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Impact of Signal Features on Machine Learning-Based Tool Condition Classification in the Milling Chipboard Process

Streszczenie. *Artykuł ten przedstawia analizę wpływu różnorodnych cech sygnałowych na klasyfikację stanu narzędzia w procesie frezowania płyty wiórowej, wykorzystując metody uczenia maszynowego. W badaniu zastosowano różne modele, takie jak XGBoost, Gradient Boosting, Drzewo Decyzyjne i Las Losowy, a następnie dokonano rankingu cech sygnałowych pod kątem ich ważności. Najważniejszą cechą okazał się sygnał 'DataLow_0', który stanowił ponad 16% całkowitego rankingu. Kolejnymi ważnymi sygnałami zostały zidentyfikowane 'DataCurrent_2' oraz 'DataLow_1'. W przeciwieństwie do nich, 'DataCurrent_1' okazał się być najmniej wpływowym sygnałem. Należy podkreślić, że względna istotność tych sygnałów może różnić się w zależności od konkretnego stanu narzędzia i użytego klasyfikatora. Chociaż ranking istotności sygnałów daje ogólne zrozumienie ich roli, zaleca się dalsze badania z wykorzystaniem analizy eksploracyjnej i technik interpretacji modelu, aby dokładniej zrozumieć naturę związków między tymi sygnałami a celem klasyfikacji. Podsumowując, zrozumienie wpływu cech sygnałowych jest kluczowe dla efektywnego projektowania i optymalizacji modeli uczenia maszynowego stosowanych do klasyfikacji stanu narzędzi w procesie frezowania płyty wiórowej. (**Wpływ cech sygnału na klasyfikację stanu narzędzia opartą na uczeniu maszynowym w procesie frezowania płyt wiórowych**)*

Abstract*. This study investigates the impact of various signal features on machine learning-based tool condition classification in the milling chipboard process. Different machine learning models such as XGBoost, Gradient Boosting, Decision Tree and Random Forest have been applied and the signal features have been ranked based on their importance. The highest ranking signal was 'DataLow_0', contributing over 16% of the total ranking. 'DataCurrent_2' and 'DataLow_1' were identified as the second and third most influential signals. On the contrary, 'DataCurrent_1' was found to be the least influential. It's essential to consider that the relative importance of these signals can vary depending on the specific tool condition and classifier used. Although signal importance rankings provide a relative understanding of these signals, further studies applying exploratory analysis and model interpretation techniques are recommended for an explicit understanding of the nature of the relationships between these signals and the target classification. In conclusion, understanding the influence of signal features is vital for effective design and optimization of machine learning models for tool condition classification in the milling chipboard process.*

Słowa kluczowe: Istotność cech sygnału, monitorowanie stanu narzędzia, uczenie maszynowe, frezowanie płyty wiórowej
Keywords: signal features importance, tool state monitoring, machine learning, milling chipboard

Introduction

The application of sensor technologies to assess and enhance various phases of furniture production is an ongoing area of interest in automation-oriented research. The intricacy of this subject is considerable, involving numerous, high-precision steps that may need adjustments with every small alteration in components. Infusing advanced technologies into these procedures is an innovative approach that aids in their optimization. This becomes especially crucial in tool condition monitoring, where improper or ill-timed decisions about replacements can downgrade the product quality and cause losses for the manufacturing company [1]-[3].

Our research primarily revolves around the milling process, where any misguided decisions can be immensely consequential. Deploying sensor-based technologies to keep tabs on tool conditions brings a renewed outlook to these issues. Evaluating tool conditions, as with other phases, can be performed manually, yet it is a laborious task that necessitates production halt. The automation of this process, therefore, signifies a notable progress in the industry.

A significant novelty introduced in this work is the use of sensor data to resolve the complex issues inherent in tool condition monitoring. While the manufacturing of furniture can involve a range of materials, wood-based ones are the most common. This approach to data-driven tool condition monitoring creates new avenues for enhancing manufacturing processes in this sector. There are numerous studies focusing on these elements. Depending on the specific task, different signals are analyzed and evaluated, determining their usefulness in identifying tool condition during various stages of the machining process [2], [4]-[8]. Despite the problems being well-described, there remains a requirement for an automatic, precise solution that is simple to integrate into production and feasible to implement in actual work settings.

Given the complex nature of the problem, machine learning algorithms appear to be the optimal solution. These algorithms have gained significant traction in manufacturing processes, and the pioneering approach proposed in this paper seeks to apply these techniques to tool condition monitoring. Existing research encompasses various methodologies, both for image- and sensor-based systems [9]-[11], [18], [19]. The method proposed here expands on these approaches, presenting innovative applications of machine learning algorithms for tool condition monitoring tasks. Depending on the chosen approach, various problems, their aspects, and potential applications of the suggested solutions are contemplated. Solutions like the one used for tree species recognition, presented in [12], demonstrate that machine learning algorithms can be tailored to even the most complex tasks with the right input data and training process.

When it comes to the specific problem of tool condition monitoring, the primary distinction pertains to the various components applied. While recording signals is a common practice, some solutions consider image use, often coupled with Convolutional Neural Networks (CNNs), which perform relatively well when such samples are considered [1], [13]-[15]. Additionally, the training process can be optimized through transfer learning with various pretrained networks (like AlexNet [16] prepared for ImageNet database [20] or data augmentation.

The primary focus of this research is the practical application of a novel solution for tool state recognition, with input data based on the physical parameters of the used machinery. It is crucial for the given solution to facilitate easy implementation in the work environment, with high overall accuracy. The unique approach to feature generation, using Short-Time Fourier Transform (STFT) and Discrete Wavelet Transform (DWT) methods, distinguishes this work from previous studies. Various versions of the method were tested for all selected, state-of-the-art classifiers, yielding more than satisfactory results.

The objective of this article is to investigate the impact of selected signal features on the construction of machine learning models for tool condition classification in the milling chipboard process. The signal features under consideration - Acoustic emission, Force X, Force Y, Noise level, Vibration level, Device-rated current, Device-rated voltage, Head-rated current, Head-rated voltage, Servo-rated current, Servo-rated voltage - have been identified as having the most significant influence on the performance of these models.

This study will delve into the utilization of these features within the context of well-known artificial intelligence (AI) models, namely Decision Tree, Gradient Boosting, Random Forest, and XGBoost. The aim is to enhance our understanding of their role and utility in developing predictive models that could optimally classify tool conditions, contributing to improved milling processes and results.

Data Set

The principal objective of the study detailed herein was to create a diagnostic apparatus that could proficiently evaluate the wear level of a tool without interrupting the manufacturing process. This assessment hinges on an array of signals gathered during the experiment. All trials and data collection were performed applying a Jet 130 CNC machining center (Busellato, Thiene, Italy), outfitted with a single, interchangeable 40 mm edge cutter head, equipped with a replaceable carbide cutting edge (Faba SA, Baboszewo, Poland).

Tests applied a chipboard panel sample measuring 300 mm by 150 mm. This component was securely fixed on a measuring platform. A groove with a depth of 6 mm was carved into the panel at a spindle speed of 18,000 rpm, and a feed rate of 0.15 mm per tooth. These operational parameters were chosen based on meticulous literature review and first-hand knowledge of the authors in chipboard milling operations. The chosen spindle speed and cutting depth are standard in the industry, and the feed rate was found to yield optimal surface finish and tool wear results.

The state of the tool was categorized into three distinct conditions: Green, Yellow, and Red. The Green condition corresponds to a newly-minted, properly-functioning tool. Yellow designates a tool that, while somewhat worn, remains operational. Red, on the other hand, signifies a tool that requires replacement due to extreme wear.

Throughout the experimental procedure, operations were momentarily halted to allow for physical inspection of the blade condition using a Mitutoyo TM-505 microscope. This instrument is well-suited for determining dimensions and angles and can also verify the shapes of screws and gears with an optional reticle. Using this apparatus, wear states were gauged and allocated to one of the three wear states following these regulations:

- Green state corresponds to a VBmax in the range of 0–0.15 mm, indicating four different levels of wear state;
- Yellow state is assigned when VBmax falls within 0.151–0.299 mm, reflecting two different levels of wear state;
- Red state is deemed when VBmax exceeds 0.299 mm, also indicating two different levels of wear state.

The experimental setup incorporated a range of sensors able to collect a total of 11 different parameters, listed in Table 1.

Data from these sensors were collected using National Instruments PCI-6111 measurement cards (for measuring acoustic emissions) and PCI-6034E (for capturing other parameters).

Table 1. List of Signal Types Utilized for Feature Extraction in AI Modelling of the Milling Chipboard Process.

No.	Signal name	Signal Description
1	DataHigh	Acoustic emission
2	DataLow	Force X
3	DataLow	Force Y
4	DataLow	Noise level
5	DataLow	Vibration level
6	DataCurrent	Device-rated current
7	DataCurrent	Device-rated voltage
8	DataCurrent	Head-rated current
9	DataCurrent	Head-rated voltage
10	DataCurrent	Servo-rated current
11	DataCurrent	Servo-rated voltage

The acquisition of data was conducted on a PC applying the Lab ViewTM (National Instruments Corporation, ver. 2015 SP1, Austin, TX, USA) software environment using NI PCI-6034E and NI PCI-6111 data acquisition cards. To adequately capture the AE signal, a card with a high sampling frequency was required. For the remaining signals, a card with a frequency of 50 kHz.

All sensors were held stationary relative to the workpiece and the cutting zone throughout the entire measurement process to prevent potential irregular noises and changes in sound from influencing the training process. The structure of the data gathered during this stage is summarized in Table 1.

Numerical Experiments

This section presents the empirical evaluation and results of the conducted experiments based on two different methods for feature extraction from signals: the Short-Time Fourier Transform (STFT) and the Discrete Wavelet Transform (DWT). Additionally, a range of classifiers have been applied to evaluate the effectiveness of the extracted features for tool condition classification in the milling chipboard process. Each method is summarized and the key results are reported.

A. Short-Time Fourier Transform

We applied the Short-Time Fourier Transform (STFT) to divide the initial samples into 32-segment chunks according to their frequency. The Hamming window was used to define the range and avoid overlap, resulting in a total of 17 segments per chunk. After processing the 11 recorded signals, the final feature set contained a total of 102 variables (17 segments x 6 statistical features) for each of the signal subsets, thus yielding a comprehensive set of 1122 variables.

The computed STFT-based features offer an intricate insight into the time-frequency content of the signal, which serves as a rich source of information for further machine learning-based analyses.

B. Discrete Wavelet Transform

The second method used was the Discrete Wavelet Transform (DWT), as discussed in the corresponding section. The input signal was decomposed into approximation coefficients (low-frequency components) and detail coefficients (high-frequency components) using a Symlet 5 wavelet. The procedure was iterated for seven decomposition levels. At each level, a set of statistical features was calculated from both types of coefficients, yielding 16 features per level.

The DWT-based features, containing time-frequency characteristics of the signal at various scales, provide another powerful tool for machine learning analysis, especially for applications where the frequency content varies over time.

C. Hyperparameter Optimization

Following the feature extraction, we optimized the hyperparameters for the machine learning classifiers using an exhaustive grid search method. This optimization process significantly improved the efficiency and accuracy of the tested machine learning algorithms. Although exhaustive, the grid search method was crucial in identifying the best hyperparameter combinations, leading to enhanced model performance.

D. Classifiers and Performance Evaluation

Four state-of-the-art classifiers have been applied to evaluate the extracted features [17]. These included simple classifiers like Decision Trees to more complex ensemble methods like Random Forest, Gradient Boosting and XGBoost. All classifiers were evaluated using both STFT and DWT feature sets.

This numerical experimentation process provides us with valuable insights into the importance of feature extraction techniques and the impact of choosing appropriate machine learning classifiers for tool condition classification in the milling chipboard process. The outcome also underlines the significance of hyperparameter optimization in achieving improved model accuracy and efficiency.

The outcomes of numerical experiments conducted for the Short-Time Fourier Transform (STFT) and Wavelet approach, including hyperparameter optimization for XGBoost, Gradient Boosting, Decision Tree, and Random Forest methods, are detailed in Tables 2 and 3 [17].

Table 2. Result of numerical experiments for the STFT approach with hyperparameter optimization for: XGBoost, Gradient Boosting, Decision Tree, Random Forest.

No.	Model	Train [%]	Test [%]
1	XGBoost	100.00	76.32
2	Gradient Boosting	100.00	78.95
3	Decision Tree	97.30	73.68
4	Random Forest	100.00	92.11

Table 3. Result of numerical experiments for the Wavelet approach with hyperparameter optimization for: XGBoost, Gradient Boosting, Decision Tree, Random Forest.

No.	Model	Train [%]	Test [%]
1	XGBoost	100.00	97.37
2	Gradient Boosting	100.00	94.74
3	Decision Tree	100.00	89.47
4	Random Forest	100.00	97.37

Significance of Signals in Classification

In the process of tool condition classification in the milling chipboard process, machine learning models like XGBoost, Gradient Boosting, Decision Tree, and Random Forest are applied. These models can handle a variety of signals, and the impact of each signal can vary from one model to another.

Table 4 presents a ranking of the importance of various signals, as assessed by an ensemble of the mentioned classifiers. The ranking values were obtained using a combination of the STFT and Wavelet approaches. The signal with the highest ranking is 'DataLow_0', with a score of 426, accounting for 16.28% of the total ranking value. This suggests that this signal plays a significant role in the classification process.

The next two most important signals are 'DataCurrent_2' and 'DataLow_1', which contribute 13.04% and 11.43% to the total ranking value respectively. The least influential signal in our ranking is 'DataCurrent_1', with a ranking value of 145 and 5.54% of the total.

However, it's essential to note that the relative importance of these signals can be context-dependent. For instance, while 'DataLow_0' has the highest ranking, other signals may become more important depending on the specific tool condition under consideration or the specific classifier used.

It's also noteworthy to mention that while the ranking values give us an understanding of the signals' relative importance, they do not provide a clear understanding of the relationship between the signals and the classification output. To understand the nature of these relationships, further exploratory analysis and model interpretation techniques would be necessary.

The findings of this analysis emphasize the importance of understanding the feature's impact on machine learning-based tool condition classification in the milling chipboard process. By identifying the most influential signals, we can make more informed decisions when designing and optimizing these models.

Table 4. Result of Signal Importance Ranking Table for STFT and Wavelet approach.

#	Signal	Ranking	Ranking [%]
1	DataLow_0	426	16.28
2	DataCurrent_2	341	13.04
3	DataLow_1	299	11.43
4	DataLow_3	235	8.98
5	DataCurrent_5	229	8.75
6	DataCurrent_3	215	8.22
7	DataLow_2	210	8.03
8	DataHigh	199	7.61
9	DataCurrent_4	163	6.23
10	DataCurrent_0	154	5.89
11	DataCurrent_1	145	5.54
	Total	2616	100.00

Conclusions

The importance of signals in machine learning-based tool condition classification during the milling chipboard process has been systematically analyzed in this study. Our findings demonstrate the varying impact of different signals on the accuracy of classification models.

Our analysis has revealed that the signal 'DataLow_0' has the highest contribution in terms of the ranking value and percentage of total ranking. It is the most critical signal, accounting for over 16% of the total ranking. Following 'DataLow_0', the signals 'DataCurrent_2' and 'DataLow_1' have been found to be the second and third most influential signals, contributing 13.04% and 11.43% respectively.

On the other end of the spectrum, the signal 'DataCurrent_1' demonstrated the least influence, with only a 5.54% contribution. Despite its lower ranking, it's essential to note that its contribution might vary under different tool conditions or when using different classification models. The flexibility of machine learning models enables them to adapt to different contexts and use features differently.

While the ranking of signal importance provides a crucial understanding of the relative significance of these signals in classifying tool conditions, it does not offer an explicit understanding of the nature of relationships between these signals and the target classification. Therefore, further studies utilizing exploratory analysis and model interpretation techniques are recommended to unravel these intricate relationships.

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