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New techniques of local damage detection in machinery based on stochastic modelling using adaptive Schur filter

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ABSTRACT

Vibration signal analysis is one of the most effective techniques of monitoring machinery and detecting local damage in their parts, e.g. bearings and gearboxes. However, such detection is sometimes difficult, especially in heavy industrial machines, because of a small proportion of damage-induced components in relation to the remaining components of registered signals. Therefore, more effective signal processing algorithms are being looked for. Moreover, local damage (cracking, pitting, spalling, breakage, etc.) in bearings and gearboxes generates broad-spectrum impulse signals, while the other type can be effectively modelled as a sum of narrowband signals. In this article, techniques based on Schur adaptive filter are proposed for local damage detection. In such an approach, the analysed signal is modelled by means of autoregressive process and the filter is described by so-called reflection coefficients. Schur algorithm is an effective algorithm with very good numerical properties and it is capable of tracking rapid changes in second order statistics of the analysed signal. Thus, the method is well-suited to analysing non-stationary signals and it is potentially interesting for use in bearing and gearbox monitoring.

Reflection coefficients describing the signal model, defined with the use of Schur algorithm, may be applied in a variety of ways, giving a chance of employing different solutions in different conditions. In the first proposed solution, detection is based on the weighted sum of derivatives of reflection coefficients, while in the other one – on new signal obtained as power in frequency bands calculated from a parametric spectrogram, whose starting point are reflection coefficients. All these operations are aimed at enhancing changes that occur in the signal at the moments when damage-induced impulses appear. The article also presents guidelines for methods of determining parameter values in the employed analyses. The proposed solutions have been applied for analysing signals coming from a two-stage gearbox of a large machine driving a mining belt conveyor and the obtained results were analysed. They prove the effectiveness of the proposed techniques. It is worth emphasizing that these techniques can be easily adapted for monitoring machinery in varying operating conditions.

1. Introduction

Detection of local damage in rotating machinery elements such as gearboxes and bearings by analysing a vibration signal is one of the most effective techniques of monitoring machines. Review papers by McFadden and Smith [20], Randall and Antoni [22] or Samuel and Pines [24] describe numerous techniques of such analysis. One of such techniques proposed by Combet and Gelman [9] is the optimal filtration method using spectral kurtosis-based Wiener filter. Descriptions of other techniques, consisting in detecting the optimum frequency band containing information about local damage, can be found in [5,15,25]. Since vibration signals are non-stationary signals, damage detection also employs adaptive filters [22,4,18,19]. They are used in varying machinery operating conditions [29]. One should also mention techniques assuming the cyclostationary character of vibration signals [1,3,28]. Other interesting methods are based on time–frequency or time-scale representation [26,10], especially wavelet transformation [15,21], empirical mode decomposition [23], blind separation [2] and other dedicated techniques [8,11].

However, in many situations, particularly in the case of heavy industrial machinery, such detection is difficult due to a relatively small power of damage impulses compared to the remaining components of the registered signal. Thus, it is essential to look for advanced techniques that would enable it. One possibility is using a Schur adaptive filter [18,19]. Its usage produces a set of reflection coefficients (RC) describing a stochastic model of the analysed

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signal. Schur adaptive filters are characterised by excellent adaptation properties and good numerical properties, and they are potentially perfect for machine monitoring and damage detection in varying operating conditions.

The present paper proposes two ways of employing the RC of a Schur adaptive filter for damage detection: (i) based on the weighted sum of reflection coefficient derivatives with a variant method of determining these derivatives and (ii) based on signal powers in adaptively selected frequency bands determined from a parametric spectrogram calculated from reflection coefficients. The latter characteristics could be further processed. The proposed techniques have been evaluated by analysing vibration signals of bearings and gearboxes of a large mining machines that normally work under non-stationary operations conditions [6,7,10,29]. Due to the properties of Schur filter, this technique could be employed for monitoring machines in varying operating conditions, although such procedures as identifying rotation speed require a certain local stability of conditions (limited fluctuation). The article is organized in the following way: Section 2 presents theoretical basis of the used techniques, Section 3 – examples of damage detection based on weighted summation of RC derivatives and signal powers in frequency bands, and Section 4 contains the recapitulation.

2. Theoretical basis of the analysis

2.1. Adaptive Schur filter

Signal processing based on AR model has been widely known for many years, e.g. [12], usually as applied to stationary signals. However, in the case of damage detection, the registered vibration signals are mostly of non-stationary character. Their main components are signals related to machine operation and they occur regardless of the presence or absence of damage. They demonstrate quite small, compared to detection signals, temporal variation of statistics and they are usually dominant in power. Another important component of vibration signals which is the subject of our interest are signals generated by damage, if any occurs. These are usually impulse and quasiperiodic signals. The period of their occurrence is strictly connected with rotation of the damaged part. The remaining vibration signal component has the character of noise. In the task of damage detection, modelling such a signal by means of a stationary AR model is then unjustified. However, we can use an adaptive filter, such as a Schur filter, for this purpose [14,27,16,17]. A realization of an orthogonal Schur adaptive filter is shown in Fig. 1 [17].

The filter is composed of P sections. Each section is completely described by means of a time-varying reflection coefficient $\rho(n,t)$. The inputs of each section are: forward prediction error, backward prediction error and reflection coefficient. The first section input is normalized samples of the analysed signal [16]. For each time instant, RC values are updated, ensuring the minimalization of error signal in the mean-square sense. Thus, RCs ensure optimal stochastic modelling of the signal for every time instant. This means that such a filter enables the model to keep up with the changes in second-order statistics of the signal.

After filter initialization [17], RC values and error signals are updated recursively, which is described by the three equations:

$$\begin{aligned}
\rho(n+1,t) &= \rho(n+1,t-1)\sqrt{1-e^2(n,t)}\sqrt{1-r^2(n,t-1)} - e(n,t)r(n,t+1)\\
e(n+1,t) &= \frac{e(n,t)+\rho(n+1,t)r(n,t-1)}{\sqrt{(1-\rho^2(n+1,t))}\sqrt{1-r^2(n,t-1)}}\\
r(n+1,t) &= \frac{\rho(n+1,t)e(n,t)+r(n,t-1)}{\sqrt{1-\rho^2(n+1,t)}\sqrt{1-e^2(n,t)}}
\end{aligned} \tag{1}$$

A very important stage of modelling, ensuring the numerical stability of the algorithm, is the normalization of successive samples of the registered signal $x_r(t)$, following the relation:

$$x(t) = \frac{x_r(t)}{\sqrt{\upsilon(t)}} \tag{2}$$

where $\upsilon(t)$ is the estimator of signal variance, with the assumption that its mean value is 0. Subsequently, $\upsilon(t)$ is calculated from the formula

$$\upsilon(t) = \lambda\upsilon(t-1) + x_r^2(t) \tag{3}$$

where λ is the forgetting constant, $\lambda \in (0,1)$, close to 1. The adaptive formula of determining $\upsilon(t)$, described by (2) and (3), reduces the influence of more distant signal samples on the current value $\upsilon(t)$.

Consequently, Schur filter parameters are: filter order P and forgetting constant λ. Their values should depend on signal properties. The filter order P should enable satisfactory modelling of the signal part which is related to "normal" device operation. Each local peak of signal power spectrum density must have two corresponding reflection coefficients. The forgetting constant λ determines the rate of signal analysis exponential window decline and this rate could be characterized by means of equivalent rectangular length T of the window in the samples, expressed by the formula $T = 1/(1-\lambda)$. It is known from estimation theory that the greater the window length, the smaller the estimation errors. However, the aim of this analysis is to detect damage-related impulses. Length T cannot be too large then. If estimating the distance between impulses is possible, then T value comparable with this distance would be a reasonable compromise.

With correctly determined values of Schur filter parameters, damage detection follows the principle that a change in instantaneous second order statistics of the analysed signal $x(t)$, caused by the occurrence of a damage impulse, will produce changes in the values of reflection coefficients $\rho(n,t)$ and estimation errors $e(n,t)$ and $r(n,t)$. This is due to not adjusting the determined signal model to the new situation.

2.2. Sum of reflection coefficient derivatives

The above mentioned changes, in the case of vibration signals coming from damaged rotating machinery elements, are actually observed [18,19]. It has been ascertained that it is more useful to observe changes in reflection coefficients than those in error signals. However, the latter are easier to grasp if reflection coefficient trajectories are differentiated [16] according to the relation:

$$d_\tau(n,t) = \rho(n,t) - \rho(n,t-\tau); \quad \tau = 1,2,\ldots \tag{4}$$

where τ is time delay. The value of τ depends on the signal, as changes in instantaneous signal statistics are sometimes fast and sometimes slow.

Moreover, it is not advantageous to analyse all signal trajectories separately. One could use their simple summing, i.e.

$$d_\tau^{(1)}(t) = \frac{1}{P}\sum_{n=1}^{P} d_\tau(n,t) \tag{5}$$

but changes caused by damage impulse $\rho(n,t)$ could be either positive or negative. Therefore, in damage detection, it is more effective to employ the weighted sum of derivatives, i.e.

$$d_\tau(t) = \sum_{n=1}^{P} w(n)d_\tau(n,t) \tag{6}$$

where $w(n)$ are the weights. A method of determining weight values, allowing for different representations of signal statistics changes in reflection coefficients, can be found in [19].