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Full-life dynamic identification of wear state based on on-line wear debris image features

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ABSTRACT

Wear state identification is a bottleneck for the monitoring of engine's condition due to its complex characteristics as system-dependent, time-dependent and physical coupling. Correspondingly, full-life dynamic identification of the wear state of an engine in service was investigated for real-time performance evaluation. As wear information carrier, images of wear debris carried by the cycling lubricant were sampled by an OLVF (On-line Visual Ferrograph) sensor. Two characteristic indexes including *IPCA* (Index of Particle Coverage Area) and *EDLWD* (Equivalent Diameter of Large Wear Debris) extracted from the on-line wear images, were adopted to characterize the wear state quantitatively by representing wear rate and mechanisms, respectively. A dynamic feature-matching model for real-time identification was studied comprehensively by referring to the stage features of wear state variation. Furthermore, a one-class model was built using the SVDD (Support Vector Data Description) method for categorizing statistical samples. By integrating the feature-matching and de-noising methods, a good identification was achieved with those samples. On this basis, a stage-based model for real-time wear state monitoring was built and verified with time-sequence monitoring samples from an engine bench test. The method shows potential as a promising on-line wear state evaluation tool, especially for full-life monitoring.

1. Introduction

Wear is one of the most important indicators of engine's performance. It affects not only the wear behavior but also the dynamic and thermodynamic performance. State monitoring is effective method to acquire the changing performance of a running machine. With the development of condition-based maintenances, real-time monitoring becomes the focus of engine's state monitoring [1]. However, wear state monitoring and identification is becoming a bottleneck in real-time monitoring due to the complex characteristics of tribological systems, such as system-dependent, time-dependent and physical coupling [2]. Therefore, the study of real-time wear state monitoring and analysis is critical to engine's full-life performance maintenance.

Although wear mechanisms have been comprehensively studied with various specific tribo-pairs, researchers still encountered many difficulties in understanding the wear state of a machine in service [3]. In the following sections, we will discuss the progress of wear monitoring technology focusing on two main aspects: monitoring methods and analysis methodologies. For monitoring methods, people have tried to obtain the real-time wear state by means of many indirect

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measurements such as vibration, temperature and performance parameter monitoring. Eventually, only the information of failure was obtained, while the initiation and propagation of the fault were absent [4]. In essence, wear is a process characterized with systematic effects and multi-field couples, thus indirect monitoring seems difficult to provide profound information about the mechanisms. Oil analysis, a direct analysis means of wear mechanisms, has been adopted in many engineering applications for wear and lubricant monitoring [5]. When applied to the real-time monitoring of an engine's performance, traditional oil analysis encounters two problems: one is the lack of on-line monitoring means, which retards obtaining the real-time information, and the other is the shortage of knowledge about full-life variations, which prevents reliable fault identification and maintenance decision making. In analysis methodologies, as analytical models are generally difficult to build for most engineering problems, most of the literatures focused on identification models based on monitoring data, namely data models [1]. Some were confined to condition data, others included event data. Event data can be used to assess current condition indicators and their performance, but needs the involvement of human. Some time-sequence data models, like the ARMA model by Jihong Yan [6] and the discrete Markov process by D. Banjevic [7], focused on trend predication and abnormality warning [8]. However, for data models, the accuracy of predication is the main problem for monitoring. Self-learning data models, like the artificial neural network model [9], have higher identification accuracy with self-adjusting property. However, the accuracy of an artificial neural network model is determined by not only suitable variables and initiations but also large number of both normal and abnormal samples [10]. Generally, data models can reflect the regularities among the mass of data, but not physical mechanisms, e.g. wear mechanisms.

Accordingly, comprehensive understanding of wear state monitoring and identification should include the following aspects:

(1) Wear states are fully determined by micro-scale wear mechanisms and macro-scale wear quantity. Therefore, data models, without physical mechanism involvements, have congenital deficiencies for characterizing wear state.
(2) Wear state is highly dependent on machines with different tribo-components and working conditions, thus is incomparable for different machines. Therefore, each machine needs a particular prediction model.
(3) Wear is affected by many factors including material properties, lubricants and even conditions, thus wear properties are random over a short period. On the other hand, wear is also a process of structure damage and material loss, thus wear properties are regular over a long term. Therefore, both dynamic and statistical methods should be taken into consideration for modeling.

In this paper, a new wear state characterization modeling method was investigated with on-line wear debris images. The characteristics of the wear debris images were adopted for characterizing wear rate and wear mechanism. For full-life monitoring, an automatic identification model was investigated with two categories: normal and abnormal. Finally, the method was examined with real-time image data sampled from an engine bench test.

2. Wear state characterization based on features extracted from on-line wear debris image

Wear state characterization is the premise of wear analysis. Furthermore, wear monitoring is the base of wear state characterization. As described above, direct monitoring is necessary to understand wear state more in depth. Wear debris is the by-product of wear process, thus the images of wear debris contain profound information of not only wear quantity but also wear mechanisms. Besides, on-line monitoring is necessary for real-time analysis. Correspondingly, an on-line visual ferrograph (OLVF) [11], providing real-time wear debris images, was adopted to monitor the lubricant in a running engine.

The principle of the on-line monitoring system is illustrated in Fig. 1 [11]. The OLVF sensor is mounted in the engine's return line. The lubricant from the engine's return line flows through the flow channel of the sensor. The wear debris carried by the lubricant is deposited under the activated magnetic force. The images of the transmitted and reflected light are sequentially captured by the CMOS unit and stored in a computer. Finally, the magnetic force is released and the flow channel is flushed. The process is repeated periodically as detailed above until it is terminated by instruction. A typical transmitted image is shown in Fig. 2. The bright zone in the image is the objective zone and the dark strips are the wear debris chains.

As seen in Fig. 2, the on-line images have the characteristics of low resolution, high contamination and wear debris chains. Because of this, it remains an unresolved task to identify each wear debris from an on-line image automatically. Practically, statistics other than accuracy is more suitable for on-line monitoring [11]. To this end, a statistical analysis was carried out and two statistical indicators were extracted. An index of particle coverage area (*IPCA*) was extracted as the quantitative indicator of wear debris concentration. It can be calculated as follows [11]:

$$IPCA = \frac{A_i}{wh} \times 100 \tag{1}$$

here, A_i is the area of overall wear debris; w and h are the width and height of the bright zone of the on-line image as shown in Fig. 2, respectively.

Another statistical indicator, the diameter index *EDLWD* (Equivalent Diameter of Large Wear Debris) for characterizing the relatively larger wear debris in the image, was constructed for wear mechanism description [12].