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Compressive sensing-based electrostatic sensor array signal processing and exhausted abnormal debris detecting

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ABSTRACT

When faults happen at gas path components of gas turbines, some sparsely-distributed and charged debris will be generated and released into the exhaust gas. The debris is called abnormal debris. Electrostatic sensors can detect the debris online and further indicate the faults. It is generally considered that, under a specific working condition, a more serious fault generates more and larger debris, and a piece of larger debris carries more charge. Therefore, the amount and charge of the abnormal debris are important indicators of the fault severity. However, because an electrostatic sensor can only detect the superposed effect on the electrostatic field of all the debris, it can hardly identify the amount and position of the debris. Moreover, because signals of electrostatic sensors depend on not only charge but also position of debris, and the position information is difficult to acquire, measuring debris charge accurately using the electrostatic detecting method is still a technical difficulty. To solve these problems, a hemisphere-shaped electrostatic sensors' circular array (HSESCA) is used, and an array signal processing method based on compressive sensing (CS) is proposed in this paper. To research in a theoretical framework of CS, the measurement model of the HSESCA is discretized into a sparse representation form by meshing. In this way, the amount and charge of the abnormal debris are described as a sparse vector. It is further reconstructed by constraining l_1-norm when solving an underdetermined equation. In addition, a pre-processing method based on singular value decomposition and a result calibration method based on weighted-centroid algorithm are applied to ensure the accuracy of the reconstruction. The proposed method is validated by both numerical simulations and experiments. Reconstruction errors, characteristics of the results and some related factors are discussed.

1. Introduction

Gas path components such as blades, fuel nozzles and combustion chambers are main fault locations of gas turbines, because they often work under severe conditions of high temperature, high speed, high stress, and so on [1]. When a fault happens at the components, some debris will fall off the corresponding location and enter the gas path. This debris has larger size (≥ 40 μm) than exhausted normal particles (5–7 nm or 20–30 nm), so it is called abnormal debris [2]. Conveyed debris in the gas path will be charged due to friction, collision and high temperature [2,3]. Generally speaking, the large debris will

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carry more charge than the normal particles. Therefore, the occurrence of abnormal debris will cause fluctuations of electrostatic field in the gas path [2,4]. Based on these principles, electrostatic monitoring has become a promising way of on-line gas path monitoring. Electrostatic sensors are embedded into the wall of an exhaust pipe to detect abnormal debris due to faults. In summary, electrostatic monitoring has advantages of robustness, real-time and low cost compared with traditional methods [3,5,6]. In particular, abnormal debris is directly caused by damages, so electrostatic monitoring is promising to detect early damages of gas path components.

It is generally assumed that, under a specific working condition, a more serious fault will generate more and larger abnormal debris and larger debris will carry more charge [2,3]. Therefore, the amount and charge of abnormal debris are important indicators of damage severity. However, a single electrostatic sensor can only detect the superposed effect on electrostatic field of all charged debris, so the amount and position of charged debris can hardly be identified. Moreover, the sensitivity of an electrostatic sensor is quite inhomogeneous [7–9], which means that output signals of an electrostatic sensor depend on not only the amount of the charge but also the position of the debris. That is to say, the output signal of an electrostatic sensor for a piece of nearby debris with small charge may be equal to that for a piece of faraway debris with big charge [10]. In a word, the amount and charge of abnormal debris can hardly be accurately detected by using a single electrostatic sensor. In order to solve this problem, it is natural to use multiple electrostatic sensors to make an electrostatic sensor array, which has already achieved great attention in the field of electrostatic monitoring.

Nowadays, array-based electrostatic monitoring is usually used for parameter monitoring of gas-solid flows [11–15], where circular electrostatic sensor arrays are a class of typical array structures [10–13]. A circular electrostatic sensor array is constructed by placing some identical electrostatic sensors uniformly around a circular pipe in one cross-section which is called the observation cross-section. This structure has an inherent advantage in electrostatic tomography, that is to image the distribution of the solid phase based on charging phenomena [11–13]. As for this application, the number of independent measurements, namely the number of electrostatic sensors, is generally far less than that of the pixels to be imaged. Therefore, the difficulty of electrostatic tomography is to solve an underdetermined equation which has infinitely many possible solutions, thus the solving process has to be constrained by using some priori conditions to find a group of optimal solutions. In previous studies, an electrostatic tomography system was usually designed for a dense gas-solid flow whose solid phase can always form an obvious profile in the observation cross-section [11,13]. In this case, l_2-minimization is a suitable constraint. It is an energy-constraint strategy whose solution methods include linear back projection [13], Tikhonov regularization [11], Landweber iteration [16], etc. As for detecting exhausted abnormal debris in gas turbines, it can be similarly regarded as a tomography problem to image the distribution of charged debris. However, at the stage of early damages, abnormal debris is quite few and sparse in both space and time. That is to say, there is only one in most cases and very few in other cases pieces of abnormal debris across the observation cross-section at the same time. In this case, sparsity is a much more suitable constraint than l_2-minimization to obtain a group of optimal solutions. Thus sparsity-based array signal processing methods can be developed for detecting exhausted abnormal debris in gas turbines.

Compressive sensing (CS) was formally proposed by Donoho [17], Candès [18] et al. in 2006. It is an innovative theory of signal acquisition, coding and encoding. CS takes full advantage of sparsity and compressibility of signals, which is much suitable to solve aforementioned sparsity-optimization problems [19–24]. Among the many existing applications of CS, sparse-target localization based on wireless sensor networks is a representative one [19–21]. In the theoretical framework of CS, position information of K sparse targets is described as an N-element-long sparse vector which has K nonzero elements ($K \ll N$). M dispersed sensors are used to obtain an M-element-long measurement vector ($M \ll N$), which is regarded as a linear compression of the sparse vector into a lower dimensional vector. Then, as long as a few conditions are met, position information of the K targets can be reconstructed with high probability from the compressed vector by solving a sparsity-optimization problem [21]. It can be seen that there are similarities in not only sparsity but also objective between the sparse-target localization and the abnormal debris detecting in gas turbines. As to our best knowledge, however, CS theory has never been used for electrostatic sensor array signal processing.

In our previous work [10], a hemisphere-shaped electrostatic sensors' circular array (HSESCA) was proposed and its spatial dynamic sensitivity was defined. On this basis, this paper aims to present a CS-based array signal processing method to advance the previous study [10] in exhausted abnormal debris detecting. This is a new application of CS to solve a practical problem, which is promising in overcoming the technical difficulty of measuring the amount and charge of abnormal debris. The left contents are organized as follows. Fundamentals of CS and basis pursuit are briefly introduced in Section 2. A measurement model of the HSESCA is built in Section 3. Key and feasible technical details of the proposed method are studied in Section 4. Numerical simulations and experiments are done for validations in Section 5 and Section 6 respectively. The main results are concluded in Section 7.

2. Fundamentals of compressive sensing (CS) and basis pursuit (BP) algorithm

Let $\boldsymbol{x}$ be an N-element-long discrete-time signal. If there is only K nonzero elements among all the N elements ($K \ll N$), $\boldsymbol{x}$ is called a K-sparse signal. In the theoretical framework of CS, if $\boldsymbol{x}$ is the original signal to be reconstructed, its compressed measurements can be represented as

$$\boldsymbol{y} = \boldsymbol{\Theta x} \tag{1}$$