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Quantitative comparison of partial discharge localization algorithms using time difference of arrival measurement in substation

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ABSTRACT

Partial discharge (PD) non-contact detection by using antenna array has gained extensive attention in air-insulated substation (AIS) monitoring. One significant superiority is that the positions of PD sources can be located by utilizing the differences of received signals. Also locating electromagnetic/acoustic radiative sources using passive sensor arrays is a continuous theme in the field of radar and sonar, and various localization methods have been developed. In this paper, we mainly concern the time difference localization techniques, which can be classified as maximum-likelihood (ML) and least squares (LS) estimators. The ML estimates positions by maximizing the probability density function, which is a high-nonlinear problem and difficult to be solved. The iteration or simplification solutions are proposed to give approximate ML results. As an alternative, LS estimators which can give closed-form solutions and with high computation efficiency are widely adopted. In this research, the theories and calculation procedures of several kinds of localization algorithms are reviewed, i.e., approximate ML, probability-based method, spherical-interpolation, Chan and squared range-difference LS, and their performances are compared by Monte Carlo simulation and experiments. The results indicate that probability-based method presents highest accuracy and computation efficiency. Among other methods, Chan, bias-reduction and squared range-difference provide satisfying localization performance.

1. Introduction

Partial discharge (PD) is a valuable symptom of insulation degradation in electrical power equipment. On-line PD monitoring instruments are mounted on some crucial equipment such as power transformer and gas-insulated substation (GIS) to assess the insulation condition, but these detection instruments only work for individual equipment [1,2]. To measure the PDs in the whole air-insulated substation (AIS), Moore et al. developed a remote PD detection and early warning system, in which a four-element antenna array is adopted to couple the electromagnetic waves radiated by PDs [3,4]. The locations of PD sources can be discovered by utilizing the waveform features such as amplitude, energy and arrival time of acquired signals. As a result, the performances of localization algorithms are of importance to accurately find the locations of PD sources.

Several kinds of localization techniques such as received signal strength (RSS), time of arrival (TOA), frequency difference of arrival (FDOA) and time difference of arrival (TDOA) have been adopted. The RSS method utilizes difference of amplitude or energy among sensors, and does not require high sampling rate and is with low hardware cost [5,6]. But the RSS only determines the source location roughly. FDOA cannot be applied to PD location due to the immobile feature of PD sources. Among these methods, the TDOA is widely adopted for its high localization accuracy [3,4,7–12]. The TDOA method is implemented with two major steps, namely, estimation of TDOAs and solving the nonlinear time-difference equations. The algorithms for TDOA estimation have been extensively studied in some Refs. [7–10]. In this research, we mainly focus on the solutions of TDOA equations. Since the TDOA equations are high-nonlinear and cannot be directly solved, numerical solution algorithms such as Newton–Raphson approach are widely adopted [3,13,14]. An initial guess close to the actual location is needed for such method to avoid local optimum. Furthermore, the method fails to convergence even the TDOA error is relatively small. Some searching algorithms such as grid-by-grid search [15–17], particle swarm optimization [18–20] and genetic algorithm [21] are adopted to find the coordinate with minimum residual error. In one of our previous published researches, the probability-based localization (PBL) algorithm is presented, which can reasonably integrate the TDOAs of multiple signals with joint probability density function [22].

Moreover, locating electromagnetic/acoustic radiative sources has

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been a continuous theme of research in radar and sonar. In these fields, theoretical models for source localization have been comprehensively built, and several effective tools such as Cramér-Rao Lower Bound (CRLB) were developed [23,24]. Moreover, some closed-form estimators such as plane intersection (PX) [25], spherical intersection (SX) [26], spherical interpolation (SI) [27], Chan [28–30], bias reduction (BiasRed) [31], squared range-difference measurement (SRD) [32] are developed and tested. These methods mainly adopt least square (LS) estimation approaches, and give direct (non-iterative) solutions. Nevertheless, owing to the differences in considered constraints, noise characteristics and solving techniques, these localization algorithms present disparate accuracy, and their performances need to be comprehensively investigated. The theoretical models and LS algorithms can be applied to PD localization in substation or power transformer. However, since the number and configuration of mounted sensors are limited by various factors such as structure of power equipment and testing space which are generally different from that of other research fields, the applicability and accuracy of different algorithms need to be tested in detail.

In this paper, we mainly concern the localization of PD sources in substation space, and several kinds of estimation algorithms in PD measurement and other research fields are adopted and their performances are quantitatively compared. In Section 2, the basic theories and computation procedures of these algorithms are summarized. Section 3 presents the root of mean square error (RMSE) and bias error to evaluate the localization accuracy, and independent and correlative TDOA errors are considered. The comparisons of various approaches are illustrated in detail in Section 4. It can be found that different algorithms have their own advantages. The PBL presents highest accuracy in almost all tests. The Chan and BiasRed methods also give small error in most of the cases, especially under correlated TDOA noise, while SRD performs well under independent noise.

2. TDOA localization algorithms

According to the differences of mathematical theories, the localization estimators are classified as two classes, namely maximum-likelihood estimators (MLE) and least squares (LS) approaches. The computation procedures of various algorithms are summarized below.

2.1. Source localization problem

The AIS can be treated as a 2-dimensional (2D) space for the relatively short height of power equipment compared to the large space of AIS [4]. The array is assumed to consist N antennas placed arbitrarily at positions $\boldsymbol{s}_i = [x_i, y_i]^T$, $i = 1, 2, \ldots, N$, and the PD source is located at $\boldsymbol{\theta} = [x, y]^T$, as shown in Fig. 1. Let the true distance between the PD source and antenna i be

$$r_i = \|\theta - \boldsymbol{s}_i\| = \sqrt{(x-x_i)^2 + (y-y_i)^2} \quad (1)$$

The difference between the distances of antennas i and j from the source is donated by

$$d_{ij} = r_i - r_j \qquad i, j = 1, 2, \ldots, N \quad (2)$$

If the first antenna is set as the reference, the time-difference equations can be written with a vector form

$$\begin{aligned} &\boldsymbol{d} = c(\boldsymbol{T} + \varepsilon) \\ &\boldsymbol{d} = [d_{21}, d_{31}, \ldots, d_{N1}]^T \qquad \boldsymbol{T} = [t_{21}, t_{31}, \ldots, t_{N1}]^T \\ &\varepsilon = [\varepsilon_2, \varepsilon_3, \ldots, \varepsilon_N]^T \end{aligned} \quad (3)$$

where c is propagation speed of electromagnetic waves, namely light speed, t_{i1} is estimated TDOA between antennas i and 1, ε_i is the measurement error. Under the measurement model (3), we are now faced with the parameter estimation problem of solving the source location information from the measured TDOAs.

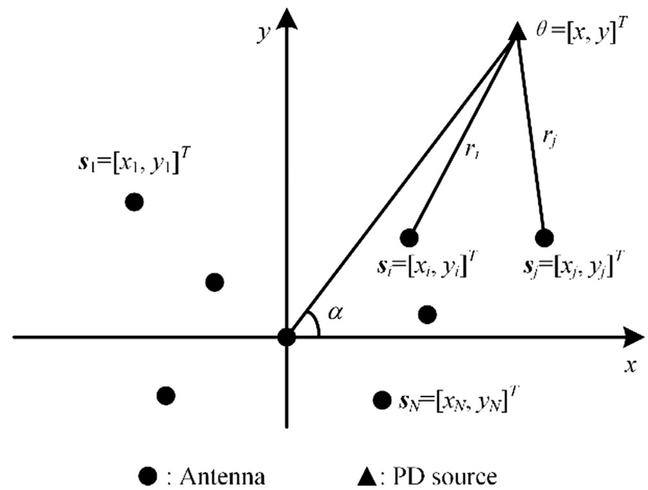

Fig. 1. Localization in 2D space.

2.2. Maximum-likelihood estimator

For line-of-sight environment, the elements of $\boldsymbol{\varepsilon}$ are zero-mean Gaussian random variables. The probability density function (PDF) of $\boldsymbol{T}$ conditioned on $\boldsymbol{\theta}$ is given by [23,29,30]

$$f(\boldsymbol{T}/\theta) = (2\pi)^{-\frac{N-1}{2}}(\det\boldsymbol{Q})^{-\frac{1}{2}}\exp\left\{-\frac{J}{2}\right\} \quad (4)$$

$$J = \left[\boldsymbol{T} - \frac{\boldsymbol{d}(\theta)}{c}\right]^T \boldsymbol{Q}^{-1}\left[\boldsymbol{T} - \frac{\boldsymbol{d}(\theta)}{c}\right] \quad (5)$$

and $\boldsymbol{Q}$ is covariance matrix of $\boldsymbol{\varepsilon}$. The ML estimation is the $\boldsymbol{\theta}$ that minimizes J. However, since the TDOA equations are highly nonlinear, it is very difficult to find an unbiased estimator.

2.2.1. Numerical searching methods

Neglecting the correlation between TDOAs, Eq. (5) becomes

$$J = \frac{1}{\sigma^2}\left[\boldsymbol{T} - \frac{\boldsymbol{d}(\theta)}{c}\right]^T\left[\boldsymbol{T} - \frac{\boldsymbol{d}(\theta)}{c}\right] \quad (6)$$

where σ^2 is the variance of measurement noise, and (6) is also known as residual error. Then the problem can be solved with common mathematical techniques such as Newton-Raphson iteration algorithm. The method has been demonstrated in many Refs. [3,13,14], and the computation procedures are not presented here. An alternative method is using search or optimization algorithms to find the coordinate with minimum residual error, in which the grid-by-grid search [15–17], particle swarm optimization [18–20] and genetic algorithm [21] are widely adopted.

2.2.2. Approximate maximum-likelihood estimation

A closed-form approximate solution to the MLE (AML) problem is derived in [30]. Setting the gradient of J (5) with respect to $\boldsymbol{\theta}$ to zero then gives

$$2\boldsymbol{\Phi}\boldsymbol{D}\theta = \boldsymbol{\Phi}(\boldsymbol{v}_1 + r_1\boldsymbol{\Psi}) \quad (7)$$

$$\boldsymbol{\Phi} = \left[\frac{\partial \boldsymbol{d}(\theta)}{\partial\theta}\right]^T \boldsymbol{Q}^{-1}\mathrm{diag}\left[\frac{1}{r_2 + r_1 + \Delta_{21}}, \ldots, \frac{1}{r_N + r_1 + \Delta_{N1}}\right] \quad (8)$$

$$\boldsymbol{D} = \begin{bmatrix} x_1 - x_2 & y_1 - y_2 \\ \vdots & \vdots \\ x_1 - x_N & y_1 - y_N \end{bmatrix} \qquad \boldsymbol{\Psi} = 2[\Delta_{21}, \ldots, \Delta_{N1}]^T \quad (9)$$

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