Engineering Science and Technology, an International Journal 19 (2016) 1781–1787

Contents lists available at ScienceDirect

Engineering Science and Technology, an International Journal

journal homepage: www.elsevier.com/locate/jestch

Short Communication

Statistical monitoring of linear antenna arrays

Fouzi Harrou *, Ying Sun

King Abdullah University of Science and Technology (KAUST), Computer, Electrical and Mathematical Sciences & Engineering (CEMSE) Division, Thuwal 23955-6900, Saudi Arabia

ARTICLE INFO

Article history:
Received 8 July 2016
Revised 4 October 2016
Accepted 22 October 2016
Available online 3 November 2016

Keywords:
Radiation pattern
Linear antenna arrays
Hypothesis testing
Fault detection
GLR test

ABSTRACT

The paper concerns the problem of monitoring linear antenna arrays using the generalized likelihood ratio (GLR) test. When an abnormal event (fault) affects an array of antenna elements, the radiation pattern changes and significant deviation from the desired design performance specifications can resulted. In this paper, the detection of faults is addressed from a statistical point of view as a fault detection problem. Specifically, a statistical method rested on the GLR principle is used to detect potential faults in linear arrays. To assess the strength of the GLR-based monitoring scheme, three case studies involving different types of faults were performed. Simulation results clearly shown the effectiveness of the GLR-based fault-detection method to monitor the performance of linear antenna arrays.

1. Introduction

Recent developments in wireless communication systems have significantly risen the demand for antenna arrays [1–4]. There is a clear need and demand for high-performance antenna array systems in numerous applications such as remote sensing, satellite communications and biomedical imaging [5–8]. Unfortunately, in practical working conditions, it is not unusual to have some failures in the antenna arrays. Faults can be due to a settling of dust particles on the antenna elements, a poor design, a failure of drive electronics, an improper use, a shift in the position of the array elements during installation, or a combination of these different causes [9]. The occurrence of faults in one or more elements in an antenna array changes the radiation pattern of the array, which degrades the performance of the entire array [10,11]. Therefore, monitoring of antennas is important to reveal any abnormalities and for their proper and effective operation. Furthermore, antennas need to be monitored so that faults can be detected, isolated, and removed to maintain efficient safe operation of the wireless system.

Complete (also termed on-off) and partial faults in a linear array of antenna elements are two types of faults commonly encountered in practice [12]. Antenna elements with on-off faults are widely encountered in practice and do not radiate. Antenna elements with partial faults (caused by interference or other factors) degradation in the desired radiation pattern. Generally, faulty array elements cannot only distort the directivity of the antenna pattern, but also the side lobe levels of the radiation pattern [13,14]. Indeed, under normal operation the measured pattern is close to the desired one due to measurement noise and errors, while it significantly deviate from desired pattern under the presence of abnormal events (faults). Along past two decades, researchers and engineers have developed several methods aimed at detecting abnormal events in antenna arrays, and including compressive sensing [15], Bayesian compressive sensing [14], neural networks [16,17], genetic algorithms [18,19], bacterial foraging optimization [20], exhaustive searches [21], support vector machines [22], and distributional approaches [23].

Anomaly detection and diagnosis are two vital components of process monitoring: anomalies are first identified and then isolated to ensure that they can be handled appropriately [24,25]. To enhance antenna systems operation, we want to monitor the antenna arrays in an efficient manner to identify any abnormality that may result in any degradation of antenna arrays performance, operation reliability and profitability, in order that we can respond accordingly by making any necessary correction to the inspected system. Statistical process control (SPC), identifies abnormalities in a process to evaluate the quality of that process [26], are some tools that can be to achieve these objective. They have been applied in numerous applications [27,28]. SPC charts take quality control data from the inspected system and plotted them over time. Various types of univariate charts have been developed, including the Shewhart chart, the cumulative sum (CUSUM) control chart, the exponentially weighted moving average (EWMA) chart, and control charts based on generalized likelihood ratio (GLR) hypothesis testing [26,29]. Some monitoring charts can be adjusted to be more sensitive to specific magnitudes anomalies. For example,

* Corresponding author.
E-mail address: fouzi.harrou@kaust.edu.sa (F. Harrou).

Peer review under responsibility of Karabuk University.

http://dx.doi.org/10.1016/j.jestch.2016.10.010
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Shewhart-type charts are more sensitive to large shifts in the process mean than to small shifts [26], while the EWMA and CUSUM charts are more sensitive to small magnitude shifts in process mean [28]. The ability to detect smaller parameter shifts can be improved by using a chart based on information from the entire process history. However, CUSUM and EWMA charts are not very effective at detecting large shifts [11]. Because the size of the shift in process mean that will occur in an application is unknown, so it is desirable to be able to effectively detect a wide range of shift sizes. When true shift magnitudes are unknown or not constant, either assumptions have to be made regarding shift sizes or capable algorithms have to be designed to estimate magnitudes of different sizes. A likelihood ratio test can be a useful approach for obtaining a control chart that can detect process changes of different sizes [30,31]. Such charts, usually called GLR charts, have been shown to be very effective in a wide variety of settings, giving them the advantage of being designed for use in several applications. An important advantage of GLR charts is that the control limit is the only design parameter that needs to be specified [32].

This paper presents a statistical method based on the principles of GLR method to detect faults in a linear array of antenna elements. The main advantage of the GLR-based monitoring chart compared with machine learning approaches, such as SVM and neural networks, is that it can be easily implemented in real time due to its low computational cost. Machine-learning-based monitoring involves complex training and has high computational cost. The remainder of the paper is organized as follows. Section 2 outlines some basic antenna array theory as it applies to this problem. Then, the GLR test that is commonly used in composite hypothesis testing is briefly described in Section 3. In Section 4, a methodology for fault detection in antenna arrays is described, followed by simulated examples that illustrate the performance of the GLR hypothesis testing method in Section 5. Subsequently this paper is concluded with recommendation for future work in Section 6.

2. Linear array antenna

Let us consider a fault-free linear array of antenna elements comprises an even number (2N) of isotropic elements. Assuming that the elements are symmetrically conjugated and are in symmetrically excited configurations about the center of the array. The normalized radiation pattern of this array is computed using the following expression [5]:

$$F_s(\varphi) = \frac{f(\varphi)}{F_{s\max}} \sum_{i=1}^{2N} a_i \cos\left(kx_i \sin(\varphi) + \psi_i\right), \tag{1}$$

where $f(\varphi)$ represents the element pattern, φ represents the angular direction, a_i and ψ_i are respectively the current excitation amplitude and phase of the i^{th} array element placed at the position given by x_i (see Fig. 1), $k = \frac{2\pi}{\lambda}$ is the wave number with a wavelength of λ,

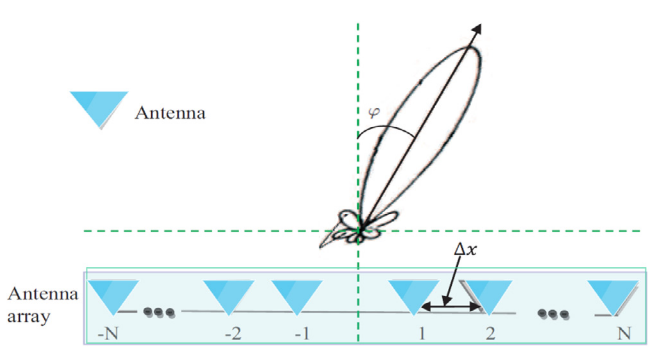

Fig. 1. Linear array having 2N elements disposed symmetrically along the x-axis.

and the position x_i is calculated using the inter-element spacing as: $x_i = (i - \frac{1}{2})\Delta x,\ i = 1, 2N$.

The measured pattern of the array are usually corrupted by errors $\xi \sim \mathcal{N}(0, \sigma^2)$, which can be modeled by additive Gaussian noise with zero-mean, and variance σ^2, so that the Eq. (2) becomes

$$F_s(\varphi) = \frac{f(\varphi)}{F_{s\max}} \sum_{i=1}^{2N} a_i \cos\left(kx_i \sin(\varphi) + \psi_i\right) + \xi. \tag{2}$$

Failure(s) in antenna arrays can be severely distort the designed radiation pattern. As discussed earlier, faults can be classified into two types: on-off and partial faults. The on-off faults in antenna arrays results when the affected elements fail completely (i.e., stop to radiate at all), which is equivalent to supposing that their corresponding excitations are zero. On the other hand, in an array affected by partial failures, the damaged elements do not completely fail but radiate a fraction of its normal power. As the number of failed elements increase in the array, the pattern become more degraded. Thus, detecting the presence of faults in antenna arrays is necessary to ensure their normal operation. A description of the GLR test, which is utilized towards this objective, is given next.

3. Generalized likelihood ratio test

A general methodology for deriving a testing procedure for a composite hypothesis-testing problem is the GLRT described here. GLR hypothesis testing is a well-known algorithm for statistical decision-making process, which is able to decide between two composite hypotheses ([33–35]). In binary hypothesis testing, when hypotheses are composite or the corresponding data probability density functions contain unknown parameters, the GLR test is a popular means for deciding between two possibilities. Specifically, it is based on the maximization of the likelihood ratio function over all possible faults ([36]), which make it usually applicable to most parametric hypothesis-testing problems. The GLR test is a widely used fault-detection technique by scientists and engineers in various disciplines, including imaging analysis ([37,38]), power systems ([39]), gas turbines ([40]), electronic systems ([41]), environmental process ([42]), and chemical processes ([43]).

Assume that we have a measured vector $Y = [y_1, y_2, \ldots, y_n] \in \mathbb{R}^n$ distributed according to one of the two following Normal distributions, $\mathcal{N}(0, \sigma^2 I_n)$ or $\mathcal{N}(\theta{\neq}0, \sigma^2 I_n)$, where θ is the mean vector (which is the value of the anomaly) and $\sigma^2 > 0$ is the variance, which is supposed to be known. The GLR test decides between the null hypothesis $\mathcal{H}_0 = \{Y \sim \mathcal{N}(0, \sigma^2 I_n)\}$ and the alternative hypothesis $\mathcal{H}_1 = \{Y \sim \mathcal{N}(\theta, \sigma^2 I_n)\}$ by comparing between the generalized likelihood ratio, $\mathcal{L}(Y)$, and a given value of the threshold, $h(\alpha)$. The likelihood ratio test statistic, $\mathcal{L}(Y)$, is given as

$$\begin{aligned} \mathcal{L}(Y) &= 2\log \frac{\theta{\in}\mathbb{R}^n sup f_\theta(Y)}{f_{\theta=0}(Y)} \\ &= 2\log\left\{ \sup_\theta \exp\left\{-\frac{\|Y-\theta\|_2^2}{2\sigma^2}\right\} / \exp\left\{-\frac{\|Y\|_2^2}{2\sigma^2}\right\}\right\} \end{aligned} \tag{3}$$

where $\|.\|_2$ is the Euclidean norm, $f_\theta(Y) = \frac{1}{(2\pi)^{\frac{n}{2}}\sigma^n} \exp\left\{-\frac{1}{2\sigma^2}\|Y-\theta\|_2^2\right\}$ is the pdf of Y. Rewriting Eq. 3 we have:

$$\begin{aligned} \mathcal{L}(Y) &= \frac{1}{\sigma^2}\left\{ \min_\theta \|Y-\theta\|_2^2 + \|Y\|_2^2 \right\} \\ &= \frac{1}{\sigma^2}\left\{ \|Y-\widehat{\theta}\|_2^2 + \|Y\|_2^2 \right\}. \end{aligned} \tag{4}$$

In Eq. (4), we obtain the maximum estimate of θ as: $\widehat{\theta} = \arg\theta \min\|Y-\theta\|_2^2 = Y$. Substituting $\widehat{\theta}$ into equation we get

$$\mathcal{L}(Y) = \frac{1}{\sigma^2}\{\|Y\|_2^2\}. \tag{5}$$