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Online Reliable Chatter Detection of Milling Flexible Part Using Synthetic Criterion

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Abstract: In machining processes, the self-excited vibration between the cutting tool and the workpiece is an important issue that can result in undesirable effects, for example, poor quality of the final surface, low dimensional accuracy, breakage of the tool, and excessive noise. To anticipate this problem, statistical features of the vibration signal, such as mean, variance, and standard deviation, have been extracted from online measurements. The synthesis criterion (SC), which is based on the standard deviation (STD) and the one-step autocorrelation function (OSAF), has been employed to detect quickly the threshold of chatter vibration. In this article, flexible workpieces with varying cutting depths have been selected to detect online chatter vibrations during milling operations. In order to collect an analog vibration signal, an STM32 card has been selected with a sampling rate up to 20 kSPS. A high-bandwidth, lightweight film piezoelectric sensor is attached to the workpiece. Unlike other sensors, such as load cells or acceleration sensors, the film piezoelectric sensors do not alter the dynamics of the system. In this research, cost-effective hardware is also developed to capture vibration signals reliably and efficiently. The experimental results confirm that the developed SC algorithm can efficiently predict the onset of chatter vibration as it was able to detect the onset of chatter vibrations within 0.18 sec. Thus, the SC algorithm can considerably enhance the milling operations of flexible parts.

Keywords: Chatter Vibrations, Flexible Parts, One-Step Autocorrelation Function (OSAF), Piezoelectric Sensor, Synthetic Criterion (SC)

Biographical notes: Hosam Shadoud received his BSc in Mechanical Engineering from Albaath University, located in the city of Homs in Syria. In pursuit of his Master's and PhD degrees, he opted to continue his studies at Ferdowsi University of Mashhad (FUM) in Iran, under the supervision of Prof. Moetakef-Imani. His research endeavors focus on the chatter detection vibrations in machining processes. **Nahid Zabih Hosseinian** completed her first master's degree at FUM, where she conducted research on decreasing the effect of undesired boring bar's vibrations via active Voice Coil Actuators (VCA). Currently, she continues her research as a second master at Ontario Tech University, Canada. **Behnam Moetakef-Imani** is a Professor of Mechanical Engineering at FUM university, in Iran. He received his PhD in Manufacturing from the McMaster University, Canada. His ongoing researches focus on CAD/CAM, Machining Dynamics, and various types of machining operations.

Research paper

1 INTRODUCTION

Milling is a highly complex process, involving the periodic cutting effects of the tool's cutting teeth on the workpiece. Regenerative waves are one of the most notable causes of self-excited or chatter vibration in milling, which can significantly impact the quality of the machined surface. Achieving a high material removal rate (MRR) and an acceptable surface quality are primary objectives of milling operations. However, as MRR increases, chatter vibrations tend to occur, necessitating the use of lower MRR and lower cutting depths to minimize undesirable interactions between tools and workpieces, as noted by Tlusty [1-2].

Dynamic vibrations play a crucial role in the cutting process due to the fluctuation of the dynamic cutting force and the flexibility of the tool and workpiece. Also, a stability lobe diagram has been developed to assist in the selection of stable cutting parameters [3-4]. In recent years, numerous research studies have been conducted with the aim of acquiring signals of chatter during the milling process. A range of sensors and signals have been employed for chatter detection, including cutting forces [5-6], vibration signals [7-9], servo current [10], sound [11-15], and acoustic emission [9].

Due to the complex non-linear characteristics of chatter during the machining process, several methods have been proposed for online chatter recognition in three distinct domains: frequency, time, and time-frequency. In this regard, a novel approach for online chatter detection based on the development of artificial neural networks was suggested by [11], [16-20]. Specifically, different schemes of the Self-organizing map (SOM) neural network, recursive neural network (RNN), and convolutional neural network (CNN) were utilized for representing the occurrence of chatter through signal feature processing and deep learning. While intelligent control systems proved to be effective for monitoring and recognizing chatter, the robustness, accuracy, and response rate of the neural network were heavily dependent on continuous self-learning, training, and testing processes [21].

In [22], a novel coherence function about the acceleration of the tool in the x direction and an audio signal chatter detection method was proposed for turning operations, which was evaluated for its ability to detect chatter in the early stages of machining in the frequency domain. The experimental findings indicate that this method was sensitive to the onset of chatter. However, this method was not entirely independent of the machining parameters, and therefore, the optimal threshold for chatter detection may need to be updated by adjusting the mentioned parameters. Besides, an on-line dependent chatter detection method in milling was investigated [23], and a discrete comb filtering method was suggested to isolate the chatter frequency.

A novel synthetic criterion (SC) for early chatter recognition proposed by [11], integrates standard deviation (STD) and one-step autocorrelation function (OSAF) for the online recognition of chatter vibrations. Furthermore, this paper presents a revised fast algorithm for OSAF that significantly improves the computational efficiency compared to the original SC algorithm, thereby saving valuable time for online suppression of chatter vibrations. The experimental setup involved the acquisition of vibration signals through two accelerometers mounted on the spindle house, thus enabling the validation and verification of the proposed SC method.

The work presented in this paper proposes a synthetic criterion (SC) for online chatter recognition. When the SC integrates standard deviation (STD) and One-Step Autocorrelation Function (OSAF), it results in an enhanced sensitivity and accuracy of chatter recognition compared to the traditional method [11]. The application of the SC method is a significant improvement in the detection of chatter vibrations during machining operations. The vibrations are captured by light weighted piezoelectric sensors that are mounted on workpieces of varying sizes. Unlike other sensors, they are distinguished by their ability to capture the vibration signals without altering the dynamics of the vibrating system. Additionally, these sensors are characterized by a high bandwidth and cost-effectiveness, making them a suitable choice for data collection purposes.

2 MODELING

Chatter vibrations are commonly observed when a machining process transitions from a stable stage to an unstable one. These signal vibrations involve three distinct stages: the stable stage, the transition stage, and the unstable stage [11]. While vibrations are negligible during the stable stage, they become more pronounced in the chatter stage. Therefore, the transition stage is particularly important for identifying chatter. Two changes occur in the transition stage: an increase in amplitude in the time domain and a shift in the dominant frequency band in the frequency domain, which lead to chatter vibrations.

This paper employs a synthesis criterion (SC) to identify chatter vibrations, which is based on the integration of the standard deviation (STD) and the one-step auto correlation function (OSAF), which will be described.

1.1. Standard Deviation (STD)

One of the characteristics of a signal is STD which provides insight into the trend of increasing signal amplitude in the frequency domain. This feature is defined by the following Equation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}} \tag{1}$$

Where, x_i is the sampled data, $\bar{x}$ is defined as the average data and N is the number of samples.

1.2. One-Step Auto Correlation Function (OSAF)

For processing random signals, OSAF is a beneficial method. It also defines the interdependence of a signal at one particular moment on the same signal at a different moment, within the time domain. If the sampling interval for chatter vibration is selected correctly, the OSAF can detect changes in the dominant frequency. A simple harmonic signal is defined by:

$$x_i(t) = A_i \, sin(2\pi f_i t + \theta_i) \tag{2}$$

Where, θ_i is considered to be a random variable. The expression of the OSAF according to the autocorrelation function is represented as follows:

$$\rho_{1i} = cos\, 2\pi f_i \Delta \tag{3}$$

The sampling interval (Δ) is determined based on the Nyquist frequency $f_n = 1/(2\Delta)$. Additionally, f_i increases as ρ_{1i} decreases. Harmonic vibration signals can be represented by the following:

$$x(t) = \sum_{i=1}^{n} x_i(t) = \sum_{i=1}^{n} A_i \, sin(2\pi f_i t + \theta_i) \tag{4}$$

The original algorithm of OSAF for this condition is as follows:

$$\rho_1 = \frac{\sum_{i=1}^{n} A_i^2 \, cos(2\pi f_i \Delta)}{\sum_{i=1}^{n} A_i^2} = \frac{\sum_{i=1}^{n} A_i^2 \rho_{1i}}{\sum_{i=1}^{n} A_i^2} \tag{5}$$

In this Equation, A_i^2 is replaced by $S(f_i)$,the power spectrum, in ith frequency (f_i). So, the following Equation will be obtained:

$$\rho_1 = \frac{\sum_{i=1}^{n} S(f_i) \, cos(2\pi f_i \Delta)}{\sum_{i=1}^{n} S(f_i)} \tag{6}$$

According to the aforementioned Equation, the original algorithm of OSAF has a monotonic relationship between ρ_1 and the dominant frequency band [11].

1.3. The Fast Algorithm of OSAF

To calculate OSAF in "Eq. (6)", the power spectrum function $S(f_i)$ should be calculated using the discrete fourier transform (DFT) method. Therefore, to improve the computational efficiently, a fast algorithm for OSAF was introduced in [11], which can detect vibration signals online. Fast OSAF calculates the required time series directly as follows:

$$\rho_1 = \frac{NC - A^2}{NB - A^2} \tag{7}$$

A, B, and C parameters are:

$$A = \sum_{i=1}^{N} x_i, \; B = \sum_{i=1}^{N} x_i^2, \; C = \sum_{i=1}^{N} x_i \, x_{i-1} \tag{8}$$

In this research, N refers to experimental samples that have been acquired at each sliding window. Furthermore, the computational efficiency of OSAF was improved by implementing "Eq. (7)", which outperforms "Eq. (6)".

1.4. Synthesis Criterion (SC)

The STD is a value that indicates the magnitude of variations in a signal in the time domain. On the other hand, the OSAF is a feature that captures the changes in the dominant frequency band of the vibration signal. By combining these two functions, the SC is generated [11], obtained as follows:

$$SC = \frac{\sigma}{\bar{\sigma}} \, (1 + 2^E) \tag{9}$$

Where, $\bar{\sigma}$ is the mean of STD of all sections calculated in the stable stage, $\sigma/\bar{\sigma}$ is the ratio of instantaneous STD and the mean of the total standard deviation. E is a sign function:

$$E = sgn(\rho_1 - \bar{\rho}_1 - 1.96 \, \sigma_{\rho 1}) \tag{10}$$

In this Equation, $(\bar{\rho}_1)$ is also considered as the mean of OSAF calculation in the stable stage, $\sigma_{\rho 1}$ is the STD of ρ_1 and the scaling factor 1.96. This scaling factor represents the quantile of 97.5% confidence interval, a number commonly used for statistical calculation, from a normal distribution. If:

$\rho_1 < \bar{\rho}_1 + 1.96 \, \sigma_{\rho 1} \rightarrow E = -1$
and
$\rho_1 > \bar{\rho}_1 + 1.96 \, \sigma_{\rho 1} \rightarrow E = +1,$
then

SC can be described as follows:

$$SC = \begin{cases} 1.5\sigma/\bar{\sigma} & , \; E = -1, \\ 2\sigma/\bar{\sigma} & , \; E = 0, \\ 3\sigma/\bar{\sigma} & , \; E = 1. \end{cases} \tag{11}$$

1.5. Online Chatter Recognition by SC

Establishing the threshold value of SC is a crucial step in online chatter recognition. The initial threshold value may be determined due to two essential conditions [11]:

$$\sigma > 1.875\bar{\sigma} \tag{12}$$

$$\rho_1 > \bar{\rho}_1 + 1.96\ \sigma_{\rho 1} \tag{13}$$

By applying both conditions simultaneously chatter vibrations occur and the threshold is equal to the following expression:

$$SC_{lim} = 1.875\ \times 3 = 5.625 \tag{14}$$

The online chatter recognition by SC is:

$$SC \geq SC_{lim} \tag{15}$$

When the SC value reaches a predetermined threshold, an alarm is triggered using the above-mentioned “Eqs. (14) and (15)”.
In order to achieve early chatter recognition and online control using the SC, the following procedure is typically followed: First, vibration signals are sampled in the stable stage of milling, and their parameters such as the A, B, and C are computed. The length of the sliding data section (N) and the calculation timers are then set by the user. In this paper, the length of data in sliding windows (N) is selected by trial and error to 300 samples. Then, $\bar{\sigma}, \bar{\rho}_1$ and $\sigma_{\rho 1}$ in each window are calculated. When the SC value reaches its threshold, chatter vibrations will be reported. Finally, by adjusting the milling parameters, chatter vibrations could be avoided.

3 THE TESTBED

To validate the SC algorithm in identifying chatter vibration, milling tests with different cutting conditions were conducted. For this process, a 4-teeth high speed steel end mill with a diameter of 10 mm and a length of 70 mm was employed. The experimental setup involved the utilization of two distinct flat strip workpieces with a width of 20, thickness of 10, and lengths of 50 mm and 70 mm, respectively, made of aluminum alloy 7075T6. As shown in “Fig. 1”.
To acquire the signals, an STM32F103C8T6 data acquisition card was used with a sampling rate of 20 kHz. To receive signals in a more suitable range, the piezoelectric sensor with two resistors of 1 and 2 mega-ohms in the form of a series circuit was connected. The sensor signal is input to pin (A0) of the stm32 card. The following is a schematic of the circuit of this sensor (“Fig. 2”):
The acquired vibration signals were analyzed by MATLAB software. In all experiments, 10 mm of workpiece was clamped in vise. The testbed is depicted in “Fig. 3”.

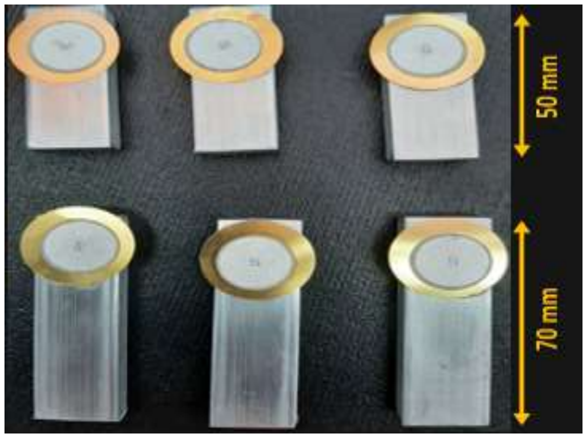

Fig. 1 Workpieces with lengths of 50 and 70 mm.

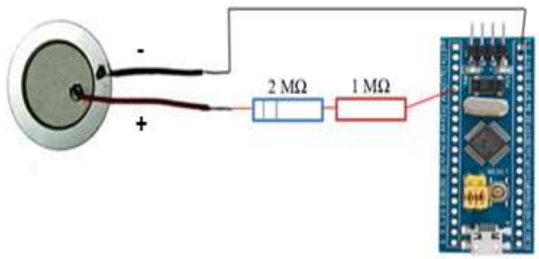

Fig. 2 Schematic of the circuit.

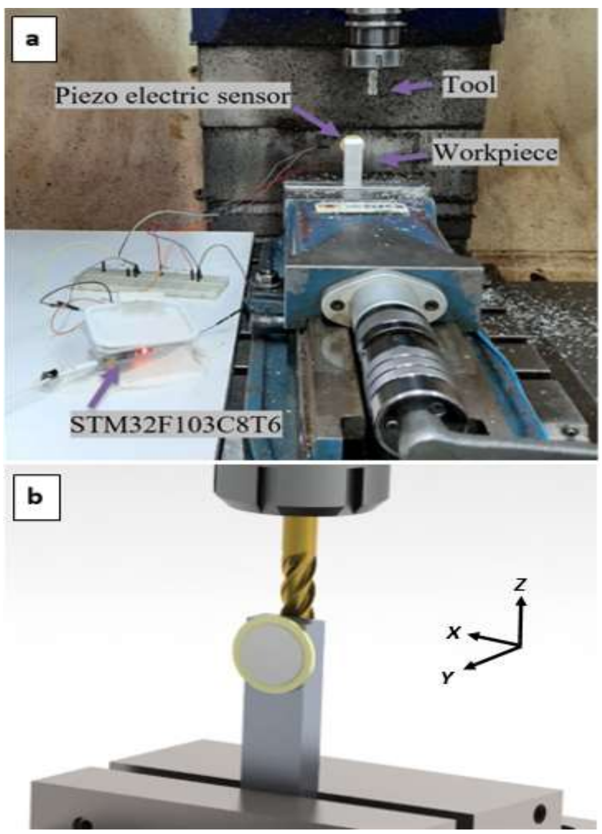

Fig. 3 (a): The Experimental setup, and (b): Model of the process.

4 EXPERIMENTAL TESTS

In this experiment, vibration signals under different cutting depths and constant spindle speeds and feeds were compared to investigate chatter during milling. These vibration signals are captured by using a piezoelectric sensor mounted on the workpiece along Y direction.

The workpieces should be fixed, so 10 mm of each piece were clamped in the milling lockdown vise. The SC for workpieces with a free length of 40 mm with a depth of 1, 4, and 6 mm and a workpiece of 60 mm with 0.5,1,4 and 6 mm, was investigated. For each section, 300 samples were selected as a computational part. To detect chatter vibrations, it is necessary to calculate the $\bar{\sigma}$, $\bar{\rho}_1$and $\sigma_{\rho 1}$ parameters of the vibration signals in the stable stage.

For the workpiece of 40 mm and at axial cutting depths of 1, 4, and 6 mm, the vibration signal was obtained. The following Figures illustrate the investigation of the chatter signal by the SC method (“Fig. 4”).

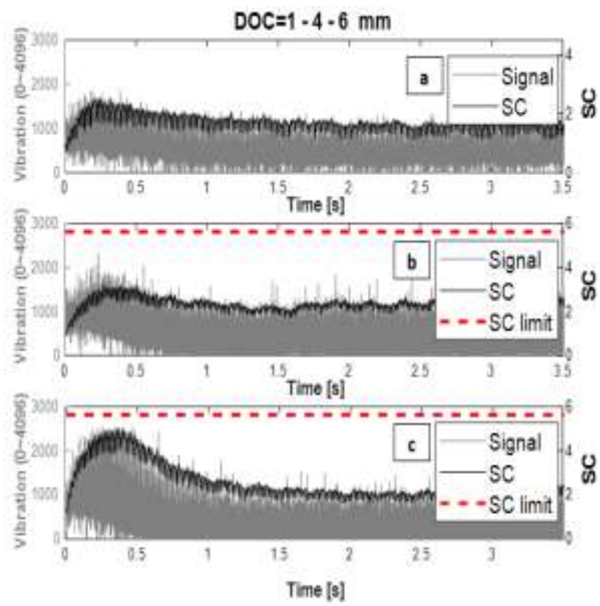

Fig. 4 Signal and the SC curve for the workpiece 40 mm and DOC: (a): 1, (b): 4 and (c): 6 mm.

During milling tests, the maximum SC values were found to be 2.5, 3.2, and 4.2 for cutting depths of 1 mm, 4 mm, and 6 mm, respectively. Notably, all three SC values were found to be less than the threshold value, indicating stable signals based on the SC method. However, increasing the free length of the workpiece resulted in higher levels of chatter vibration. To identify the most stable signal using the SC method for a 60 mm workpiece, two cutting depths of 0.5 mm and 1 mm were utilized, with the corresponding SC values presented in “Fig. 5”.

During the conducted milling tests, it was observed that the vibration signal remained stable at cutting depths of 0.5 mm and 1 mm.

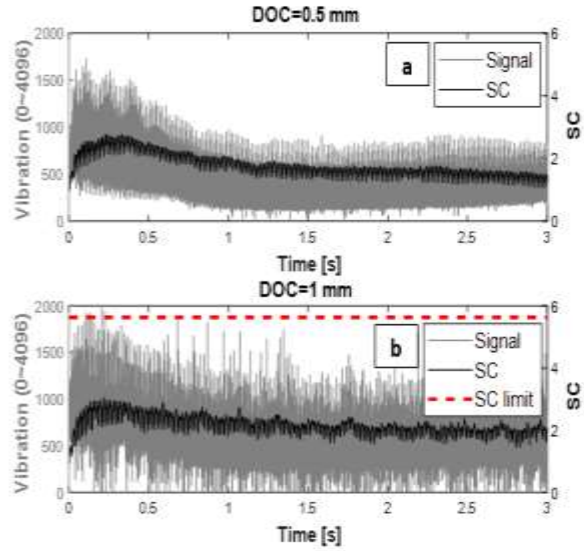

Fig. 5 The comparison of stability by SC method between DOC: (a): 0.5 and (b): 1 mm for the workpiece 40 mm.

Figure 6 presents the vibration signals for cutting depths of 0.5 mm, 4 mm, and 6 mm, as depicted using the STD and the OSAF diagrams in the time domain. Specifically, “Fig. 6 (a)” demonstrates a signal with a cutting depth of 0.5 that remains in a steady state, with minor fluctuations observed throughout the milling process, with different peak-to-peak ranging between 140 and 900 integer values.

During this process, the vibration signal exhibited significant fluctuations at cutting depths of 4 mm and 6 mm, as evidenced by the STD diagram. Specifically, at a cutting depth of 4 mm, the peak-to-peak fluctuations in “Fig. 6 (d)” remained less than 1008 integer values before 0.17 seconds. However, after this point, the difference increased to approximately 2920 integer values. Similarly, at a cutting depth of 6 mm in “Fig. 6 (g)”, the maximum difference was 2213 integer values before 0.1 seconds, with this difference significantly increasing to 3050 integer values. In the STD diagram, the fluctuations observed at a cutting depth of 0.5 mm in “Fig. 6 (b)” remained within a narrow range, with a peak-to-peak value of approximately 56.2 around a mean value of 200. However, “Figs. 6 (e) and (h)”, which demonstrate STD at cutting depths of 4 mm and 6 mm, the mean value increased sharply after 0.25 seconds and 0.15 seconds, respectively, reaching values of 764 and 954, respectively. Similarly, in the OSAF diagram, the amplitude widened at cutting depths of 4 mm and 6 mm, as shown in Figs 6 (f) and (i). They evidenced peaks in 0.14, and 0.06 seconds which reached 0.904 and 0.986 respectively. The signal, in turn, fluctuated around 0.4

and 0.65, respectively, at the end of the domain. Conversely, at the cutting depth of 0.5 mm, the OSAF diagram exhibited limited fluctuations around 0.94, within a range of approximately 0.0806, as depicted in “Fig. 6 (c)”.

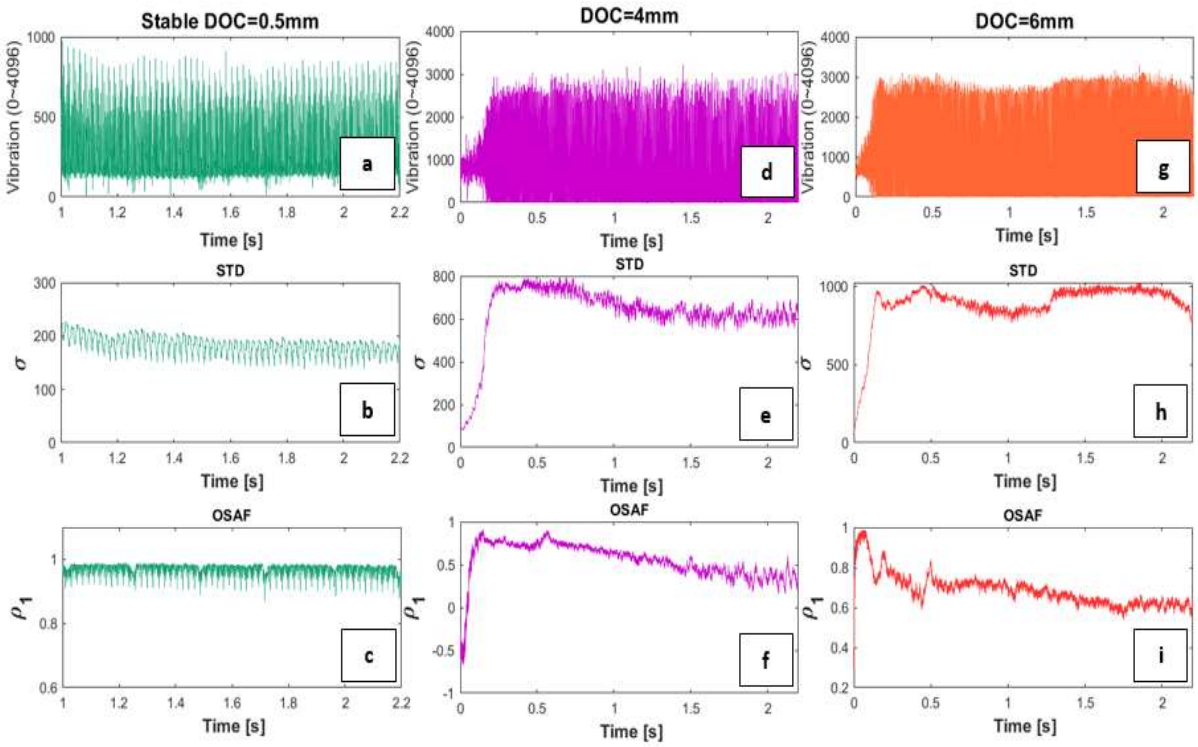

Fig. 6 The vibration time domain curve, STD, and OSAF curves. (Left) DOC 0.5 mm, (Middle) DOC 4 mm, (Right) DOC 6 mm.

So, this method is utilized for chatter detection at cutting depths of 4 mm and 6 mm. As depicted in “Figs 7 and 8”, in these two depths of cut, chatter vibrations were observed. Specifically, a sharp increase in the SC was noted at the beginning of the 4 mm cutting depth, in “Fig. 7 (b)” with a maximum value of approximately 6.67 reached more than the SC threshold, being reached by 1.3 seconds.

The SC curve subsequently fluctuated around its threshold value for the remainder of the recorded time. Similarly, the SC curve for a cutting depth of 6 mm, as shown in “Fig. 8 (b)”, exhibited an initial increase within the first 0.15 seconds, with the value exceeding the threshold range of SC_{lim} of 7.5 to 8.8.

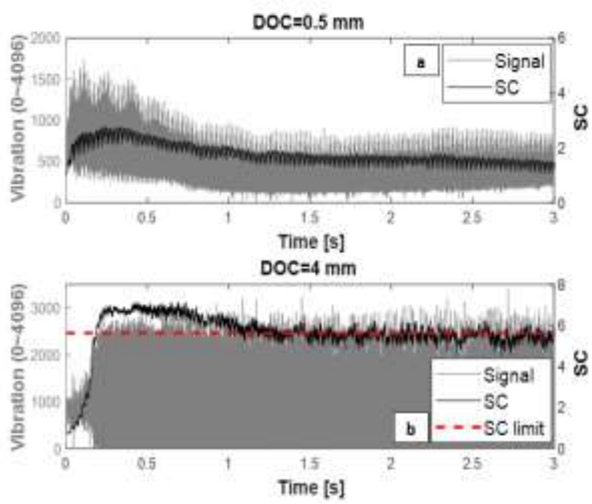

Fig. 7 The signal and the SC curve for the workpiece 60 mm and DOC: (a): 0.5 and (b): 4 mm.

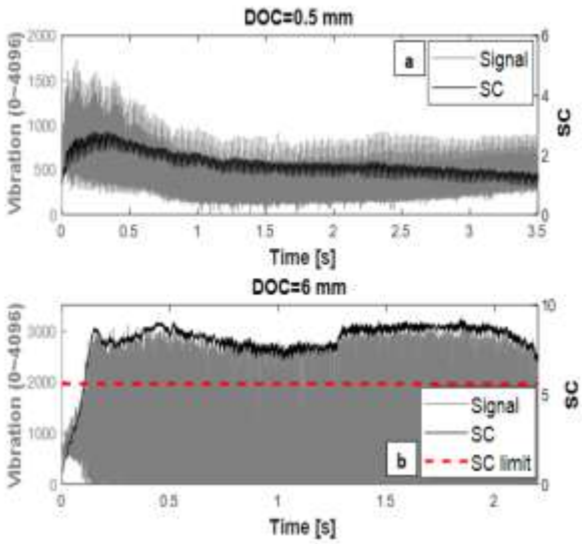

Fig. 8 Signal and the SC curve for the workpiece 60 mm and DOC: (a): 0.5 and (b): 6 mm.

Figure 9 showcases the Discrete Fourier Transforms (DFTs) of the vibration signals obtained from the free length workpiece measuring 40 mm in length and subjected to cutting depths of 1, 4, and 6 mm, along with the workpiece measuring 60 mm in length and subjected to cutting depths of 0.5, 1, 4, and 6 mm in “Fig. 10”.

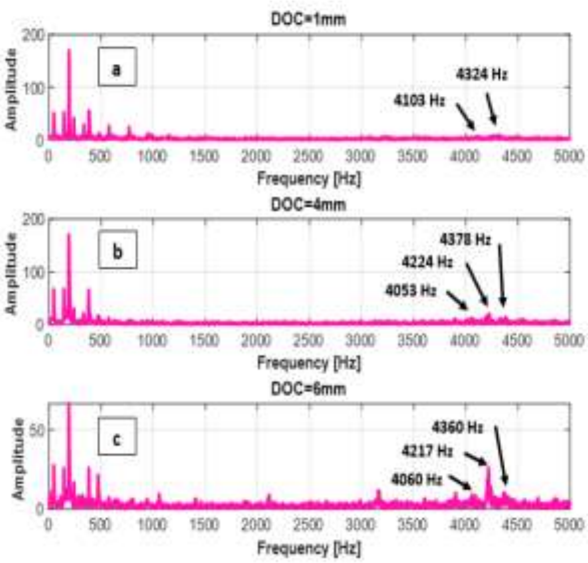

Fig. 9 DFT for the workpiece 40 mm. (a): DOC 1 mm, (b): DOC 4 mm, and (c): DOC 6 mm.

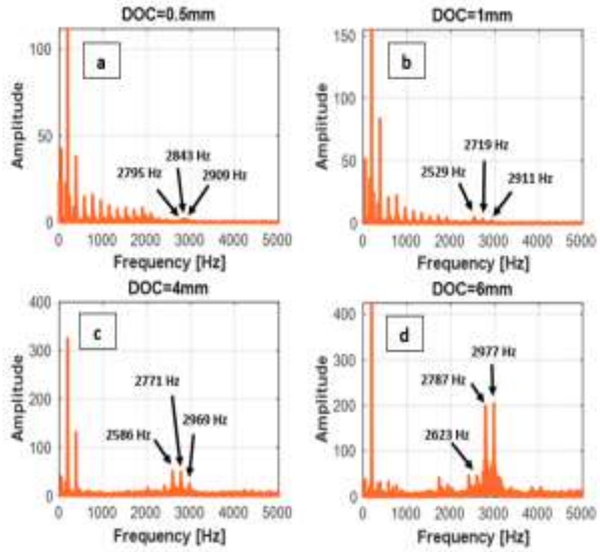

Fig. 10 DFT for the workpiece 60 mm. (a): DOC 0.5 mm, (b): DOC 1 mm, (c): DOC 4 mm, and (d): DOC 6 mm.

According to the findings presented in “Fig. 9”, the free-length workpiece measuring 40 mm exhibits a dominant frequency of approximately 4200 Hz. Notably, this frequency had a significant increase in amplitude, rising from 9.8 at a cutting depth of 1 mm to 25.82 at a cutting depth of 6 mm. Similarly, the dominant frequency observed at a cutting depth of 6 mm in “Fig. 10”, is approximately 2780 Hz, with the amplitude of the corresponding DFTs exhibiting an upward trend, increasing from 1.7 to 208 as the cutting depths vary from 0.5 to 6 respectively. These results indicate a decline in the dominant frequency of the signal with increasing free length of the workpiece, while the energy of the signal is shown to be directly proportional to the amount of axial depth of cut.

Figure 11 shows the milling surface of the workpiece with a free length of 60 mm and cutting depths of 0.5,1,4, and 6 mm. The machined surfaces depicted in “Figs. 11 (a) and (b)” exhibit a smooth texture with no visible chatter marks, thereby indicating a stable machining process with cutting depths of 0.5 and 1 mm. In contrast, the machined surfaces illustrated in “Figs. 11 (c) and (d)” demonstrate evidence of chatter vibration, evident from the visible chatter marks present at cutting depths of 4 and 6 mm, respectively. These experimental findings are consistent with the observations obtained from our developed online SC method.

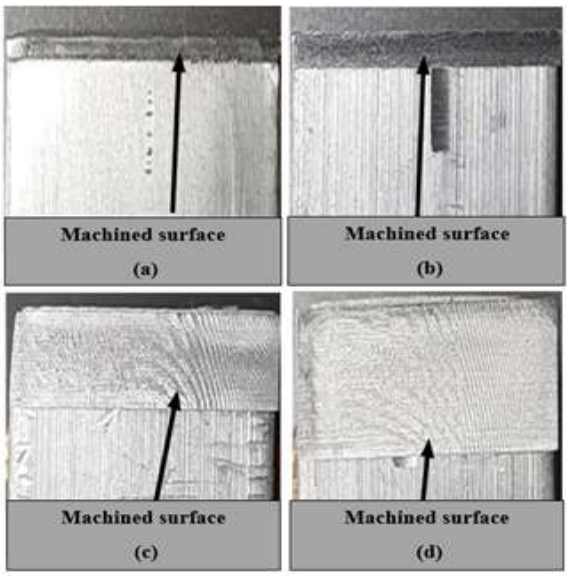

Fig. 11 Machined surface for the workpiece 60 mm. (a): DOC 0.5 mm, (b): DOC 1 mm, (c): DOC 4 mm, and (d): DOC 6 mm.

5 CONCLUSIONS

The primary objective of this study was to employ the SC method for the online detection of chatter vibrations during the milling process. This method involved the combination of the STD and the OSAF techniques. To validate the efficacy of the SC method, milling tests were designed and conducted, aimed at detecting chatter vibrations promptly. The SC method was proposed due to its robustness and high detection speed, making it a potent tool for the online recognition of chatter during the milling process. The use of the SC was essential for detecting chatter vibrations in the stable signal at different workpiece lengths. As the length of the workpiece increased, the cutting depth required for the stable signal to detect chatter decreased. Also, for analyzing the vibration signals, accelerometers were employed; however, in this paper, piezoelectric sensors were utilized. Owing to the lightweight of the sensor, there is no interference to the dynamic of the system at all. Additionally, the high bandwidth of these flexible sensors along with cost-effectiveness, make them an ideal choice for capturing vibration signals reliably and efficiently. The experimental results confirm the efficiency of the proposed algorithms in predicting the onset of chatter vibration using the developed hardware.

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