Bearing defects diagnostics using the principal components analysis

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Abstract. In this paper a new method of bearing defects detecting and defect severity assessment based on the results of singular spectrum decomposition (SSD) of the vibration signal is proposed. The presented results of equipment diagnostics in the laboratory conditions have demonstrated the applicability of signal representation in the principal component basis to improve diagnostic sensitivity.

1. Introduction
Bearing defects of the electrically driven mechanisms are commonly detected using vibration analysis as a simple, repeatable and non-destructive method. Common approaches to processing of diagnostic signals such as spectral analysis [1,5], envelope analysis [5,6] are aimed at highlighting defect signs on a background of noise and interferences. On the other side it is shown [4,5] that increase of signal's chaoticness itself can be early and definite sign of the object's defect. The share of nonlinear and stochastic components increases due to the factors like clearances and friction.

Implementing of simple and accurate methods of bearing defects detecting has a practical interest for industry. This research applies a multidimensional analysis of determined and stochastic parameters of a diagnostics object – ball bearing. It is proposed to improve methods of diagnostics with the principal components analysis (PCA).

2. Diagnostics method
The proposed approach has a singular value decomposition (SVD) in its basis. SVD in the calculation method asserting that a matrix \([A]\) of rank \(L\) can be decomposed to the three matrices: orthogonal matrix \([U]\), diagonal matrix \([S]\) and transposed orthogonal matrix \([V]^T\) in the following way

\[
[A] = [U][S][V]^T,
\]

where \(U^TU = I\) and \(V^TV = I\), \(S\) – diagonal matrix containing singular values (square root of the eigenvalues) that can be presented as \(S = \text{diag}(\sigma_1, \sigma_2, \sigma_L)\) where \(L = \min(m,n)\). The numbers \(\sigma_i\) (\(i=1,2,…, L\)) are called singular values of \([A]\). The singular value defines significance of the corresponding component in the \([V]\).

In the diagnostics practice the most of registered signals are rather time series than matrices. So in this paper the operation of hankelization is applied to the signals. The Hankel matrix for the discrete vibration signal \(x_i (i=1,2,…,N)\) can be obtained with the sliding window of width \(m\) in the way
where \( m+n-1 = N \).

The Hankel matrix \([A]\) from (2) is used for singular value decomposition according to (1). The SVD method gives an opportunity to get the matrix \([\hat{A}]\) of rank \( l \leq L \) reflecting the share of the most significant components. This matrix is obtained as [7]:

\[
[\hat{A}] = [U_l][S_l][V_l]^T,
\]

where \([\hat{A}]\) is the matrix \([A]\) reconstructed by using commonly the first, most significant components (principal components or PC). The rest of the singular values correspond to the components with smaller share in the initial signal:

\[
\sigma_i > \varepsilon, \quad i=1, \ldots, l; \quad \sigma_i \leq \varepsilon, \quad i=l+1, \ldots, L,
\]

where \( \varepsilon \) is significance threshold.

However, with respect to the diagnostic signals «strong components» (i.e. the ones that are multiplied by big singular values) may not represent important diagnostic information. On the contrary, components of the source signal with a defect influence are probable to have smaller values and greater numbers.

Typical vibration signal of a defective bearing can be modeled as

\[
x(k) = y(k) + n(k),
\]

where \( y(k) \) is a determined part and \( n(k) \) is «noisy» (stochastic and chaotic) part.

Accordingly the matrix \( A \) corresponding to \( x(k) \) has two parts: determined data part \([A']\) containing information about shafts and bearings harmonics etc. (indirect defect information), and noisy data part \([N]\) defined by specific defect influence. The following equation can be obtained from (1) and (2):

\[
[A] = [\hat{A}] + N = [U_l \quad U_0] \begin{bmatrix} S_l & 0 \\ 0 & S_0 \end{bmatrix} [V_l^T \quad V_0^T],
\]

where \([A']\) and \([N]\) correspond with \( y(k) \) and \( n(k) \), \( S_1 \) contains components with bigger numbers \( s > \varepsilon \), \( S_0 \) – smaller numbers \( s < \varepsilon \).

The numbers \( s \) and \( \varepsilon \) can be obtained by representing \([A]\) on the singular value spectrum (SVS) and choosing the respective rank where singular values tend to zero. So the information about proportion between determined, stochastic and chaotic components in \([A]\) becomes available (Fig. 1). Increase in the share of chaotic components can be considered as an early sign of a defect.

![Typical singular value spectrum](image)

**Figure 1.** Typical singular value spectrum

The practical problem of the use of SVD in signal processing is the estimation of the thresholds separating the determined information from the variable and noisy one. The SVD method usually
includes a reconstruction procedure that is performed by arithmetic averaging along the side diagonals of the matrix \([A]\) or \([N]\). This procedure is not mandatory in this study.

The principal components selected from the vectors of the matrix \(U\) resulting from decomposition (2) define the basis for projecting the diagnostic data. The technical state of an object is connected with the data location in the chosen basis. Opponents of the method, however, argue that the resulting projections allow us to evaluate only the relative state, and not the working ability and especially not a specific defect [10]. Such an objection applies only to the classical algorithm of the method [11], which uses the entire array of data (working and faulty states) to build the basis, and the classification results are relative. Method of PC in the interpretation proposed by Trendafilova [9] assumes the initial construction of the basis and the subsequent projection of the analyzed data upon it. The initial data are the results of diagnosis corresponding to the working state. This data should be presented as a matrix (1).

Another problem of PC method application is the choice of the basis directions and their numbers. In most works [10-12] this problem is solved on the basis of SVS analysis. It is assumed that the components with the highest eigenvalues are sufficiently informative to characterize the data array.

However, it is logical to assume that the singular values of the samples of the working and analyzed states can differ significantly. The assumption is based on the fact that the effect of the fault increases the contribution of greater (stochastic and chaotic) components. In this situation, to ensure selectivity, it is advisable to compare the SVS's and choose the components that correspond to the greatest difference in eigenvalues. Thus, to improve diagnostic data analysis methods, it is proposed to represent diagnostic data in the basis, the components of which reflect the contribution of determined, stochastic and chaotic components. To build the space it is proposed to use the dataset corresponding to the working state of the object.

3. Experimental testing of the diagnostics method

An experiment has been conducted to test the proposed method based on the representation of diagnostic signal in the space of determined, stochastic and chaotic components. During the experiment an abrasive wear of ball bearings was performed using test facility shown at the fig. 2. The level of vibroacceleration has been measured after 10, 20 and then every 20 minutes of wear till 140 minutes from test start.

![Figure 2. Test facility. Bearing support, view along the shaft axe](image)

Initially, the signals of bearing vibroacceleration were processed with the conventional approaches, e.g. the root mean square (RMS) values of the defect-free bearing and bearing after abrasive wear were calculated. An abrupt increase followed by decrease and subsequent smooth growth has been
observed on all measuring channels (so the clear match between technical state of tested element and vibroacceleration level was not observed).

Subsequently, the vibration signals were processed using singular decomposition; the singular value spectra (SVS) were obtained. As a result, the form of the spectrum corresponds to the technical state of tested element. SVS of the defect-free bearing shows prevalence of determined components: the first ten components mainly describe the signal and the share of greater components is insignificant.

![Figure 3. Singular value spectra of the diagnostic signals](image)

The first ten minutes of wear are characterized by growth of the determined and stochastic components (which can be seen on the graph as an increase of the share of components number 1-100). Subsequent wear (next series) is represented in the SVS as a relative decrease of the components 1-100 and increase of the greater components interpreted in this research as chaotic.

Thus, the preliminary processing of the diagnostic data shows that using first PC is not sufficient for correct assessment of equipment degradation status despite this approach being recommended by the literature on PCA application.

The next step in the experiment data processing was projecting the signals onto the principal component basis. Initially, the data has been projected onto the first three components to demonstrate several features of degradation process (Fig. 4a).

![Figure 4. Projecting the signals onto the PCs](image)

a) PC №1-3; b) PC №1,55,110
The first three components at the Fig. 4a coincide with the axes X, Y, Z. The plotted projections show that the initial fault appears as an abrupt change of the projection in the PC basis. The subsequent alignment of moving parts is reflected as a return of the characteristics to their initial location. Such diagnostics results do not allow to distinguish fault stages, and degradation can be erroneously considered as an improvement of the bearing's technical state.

In order to improve diagnostics accuracy, we propose to select as a basis for projection three PC's which reflect determined, stochastic and chaotic components in the signals. Based on the signal's SVS we have chosen the components №1, 55, 110 (coincide with the axes X, Y, Z at the Fig. 4b).

Seven clusters plotted on the Fig. 4b represent stages of defect development: initially, an increase of X and Y (determined and stochastic) components with the subsequent growth of Z (chaotic) component has been observed. This the stages of degradation process can be differentiated. The described experiment demonstrates an ability to improve diagnostics accuracy by building reference basis considering the shares of determined, stochastic and chaotic components.

4. Summary

As development of a bearing defect is driven with determined, stochastic and chaotic factors, the corresponding signal’s (informative) features have to be identified to improve diagnostics sensitivity and selectivity. The conventional approaches are unable to identify the chaotic dynamics in the signals. So, identification of informative elements based on the PCA is a simple and effective strategy.

It is proposed:
- to determine a proportion between determined, stochastic and chaotic components using SVS.
- to represent the signal in the reference basis of principal components corresponding with the biggest difference between singular values obtained by signal decomposition (it is more effective than using only the first components with the greatest values).

The results of the experiment on bearing abrasive wear using the proposed method have demonstrated that defect signs were (more) successfully distinguished as compared with the most common approach (evaluation of RMS vibroacceleration) and even with conventional PCA algorithm. The result obtained indicates the possibility to implement the proposed method for the diagnostics of electromechanical equipment in industrial environment.

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