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Autonomous chatter detection using displacement sensors in turning

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Abstract

Chatter vibrations lead to poor surface finish and tool wear. A reliable chatter detection is prerequisite for its avoidance. The paper presents the lathe spindle equipped with displacement sensors used to detect chatter vibrations. The sensors are integrated with the machine tool through communication with the CNC control system and protected against cutting fluids and chips. The data collected during machining is used to calculate the chatter indicator which is based on the multiple sampling per revolution procedure. The use of displacement sensors made it possible to define an additional indicator that allows distinguishing between the appearance of chatter vibrations and the entry or exit from the workpiece. This, in turn, allowed the use of an artificial neural network as a machining state classifier, characterised by a simple structure which positively contributes to computational efficiency. The network was trained and the optimal number of input parameters was elaborated. The neural network is an integral part of the chatter detection algorithm which operates on data updated every revolution of the spindle. The use of the neural network eliminated the need to determine the threshold value, which was an obstacle to the autonomy of the detection process. Numerous experimental tests have confirmed the reliability of the proposed algorithm.

intelligent spindle, chatter, detection of chatter

1. Introduction

Regenerative chatter leads to a poor surface finish, premature tool wear and in extreme cases machine tool damage. Therefore, it is very important to monitor the occurrence of chatter vibrations. Researchers use various signals such as accelerometers, microphones, AE sensors, force sensors for monitoring the cutting process [1]. Frequently accelerometers used for chatter detection in turning are attached to the tool [2]. This limits applicability to the machining process without coolant. Force sensors can be used for effective chatter detection [3] but the main limitation is a frequency bandwidth and price of dynamometers. Sound signals are used by many researchers to detect chatter [4,5]. The main disadvantage of microphones is their susceptibility to interference from the environment. Hence, their use in industry may not be as effective as in laboratory applications.

Acquired signals are processed to extract features sensitive to the chatter occurrence. Frequently chatter detection methods are based on threshold criterion *i.e.* chatter is identified when a chatter indicator exceeds a preset threshold value. Establishing a threshold value usually requires processing a large, even huge, number of signals and classifying them into chatter/stable cases. A necessity to perform tests required for establishing a threshold value is an obstacle in the autonomation of the monitoring process. Several researchers proposed methods for automated threshold calculation. Albertelli et. al. [6] used signal collected before entering in the workpiece and applied 3σ principle to autonomously compute threshold value. Li *et. al.* [7] compared the difference of power spectra entropy determined for the unfiltered signal and signal with removed harmonics of spindle rotational speed. Unfortunately, despite universal threshold value, this method cannot be fully automated because it requires the identification of natural frequencies prior to the cutting process.

Recently more and more intelligent algorithms are used for chatter detection. Intelligent algorithms used for chatter detection include support vector machine [8], neural network [9], k-means clustering algorithms [10], self-organizing map algorithms [11]. These methods provide better robustness and adaptability to changing cutting conditions than threshold methods but require a lot of data for training procedure. Rahimi *et. al.* [12] presented chatter detection with a hybrid machine learning and physics based model. Diagnostic decision is based on the output from machine learning algorithm combined with energy ratio [13]. Machine learning algorithm distinguishes between chatter and transient states whereas physical-based approach improved chatter detection accuracy. Although the reduction of the network architecture to achieve better computational efficiency was performed, the time needed to build the spectrogram and perform calculations is still significant.

This paper proposes an application of displacement sensors for chatter detection in turning. The sensors are integrated with the machine tool through communication with the CNC control system and protected against cutting fluids and chips. Because the sensors enable measurement of the DC component, entry and exit from the material can be distinguished from chatter occurrence. Consequently, a very simple neural network could be used to determine stable and unstable states. Input parameters to a neural network include chatter indicator and its standard deviation. Chatter indicator proposed in the paper is calculated using once-per-revolution sampling [14,15]. In this paper, chatter indicator is constructed which is adapted to handle signals coming from sensors not located in close proximity of the cutting process.

2. Experimental setup

Cutting tests were performed on AFM TAE 35 horizontal lathe equipped with the EddyLAB T05-G-KA-112 displacement

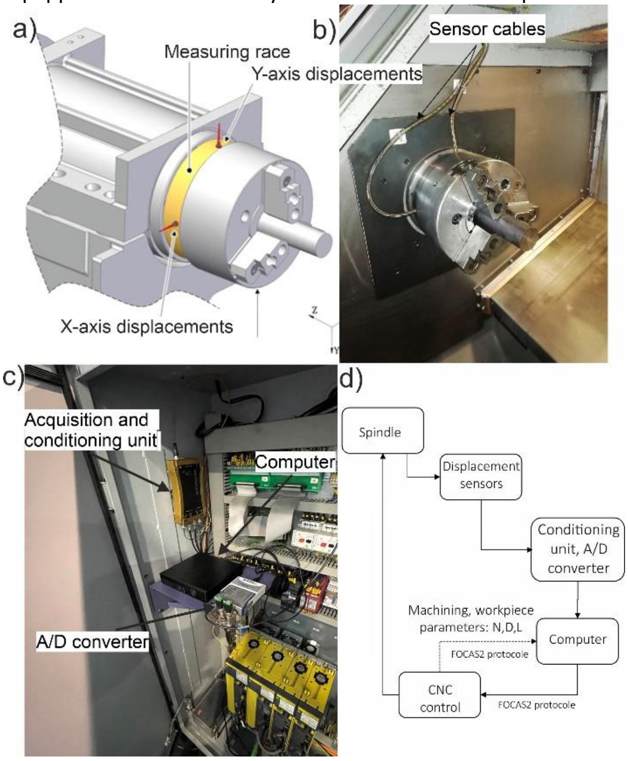

Figure 1. Experimental setup a) location of the sensors, b) spindle with built-in sensors, c) electrical cabinet equipped with signals conditioning unit, A/D converter and computer, d)scheme of the monitoring system

sensors integrated with the lathe spindle. The sensors measure relative displacements between the headstock and the spindle (Figure 1a). The sensors are protected from metal chips and cutting liquids enabling industrial application of the system (Figure 1b). Signals from the sensors are transferred to the TX2-24-16-420A signal acquisition and conditioning module. This module is connected to the National Instruments A/D converter NI9234 and the NI9162 USB module with a sampling frequency of 51.2 kHz. This system is connected to a DELL OptiPlex 3090 i5 computer. The above elements are placed in the machine's electrical cabinet, as shown in Figure 1c. The general scheme of the chatter detection system is shown in Figure 1d. Figure 2 presents an illustration of cutting tests carried out to confirm

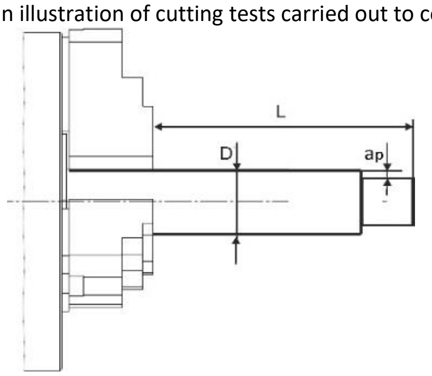

Figure 2. Basic parameters of the cutting tests

the effectiveness of chatter detection. The cutting tests were carried out for 3 workpieces with 3 sets of cutting parameters. The parameters of the cutting tests are given in Table 1.

Table 1 Cutting parameters used in experimental tests

	D [mm]	L [mm]	ap	ap	ap	f [mm/rev]
	30	190	0.5	1.5	2.0	0.15
	35	205	0.5	1.5	2.0	0.15
	40	220	0.5	1.5	2.0	0.15
N [rpm]			1400	1700	1700	

3. Computation of chatter and machining indicators

Signals from displacement sensors are denoted to as *X(t)* and *Y(t).* Then amplitude calculated as:

$$R(t) = \sqrt{X(t)^2 + Y(t)^2} \tag{1}$$

is used to build the $\boldsymbol{R_k}$ matrix. Each row of the matrix corresponds to one revolution. The matrix is updated every revolution. Assuming that n_τ samples are recorded during one revolution and considering 3 subsequent revolutions, this matrix takes form:

$$\boldsymbol{R_k} = \begin{bmatrix} R_{(k-3)n\tau+1} & R_{(k-3)n\tau+2} & \cdots & R_{(k-2)n\tau} \\ R_{(k-2)n\tau+1} & R_{(k-2)n\tau+2} & \cdots & R_{(k-1)n\tau} \\ R_{(k-1)n\tau+1} & R_{(k-1)n\tau+2} & \cdots & R_{kn\tau} \end{bmatrix}. \tag{2}$$

Standard deviation estimator is calculated for each column of the matrix:

$$\hat{\sigma}_{:,j} = \frac{T_{:,j}}{\alpha_3}, \tag{3}$$

where $T_{:,j}$ is range of the *j-th* column, α_3 is statistical constant. Finally, these values are averaged to calculate chatter indicator at *k-th* spindle revolution:

$$CI(k) = \frac{1}{n_\tau}\sum_{j=1}^{n_\tau} \hat{\sigma}_{:,j}\,. \tag{4}$$

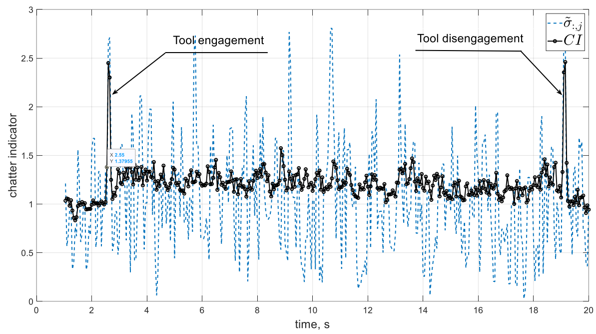

Figure 3. Comparison of the chatter indicator (CI) and standard deviation calculated once per revolution during stable cut

Neural network model applied in the monitoring algorithm uses standard deviation of the chatter indicator calculated as:

$$\hat{\sigma}\big(CI(k)\big) = \sqrt{\frac{1}{n_\tau - 1}\sum_{j=1}^{n_\tau}\left(\hat{\sigma}_{:,j} - CI(k)\right)^2}. \tag{5}$$

Figure 2 shows chatter indicator (black line) and standard deviation calculated for a single column during stable cut. Large variability of non-averaged standard deviation standard makes it unsuitable for a reliable chatter detection.

Transient states *i.e.* entry into the workpiece and exit from the workpiece result in an increase of chatter indicator. So, to avoid false alarms an additional machining indicator (*MI*) is introduced. Application of displacement sensors enabled measurement of the DC component of spindle deflection. This component changes during transient states. Hence, when the tool enters (or leaves) the workpiece DC component of *R(t)* signal changes at each rotation. This is reflected by the range of average values of *R(t)* calculated over present *(k)* and two preceding revolutions:

$$MI(k) = \max(\bar{R}_k, \bar{R}_{k-1}, \bar{R}_{k-2}) - \min(\bar{R}_k, \bar{R}_{k-1}, \bar{R}_{k-2}), \tag{6}$$

where: $\bar{R}_k, \bar{R}_{k-1}, \bar{R}_{k-2}$ are averages of the rows of $\boldsymbol{R_k}$ matrix.

Transient states are identified when *MI* exceeds threshold values determined during air-cutting as:

$$UCL(MI) = D_4(3)\overline{MI}_{ac} = 2.575\overline{MI}_{ac}. \tag{7}$$

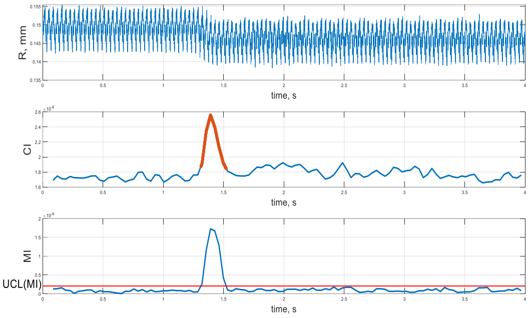

Figure 4. Displacement amplitude, chatter indicator (CI) and machining indicator (MI) - identification of tool entry

Figure 3 presents signal *R(t),* chatter indicator *CI* and machining indicator *MI* during stable cut. As tool enters the workpiece machining indicator exceeds threshold value (red line). Hence, a transient state is identified and corresponding chatter indicator is neglected. The decrease of the machining indicator below the threshold means full entry into the material. Further classification of the state *i.e.* labelling states as stable or chatter is performed by the neural network.

4. Artificial neural network

The assumption when selecting the structure of the neural network was its simplicity. Low number of operations performed by a neural network enables real-time operation of the monitoring system. Moreover, it requires small amount of data for teaching purposes which is beneficial when implementing the monitoring system in industrial plants producing small production batches. Limitation of detectable states to two (stable and chatter) is a major contributor to network simplification. Hence, the neural model consists of only one perceptron – general schema of the perceptron and transfer function used are shown in Figure 5,

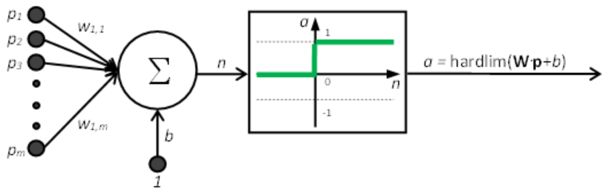

Figure 5. Neural network model

4.1. Selection of features

Time domain features were selected as the inputs to the neural network. Selected features include mean value, standard deviation, variance of chatter indicator and Y axis displacements. These features were calculated from signals corresponding to air cut and steady-state cut (Table 2). The cutting tests used for training and validation of the network were carried out with parameters given in Table 1. Hence, 9 different cutting configurations were used. Each configuration was repeated 3 times which gives 27 cutting tests. Cutting tests with depth of cut equal 0.5 mm were stable (9 cuts), whereas remaining 18 cuts (ap=1.5; 2.0 mm) were unstable. Training of the neural network was performed using 18 cutting tests (12 unstable and 6 stable). The rest of the data (6 unstable and 3 stable cuts) were used for the neural network validation. Initially, the net with 12 input was designed and trained. Then the number of inputs was gradually reduced to two inputs. Finally, 10 models with different combinations of inputs were subjected to training procedure.

Table 2 Tested neural network models

	Model no.									
set of features desribing sample	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
mean of chatter coefficient (air cutting)	1	1	1	1	0	1	1	1	0	0
standard deviation of chatter coefficient (air cutting	1	1	1	1	1	0	1	0	1	0
variance of chatter coefficient (air cutting)	1	1	1	1	1	1	0	0	0	1
mean of signal in axis Y (air cutting)	1	0	0	0	0	0	0	0	0	0
standard deviation of signal in axis Y (air cutting)	1	1	0	0	0	0	0	0	0	0
variance of signal in axis Y (air cutting)	1	1	1	0	0	0	0	0	0	0
mean of chatter coefficient (machining)	1	1	1	1	0	1	1	1	0	0
standard deviation of chatter coefficient (machining	1	1	1	1	1	0	1	0	1	0
variance of chatter coefficient (machining)	1	1	1	1	1	1	0	0	0	1
mean of signal in axis Y (machining)	1	0	0	0	0	0	0	0	0	0
standard deviation of signal in axis Y (machining)	1	1	0	0	0	0	0	0	0	0
variance of signal in axis Y (machining)	1	1	1	0	0	0	0	0	0	0
number of features used in model	12	10	8	6	4	4	4	2	2	2
performace goal (error = 0) meet?	YES	YES	YES	YES	NO	YES	YES	NO	NO	NO

It turned out that nets with only two inputs (Model no. 9 and 10) could not be successfully trained. Therefore, in order to minimize number of inputs, the neural network with 4 inputs (Model no. 7) was chosen for further investigation. Figure 6 shows mean values of chatter indicator during air cutting and

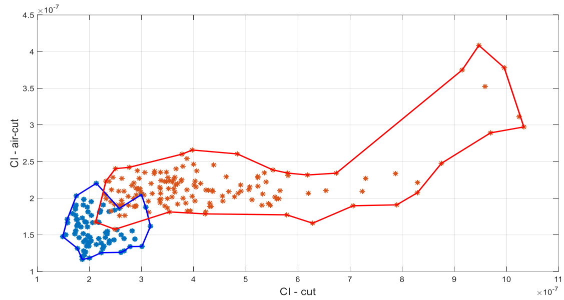

Figure 6. Values of chatter indicator during air cutting (Y-axis) and cutting (X-axis) during stable (blue) and unstable (red) cuts

actual cutting. Blue and red markers correspond to stable and unstable cuts respectively. These two sets intersect which means that such a combination of input parameters is not capable of distinguishing between stable and unstable cuts. Obviously, determination of the universal threshold values is impossible due to observed overlap in chatter indicator values for stable and unstable cuts.

5. Application of the method for on-line chatter monitoring

Monitoring of the cutting process can be described by the following steps:

1. Start of the cutting. The machine executes instructions from the G-code. One of the preliminary instructions executed after is initialization of the monitoring process (M500). Sensors begin to record signals. Matrix $\boldsymbol{R_k}$ is built.
2. Check whether $MI(k)$ exceeds threshold value. Exceeding threshold value means entry into the workpiece. Data recorded before tool entrance is used to calculate mean value and standard deviation *of* $CI_{air\_cutting}(\overline{CI}_{air\_cutting}, \hat{\sigma}(CI_{air\_cutting}))$.
3. After $MI(k)$ decrease below threshold value, chatter indicator *CI(k)* and standard deviation $\hat{\sigma}(CI(k))$ are calculated at each workpiece rotation. These values along with the $\overline{CI}_{air\_cutting}$ and $\hat{\sigma}(CI_{air\_cutting})$ are fed to the neural network. The neural network returns one from two possible states: “stable” and “chatter”.
4. If chatter is detected the monitoring algorithm changes the spindle speed to match rotational frequency harmonic with natural frequency by taking into account permissible cutting speed as $N_{opt} = 60f_c/k$ with $k = 1,2,\ldots, f_c$ – chatter frequency.

Otherwise, the spindle speed is kept constant. In both cases four input parameters are continuously fed to the neural network (Step 3 is repeated).

5. Check whether $MI(k)$ exceeds threshold value. Exceeding threshold value means exit from the workpiece.

Effectiveness of the chatter monitoring was verified using all data employed for training and validation. Also additional 9 cutting tests were used. It must be noted that according to the algorithm presented above, the parameters fed into the neural network are updated every rotation contrary to the training process when a single value of each parameter was used.

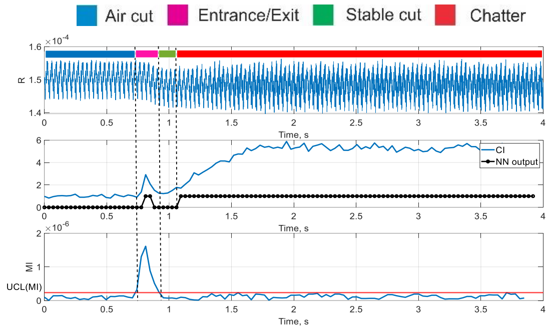

Figure 7. Detected machining states during unstable cut. Cutting conditions: ap=1.5 mm, N=1700 rev/min, D=35 mm, L=205 mm

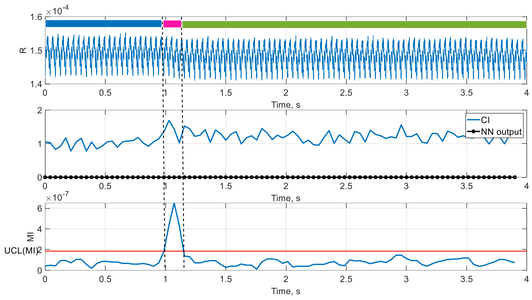

Figure 8. Detected machining states during stable cut. Cutting conditions: ap=0.5 mm, N=1400 rev/min, D=35 mm, L=205 mm

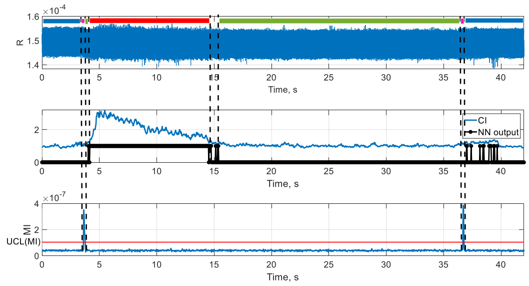

Figure 9. Detected machining states during unstable/stable cut. Cutting conditions: ap= 0.5mm, N=1800 rev/min, D=40 mm, L=205 mm

Figures 7-9 present performance of the method. The machining indicator detects entrance and exit from the workpiece. Then the neural network is activated to qualify state as stable or unstable. It is observed in Figure 9 that NN returns value "1" (chatter) after the tool leaves the workpiece. This is associated with rapid motion with high acceleration and deceleration causing vibration but having no effect on DC component of the displacement signals. Hence the machining indicator remains below threshold value and the state is qualified as "air cut".

5. Conclusion

The requirements for the proposed chatter monitoring system were integration with the machine tool, reliability of inference, computational efficiency and autonomy. Integration with the machine tool means communication with the machine tool's CNC system and a sensors location that does not limit the machine tool's machining capabilities including use of cutting fluids. The proposed system meets these conditions, which made it impossible to locate the sensors close to the cutting point. However, the proposed *CI*, thanks to averaging, allows reliable evaluation of the process state. Autonomy of the system was achieved by using the neural network. An additional advantage of the proposed neural network is simplicity, which translates into computational efficiency.

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