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Diagnosis of artificially created surface damage levels of planet gear teeth using ordinal ranking

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ABSTRACT

Effective diagnosis of damage levels is important for condition based preventive maintenance of gearboxes. One special characteristic of damage levels is the inherent ordinal information among different levels. Retaining the ordinal information is therefore important for diagnosing damage levels. Classification, a machine learning technique, has been widely adopted for automated diagnosis of gear faults. However, classification cannot keep the ordinal information because the damage levels are treated as nominal variables. This paper employs ordinal ranking, another machine learning technique, to preserve the ordinal information in automated diagnosis of damage levels. As to ordinal ranking, feature selection is important. However, most existing feature selection methods are for classification, which are not suitable for ordinal ranking. This paper designs a feature selection method for ordinal ranking based on correlation coefficients. A diagnosis approach based on ordinal ranking and the proposed feature selection method is then introduced. This method is tested on diagnosis of artificially created surface damage levels of planet gear teeth in a planetary gearbox. Experimental results show the effectiveness of the proposed diagnosis approach. The advantages of using ordinal ranking for diagnosing gear damage levels are also demonstrated.

1. Introduction

Gearboxes are widely employed in automotive, aerospace, and various other industries to provide speed and torque conversions. Effective diagnosis of gear faults is critical to the reliable operation of a mechanical system. Majority of the reported investigations on gear fault diagnosis focus on the detection of the presence of a fault [1] and identification of the fault modes, such as pitting [1], crack [2] and tooth breakage [2]. The fault propagation is, however, not studied as much.

Information on fault propagation reveals the severity of a fault, so it is very helpful in scheduling preventive maintenance or other actions to avoid a failure. Feng et al. [3] reported that the regularization dimension of gearbox vibration signals increased monotonically with the gear fault severity. Ozturk et al. [4] stated that the scalogram, especially its mean frequency variation, provided early indications of the presence and progression of gear pitting. These methods find an indicator that monotonically varies with fault levels. The fault level can then be estimated by checking the value of this indicator. However, such methods need expertise from a diagnostician to apply them successfully and cannot distinguish fault levels automatically. To alleviate this problem, researchers have used classifiers to automatically classify different fault levels [5,6]. For example, Lei and Zuo [6] proposed a weighted KNN classification method for gear crack level identification. In these methods, the fault level is regarded as a nominal variable, and the problem of diagnosing fault levels is treated as a classification problem. As a result, the ordinal information among fault levels is ignored [7]. For example, a moderate fault is worse than (<) a slight fault but is better than (>) a

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severe fault; however, in classification, the severe, moderate and slight faults are parallel to each other and cannot be compared using ">" and "<" operations. Having ordinal information is the main characteristic of fault levels, which makes the diagnosis of fault levels more complicated than the diagnosis of the fault modes. How to utilize and retain the ordinal information is therefore an important issue.

Planetary gearbox is a type of gearbox whose planet gears are mounted on a carrier which itself may rotate relative to the sun gear. It has many advantages over the traditional (fixed-shaft) gearbox, e.g. high power output, small volume, multiple kinematic combinations, etc. [8]. Nevertheless, planetary gearboxes are structurally more complicated and possess several unique behaviors that are not found in fixed-shaft gearboxes. For instance, gear meshing frequencies of planetary gearboxes are often completely suppressed, and sidebands are not as symmetric as those of fixed-shaft gearboxes [8]. Barszca and Randall [9] found that the conventional analysis methods did not detect a tooth crack in a planet gear. They then proposed a diagnosis method based on spectral kurtosis and achieved good results. Bartelmus and Zimroz [10] found that a planetary gearbox with a fault was more susceptible to load than a healthy gearbox. Based on this observation, they proposed a new feature for monitoring a planetary gearbox in non-stationary operating conditions in [11,12].

The objective of this paper is to develop an intelligent method for diagnosing damage levels of planet gears in a planetary gearbox. In order to reserve the ordinal information in damage levels, ordinal ranking will be employed. Ordinal ranking [13,14] (also called ordinal classification [15] and ordinal regression [16]) is a supervised machine learning technique that uses an ordinal variable as its label. Details on ordinal ranking will be introduced in Section 2. Feature selection is a necessary procedure for ordinal ranking, particularly because it can enhance accuracy and improve the efficiency of training [17]. Most existing feature selection methods are actually developed for classification problems, which makes them work less effectively in ordinal ranking problems. For example, Mukras et al. [18] found that the standard feature selection method using information gain failed to identify discriminatory features in an ordinal ranking problem. The reported work on feature selection dedicated to ordinal ranking is very limited. Baccianella et al. [19] proposed feature selection methods based on information gain for ranking in text-related applications. Geng et al. [17] proposed a feature selection method based on mean average precision (MAP) and Kendall's tau correlation coefficient for ranking in information retrieval. In this paper, a feature selection method based on correlation coefficients will be designed.

The rest of the paper is organized as follows. Section 2 introduces the concept of ordinal ranking and describes a reported ordinal ranking algorithm. Section 3 proposes a feature selection method for ordinal ranking. Section 4 describes the planetary gearbox test rig for experimental data collection. Section 5 explains the feature calculation and extraction for the planetary gearbox. Section 6 presents an approach for diagnosis of damage levels based on ordinal ranking. Section 7 tests the diagnosis approach with experimental data and discusses the results. Finally, conclusion comes in Section 8.

2. Ordinal ranking

2.1. Review on ordinal ranking

Steven [20] divided the scales of measurement into four types: nominal, ordinal, interval, and ratio. The nominal scale is for variables that have two or more categories but do not have an intrinsic order, e.g. types of fruits. When only two categories are involved, the variable is called binary, e.g. gender. The ordinal scale is rank-ordered but does not have metric information, e.g. grades of students (A+, A, A−, B+, . . . , F). The interval scale and the ratio scale are for continuous variables which have metric information. In supervised machine learning, a training set in the form of $\boldsymbol{T}$=[$\boldsymbol{X}$, $\boldsymbol{y}$] is given, where $\boldsymbol{X}$ is the input set (the feature set) and $\boldsymbol{y}$ is the output set (the label). According to the label's measurement scale, supervised machine learning problems can be grouped into three categories: if the label is a nominal variable, the problem is called classification; if the label is a continuous variable, the problem is called regression; if the label is an ordinal variable, the problem is called ordinal ranking [13]. In this paper, we call the labels of ordinal ranking, ranks.

Ordinal ranking is similar to classification in the sense that the rank $\boldsymbol{y}$ is a finite set. Nevertheless, besides representing the nominal variables as classification labels, ranks of ordinal ranking also carry ordinal information. That is, two ranks in $\boldsymbol{y}$ can be compared by the "<" (better) or ">" (worse) operation. Ordinal ranking is also similar to regression, in the sense that ordinal information is similarly contained in $\boldsymbol{y}$. However, unlike the real-valued regression labels; the discrete ranks do not carry metric information. That is, we can say rank A is better than rank B, but it is hard to say quantitatively how much better rank A is.

A commonly used idea to conduct ordinal ranking is to transform the ranking problem to a set of binary classification problems, or to add additional constraints to traditional classification formations. Herbrich et al. [16] proposed a loss function between pairs of ranks, and then applied the principle of structure risk minimization to solve the ordinal ranking problem. However, because there are $O(N^2)$ pairwise comparisons out of N training samples, the computation complexity is high when N is large. Crammer and Singer [21] generalized the online perception algorithm with multiple thresholds to predict r ranks. The feature space was divided into r parallel equally-ranked regions, where each region stood for one rank. With this approach, the loss function was calculated pointwisely and the quadratic expansion problem was avoided. Following the same idea, Shashua and Levin [14] generalized support vector machine (SVM) into ordinal ranking by finding $r-1$ thresholds that divided the real line into r consecutive intervals for the r ranks. Chu and Keerthi [22] improved the approach in [14] and proposed two new approaches by imposing the ordinal inequality constraints on the thresholds explicitly in the first approach and implicitly in the second one. Among the above methods,