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Rolling element bearings diagnostics using the Symbolic Aggregate approXimation

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ABSTRACT

Rolling element bearings are a very critical component in various engineering assets. Therefore it is of paramount importance the detection of possible faults, especially at an early stage, that may lead to unexpected interruptions of the production or worse, to severe accidents. This research work introduces a novel, in the field of bearing fault detection, method for the extraction of diagnostic representations of vibration recordings using the Symbolic Aggregate approXimation (SAX) framework and the related intelligent icons representation. SAX essentially transforms the original real valued time-series into a discrete one, which is then represented by a simple histogram form summarizing the occurrence of the chosen symbols/words. Vibration signals from healthy bearings and bearings with three different fault locations and with three different severity levels, as well as loading conditions, are analyzed. Considering the diagnostic problem as a classification one, the analyzed vibration signals and the resulting feature vectors feed simple classifiers achieving remarkably high classification accuracies. Moreover a sliding window scheme combined with a simple majority voting filter further increases the reliability and robustness of the diagnostic method. The results encourage the potential use of the proposed methodology for the diagnosis of bearing faults.

1. Introduction

Rolling element bearings are a very critical component in various machines, and account for 45–55% of asynchronous motor failures according to a report from the Electric Power Research Institute (ERPI) [1]. The last two decades, the interest for efficient and robust diagnostics of roller element bearings via condition monitoring approaches as well as advanced signal processing has seen an extremely high increase. Of paramount importance in the diagnostic task are two items: 1) the feature extraction of damage sensitive features from the recorded condition monitoring signals and 2) the pattern recognition approach that leads to fault identification. Regarding the 1st item, wavelet analysis [2–4], empirical mode decomposition (EMD) [5,6] envelope analysis [7], cepstrum analysis [8], Kurtogram [9], nonlinear feature extraction [10], and other tools are utilized [11]. Regarding the 2nd item, artificial neural networks (ANNs), support vector machines (SVMs) [4], hidden Markov models (HMMs) [3], and particle filters [7] are used for pattern recognition and fault identification but their success highly depends upon the diagnostic potential of the extracted features.

More specifically, in [2] the condition of an electric motor with two rolling bearings with one normal state and three faulty states each was studied. De-noising via the continuous wavelet transform (CWT) was conducted and support vector

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machines (SVMs) were used for the fault classification task with 100% accuracy. Ocak et al. [3], developed a new scheme based on wavelet packet (WP) decomposition and HMMs for the condition monitoring of bearing faults. In this scheme, vibration signals were decomposed into WPs and the node energies of the 3-level decomposition tree were used as features. An HMM was trained to model the normal bearing operating condition and its probabilities were then used to track the condition of the bearing. The normalized WPs quantifiers as a new feature set was introduced in [4] for the detection and diagnosis of localized bearing defect and contamination fault. Unlike the conventional feature extraction methods, which use the amplitude of wavelet coefficients, these new features were derived from probability distributions and are more robust for diagnostic applications.

In [5] EMD was utilized for the extraction of only four features both from the time and the frequency domain of two specific intrinsic mode functions (IMFs) which were then fed to an ensemble anomaly detector consisted of very simple individual detectors capable of detecting four different types of seeded faults in a benchmark data set [12]. Envelope analysis using Hilbert transform was used in [7] and the energy ratio of specific components extracted from the frequency spectra of the envelop signal were combined with static (KNN) and dynamic (particle filters) anomaly detectors with very promising results for bearings suffering with different fault severities and under different operating conditions. The minimum variance cepstrum (MVC) method for the detection of the signature periodic fault signals was investigated in [8] and automotive ball bearings and the results compared favorably to other well established techniques such as the wavelet transform and the complex envelop analysis. Wang and his co-workers proposed an enhanced Kurtogram whose kurtosis values are calculated based on the power spectrum of the envelope of the signals extracted from WP nodes at different depths [9]. The nodes corresponding to the highest kurtosis can then be considered for further analysis. The proposed method combined with autoregressive (AR) filtering performed well both in simulated signals corrupted by noise as well as real experiments involving bearings with outer race, inner race and rolling element faults. Nonlinear feature extraction based on recurrence quantification analysis (RQA) for feature extraction was proposed in [10]. Two of the extracted features manifested a monotonic behavior in relation to fault severity in bearing faults making them a viable candidate for severity assessment. In [11] Wiener entropy along with the WPT nodal energies were used as inputs to a support vector regression machine for the prediction of the remaining useful life (RUL) of bearings in an accelerated test framework with the results being in good agreement to the actual RUL curve for all the tested cases.

It is apparent that a plethora of feature extraction methods have been employed in the field of condition monitoring. Numerous possibilities exist and the number of features that one can extract from a diagnostic signal can be very large. At the same time, a lot of work has been carried out in the direction of transforming continuous valued time series data to a discrete representation, through a process known as discretization or symbolization. The reason for that trend is that discrete representations offer a much higher numerical computation efficiency (through dimensionality reduction) leading to faster execution, which is crucial for online implementations as well as for computations involving huge amounts of data [13,14]. Additionally, symbolization provides the the opportunity to apply methods from the mature fields of bioinformatics and text mining, etc. [13]. Especially in the field of condition monitoring and anomaly detection of electrical, mechanical and electromechanical systems a similar approach has been pursued by professor Ray and his coworkers using primarily D-Markov machines [15–17].

Symbolic time series representation is another concept from the data mining field not often encountered for bearing fault monitoring. In two characteristic works, Boutros and Liang [18] submit the vibration signals to bandpass filtering and a monitoring index vector is calculated which is then assigned a symbol using a codebook generated using k-means clustering. The discrete observation sequence is then used by an HMM for fault localization and severity assessment with very high reported accuracy rates. Sanjith et al. [19] utilize a symbolic representation of vibration data and the created dictionaries are used to form two indices that can be used to discriminate between healthy bearings and bearings with various seeded faults.

In this work, a novel approach is utilized for the analysis of vibration signals, transforming them into a discrete valued sequence and an “intelligent icons”—like approach for feature extraction [20,21]. The creation of the discrete value sequence is based on the Symbolic Aggregate approXimation (SAX), which was introduced in [13] as a method for indexing. However since its introduction SAX was further exploited for anomaly detection and classification using time series bitmaps [22] or intelligent icons [20,21]. These representations can be used as features in a standard classification framework, rather than mere visualization tools. Along this path, SAX and the intelligent icons schemes are used for non-conventional feature extraction from vibration recordings. The results of this work suggest that this new representation is very efficient for the condition monitoring and fault identification of bearings providing thus an extra tool for the practitioners in the field.

The rest of the paper is structured as follows: Section 2 presents in brief the SAX approach and the intelligent icons algorithm, putting more emphasis on a modification of Piecewise Aggregate Approximation (PAA), which is part of the SAX framework. In Section 3 the involved data set and the conducted experiments are presented along with the achieved results. The paper is concluded with Section 4 with some discussion and some future directions.

2. Methodology

The proposed method for bearing fault detection/diagnosis consists of a series of steps that are depicted in Fig. 1. First, the signal acquired by an accelerometer is segmented to contain, as it will be explained later on, approximately 10 revolutions of data. Then each extracted segment undergoes SAX analysis i.e. z-score normalization to have zero mean and