Original scientific paper
Received:18.08.2023
Accepted: 20.10.2023
UDK: 674.023.053

THE SOUND SIGNAL PROCESSING AND DEEP LEARNING NETWORK AS TOOLS FOR DETERMINING THE CIRCULAR SAW BLADE SPEED

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ABSTRACT

The rotation of a saw blade presents one of the most important cutting parameters, often regarded as cutting speed. The purpose of this paper was to determine the discrete values of the circular saw blade speed by means of a deep learning network. During idle rotation of the saw blade, certain sounds are produced, which are recorded and later processed in MatLab software, making them suitable for further analysis and training the deep learning network. For the chosen values of the circular saw blade rotational speed, set at 2000, 3000, and 4000 rpm, a total of 600 recordings were made (200 for each speed) in the form of wave format. All of them were converted into a power spectrum by Fast Fourier Transformation (FFT) in order to determine the spectral areas of the most importance, and later the spectrograms were made using Short Time Fourier Transform (STFT) as the magnitude squared of STFT. The obtained spectrograms formed the data base for training and testing the deep learning network. A pre-trained network shows an accuracy of 100%.

Key words: sound signal, signal processing, FFT, SFFT, spectrogram, deep learning, machine learning

1. INTRODUCTION

Intelligent machining presents an inevitable step in shaping computer-integrated manufacturing as a logical advance for Industry 4.0. Process monitoring through the implementation of different types of sensors, data acquisition, and data processing obtains preconditions for intelligent machining (Mishira et al., 2018.). Apart from the commonly used force measuring approach (Li et al. 2018; Liu et al. 2018; Su et al. 2013; Zhou et al. 2018) or vibration monitoring (Fu et al. 2019), sound and acoustic analysis are also of great interest for monitoring the cutting process (Cao et al. 2017; Kothurn et al. 2018; Kishawy et al. 2018).

Machine learning and its implementation become unavoidable in the novel technological processes in the sense of elevating process performances and thus its quality. So far, different techniques have been developed in order to achieve these tasks, such as decision trees, support vector machines, regression analysis, Bayesian networks, K-nearest neighbor classifiers, deep learning, etc. Deep learning itself represents a part of the broader field of machine learning, which is a component of the larger domain of artificial intelligence.

During the cutting process where the circular saw blade is involved, different parameters of the process are to be monitored, e.g., power, force, surface quality, and circular saw blade factors. This paper is dealing with one of the features of a circular saw blade: saw blade rotation speed. Saw blade rotation produces a certain sound, also known as whistling, that is generated by the teeth geometry and blade vibrations during machining (Agilera 2011; Kminiak et al. 2015; Kvietkova et al. 2015; Svrzic et al. 2021). The design of the optimal cutting system with respect to saw blade factors could be achieved through sound signal analysis and decision-making. If the circular saw blade is idling, the sound is generated only due to saw blade movement. This sound could be recorded and analyzed, hopefully giving useful information about the present rotational speed. However, machining systems also produce a certain amount of noise attached to their engines and transmissions. Such a sound signal is to be processed and subjected to a deep learning process, making it possible for machine decision-making and process monitoring.

2. EXPERIMENTAL

The experiment took place at the Laboratory for Machines and Apparatus at the Faculty of Forestry, University of Belgrade (Beograd, Serbia). The machining system used for cutting the wood samples was a Minimax CU 410K combined machine (SCM, Rimini, Italy) equipped with a 3 kW three-phase asynchronous electrical motor. The rotational speed of the motor was set by a custom-made frequency regulator. For the speeds of 2000, 3000, and 4000 rpm, the corresponding frequencies were 25.3, 38, and 50.5 Hz, respectively. The saw blade used in the experiment was FREUD LU2B 0500 with dimensions of 250 mm (diameter) x 3.2 mm (width) x 30 mm (inner diameter) and 48 saw teeth (fig. 1). The saw blade is, according to the manufacturer, intended for cross- and rip-cutting of soft and hardwood species up to 50mm and for chipboards up to 60 mm in thickness. Measurement equipment consisted of: dbx RTA-M Measurement microphone with back electret-condenser, placed on an anti-vibrational rack, a Focusrite Scarlet SOLO USB audio interface, and a personal computer (fig. 2a, b).

***Figure 1:** FREUD LU2B 0500 saw blade*

The software used for recording sound signals was Audacity, an open-source, cross-platform audio software. Slicing and trimming of the signals obtained was done by WavePad Sound Editor, developed by NCH software. Measurements were performed at a 44100 Hz sampling rate.

***Figure 2a**: RTA-M Measurement microphone*

***Figure 2b**: Scarlet SOLO audio interface*

The experimental setup is presented in Figure 3.

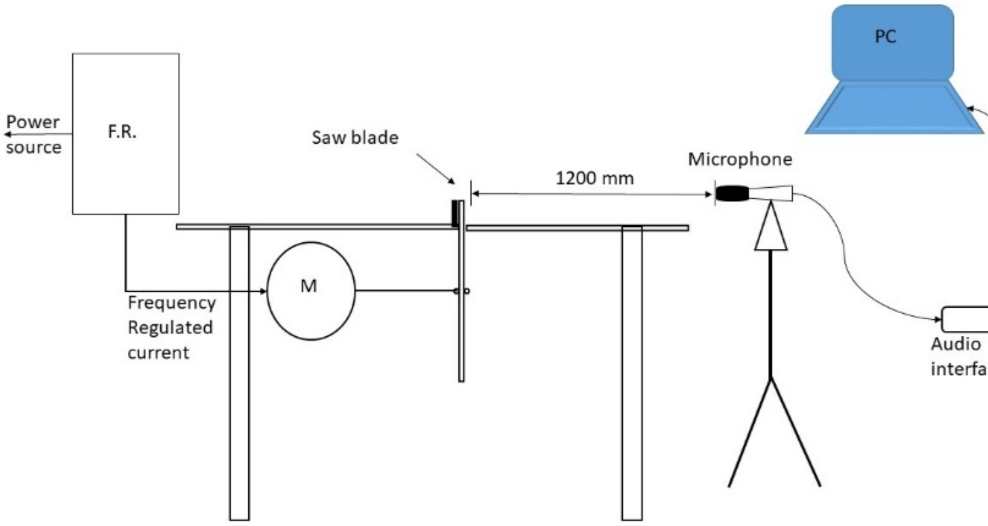


***Figure 3**: Experimental setup*

The sounds generated throughout the experiment originate from moving machine parts (electromotors, bearings, spindles, etc.) and from saw blade whistling. Those sounds were detected by the microphone and recorded on the PC as wave files. Originally, the length of wave files was 4 minutes for each saw blade rotational speed. On these recordings, spectral analysis was performed by means of FFT and STFT. The use of just FFT wasn't enough for detailed analysis because the obtained power spectrum involved lots of noise or parasitic frequencies. Further implementation of STFT, involving Hann's window function, thus obtaining a spectral density graph, significantly smoothed the spectral line, thus pointing to which spectral areas are to be carefully observed. This is particularly important for creating inputs to a database for a deep learning network. Generally, there are some rules concerning raw data preparation: 1) Making data suitable for network architecture; 2) Dimensionality reduction – making patterns more obvious; and 3) Data need to be prepared in order to cover the entire solution space.

The next step was to slice entire recordings of 4 minutes into smaller, even parts with a length of 1 second, which was done by WavePad software. Now, it was possible to create a database for training deep learning networks. The first step was to import all 240 short-lasting recordings of sound signals for each saw blade speed and transform them into 2D images of 3D spectrograms. Spectrograms are 3D (frequency-time-power) charts obtained by the STFT, or wavelet transform, of original sound signals. 2D presentation involves using an RGB scale to present the power of certain peaks or spectral areas. These 2D spectrograms were saved in JPG format and presented training data for a deep learning network, which was a GoogleNet transfer learning network specially designed for image recognition.

Some adjustments were made specific to the number of classes, the initial learning rate, which was set to 0.0001, the validation frequency, the maximal number of epochs, and the percentage of data used for validation.

3. RESULTS

As a result of the data recording, a raw sound signal was acquired, which is presented in Figure 4.

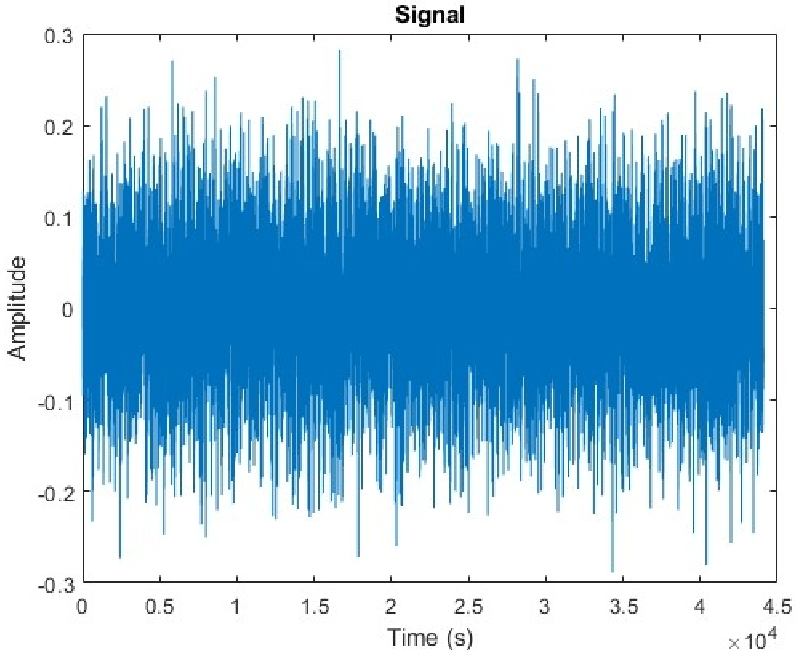


Figure 4: *Sound signal of circular saw blade idling noise at 3000 rpm*

It is impossible to extract any useful information from the recording presented in Figure 4. It is the same case with all other recorded signals, so it was obvious that further signal processing is needed. The first step was to perform FFT in order to extract characteristic spectral peaks.

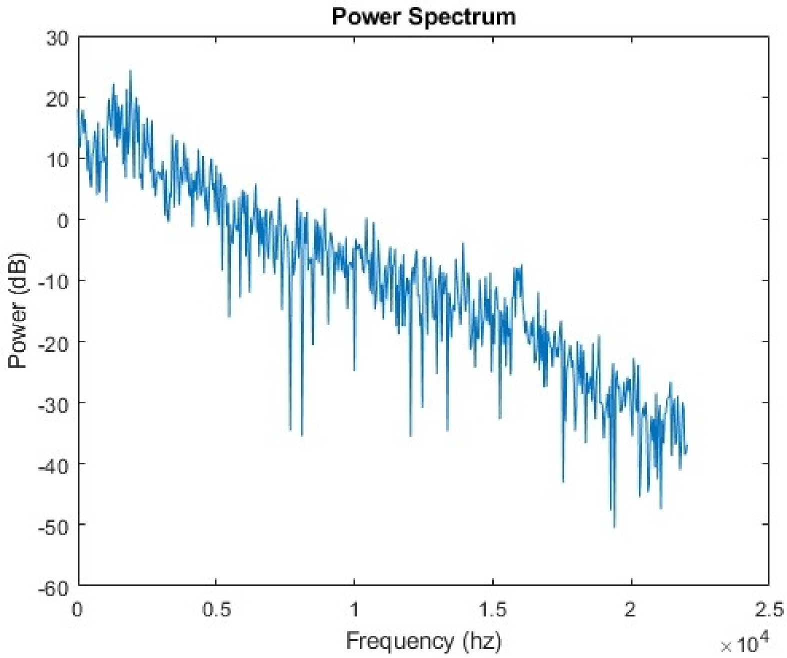


Figure 5: *Power spectrum of a recorded sound signal*

The power spectrum hasn't provided enough information for any decision concerning further steps in deploying deep learning networks. The smoothing of the power spectrum graph needed to be done before introducing STFT. The spectrum of all tree-recorded sets of data is presented in Figure 6.

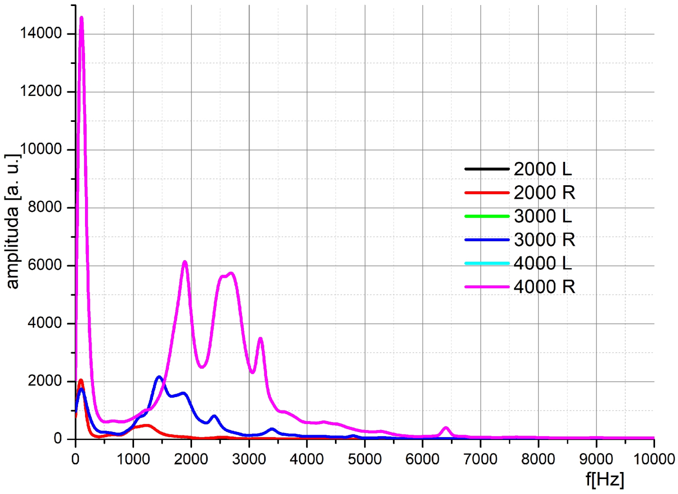
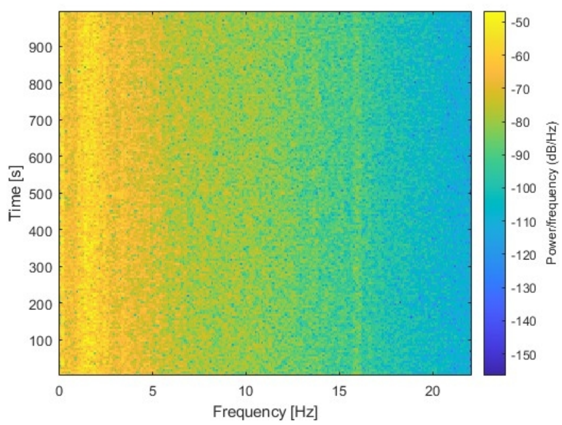


Figure 6: *2000, 3000 and 4000 rpm spectral density*

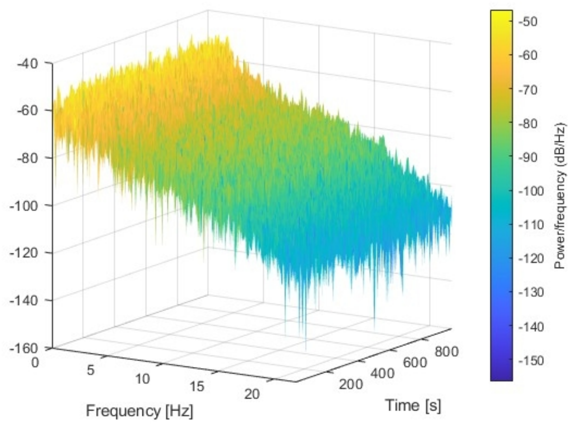
The legend in Figure 6 with L and R marks stands for left and right recording channels, which are the same, so there are only tree lines: purple for 4000, blue for 3000, and red for 2000 rpm. Now it is clearer what was happening. Spectral areas between 0 and 500 Hz have very distinguished peaks for all speeds, increasing with the increasing speed of the processing system. These peaks are addressed to the sounds created by the machine itself, i.e., the rotation of the electromotor, spindle, and transmission. Another interesting spectral area is from 1000 up to 3500 Hz. There is an obvious increase in the magnitude of the signal at those frequencies, and they are subjected to the rotation of the circular saw blade. This assumption is based on simple mathematics: 2000 rpm is about 66 rps, multiplied by 48 saw blades, giving a frequency of about 1600 Hz; for 3000 rpm, the frequency is 2400 Hz; and for 4000 rpm, the value of the frequency is 3168 Hz.

It is logical to conclude that both spectral areas are affected by processing system dynamics and that they will have an influence on the spectrograms to be obtained, so according to the rules of data preparation for the deep learning procedure, it was decided to keep the whole spectrum for further steps of analysis.

As already said, spectrograms present a 2D image of frequency change in time with belonging values of power, where the power is determined by color according to the RGB scale (the hotter the color, the greater the power).



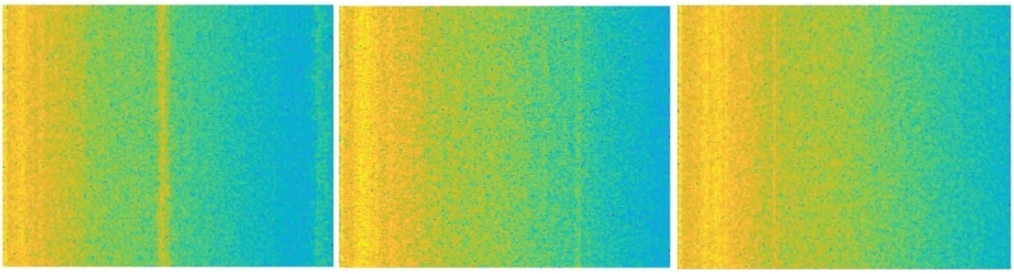
(a)



(b)

Figure 7: *Spectrograms presented in (a) 2D and (b) 3D*

2D spectrograms in the JPG format present input data for a deep learning network. The window length for STFT was set in accordance with the second rule of data processing, making patterns more obvious. In that sense, the number of samples per window was set to 512, and the overlap of windows was 50%. According to the same rule, all axes, legends, color bars, and ticks were removed from acquired spectrograms.



(a) (b) (c)

Figure 8: *Adjusted spectrograms for (a) 2000 rpm, (b) 3000 rpm, and (c) 4000 rpm*

The deep learning data base consisted of three directories: Spec2000, Spec3000, and Spec4000, each containing 200 JPG spectrograms.

The GoogleNet network performed the learning and validation process for more than two and a half hours.

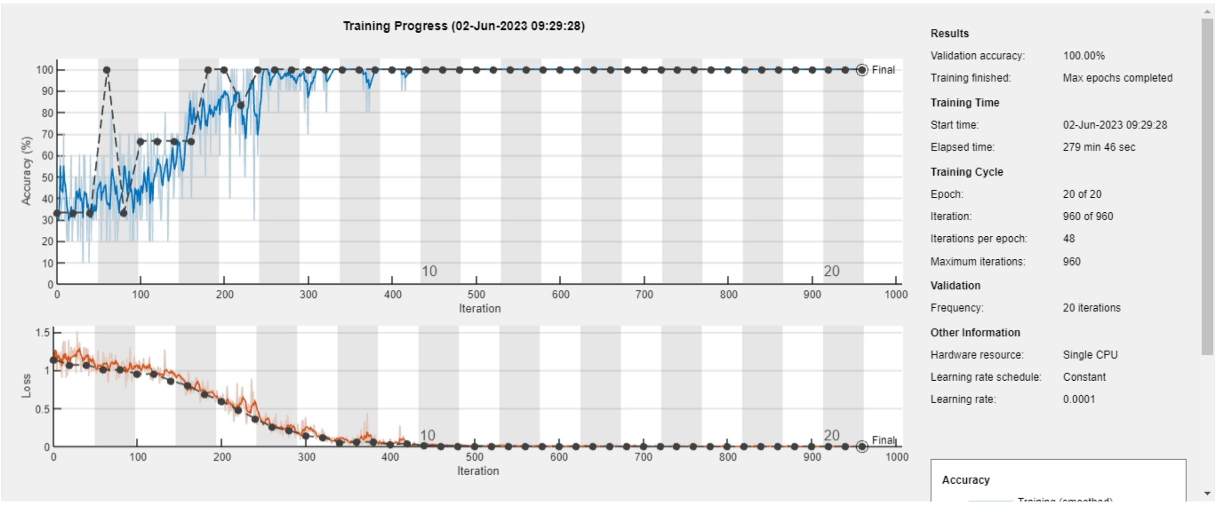


Figure 9: *Deep Learning Process Report*

The process was conducted through 20 epochs and 960 iterations. Accuracy validation was calculated after each of the 20 iterations.

According to the deep learning process report, the accuracy rate obtained was 100%, meaning that there is no doubt whether the signals would be properly recognized and therefore the decision made was correct.

From the report, it was obvious that the maximum accuracy was reached and didn't change at about the 500th iteration. This practically means that fewer input data were needed than originally set, but also that signal processing and spectrogram preparations were done in a satisfactory manner.

4. CONCLUSIONS

Based on all that was previously said, it is possible to conclude that:

- This research presents an entry-level paper for the possible use of sound signal identification as a tool for process monitoring in woodworking practice;

- The experimental setup proved to be adequate for this kind of research, providing satisfactory data for further steps of analysis;
- The proposed software packages offered rather good signal management and transformation;
- STFT proved to be an exceptional tool for investigating the frequency spectrum, enabling easy insight into areas of the greatest interest concerning the implementation of deep learning networks;
- Spectrogram pictures were the right choice as input data for the deep learning process;
- The GoogleNet transfer learning process proved to be adequate for this type of investigation, giving a perfect score in the validation process;
- According to everything presented, it was possible to exactly determine the rotational speed of the circular saw blade and processing system;
- There is a broad field of future research concerning process identification and process monitoring, such as the determination of cutting parameters when the tool is in contact with material, the assessment of the tool's sharpness during cutting, process power consumption, etc.

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