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WAVELET TRANSFORM PACKET FOR SIGNAL ANALYSIS USING STANDARD DEVIATION AND SIGNAL SPECTRUM

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Abstract.*The paper presents the research results and the possibilities of applying the standard deviation and amplitude spectrum for chatter vibration detection using the wavelet transform packet as a tool for signal decomposition that was recorded during machining. An analysis of the signal spectrum was additionally performed, which is represented by a spectrogram. Two experiments were performed, where the cutting force signal and acceleration signal, recorded during the machining processes, were analyzed. The recorded signals were decomposed using the wavelet transform packet with the mother wavelet 'db4', and then the standard deviation in the time domain and the amplitude spectrum in the frequency domain were calculated for each level of the decomposed signal. The application of wavelets in this study is intended to enable a better assessment of the quality of standard deviation and amplitude spectrum in chatter vibration detection.*

Key words:*Chatter vibration, Wavelets, Spectral analysis, Standard deviation.*

1. INTRODUCTION

Chatter vibration is a phenomenon in machining processes with a long tradition of study spanning over a century. Initial works in this field focused on constructing stability lobes, involving experimental tests to determine cutting depth limits at different spindle speeds. Machining inclined planes in milling or conical surfaces in turning allowed for machining with variable cutting depths during tool translation. Increased noise and extremely rough surface quality were indicators of chatter vibration occurrence. Contemporary perspectives on such system investigations suggest that conducting numerous experiments is necessary to obtain stability lobes with a certain degree of accuracy, which requires time and resources.

The development of models representing the interaction between the cutting process model and predefined modal parameters of the machining system has enabled more

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accurate models of stability lobes [1]. These models were later enhanced with a process damping model, making them even more accurate and efficient [2].

The advent of computers and sensors enabled the first measurements of certain physical quantities during the machining process. Segments of measured signals were analyzed by statistical features such as standard deviation, kurtosis, and skewness in the time domain, yielding specific results [3-6]. The idea behind such an analysis was to define a threshold or the moment when chatter vibrations occur. A more comprehensive signal analysis was conducted by translatingthe acquired signal into the frequency domain. The Fast Fourier Transform (FFT) showed a significant difference in amplitude spectrum values between stable cutting and cutting with chatter [7].

The appearance of the wavelet transform as a tool for signal analysis in the time-frequency domain has allowed for much faster analysis and filtration of signals compared to individual methods. Signal processing with wavelets has localized signals into parts of characteristic amplitudes and frequencies. Exceptional properties of wavelets have been observed during online signal analysis in the machining process, making this mathematical tool efficient for chatter detection during machining processes [8 - 10].

The main contribution of this paper is the consideration and assessment of the standard deviation and amplitude spectrum in chatter detection using wavelets in decomposing and filtering signals from sensors measured during the machining process. Chapter 3 describes signal analysis using wavelets through two examples. The discussion, conclusions, and directions for further research are outlined in Chapter 4.

2. WAVELETS

A specific set of functions known as wavelet transforms enable localized signal analysis in both the time and frequency domains. This localization allows precise determination of when and where specific frequencies occur in the signal. They are particularly useful compared to other signal analysis methods, such as the Fast Fourier Transform. While FFT uses sine and cosine functions to analyze the entire signal, wavelet transformation employs different types of mother wavelets that are localized in time. One fundamental characteristic of wavelets is their ability to adapt to changes in the signal with different frequencies.

Wavelet transformation is often used to decompose signals into components with different levels of resolution, which is valuable in various applications. Initially, the signal is decomposed into an approximating (low-frequency) part and details (high-frequency components). Then, the approximating part is further decomposed, and this process can be repeated to obtain more signal details at different levels. The signal decomposition process using wavelets is illustrated in Fig. 1. This ability to decompose into different frequency components allows for a better signal analysis compared to traditional methods, especially when signal changes are localized in specific time segments. In this study, the analysis of two types of signals was performed. The signal was decomposed into 3 levels, including an approximation level (cA3(t)) and 3 detail levels (cD1(t), cD2(t), cD3(t)). Fig. 1 displays the hierarchical structure of the decomposed levels.

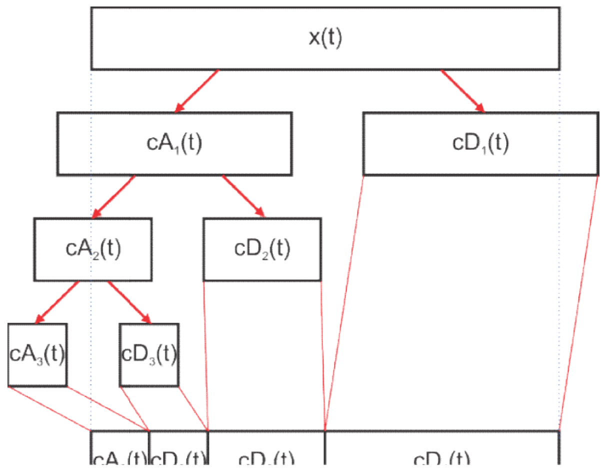

Fig.1 Wavelet decomposition tree

In Fig. 1, it is evident that the lengths of the vector from the final approximation level, cA3(t), along with the obtained detail levels cD1(t), cD2(t), cD3(t), together represent the overall length of the original signal undergoing decomposition.

3. EXPERIMENTAL EXAMPLES

Within this chapter, an analysis will be conducted on the potential application of the standard deviation and amplitude spectrum for detecting chatter vibrations on components of signals (cutting force or acceleration) recorded during the cutting process. Equation 1 represents the formulation of the standard deviation in the time domain.

$$x_{std} = \sqrt{\frac{1}{n-1}\sum_{i=0}^{n}(x_i - x_m)^2} \tag{1}$$

3.1. EXP1: End milling

The first experiment presents end milling of one pre-machined part made of ENAW 7019 alloy that was milled on a horizontal machining center (LOLA HMC500).The results of the measurements come from a previous research project [11]. The workpiece was fixed to the plate of the 4-component dynamometer, with strain gauges, which was used for measuring cutting forces (Fig. 2a). Fig. 2b shows a force signal recorded during the contour milling, where variations were made through variable axial (0-8mm) and radial (0-16mm) depth of cut along the tool path. Feed rates along tool path were variable, according to the results of the algorithm for federate scheduling. In this experiment the tool was an HSSE flat end mill ø16, with 4 flutes. Force signal was recorded with a sampling rate of 2000 S/s.

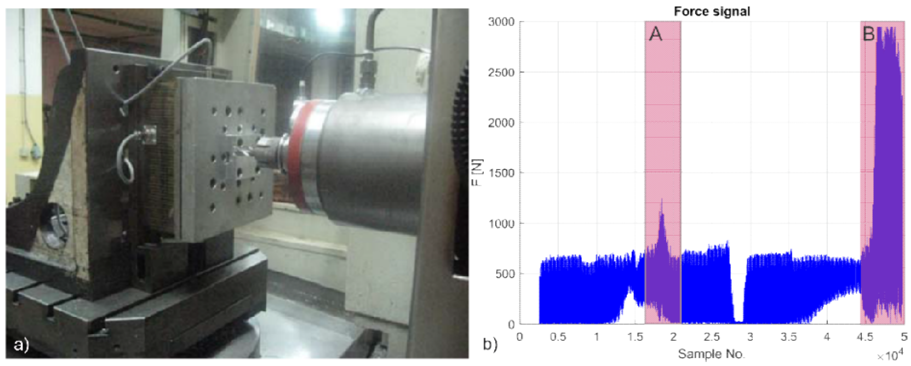

Fig. 2 EXP1:a) Experimental setup on horizontal machining center, b) recorded force signal

Area A in Fig. 2b represents the part of the signal where the tool entered the chatter zone but quickly exited that state. In the second case, area B represents a part of the signal with absolute chatter vibration. As mentioned earlier, the vibration is accompanied by significant noise and pronounced chatter marks on the workpiece surface (area B), which is shown in Fig. 3.

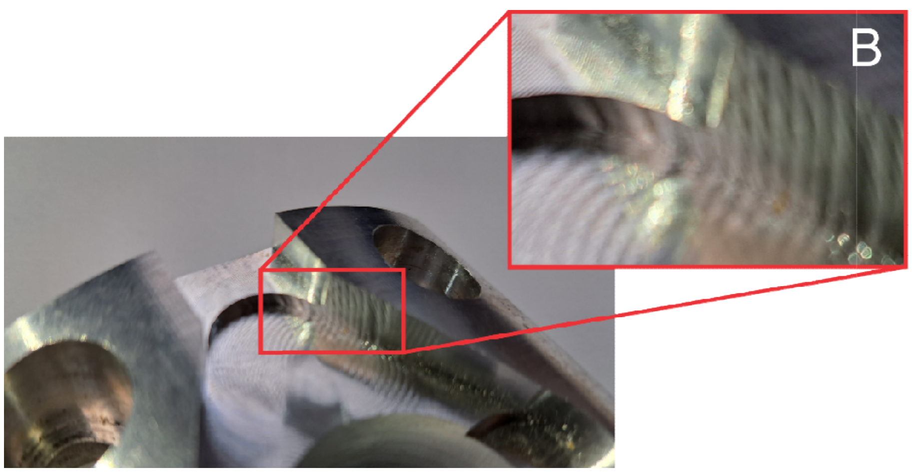

Fig. 3 EXP1:Machining surface at the zone of the evolved chatter

The recorded force signal was decomposed using the MATLAB function *wavedec*[12]. This function requires input parameters, including the isolated vector of the signal to be decomposed, the number of levels for decomposition, and the type of transformation function, i.e., the mother wavelet used for transformation. The signal was decomposed into 3 levels using the '*db4*' (Daubechies 4) wavelet. The obtained results in the time domain are presented in Fig. 4.

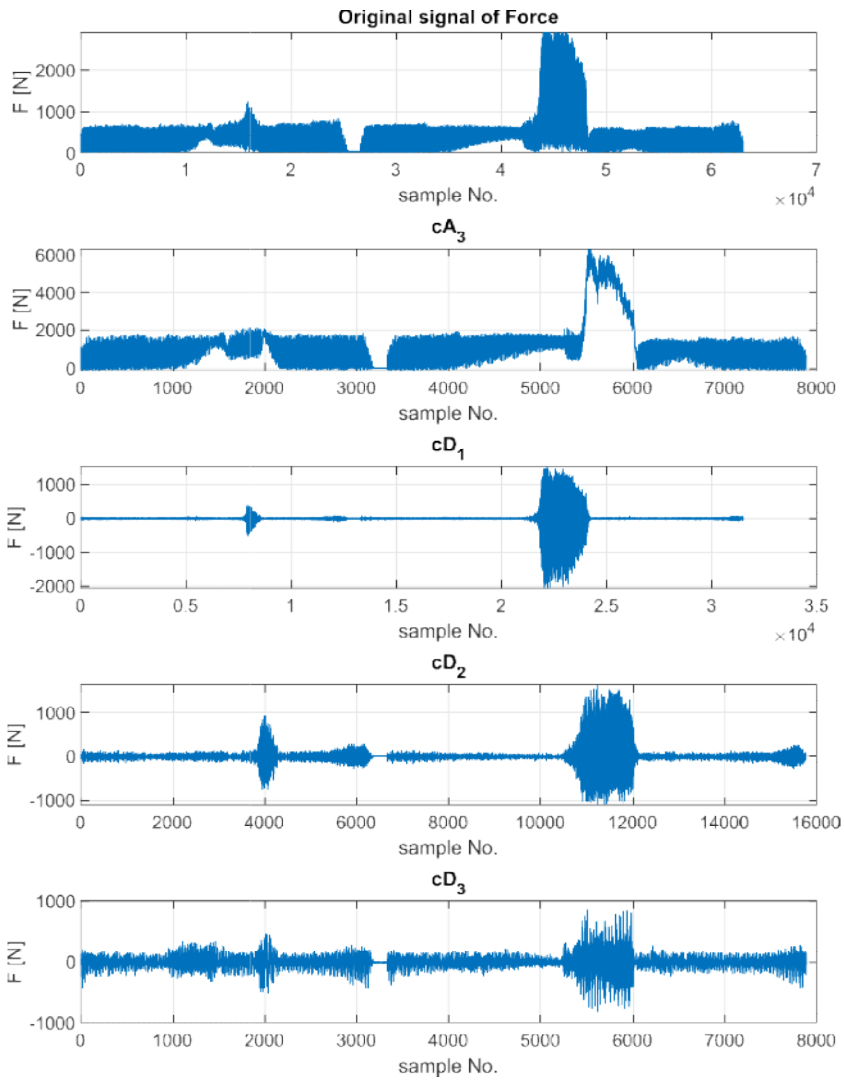

Fig.4 EXP1:Result of decomposition force signal in the time domain

The levels of detail contain higher-frequency components of the original signal, making them intriguing for analysis in both the time and frequency domains. The frequency domain analysis for each level of detail depicted in the previous figure was conducted using a Short-Time Fourier Transform (STFT). In Fig. 5a, the spectrogram of the force signal and decomposed levels are presented. Notably, the graph exhibits the highest amplitude levels at two points, aligning with the natural frequencies. Typically, the signal's highest frequencies stem from the flexibility of the most sensitive element in the machining system, while lower frequencies originate from other components such as the workpiece, dynamometer (in this case), and the machine's worktable. The first level, cD1, reveals two distinct frequencies at 400Hz and 600Hz, corresponding to the instances of chatter frequencies in signal segments A and B. These identified frequencies may also manifest at a lower level, as observed in cD2. However, the last level primarily represents the lowest frequencies in the signal and is not pertinent to chatter vibration detection. The further analysis is focused on standard deviation, with the results illustrated in Fig. 5b.

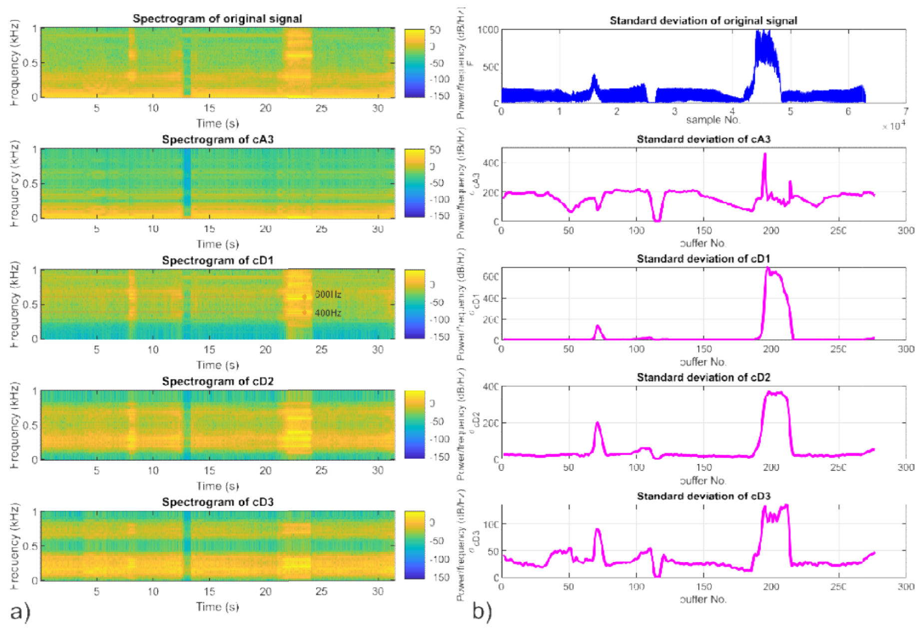

Fig.5 EXP1: a) Spectrogram of force signal and decomposed levelsof EXP1, b) Standard deviation of the signals of decomposed levelsof EXP1

To compute the standard deviation for both the original signal and the decomposition levels (approximation and details) in the time domain, we employed buffers comprising 225 samples for each buffer of the decomposed levels. The research results indicate that standard deviation can be considered a relevant indicator for effective chatter vibration detection. Furthermore, it is noteworthy to mention that the decomposed signal level cD1 yields significant results, especially when dealing with signals exhibiting pure 'chatter.' This level not only provides insights into the presence of chatter vibrations but also highlights the highest signal amplitudes, thereby enriching the analysis. It is important to emphasize that these findings point to the potential application of standard deviation as a reliable criterion for monitoring chatter vibrations, offering a deeper understanding of signal dynamics in the time domain.

3.1. EXP2: Internal turning

Due to the varied nature of signals that may occur in machining operations, an identical signal analysis will be conducted on the accelerometer signal obtained through measurements during the turning of the internal cone. Figure 6 presents the dimensions of the internal cone that was produced. The depth of the cut has a uniform change along the tool path.

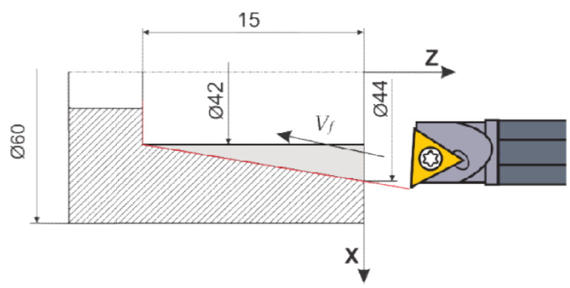

Fig. 6 EXP2: Cutting area in machining process [3]

The workpiece material was 42CrMo4 steel. The turning process was on the Echo-Eng TCN410 - 2 axis CNC lathe. Figure 8a illustrates the workpiece and tool used in the experiment. The cutting tool, R S36.8-25-16, featured a TPMR 160312 4C40 P40 TiN-coated carbide insert. Conducting a set of three experiments, the feed values were varied at 0.15, 0.16, and 0.18 mm/rev, where the cutting speed was set to 90m/min. To capture the machining dynamics, an accelerometer (PCB Piezotronics 352C03) was securely attached to the tool shank. Data acquisition utilized the cDAQ NI 9174, equipped with the S/V Input Module NI9234 and driven by NI-LabView, with a sampling frequency of 1024 S/s. Fig. 7 presents the results of modal analysis of the tool/tool holder subsystem of the TCN 410 CNC lathe, which was used in the experiment.

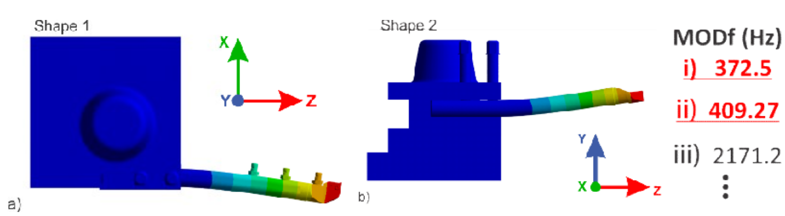

Fig. 7 EXP2: FEM analysis of tool/toolholder subsystem [3], a) first shape of natural frequency of 372.5Hz, b) second shape of natural frequency of 409.27Hz

The analysis was performed in the Ansys software environment. The first two mode shapes of the structure are shown. The first mode (deflection in the x direction) occurs at a frequency of 372.5 Hz. This information is of great importance because the identical frequency occurs during signal processing, which will be discussed further.

An example of the acquired acceleration signal, specifically for the case of a 0.16 mm/rev feed value, is depicted in Fig. 8b.The area where chatter vibration occurred is marked as region A, which is presented in Fig.8b. In this tool step, an experimental modal analysis procedure and dynamic analysis using Ansys software of the tool/holder were conducted. The predominant modes exhibit frequencies of 372.5Hz in the X direction and 409.27Hz in the Y direction [3, 13, 14]. These data are of particular significance when analyzing the one-sided spectrum of the signal for each level of the decomposed signal.

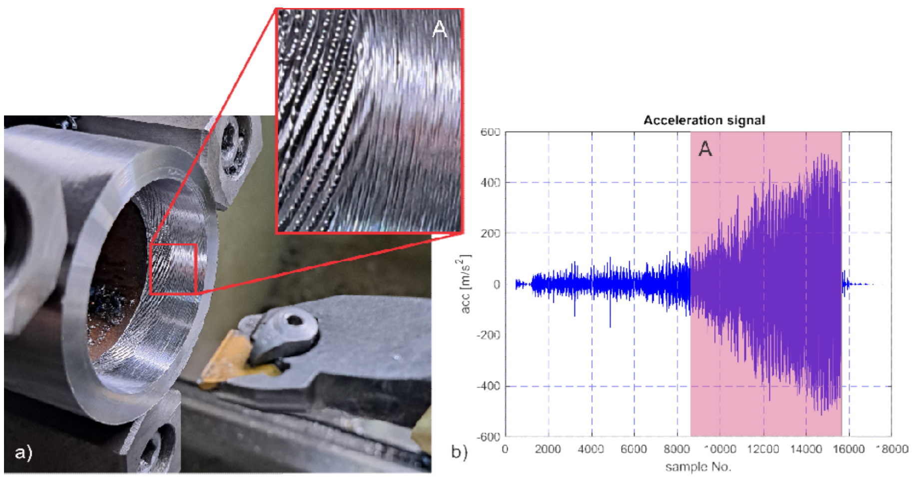

Fig. 8 EXP2:a) Experimental setup and quality of machining surface, b) recorded acceleration signal

Fig.9 represents the decomposition of the original acceleration signal in 3 levels, using Daubechies 4 wavelet (‘*db4*’).

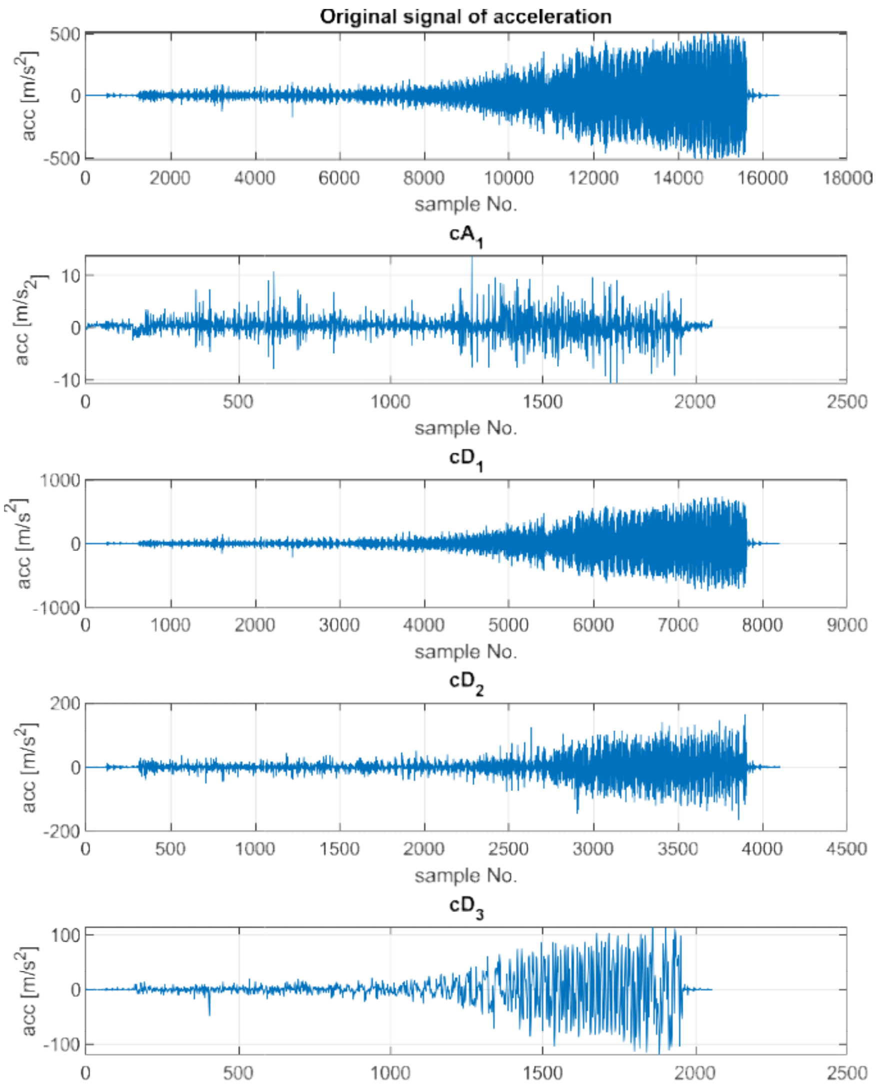

Fig. 9 EXP2:Result of decomposition acceleration signal in the time domain

After decomposing the acceleration signal, a transformation into the frequency domain was performed using STFT, Fig. 10a. Similarly to the previous example, the first level of details cD1 contains the highest amplitudes in the amplitude spectrum, which is presented on the spectrogram, Fig. 10a. What is particularly noteworthy is the insight that the maximum amplitude value occurs at a frequency of 378.9 Hz, which is identical to the first natural frequency.

The examination of the amplitude spectrum using wavelets provides opportunities for more sophisticated research, allowing for the identification of specific frequency components in the signal originating not only from the tool but also from other elements within the machining system. In Fig. 10b, the standard deviation results for both the original signal and each decomposed signal level are illustrated. Similar to the earlier case, the first level of detail cD1 exhibited the most promising results. All the dominant amplitudes in the signal are within the cD1 level, emphasizing the potential applicability of utilizing only the first level of detail in chatter vibration detection.

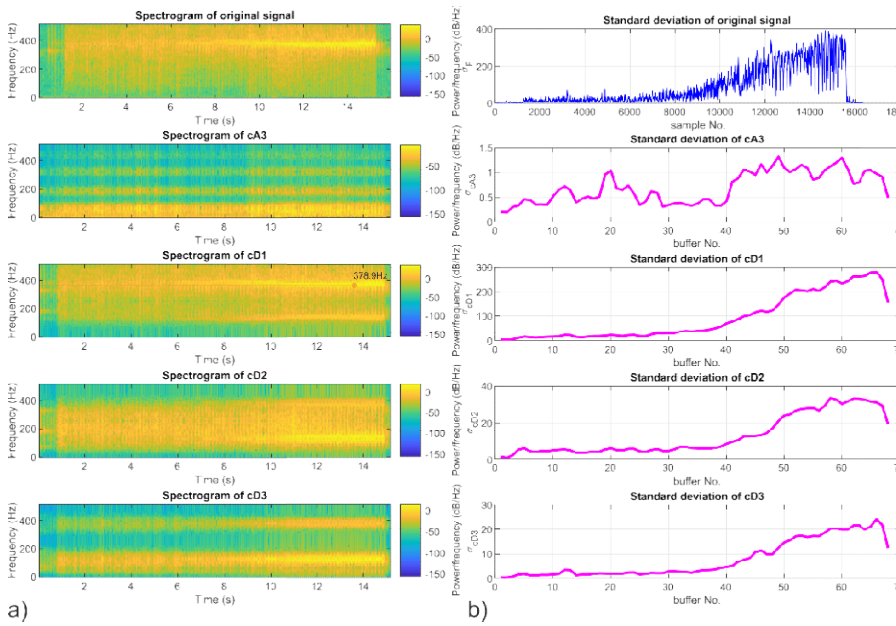

Fig. 10 EXP2: a) Spectrogram of accelerometer signal and decomposed levels of EXP2, b) Standard deviation of the signalsof decomposed levels of EXP2

4.Conclusion

This study employed a wavelet transform packet to examine force and acceleration signalsfrom the machining process, yielding noteworthy outcomes, particularly through the scrutiny of the initial decomposed level of detail. The efficacy of the standard deviation at the first level of detail emerged as a significant feature, showing the possibility of defining a classification criteria in detectingchatter vibrations. Moreover, the amplitude spectrum for the first level of detail accentuates key frequencies, including the initial natural frequency, corroborated by spectrogram analysis. These discoveries suggest potential directions for further exploration, such as analyses of higher decomposed levels and defining parameters for more precise identification of specific chatter vibration characteristics.

Furthermore, the study could be extended by including additional signal analysis methods for a comprehensive understanding of the dynamics of the cutting process. Additionally, investigations could be directed toward customizing wavelet transformations for various types of industrial signals, aiming to enhance accuracy in monitoring chatter vibrations, which is contingent upon the choice of the mother wavelet.

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REFERENCES

1. Altintas, Y., 2012, Manufacturing automation: Metal cutting mechanics, Machine tool vibrations, and CNC design, Second Edition, University of British Columbia.
2. Andreas O., Rauh S., Kolouch M., Radons G., 2014, Extension of Tlusty' s law for the identification of chatter stability lobes in multi-dimensional cutting processes, International Journal of Machine Tools and Manufacture, 82, pp. 50-58.
3. Vorkapic, N., Kokotovic, B., Zivanovic, S., 2023, Comparison of signal features from time and frequency domain for chatter detection, 39th International Conference on Production Engineering of Serbia, ISBN 978-86-6022-610-7, pp. 42-47, Novi Sad, 26-27. October 2023.
4. Ye, J., Feng, P., Xu, C., Ma, Y., Huang, S., 2018, A novel approach for chatter online monitoring using coefficient of variation in machining process, The International Journal of Advanced Manufacturing Technology, 96, pp. 287-297.
5. Zheng, Q., Chen, G., Jiao, A., 2022, Chatter detection in milling process based on the combination of wavelet packet transform and PSO-SVM, The International Journal of Advanced Manufacturing Technology, 120 (1-2), pp. 1237-1251.
6. Chen, Y., Li, H., Jing, X., Hou, L., Bu, X., 2019, Intelligent chatter detection using image features and support vector machine, The International Journal of Advanced Manufacturing Technology, 102, pp. 1433-1442.
7. Yao, Z., Mei, D., Chen, Z., 2010, On-line chatter detection and identification based on wavelet and support vector machine, Journal of Materials Processing Technology, 210(5), pp. 713-719.
8. Xie, M., Yu, X., Ren, Z., Li, Y., 2022, Milling chatter recognition based on dynamic and wavelet packet decomposition, Mechanical Sciences, 13(2), pp. 803-815.
9. Yesilli, M., C., Khasawneh, F., A., Otto, A., 2020, On transfer learning for chatter detection in turning using wavelet packet transform and ensemble empirical mode decomposition, CIRP Journal of Manufacturing Science and Technology, 28, pp. 118-135.
10. Pan, J., Lui, Z., Wang, X., Chen, C., Pan, X., 2020, Boring chatter identification by multi-sensor feature fusion and manifold learning, The International Journal of Advanced Manufacturing Technology, 109, pp. 1137-1151.
11. Kokotovic, B., Vorkapic, N., 2018, Feedrate optimization for 2.5D milling operations, FME Transactions, 47(3), pp. 613 – 623.
12. MATLAB version: 9.13.0 (R2022b), Natick, Massachusetts: The MathWorks Inc.; 2022.
13. Howard, C., 2021, Modal Analysis using the Brüel and Kjaer Photon and Vibrant ME'Scope, University of Adelaide.
14. Avitabile, P., 2021, Experimental modal analysis, Sound and vibration, 35(1), pp. 20-31.