Application of spectral analysis methods for data preprocessing of anomaly detection problem of vibration diagnostics in non-destructive testing

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Abstract. The paper is devoted to the problem of primary data processing obtained in the vibration measurements during the processing of the workpiece on a milling machine with computer numerical control. An experimental setup is described and an algorithm for analysing vibration diagnostics signals using a mathematical machine learning tool is proposed. Special attention is paid to the study of the rigidity characteristics of the machine at different relative positions of its components. The analysis of the equipment design and factors affecting the ongoing process is carried out, as a result of which the received signal is processed and its characteristic fragments in the time and frequency domains are identified. The data is prepared for further use in solving the problem of detecting anomalies of the technological process, which implies predicting the progress of the technological process based on a mathematical model constructed using machine learning methods, and identifying deviations of the real technological process from the forecast. Preliminary preparation is carried out using the windowed Fourier transform. Various variants of windows in the transformation are considered, including those constructed using atomic functions. Calculations are performed using the Python 3.9 language, the main results are supported by graphs. The development of training methods for the considered models of neural networks is the subject of further research.

1. Introduction

Within the framework of the industry 4.0 concept, cyber-physical systems are being integrated into production. Providing industrial equipment with computing resources allows for real-time diagnostics of equipment for early detection and troubleshooting, which increases the productivity of the technological process by preventing unexpected downtime [1].

Identification of anomalies of the technological process at the early stages allows to minimize the percentage of defects, as well as to avoid accidents due to timely measures taken. From the point of view of the equipment, monitoring of the technological process allows you to detect the origin of machine defects, which helps to carry out maintenance and repair of the machine in time.

There are several approaches:

1. Periodic scheduled inspection, usually determined from the average time to failure.
2. Maintenance in response to a specific event, such as the destruction of a machine component. This approach is associated with significant downtime of equipment for repair.

3. Maintenance based on its actual condition. This minimizes downtime and equipment repair costs, but requires a large amount of data to build an analyzing model [2].

Of particular interest is the control of processes occurring directly in the cutting zone. According to statistics, about 20% of equipment downtime is associated with tool wear. From publications on this topic, it can be seen that an accurate system for monitoring the condition of the tool allows you to increase productivity by 10–50% [3–6].

In addition to the wear of the cutting tool, the course of the technological process is affected by vibrations that occur during the processing. Depending on the processing parameters, the frequency pattern in the cutting area changes, which can lead to resonance and equipment failure. In addition, the frequency pattern changes depending on the relative location of the machine components, the heat distribution, the total operating time of the machine, and other factors. Spectral analysis methods allow you to identify the frequency pattern at a specific time, filter the signal, and select a set of data for further analysis.

2. Description of the experimental setup
The technological process [7] of milling on the modular machine Dobot Mooz 2 [8, 9] was chosen as the object of research [10–13]. The complete set of this machine contains industrial-type guides, which provides high technological parameters of processing, and also allows you to transfer the analysis method of this model machine to real industrial equipment. Figure 1 shows a general view of the assembled installation. In the experiment, the processing of model plastic of the Obomodulan-1600 brand is carried out, which is used for rapid prototyping, the manufacture of equipment for vacuum forming, the creation of models, etc. The main technological properties are presented in table 1.

| parameter                           | value                                      |
|-------------------------------------|--------------------------------------------|
| density                             | $\rho = 1600 \text{ kg/m}^3$               |
| compressive strength                | $R_c = 116 \text{ MPa}$                   |
| bending strength                    | $R_b = 75 \text{ MPa}$                    |
| coefficient of thermal expansion    | $\alpha = 4.9 \cdot 10^{-5} \text{ K}^{-1}$|
| shore hardness                      | 88–89                                      |
| heat resistance                     | $T = 94^\circ \text{C}$                   |

Table 1. Technological parameters of the Obomodulan-1600 model plastic.

Figure 1. General view of the assembled installation.
The processing is carried out in a rectangular area, the trajectory of the tool is set by the control program of the (CNC). On the front panel of the spindle unit, a STEVAL-MKI022V1 breadboard is installed, connected to a laptop, which collects and records data. Figure 1 shows a general view of the assembled installation.

The output is a file with the extension '.dat', containing the values of the projections of the vibration acceleration vector along three axes. A fragment of the obtained data is presented in table 2.

Table 2. A fragment of the data obtained during the experiment.

| X (mg) | Y (mg) | Z (mg) |
|--------|--------|--------|
| -343   | 359    | 324    |
| -437   | 476    | 292    |
| -97    | 519    | 265    |
| -89    | 738    | 46     |

To form a sample of training data, two types of experiments are performed:
1. The tool moves along the trajectory set by the control program, as a result of which the model plastic is processed.
2. While maintaining the same processing parameters, the experiment is carried out without installing the workpiece, i.e. the same control program is executed, but at idle.

2.1. Primary data processing
For further processing, we switch from the sensor coordinate system to the machine coordinate system

\[
\tilde{X}(t) = X(t), \tilde{Y}(t) = Z(t), \tilde{Z}(t) = Y(t),
\]

where \(\tilde{X}(t), \tilde{Y}(t), \tilde{Z}(t)\) are the functions in the new coordinate system. After that, the data is reduced to a dimensionless form according to the formulas

\[
x(t) = \alpha \cdot \tilde{X}(t), y(t) = \alpha \cdot \tilde{Y}(t), z(t) = \alpha \cdot [\tilde{Z}(t) + \beta],
\]
where $\alpha = 8^{-1}(mg)^{-1}$, $\beta = 1mg$. We denote the functions of a signal with processing as $x(t)$, $y(t)$, $z(t)$, and for a signal without processing as $x_0(t)$, $y_0(t)$, $z_0(t)$. The function $x(t)$, $y(t)$, $z(t)$ fragments are shown in figure 2.

For both experiments, the length of the vibration acceleration vector is calculated for each moment of time according to the following formulas

$$v(t_i) = \|\langle x(t_i), y(t_i), z(t_i)\rangle\|_2,$$  \hspace{1cm} (3)

$$v_0(t_i) = \|\langle x_0(t_i), y_0(t_i), z_0(t_i)\rangle\|_2.$$  \hspace{1cm} (4)

The obtained dependences on the time interval $[0; 60]$ are shown in figure 3. It shows the frequency of the received signals, but for a more complete analysis of the technological process, it is necessary to consider the spectra of these signals. Understanding the frequency pattern will allow for more fine-tuning of equipment and tooling to avoid resonance zones, reduce the overall level of vibration and, as a result, improve the quality of the treated surface.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure3.png}
\caption{The obtained experimental dependences: (a) - $v(t)$, $t \in [0; 60]$; (b) - $v_0(t)$, $t \in [0; 60]$.}
\end{figure}

2.2. Spectral analysis

Since the problem of detecting anomalies involves working with a non-stationary signal, we will construct signal spectrograms using the window Fourier transform

$$F(m, w) = \sum_{n=-\infty}^{\infty} v(n) \cdot w(n - m) \cdot e^{-i\omega n},$$

here $w(n - m)$ is a window function. Let’s assume the window width is $N = 50$ points. Consider several types of window functions below.

Rectangular window is

$$\varphi_1(x) = \begin{cases} 0, x < 0.2N, \\ 1, 0.2N \leq x \leq 0.8N, \\ 0, x > 0.8N. \end{cases}$$  \hspace{1cm} (6)

Windows based on membership functions. By the membership function, we mean an infinitely smooth function formed by the product of two simple hyperbolic tangents

$$\mu(a, b, x) = \frac{1}{4}(1 - a \cdot \tanh(\bar{x} - b))(1 + a \cdot \tanh(\bar{x} - b)),$$  \hspace{1cm} (7)

where $\bar{x} = x - \frac{N}{2}$ provides the function shift. Then we take

$$\varphi_2(x) = \mu(0.2, 15).$$  \hspace{1cm} (8)

Figure 4 shows the construction of this membership function.
The third window function is assumed to be equal to

$$\varphi_3(x) = \mu(2,15).$$

(9)

Atomic window function \(\varphi_4(x)\) is

$$\varphi_4(x) = \text{up}(\frac{x}{30}).$$

(10)

where \(\text{up}(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp(jux) \prod_{k=1}^{\infty} \text{sinc}(u \cdot 2^{-k}) du.\)

The windows are normalized in width at the level that can be seen in figure 5.

In our case, for each type of experiment, we construct spectrograms using the designated windows (figure 6).

For further consideration, we take the spectrograms obtained using a rectangular window and a function \(\text{up}(x)\). For clarity, figure 7 shows a three-dimensional graph of the spectrogram of the first signal using the window function \(\text{up}(x)\).

We can see the predominance of low frequencies, so to understand the frequency pattern in the middle of the interval under consideration, we multiply the spectrogram by the weight function

$$F(m,w) = \theta(m) \cdot \sum_{n=-\infty}^{\infty} v(n) \cdot w(n-m) \cdot e^{-j\omega n},$$

(11)
Figure 6. Spectrograms using different types of window functions. Cases (a), (c), (e), (f) refer to the first type of experiment, (b), (d), (f), (h) – to the second type of experiment.

Here \( \theta(m) = \frac{1}{2} \left[ 1 - \cos \left( \frac{2\pi m}{N-1} \right) \right] \) is the weight function. Figure 8 shows the spectrograms constructed using the weight function.

Since the frequency pattern of the second signal does not contain obvious peaks, which is explained by low loads during processing at idle, we assume the hypothesis of the stationarity of the received signal. Then the constant contribution of the machine's own vibrations to the frequency pattern is defined as the vector of the averages in the spectrogram of the second signal. From the spectrograms constructed using a rectangular window and a function, we subtract the constant components calculated for each window function.

Figure 7. Three-dimensional image of the obtained spectrogram of the first signal for the window function \( \text{up}(x) \).
Figure 8. Spectrograms of the same signals constructed using the weight function.

Figure 9. Frequency pattern of vibrations with remote average noise.
Thus, the constant component associated with the natural vibration frequencies of the machine is removed from the overall processing signal, which allows you to identify peaks directly related to the processing of the workpiece.

3. Conclusions
When preparing data for training the neural network, an experiment was conducted to measure the level of vibration accelerations during the processing of the workpiece and idling. The analysis of the equipment design is carried out to identify weak points in this version of the machine. During the experiment, the zones of maximum vibrations with accuracy losses are identified, as a result of which the conclusions made during the design analysis are confirmed. Finding the zones of maximum vibration allows you to determine the optimal placement of the workpiece in the working area of the machine and choose the right tooling. From the spectrogram corresponding to the signal with processing, the part directly related to the processes occurring in the cutting zone is isolated, and the "noise" associated with the mutual movement of structural units, etc., is separated. Based on the obtained data, we can build a model that predicts the frequency pattern. Comparison of the forecast with the actual course of the technological process will allow real-time identification of critical deviations of the vibration level and frequency pattern from the norm, which will solve the following tasks:

- avoid falling into areas of possible resonance;
- facilitate the analysis of the flow of the technological process and make a more subtle selection of processing modes and other technological parameters;
- make additions to the machine design for increasing the resistance to the identified frequencies.

The ability to detect anomalies in real time increases the productivity of the technological process by monitoring the condition of the equipment directly during operation, without interrupting the processing cycle for diagnostics that require disassembly of the machine, and other measures that lead to equipment downtime.

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