Milling process diagnosis using computational intelligence methods

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Abstract. The paper presents the results of research aimed at developing a method for hard-to-machine metal alloy milling process diagnosis using computational intelligence methods. To diagnose the process, a signal from an accelerometer mounted on the spindle of a CNC machine was used. The data were recorded during milling of Inconel 625 alloy workpieces, performed by sharp and blunt cutters. The acceleration signal metrics, both in the time and frequency domains were used to develop the classifiers. Based on the experiments, it has been demonstrated that it is possible to effectively diagnose Inconel alloy workpieces milling process using shallow computational intelligence methods (decision trees, k-NN and linear support vector machines). Python was used for data processing and visualisation as well as classifiers development and testing.

1. Introduction

Despite new developments in manufacturing techniques (e.g. additive), machining still plays a significant role in the production practice. The concept of Industry 4.0 assumes automation and robotisation of production processes as well as limited participation of machine operators in technological processes supervision [1-2]. Therefore, there is a need for intensive scientific research to develop processes diagnostic methods that exhibit intelligence, robustness and adaptation to disturbances as well as environment changes [3-4]. The main purpose of the system monitoring the intelligent technological process conditions is to perform actions to prevent the production of out-of-specification components [5-6]. Intelligent computer systems that perform the diagnosis of technological processes in real-time enhances the efficiency, productivity and accuracy of manufacturing processes as well as increases the cutting tool life especially involved in processing new and demanding materials.

Numerous diagnostic methods are found in the specialist literature for various technological processes [7-8], CNC machines parts [9] and machine tools [10-11]. In this work, a method for Inconel 625 workpieces milling process diagnosis is developed as a continuation of our former research activity in the field [2,8,9,12]. The Inconel 625 is a highly demanding material used in critical applications, such as aerospace, chemical, and oil production industries [10]. The objective of this work is to develop a diagnostic method which can be used in the future as an element of the real-time milling supervision system, which has been developed in Rzeszów University
of Technology (Department of Computer and Control Engineering) [12]. To diagnose the process, a signal from the accelerometer mounted on the lower bearing of the CNC machine spindle was used. The data for the diagnostic method development was recorded during milling of Inconel alloy workpieces, performed by the use of sharp and blunt cutters, and subsequently subjected to analysis by means of shallow computational intelligence (CI) methods. Python programming environment was used to perform data processing and visualisation as well as classifiers development and testing.

This paper is composed of the following Sections. Section 2, describes the testbed and experiments. Section 3 is devoted to the milling process diagnosis using computational intelligence methods. In Section 4, the results are presented. In Section 5, the conclusions are formulated.

2. Testbed and experiments description

2.1. Testbed and data acquisition system
The experiments were conducted in the laboratory testbed consisting of Haas VM-3 CNC machine equipped with an inline direct-drive spindle (Figure 1) and a set of sensors: 7 accelerometers (sensitivity 100 mV/g) integrated with temperature sensors, 1 acoustic emission sensor (sensitivity 53 mV/Pa) and 1 force and torque sensor (3-axis). Two accelerometers are mounted on the lower bearing of the spindle, the next two are mounted on the higher bearing of the spindle, additional two accelerometers are mounted on Z-axis and the last one is mounted on the workpiece. The acoustic emission sensor is mounted in the machine cabin. The force and torque sensor is mounted in the chuck. In this study, a signal from the accelerometer mounted on the lower bearing of the CNC machine spindle was used (Figure 1).

![Figure 1. Haas VM-3 CNC machine (left picture) and CNC spindle with acceleration sensors mounted on lower bearing (right picture).](image)

During the experiments, the data from the sensors were collected using a platform for rapid prototyping of intelligent diagnostic systems [12] which was composed of Beckhoff Industrial PC (IPC C6920), TwinCAT 3, MATLAB/Simulink projects and distributed input/output system based on EtherCAT protocol. IPC was used for signal acquisition and communication with a PC computer equipped with MATLAB/Simulink system, which performed data collection in External Mode. The PC computer received data from IPC and stored it as binary MATLAB files (mat) on the hard drive. The signal duration stored in one file and the sampling interval were equal to 640 ms buffer (16 000 samples) and 40 μs, respectively (25 kHz sampling frequency). The real-time PLC module for data
acquisition operated with the main sampling interval of 2 ms. In the analog input modules EL3632 from Beckhoff, used to connect acceleration sensors, the oversampling factor (defined as the number of probes per one main sampling interval) was set to 50.

2.2. Experiments
During each experiment, one Inconel disc (Figure 2) was machined with a four-teeth milling cutter at the spindle speed of 862 rpm (revolutions per minute), which corresponds to 14.36 Hz. During each experiment one complete circular milling trajectory was performed at the edge of a disc using the same tool. Two types of milling cutters were tested: sharp and blunt. In the case of sharp tools, the resulting surface roughness was 0.55 µm and for blunt tools 1.05 µm.

![Figure 2. Inconel disc with the trace of circular trajectory performed at the edge of the disc with different tools (sharp or blunt) for each disc quarter.](image)

In this study, the data from 11 discs machining processes were used (7 executed with sharp tools and 4 with blunt tools). Each data buffer (640 ms, 16 000 samples) was used to calculate one set of time and frequency metrics. Data pre-processing phase defined two sets of labelled data (class) (Table 1).

| Class  | Cutter | Surface roughness | Number of buffers |
|--------|--------|-------------------|-------------------|
| Sharp  | Sharp  | 0.55 µm           | 1085              |
| Blunt  | Blunt  | 1.05 µm           | 624               |

2.3. Measured and transformed signal
Figure 3 shows the acceleration signal plot for exemplary buffers of Sharp and Blunt classes.

In order to calculate frequency domain metrics, Fast Fourier Transform (FFT) was performed for each time data buffer. The length of FFT is equal to N=16384, taking into account 25 kHz signal sampling frequency, it leads to 1.56 Hz resolution of the transformed signal. Figure 4 shows the acceleration signal in the frequency domain for the exemplary data buffer.
3. Milling diagnosis using computational intelligence methods

3.1. Programming tools used in the study
Data processing and classification experiments were carried out in Anaconda environment with Jupyter Notebook (Python version: 3.6.6). All classifiers were developed via Scikit-learn library, which provides the most commonly used CI algorithms (e.g. generalised linear models, support vector machines, decision trees). Scikit-learn tools for measuring the performance of classifiers, such as...
classification metrics and cross-validation methods, were used in the study. Pandas and NumPy libraries were applied for data processing, while Matplotlib with Seaborn for the visualisation of the signals and extracted features.

3.2. Features calculation
Various features were calculated in the time and frequency domains from each 640 ms data buffer, that is 22 in the time domain and 10 in the frequency domain. The time signal metrics used in the study are mentioned below [7]:
- Maximum
- Minimum
- Peak to peak – the difference between the maximum and the minimum value of the signal
- Median
- Maximum of the absolute value of the signal
- Mean
- Mean of the absolute value of the signal
- Variance
- Root mean square
- Standard deviation
- Energy
- Energy of the centered signal
- Kurtosis
- Skewness
- Moment order i (i = 5:10)
- Shannon entropy
- Signal rate

Features of the acceleration signal extracted in the frequency domain are mentioned below [9]:
- RMS amplitude spectrum in the frequency ranges: 0 Hz – 500 Hz, 500 Hz – 1000 Hz, 1000 Hz – 1500 Hz, 1500 Hz – 2000 Hz, 2000 Hz – 2500 Hz
- Area under the amplitude spectrum in the frequency ranges: 0 Hz – 500 Hz, 500 Hz – 1000 Hz, 1000 Hz – 1500 Hz, 1500 Hz – 2000 Hz, 2000 Hz – 2500 Hz

3.3. Features normalisation and selection
The calculated features were in different scales and units, which is why a normalisation procedure was performed to obtain better convergence of CI methods, especially those optimised by gradient descent [13-15]. K-nearest neighbors algorithm used in the study is also highly sensitive to normalisation because features with a larger range will have a higher influence impact on the calculated distance [16]. In our case, the features were scaled to the range between 0 and 1 with the following formula:

\[ z = \frac{x - \min(x)}{\max(x) - \min(x)} \]  

(1)

where \( \min(x) \) and \( \max(x) \) are minimum and maximum values of a feature, respectively, \( x \) is the value of the feature before normalisation and \( z \) is the value of the feature after normalisation.

Features selection method has been used to obtain high classifier performance with the smallest number of features. It helps reduce the computing time of classifier predictions and features calculation, especially with respect to real-time supervision systems. Logistic regression with L1 regularisation was used in this study [17-19]. Linear models with L1 norm are highly likely to estimate coefficients as zero, thus leading to sparse solutions with the most relevant features, which can be further processed by logistic regression itself or by other classifiers. During the process of feature selection, C is the most important parameter, responsible for the strength of regularisation and when it
is lower, and then regularisation is stronger. In the experiments, parameter C in logistic regression was set to 0.1 and only two features were selected:

- F1: Area under the amplitude spectrum in the frequency range 0 Hz – 500 Hz
- F2: Area under the amplitude spectrum in the frequency range 1000 Hz – 1500 Hz.

3.4. Computational intelligence methods

In this study, three different (one linear and two nonlinear) CI methods were examined:

- Single decision tree (SDT)
- K-nearest neighbor (K-NN)
- Linear support vector machine (Linear SVM)

In scikit-learn SDT implementation, CART algorithm is used. Gini impurity was the criterion for the information gain. Moreover, the decision tree classifier has not been cropped with max depth parameter set to none, as a result, there is a low risk of overfitting, given that only two features were used.

K-NN model was implemented with 5 neighbors, uniform weights and Euclidean distance as metrics. Linear SVM has been implemented with L2 regularisation, squared hinge as loss and penalty parameter C set to 1. All of these algorithms are well described in the literature, e.g. in [20], therefore they were not further elaborated in this article.

4. Results

The performance of each classifier was measured with the 10-fold cross-validation with three indicators: accuracy, sensitivity and false alarm rate. In this work, class Sharp is treated as a negative example (N) and Blunt is treated as a positive example (P). Accuracy is calculated as Acc=(TP+TN)/(TP+TN+FP+FN)-100%, sensitivity is obtained from the formula: Sen=TP/(TP+FN)-100% and false alarm rate value is defined as FAR=FP/(FP+TN)-100% (TP – true positive, TN – true negative, FP – false positive, FN – false negative).

Only 2 most relevant features (i.e. F1, F2) provided by logistic regression with L1 norm used as feature selector were used for each classifier. Results for all methods are shown in Table 2 (mean value and standard deviation obtained for the 10-fold cross-validation).

| Algorithms   | Acc [%]     | Sen [%]     | FAR [%]     |
|--------------|-------------|-------------|-------------|
| SDT          | 99.94+/-0.18 | 99.84+/-0.49 | 0.0+/-0.0   |
| KNN          | 99.94+/-0.18 | 100+/-0.0   | 0.09+/-0.27 |
| Linear SVM   | 99.94+/-0.18 | 100+/-0.0   | 0.09+/-0.27 |

As it can be seen from Table 2, all the classifiers managed to achieve nearly perfect scores with only two best features, which were extracted in the frequency domain. It seems that the patterns located in the area under the amplitude spectrum in frequency ranges: 0 Hz - 500 Hz and 1000 Hz – 1500 Hz, found by logistic regression, are enough to develop a classifier that can separate two classes: Sharp and Blunt. Along with the performance, the time for making predictions and calculating features is another important factor for practical implementations of milling process supervision systems. Methods that do not require high computational power for making predictions (e.g. SDT) and use only two features are exhibit a great prospect for practical purposes.

5. Conclusions and future work

In this paper, the diagnosis problem for a milling process of Inconel 625 workpiece performed with sharp and blunt tools was considered. Two classes were examined, i.e. Sharp and Blunt. The data set consisted of 1709 records with 32 features in the time and frequency domains. The feature selection procedure was applied in order to extract the most significant attributes. As a result, 2 out of 32
attributes were selected and used for classifiers development. The area under the amplitude spectrum was selected as the most significant predictor calculated for two frequency ranges: 0 Hz – 500 Hz and 1000 Hz – 1500 Hz.

Three well known shallow CI methods were applied, i.e.: a single decision tree, the k-nearest neighbor and a linear support vector machine. The accuracy, sensitivity and false alarm rate were used to evaluate the performance of the algorithms. The values of these indicators were very high for all the methods for the 10-fold cross-validation testing method.

It was experimentally proved that it is possible to diagnose, with highly satisfactory performance, the milling process of Inconel 625 by means of CI methods. It is worth to emphasize that judging by its efficiency presented in the study, the implementation of the developed diagnostic methods in real-time operation seems to be possible. The result of the feature selection procedure shows that only 2 attributes of acceleration signal are sufficient for accurate diagnostics. For real-time purposes, the method with the lowest computational power requirements (e.g. SDT) can be used for the industrial implementations of milling process supervision systems. However, further research is required in this field.

**Acknowledgments**

This project is financed by the Minister of Science and Higher Education of the Republic of Poland within the "Regional Initiative of Excellence" program for years 2019 – 2022. Project number 027/RID/2018/19, amount granted 11 999 900 PLN.

6. **References**

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