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Frequency as a key parameter in discriminating the failure types of thermal barrier coatings: Cluster analysis of acoustic emission signals

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ABSTRACT

A key parameter in discriminating the failure types of thermal barrier coatings (TBCs) was found out by using the *k*-means cluster analysis of acoustic emission (AE) signals. It is shown that there are five classes of mechanisms, including surface vertical cracks, opening interface cracks, sliding interface cracks, substrate deformation and macroscopic cleavage or spallation. Except for the last one, the other four classes can be clearly distinguished from their peak frequency distributions in the ranges of 170–250, 400–500, 260–350 and 40–150 kHz, respectively. However, AE signals overlap with each other in other parameter spaces, e.g., amplitude, energy, rise time, and duration time. The results indicate that the frequency can be applied to identify the AE source mechanisms in TBCs.

1. Introduction

As one of the most reliable methods for increasing the service temperature of aeroengines, thermal barrier coatings (TBCs) have been widely applied in vanes, turbine blades and combustors [1–3]. The TBCs commonly comprise an insulated ceramic coating, an antioxidant adhesive bond coating, and a substrate enduring mechanical loading. Another oxide layer is formed between bond and top ceramic coating due to high temperature exposure. However, each layer and its interfaces have remarkably different physical, thermal and mechanical properties, resulting in various levels of failure risk under the most extreme service conditions. The complex shape and structure of the TBCs, along with harsh operating conditions, make the prediction of their failure and service life very difficult and even intractable [1,4]. To elucidate failure mechanisms and assess their service reliability, therefore, it is desirable to real-timely monitor the failure process of the TBCs.

Because of containing rich damage-related information such as deformation and crack nucleation and propagation, acoustic emission (AE) is a suitable tool to investigate the failure behavior of the TBCs. As a typical non-stationary process, information on failure is difficult to obtain by the AE waveform in a time space, so other parameters (e.g., amplitude, energy, rise time, count and frequency) are commonly extracted to qualitatively analyze failure mechanisms [5,6], to optimize material compositions and preparation techniques [7,8], and to study influence factors on mechanical properties [9,10]. We have also developed a wave guide technique, by which AE can be used to monitor failure of the TBCs under cyclic heating [11]. As a coating/substrate system, there are various kinds of failure types in the TBCs, for example, cracks in layers, delamination at interfaces and deformation in substrate [10–12]. Therefore, the key problem to analyze the failure behavior of the TBCs by using the AE method is how to discriminate these failure types form their AE signals.

It is shown that, in a failure process with an identical measurement condition, the AE signals associated with the same failure mechanism are similar but those from different failure mechanisms are distinctly different. Thus it is possible to discriminate the failure types via the similarity analysis of AE signals. Berndt and Herman [13,14] investigated the failure mechanisms of the plasma-sprayed TBCs by using the statistical evaluation of the AE spectra and found that the failure process can be analyzed in terms of cumulative counts or a peak count rate. Ma and Takemoto [6] studied the fracture behavior of the TBCs under four-point bending and reported that the phases of longitudinal and transverse waves in their time-domain waveforms can be used to identify the crack type. However, our experiments showed that the frequency spectra of the AE signals are strongly dependent on the fracture types of the TBCs [9–12], which was also observed in composite materials [15] and large-scale rupture such as volcano-induced seismicity [16]. Based on the Fourier and wavelet transforms of the AE signals, four failure mechanisms have been found in the TBCs under various kinds of loadings [17]. The AE domain frequency fluctuating at 210 kHz corresponds to surface vertical cracks generated by tensile stress in ceramic coating,

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290 kHz to sliding interface cracks produced by shear stress at ceramic/bond coating interface, 430 kHz to opening interface cracks due to tensile stress at the ceramic/bond coating interface, and 130 kHz to substrate deformation. Based on the inverse processing of an AE signal, Pao revealed that the time-domain AE features such as duration and waveform are dependent on the failure type of a material [18]. Therefore, it is necessary to extract a key parameter from the AE signals, which can be applied to discriminate the failure types of the TBCs.

To find out such a key parameter, the cluster analysis based on multivariate statistics has been performed to recognize the patterns of AE signals. As one of the unsupervised pattern recognition methods, the signals can be clustered according to their characteristics without introducing any assumptions on the number or structure in advance [15,19]. Choosing a parameter such as the similarity coefficient or distance in a certain parameter space, the similarity between the signals is measured and then separated from each other according to a criterion in the space [15,19–22]. That is, there is not a limitation on the number of failure types and reference signals in clustering, and the AE signals are clustered or separated from each other according to their similarity or difference. Thus, the type discrimination is strongly dependent on the reasonability of a chosen parameter, which can be justified by the result of a clustering analysis.

In this paper, the crack type discrimination of the TBCs and its corresponding key parameter are investigated by clustering the AE signals. The paper is organized as follows. In Section 2, the k-means clustering method and its algorithm are introduced. The experimental details such as the detection of the AE signals are described in Section 3. Section 4 is dedicated to the clustering analysis on the AE signals recorded from the TBCs under tension and compression. The results of the crack type discrimination and key parameters are discussed in Section 5. Finally, a brief summary is given in Section 6.

2. The *k*-means clustering

As mentioned, the waveform, duration, peak frequency, and phase of various kinds of wave components can be used to discriminate the crack types of the TBCs associated with different failure mechanisms. However, it is unclear which parameter of the AE signals is representative enough to be applied as a classifier. Therefore, a multivariate analysis of the AE signals via the k-means clustering method is conducted to recognize the crack type of the AE signals. The clustering process of the AE signals is as follows. First, the AE signals are recorded from the failure process of the TBCs under loading. Second, the AE parameters possibly related to the failure mechanisms are extracted for clustering analysis. Then, a parameter to measure the similarity of the AE signals is chosen and the k-means clustering is carried out. Finally, the crack type of the AE signals and the key parameter are analyzed according to the results of the clustering analysis. Obviously, the selection of the AE parameters, the definition of the similarity measure and the clustering algorithm are emphases of the clustering analysis.

2.1. Selection of AE parameters

In the cluster analysis, the AE signals are treated as pattern vectors that are difficult to describe by their non-stationary waveforms, and thus, a number of AE parameters are extracted to characterize the feature of the signals. AE is a release and transmission of elastic energy produced by cracking or other activities. Accordingly, information on AE activities such as length, number, and type of cracks can be reflected through the parameters of AE signals. Commonly, AE counts and hits reflect the number of cracks. Amplitude, effective or average voltage, and energy are used to describe the strength of the AE signals, which is associated with the length and/or type of cracks. Although there is still a lack of a clear physical meaning, the duration and rise time are important to the size and/or type of cracks [18]. The parameters in a frequency space such as the peak frequency [10] and wavelet energy coefficient [11,12] have also been proved to contain information of crack types. However, some parameters are dependent, e.g., energy depends on effective or average voltage and duration. To comprehensively reflect the information of crack types and extract independent parameters, five parameters are selected, including amplitude, peak frequency, energy, rise time, and duration. Before clustering, these parameters with different physical dimensions are normalized in the range of [−1, 1] to construct the pattern vector and eliminate the physical dimension effect on the classification. The mean variance normalization [15] is one of the most commonly used methods in data standardization, and its principle is to transform the data to a standard normal distribution with the mean value of 0 and the standard deviation of 1. For a specimen with n AE signals, the mean variance normalization for the i-th parameter can be defined as

$$x_i' = \frac{x_i - \overline{x}}{\sigma} \tag{1}$$

where x_i and x_i' are original and standardized parameters of the AE signals, and $\overline{x}$ and σ are their mean and standard deviation, respectively.

2.2. Similarity measure

The similarity of samples should be determined before the partition of the AE signals. Selecting an appropriate similarity measure is the basis to guarantee the efficiency of the clustering analysis. Distance and similarity coefficient are the two most commonly used metrics to measure the similarity between signals and variables [19–23]. To measure the similarity of the failure mechanisms between the AE signals, therefore, the Euclidean distance is adopted and defined in a space with five variables [22], that is

$$d_w^2\left(\mathbf{X}^l, \mathbf{X}^m\right) = \sum_{j=1}^{5} \lambda_j \left(X_j^l - X_j^m\right)^2 \tag{2}$$

where λ_j is the j-th eigenvalue, X_j^l and X_j^m are the j-th coordinates of the vectors $\mathbf{X}^l$ and $\mathbf{X}^m$, respectively. The shorter the Euclidean distance, the more similar are the signals in the space. Therefore, for a given AE parameter that is appropriate to the failure type classification, the clustering result can be obviously distinguished from the distribution feature of the AE signals. The signals with the same damage type should gather together in a dense region, and in contrast, the signals from different damage types separate each other.

2.3. The *k*-means algorithm

Based on the k-means algorithm, n input vectors $(\mathbf{X}^1, \boldsymbol{X}^2, \ldots, \mathbf{X}^n)$ or signals are partitioned into k clusters with the centers of $(\mathbf{C}^1, \mathbf{C}^2, \ldots, \mathbf{C}^{k)}$. Using the nearest mean, each input vector is allocated to a cluster. Such a clustering algorithm can be described as follows [15,19–23]:

1. Assume the number k of clusters and randomly initialize each cluster center $\mathbf{C}^p$, where p is from 1 to k.
2. Calculate the Euclidean distance between the vector and the centers of the clusters and then assign each input vector (or pattern) to the nearest cluster.
3. Recalculate the location of the cluster center according to the nearest mean. Here it is worth noting that the distance of all input vectors in the same cluster to this new center is minimized, which can be expressed as

$$\sum_{p=1}^{k} \sum_{\mathbf{X}_q \in \mathbf{C}_p} \left\| \mathbf{X}_q - \mathbf{C}_p \right\|^2 \rightarrow \textbf{minimum}. \tag{3}$$

4. Repeat steps 2 and 3 until there are no changes in these center locations.