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WAYSIDE DIAGNOSIS OF METRO WHEELSETS USING ACOUSTIC SENSOR DATA AND ONE-PERIOD ANALYSIS

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Abstract: This research promises a wheelset fault diagnosis methodology for metro train sets using wayside acoustic sensor information. Throughout the research, two different feature extraction techniques; Wavelet Packet Energy (WPE) and Time-domain Features (TDF) are employed in association with two state-of-art classifiers Fisher Linear Discriminant Analysis (FLDA) and Support Vector Machines (SVMs). The database is prepared by the acquisition of wayside acoustic sensor data accompanied by optical gates that detect wheelset center position while multiple passing of a single metro train set of type 81-71M is in daily operation with the contribution of a novel approach; one-period analysis. Acquired database is then divided into two classes which represent the healthy and faulty states of the wheelsets referring to the ground truth information of a faulty wheelset. Since the faulty states are insufficient to demonstrate the real classification performance, an adaptive synthetic sampling technique (ADASYN) is utilized to increase the number of faulty states. Promising results are observed up to 93 % in classification of faulty wheelsets of the metro with the proposed techniques on acoustic sensor data. This study may aid to maintenance specialists by providing a cost effective monitoring of faulty condition of metro wheelsets.

Keywords: Wheelset fault diagnosis, Wavelet packet energy, Time-domain features, One-period analysis, Condition monitoring.

1. Introduction

Condition monitoring of a railway vehicle, which is cost effective in comparison to on-condition repairs, is a tough job due to varying environmental conditions and different operational parameters related to the vehicle. Stationary diagnostics approaches are costly and complex because of high number of sensors (Ward et al., 2010) and calibration difficulties. Thus, a wayside monitoring approach is sufficient to detect abnormal condition of a railway vehicle. Several approaches are already proposed in the literature for wayside; acoustic bearing fault diagnosis (Liu et al., 2014), wheel profile and wheel impact detection using ultrasound and laser systems (Ngigi et al., 2012) and wheel defect detection (Jakimovska et al., 2015).

This paper is focused on some efficient methods that provide condition monitoring of metro wheelsets by using acoustic sensors on wayside due to the existence of cost friendly techniques is limited in the literature.

The organization of the paper is as follows: Proposed methods are given in Section 2. Data recording and measurement system is told in Section 3. Analysis results and discussion are given in Section 4. Finally, conclusion part is presented in Section 5.

2. Proposed Methods

In fault diagnosis, it is vital to form signal samples into representative way of related class as well as maintaining the dimensions in acceptable range due to possible complexity in classification. Several approaches are presented in the following sections.

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2.1. One-period Analysis

In wayside diagnostics, signal characterization is affected significantly due to speed variations of different vehicle passes. In this research, to overcome this issue, a novel one-period analysis (Kilinc et al., in press) is presented. In this method, sample interval for each individual wheelset is calculated according average of wheel perimeters referring to the latest revision parameters and signals are recorded so that they cover one rotational period of each bogie wheelset. Thus, the effect of wear which may significantly change the wheel radius on each wheelset is diminished.

2.2. Time-domain Features

Time-domain statistics is a common approach in fault diagnosis especially for one-dimensional signals which also exists in contemporary literature (Poulimenos et al., 2006). In the proposed framework, eight Time-domain Features (TDF) are selected as in Eq.(1) as proposed in the research (Yu et al., 2015) which investigates characteristics of machinery faults. For each sample that is retrieved by one-period analysis, those features are calculated and 8x1 size feature vectors are created.

 $TDF = [energy, mean, std_deviation, max, min, kurtosis, skewness, crest factor]$ (1)

2.3. Wavelet Packet Energy Features

In railway vehicle diagnostics, most signal characteristics behave in a non-stationary manner (Mao et al., 2015). Calculating Wavelet Packet Energy (WPE) is a simple and efficient way of dealing non-stationary behavior. Firstly, Wavelet Packet Transform (WPT) for each sample is calculated. Since WPT is not time-invariant (Yen et al., 2000), energy components of WPT is calculated for each level and WPE features are achieved. In this research, for both classes, five-level WPE features are calculated which result feature vector size is $2^5 \times 1$.

3. Signal Acquisition and Database

In this study, a wayside measurement system is installed into a metro tunnel near Dejvická Metro Station which is located on Prague Metro Line-A due to the opportunity of small variations in operational speed of train sets. In order to obtain acoustic characteristics of each train passing, a pre-polarized free-field microphone (M_1) is mounted between sleepers and signal recording is performed at 51.2 kHz with the instrumentation device NI-cDAQ-9234 during all day long. Thanks to an optical gate (G_A) that is placed exactly in the same cross section with the microphone that detects each wheelset centers at 500 Hz rate. Measurements are carried out in the project Competence Centre of Railway Vehicles, No. TAČR TE01020038. All metro train sets that travel on Line-A have five 4-axles passenger cars (total number of wheelsets are 20, all wheelsets are powered). One-day duration of measurements make it able to investigate 226 passes of 40 unique metro train sets type 81-71M. The wayside measurement system and arrangement of sensors allocation is shown in Fig. 1.



Fig. 1: Measurement system nearby Dejvická metro station.

Since multiple passing's of each vehicle are existed, the database includes 8 signal samples of a known faulty wheelset that has wheel flats on both wheels. Two datasets, A1-A2 and B1-B2 are prepared to detect faulty wheelsets; the former is consistent of randomly chosen 8 normal wheelset samples against 8

faulty samples of the train set that has faulty wheelsets while the latter includes 64 normal against 64 faulty samples. Since the number of faulty samples are limited, B2 (faulty) samples are generated from A2 by a contemporary adaptive synthesizing method (ADASYN) (He et al., 2008) to achieve more accurate model evaluation.

4. Results and Discussion

In the analyzes, two feature extraction techniques TDF and WPE are applied on the signal samples after one-period analysis and sufficient number of cross validation is performed to obtain classification results. The complexity of the problem may be seen in Fig. 2 which shows the classes in datasets A1-A2 in two-dimensional form by using the common dimension reduction technique; Principal Component Analysis (PCA) (Ferraz et al., 1998).



Fig. 2: Class distribution of feature vectors of dataset A1-A2 after 2D-PCA; TDF (left), WPE (right).

Classifier	% Classification Accuracy		Training	Testing	Total Samples	Class Label	
						Normal	Faulty
SVM (4-fold)	WPE	TDF	[2x2]	[6x2]	16	A1	A2
Average	68.80	62.50					
Std. Dev.	12.5	14.4					
FLDA (4-fold)	WPE	TDF	[2x2]	[6x2]	16	A1	A2
Average	62.50	56.25					
Std. Dev.	32.3	23.9					
SVM (8-fold)	WPE	TDF	[8x2]	[56x2]	128	B1	B2
Average	82.80	85.90					
Std. Dev.	14.5	5.5					
FLDA (8-fold)	WPE	TDF	[8x2]	[56x2]	128	B1	B2
Average	82.00	93.00					
Std. Dev.	10.3	7.0					

Tab. 1: Classification accuracies of proposed methods of raw (A1-A2) and synthesized (B1-B2) datasets.

After utilizing training process on the classifiers; linear Support Vector Machine (SVM) and Fisher Linear Discriminant Analysis (FLDA) the average classification rates and their standard deviation are acquired. Referring to Tab. 1:, highest classification rate of A1-A2 datasets, which has short number of

normal and faulty samples, is observed as 68.80 % with linear SVM kernel while on adaptively generated samples according to ADASYN; datasets B1-B2 shows promising results with TDF feature extraction technique as much as 93 %.

5. Conclusions

In this research, two different feature extraction techniques are applied on acoustic signals that are retrieved from real world conditions of a metro after the novel one-period analysis. Since the dataset is limited to only eight number of known faulty wheelsets, an adaptive upsampling technique; ADASYN is applied on faulty conditions in order to see classification performance when enough measurements are acquired.

According to the results, accuracy of classification of short datasets A1-A2 with acoustic sensor data is considered to be insufficient. However, after equalizing the faulty minority class from the samples of real world conditions, more plausible results are obtained up to 93 % by the utilization of TDF feature extraction after one period analysis on datasets B1-B2.

Further effort on pre-processing may improve classification accuracy by discarding the effects of unwanted environmental behavior in metro tunnels which badly affects acoustic sensor activity. This research may be a contribution for maintenance specialists and others who are interested in cost-efficient condition monitoring systems of railway vehicles.

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