Optik - International Journal for Light and Electron Optics 172 (2018) 561–570

Contents lists available at ScienceDirect

Optik

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

Original research article

Optical fiber intrusion signal unmixing by constrained quadratic programming approach

Yuan Zhang, Kaixin Tian, Liping Pang*, Hongquan Qu, Qing Tian, Zhu Han

School of Electronic and Information Engineering, North China University of Technology, Beijing 100144, China

A R T I C L E I N F O

Keywords:
Intrusion signal unmixing
Constrained
Quadratic programming
OFPS

A B S T R A C T

Optical fiber intrusion signal detection is an effective long-distance sensing technology for perimeter intrusion behavior. The existing optical fiber pre-warning system (OFPS) has been able to detect and identify a variety of intrusion behaviors. However, when various intrusion behaviors occur at the same time, identification performance in OFPS will decrease. In this paper, we model the mixed intrusion signal from a geometric perspective at first, and then the unmixing method is studied under the model constraint condition. We set the model error function as an objective function, and transform the unmixing problem into a constrained quadratic programming problem. Through iteration, the pure intrusion signals and their proportion are obtained. This method does not require prior knowledge such as the number of pure components and corresponding characteristics. Compared with the conventional methods, the proposed algorithm can obtain more accurate features under unsupervised conditions.

1. Introduction

Optical fiber sensors can sense and locate the intrusions around the fiber link [1,2]. The main principle is that the intrusion behavior causes a weak vibration in the corresponding position of optical fiber, and this weak vibration changes the refractive index at the corresponding position. Under normal circumstances, most optical fiber signals propagate forward due to the full reflection effect, but the refractive index change greatly improves the probability of the backscatter light. The system further collects these backscattered light signals and carries out signal detection to extract the intrusion signals. The time delay of the intrusion signal determines the intrusion position, and the intrusion vibration can also modulate the backscattered light signal. Thus, the detected intrusion signals carry the characteristics associated with intrusion behavior, such as the power spectrum distribution which is called as spectrum for short in the rest of the paper.

There are many different kinds of intrusion behaviors, so their spectrum curves are accordingly different. The spectrum generated by a specific intrusion behavior is called the characteristic spectrum that can be obtained through laboratory calibration [3]. We expect the signal collected by the system at a time is pure intrusion signal because the characteristic spectrum of pure signal will be easy to identify. However, in reality, the intrusion behavior is often accompanied by various factors. For example, when people use electric drills, footwork also exists. In this case, the intrusion signal should actually be regarded as a mixture of various types of pure signals, and its spectrum is also the mixed spectrum. In order to accurately analyze the type of intrusion signals, the OFPS system must have the ability to unmix signals.

The mixed signal spectrum in OFPS is formed by the linear superposition of characteristic spectrum components, and the

* Corresponding author.
E-mail address: pangliping@buaa.edu.cn (L. Pang).

https://doi.org/10.1016/j.ijleo.2018.07.060
Received 27 June 2018; Received in revised form 10 July 2018; Accepted 16 July 2018

proportion of each component is distributed within the interval of [0,1]. From the perspective of statistics, the mixed signal samples are distributed within a simplex whose endpoints are the characteristic spectrums. Therefore, the essence of the OFPS unmixing problem is to find the endpoints of the simplex where the sample data is located. According to this model, two kinds of unmixing methods are proposed. The first type uses the simplex volume as the objective function to solve by mathematical optimization method, which is called SVA algorithm [4–7]. The second type is based on matrix decomposition and makes blind separation for the mixed signal [8–10]. The related typical algorithm is the NMF [11–13]. The problem with these two types of methods is that they need to know the number of characteristic spectrums in the samples. Thus, the number of mixed signal types must be known before unmixing. If there is already prior knowledge of the unmixed samples, it is feasible to use these two methods. However, the monitoring distances of the optical fiber sensors is usually dozens of kilometers, and the intrusion behavior is also random. As a result, the number of intrusion signal types cannot be judged in advance. Hence, the purpose of the new algorithm proposed in this paper is to achieve unmixing without knowing the number of intrusion signal types.

In order to solve the above problem, this paper proposes an unmixing method based on iterative quadratic programming. First, we establish the residual error model of the characteristic spectrum estimation, which is a convex function with the characteristic spectrum as its parameter. Then, by using the constrained quadratic programming method to solve the model equation, the estimated characteristic spectrum is obtained. The constraint condition comes from two aspects: one is the equality constraint determined by the linear mixed model, and the other is the inequality constraints caused by the physical limitations of characteristic spectrum proportion. Further, through an iterative strategy, the estimated spectrum constantly approaches the simplex endpoint in the high-dimensional space. In the end, we realize unmixing and get accurate characteristic spectrums. Moreover, since the proportion of the characteristic spectrum reflects the composition ratio in the mixed signal, the characteristic spectrum with a very low proportion will be excluded. We use actual data to verify the effectiveness of our algorithm. Compared with the SVA and NMF methods, the proposed algorithm can extract more accurate features under unsupervised conditions.

This paper is organized as follows. In Section 2, we introduce the signal model for OFPS unmixing. The details of iteration quadratic programming approach are given in Section 3. The experimental analysis of actual data is described in Section 4. Finally, the conclusion is provided in Section 5.

2. The residual error model for OFPS unmixing

The optical fiber in OFPS is usually buried underground with the object to be monitored. If there is any form of vibration above it, the vibration will propagate to the corresponding position of the optical fiber and modulate the backscattered light signal inside the fiber. If various types of vibrations occur simultaneously, the backscattered light signal is modulated by superimposed vibration and then converted to the digital signal via a series of signal processing. Next, the digital signals are detected by the detection unit [14,15] and then the feature extraction [16,17] is performed. In this paper, the power spectrums are regarded as the signal features. The power spectrum is then sent to the unmixing unit for signal unmixing. Finally, the unmixed components are identified by the recognition unit [18,19]. The algorithm studied in this paper is applied to the unmixing unit as shown in Fig. 1.

We assume the total number of the mixed intrusion signal samples is N, and these samples are formed by superimposing K pure intrusion signals according to the linear model, where $\mathbf{w}_j$ is the spectrum corresponding to the j-th intrusion signal, $j = 1,2, \ldots,K$. The dimension of $\mathbf{w}_j$ is L, which is the number of frequency bands. Then, the i-th observed spectrum $\boldsymbol{\gamma}_i$ can be expressed by

$$\boldsymbol{\gamma}_i = \mathbf{W}\mathbf{h}_i + \mathbf{n} \tag{1}$$

where $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_k]$ is an $L \times K$ matrix whose columns are the characteristic spectrums, and $\mathbf{h}_i = [h_{1i}, h_{2i}, \cdots, h_{Ki}]^T$ is a scalar representing the fractional abundance of the characteristic spectrum $\mathbf{w}_j$ in the observed spectrum $\boldsymbol{\gamma}_i$. $\mathbf{n}$ is an additive observation noise vector. Considering abundance sum-to-one constraint, $\mathbf{h}_i$ should satisfies the following condition,

$$\sum_{j=1}^{K} h_{ji} = 1, \;\; h_{ji} \geq 0, \;\; i = 1, 2, \cdots, N \tag{2}$$

For all the observed samples, the estimated characteristic spectrums should make the expected overall residual error smallest. Here, we define the residual error as

$$\mathrm{RS} = \sum_{i=1}^{N} || \boldsymbol{\gamma}_i - \mathbf{W}\mathbf{h}_i ||_2^2 \tag{3}$$

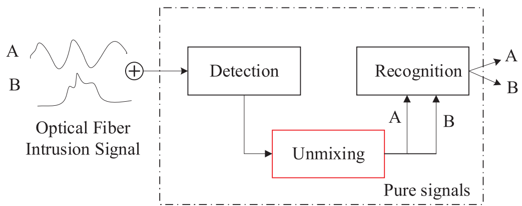

Fig. 1. The processing flow of OFPS intrusion signal detection and identification.