard deviation in error at various locations was plotted as a function of distance in Figure 11 (b). It may be observed that the profile of standard deviation in error is flat indicating that it is similar in both near field and far field regions. Hence it may be concluded that the large errors obtained for distances less than $8\lambda$ in Figure 11 (a) indeed corresponds to near-field errors. It may also be observed from Figure 11 (b) that for the measurements performed in far-field, the error obtained in the distance estimate is well within 1 cm.

Further, experiments were repeated at seven different positions of Sensor 1 and Sensor 2 and the distances estimated from the CRP analysis of ALE-filtered trace are shown in Table 1. The distances of the sensors from the source were selected appropriately such that the TDOA values include positive, negative and zero delays. The actual distance which is calculated as the difference in distances between the two sensors is compared with the distance value estimated through CRPA method. The standard deviation of the error in distances obtained in this case is 0.45 cm. In order to justify the results, distance estimation was attempted at the same positions using another acoustic frequency of 150 kHz, the results of which are presented in Table 2. The standard deviation in error in distances obtained for this excitation frequency is 0.43 cm.

![Figure 11](image2.png)

Figure 11. Variation in error of the estimated distance with actual distance (a) Error measurement over different trials (b) Plot showing mean and standard deviation in error over all trials.

Another issue that needs further investigation is the need for pre-filtering before the CR Plot Analysis. In order to study this aspect, two sensors were placed 10 cm and 7 cm away from the source and signals were captured as the drive voltage of the transducer was reduced. The distance estimation is performed with and without ALE. The results averaged over 5 trials are presented in Figure 12. It may be observed that applying a pre-filtering tool like ALE improves the accuracy of location identification. However at the lowest drive voltage, the improvement obtained through ALE is not significant enough, possibly due to the errors in filtering process at extremely low SNR.

The experimental work presented in this paper involves the use of an acoustic transducer to generate acoustic emissions in a controlled manner. Future work involves testing and verification of the proposed scheme with real discharge signals in a transformer environment. There also exists a possibility of extending the CRPA to multiple dimensions for performing a
direct 3-D localization.

### Table 1. Distance estimation performed at frequency of 200 kHz

<table>
<thead>
<tr>
<th>Position Index</th>
<th>Distance from source sensor 1 (cm)</th>
<th>Distance from source sensor 2 (cm)</th>
<th>TDOA estimate (µs)</th>
<th>Distance estimate (cm)</th>
<th>Actual distance (cm)</th>
<th>Error (cm)</th>
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![Table 1 Diagram](image1)

### Table 2. Distance estimation performed at frequency of 150 kHz

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<th>Distance from source sensor 2 (cm)</th>
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![Table 2 Diagram](image2)

Figure 12. Comparison of error in distance estimates for raw and ALE filtered data.

### 5 Conclusion

In this paper, we explore the use of Cross Recurrence Plot Analysis based technique on signals detected by FBG sensors for detection and localization of partial discharges in power transformers. Detailed simulations are performed to assess the performance of the proposed technique for the cases of low SNR and signals with different SNR values. Optimum threshold settings are investigated through simulations and 1σ was found to be a good choice. A novel technique of extracting the frequency from CR plots is presented and frequencies of single as well as multiple-tones signals were extracted successfully. Experimental studies were conducted under controlled conditions and location estimation was attempted with the proposed technique. Near field manifestations on the error estimates were observed and verified experimentally. Finally, the use of a pre-filtering tool such as ALE was found to improve the accuracy of location estimation to have errors of the order less than a centimeter under conditions providing sufficient SNR.

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