10th INTERNATIONAL CONGRESS ON MACHINING

7 - 9 NOVEMBER 2019

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CHATTER DETECTION IN MILLING WITH ACOUSTIC EMISSIONS AND DEEP LEARNING

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Abstract

One of the main pillars of Industry 4.0 is the use of Machine Learning algorithms to make accurate predictions of the manufacturing environment in order to make informed decisions. Deep Learning algorithm, which is a subfield of machine learning, has been widely used and proven more effective than other classic computational intelligence methods in many fields such as aviation-aerospace, automotive, health, and finance. Deep learning algorithms, which lead to revolutionary new products and applications in these sectors, have also been gaining attention in the field of machining to make machine tools more intelligent to improve manufacturing efficiency. In this study, Convolutional Neural Networks (CNN) which is an architecture of deep learning has been implemented to detect chatter in a slot milling process. Chatter is vibrational phenomena and has severe effects on machining performance. The undesirable vibrations caused by chatter, may cause lower surface qualities and even tool breakages. Since chatter lowers the performance of the machining operations, it is very crucial to detect and take timely action. In this research, an acoustic emission (AE) sensor was mounted to the milling machine and collects acoustic emissions. Captured data was used for training and testing by the estimation model in order to detect chatter.

Keywords: Chatter detection, Milling, Deep learning, Convolutional Neural Networks

1 Introduction

Machining is one of the most preferred subtractive methods to manufacture parts. In this method, high labor cost, machining market demands, complexity, and uncertainty are common issues faced by manufacturers. These encountered problems encourage the studies on automated production. In addition, thanks to automated manufacturing, it is aimed to produce faster with higher yields. Therefore, automated manufacturing techniques have become promising in order to enhance productivity, machining reliability and failure prediction [1]. Efficient unmanned manufacturing techniques can be applied during the production by using automatic and advanced machining state monitoring methods. Also, machining state monitoring methods provide to protect the machine tool, cutting tool breakage, tool wear and detect chatter [2], [3], [4],[5]. Monitoring methods can be divided into two groups; automatically and manually. Manual tool condition monitoring by the operator is both expensive and inefficient. It can result in vital damage to the cutting tool, machine tool, and workpiece. However, with the increase in the usage of sensors, automatic tool condition monitoring methods are recently being studied. With this method, the chatter or tool wear can be detected without encountering a considerable problem [3], [6], [7]. As the market evolves, many sensors become indispensable parts of machine tools [4]. For this reason, monitoring of signals such as vibrations or acoustics emissions (AE) measured in real-time during the milling or turning plays a vital role in the immediate detection of errors that may occur in the cutting tool or machine tool. Moreover, real-time monitoring using sensors prevent from unexpected tool wear, breakage and indefinite chatter since the necessary measures can be taken at the right time [8].

Chatter formation known as self-induced vibration is a complicated phenomenon in metal cutting. It is caused due to strong relative vibration between workpiece and cutting tool at specific combinations of process parameters such as depth of cut (mm) and spindle speed (rev/min) [9]. The first study on Chatter formation was carried out by [10]. So far, chatter related research has been implemented for more than a century. Nevertheless, several studies are still underway to develop a method to detect chatter more efficiently and automatically. It is very important to develop a method that will detect chatter effectively because it adversely affects surface quality, cutting tool life and machine tool life during the machining such as turning, milling, broaching, polishing, etc. [11]. By further developing Taylor's study [10], Altintas and Budak [12] developed chatter stability lobes to show the formation of chatter at different combinations of process parameters such as depth of cut (mm) and spindle speed (rev/min).

Following the studies of Taylor [10] and Altintas and Budak [12], monitoring based studies have been increased in order to detect chatter. In the monitoring techniques applied for chatter detection, data such as acoustic, vibration, temperature, cutting force are collected using various sensors such as AE sensor, accelerometer, thermocouple, dynamometer. There are generally three types of vibration in machining operations such as free vibration, forced vibration, and self-excited vibration. The impact occurred during the machining process causes free vibration. In gears, bearings, spindles, imbalance induces forced vibration. Also, self-excited vibration is caused by alternative force. It arises from the interaction between workpiece and the cutting tool [8]. Various vibration problems in machining are shown in Fig. 1.

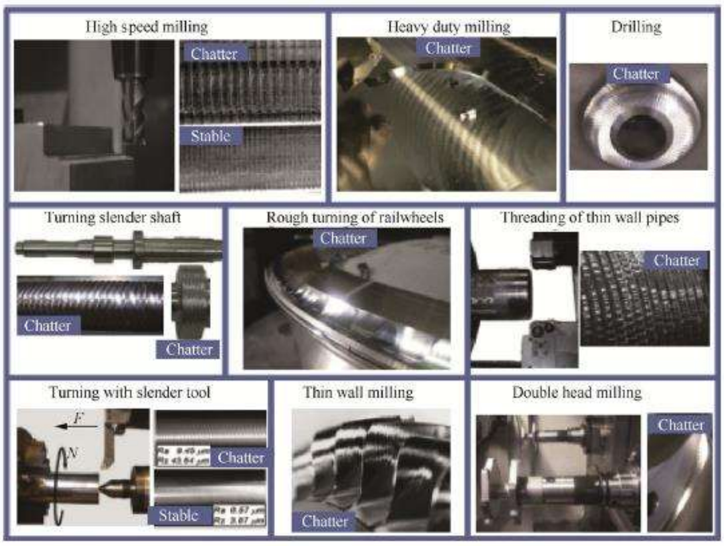

Figure 1. Challenging chatter problems in machining processes [8].

In advanced monitoring for chatter detection, the signal outputs are generally generated as an analog signal in the form of a time series. Acoustic emission signals are one of the most preferred method in the monitoring process. These signals are measured as a time series using an acoustic emission sensor or microphone to detect chatter. Acoustic emissions obtained using an AE sensor are utilized by researchers in many studies. Delio [13] used acceleration, displacement, and AE sensor in order to detect chatter. They compared the performance of these sensor types in the monitoring of the chatter formation. The result of their study shows that acoustic emission signals are more efficient to detect chatter. Altintas and Chan [14] have studied on a spectrum analysis of the acoustic signal during the machining process. They used the maximum amplitude in the spectrum for chatter detection. Schmitz et al. [15] have developed an indicator of chatter. Thanks to the developed indicator, they analyzed statistical variance in the acoustic emissions obtained at each rotation of the spindle. Kishawy et al. [16] have studied on detection of chatter vibration, cutting tool wear, tool breakage, and build-up edge. In their study, acoustic emission signals were monitored during the turning operation to detect chatter occurrence.

A non-stationary and nonlinear signal is observed in acoustic, vibration or cutting force data which collected as time-domain information when chatter occurs during milling. Usually, Fast Fourier Transform (FFT) is applied to convert time-domain data to frequency-domain to describe feature for the non-stationary and nonlinear process. Zhang et al. [17] have developed a novel approach based on energy entropy in order to identify chatter phenomena. They observed that in the stable state which consists of stationary signals, the rotation frequency was dominant on frequency-domain data as shown in Fig 2. Nevertheless, the energy of the milling operation is dominated gradually by chatter frequency when a non-stationary condition is observed.

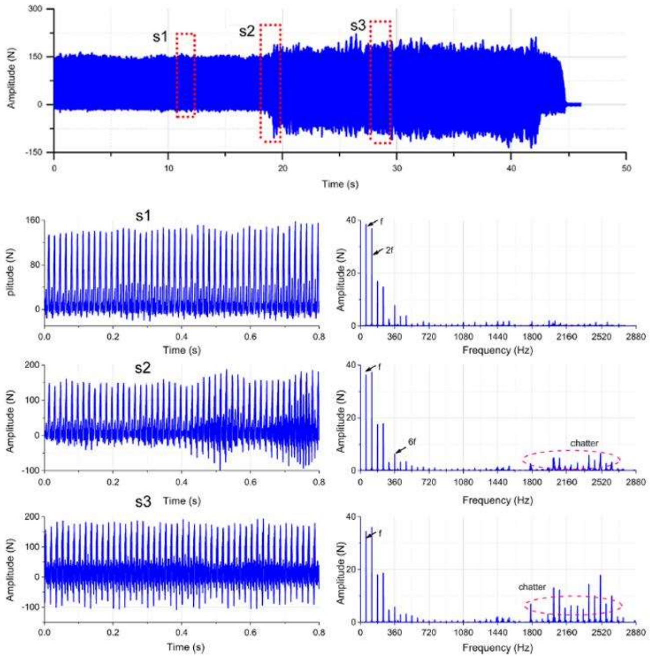

Figure 2. Stationary and non-stationary conditions [17]

In another study, vibration data were collected using an accelerometer to identify milling chatter [18]. The dominant frequencies observed in the stable cutting state gave place to frequencies resulting from the chatter as shown in Fig. 3. In other words, they analyzed dominant frequencies and then determine chatter formation.

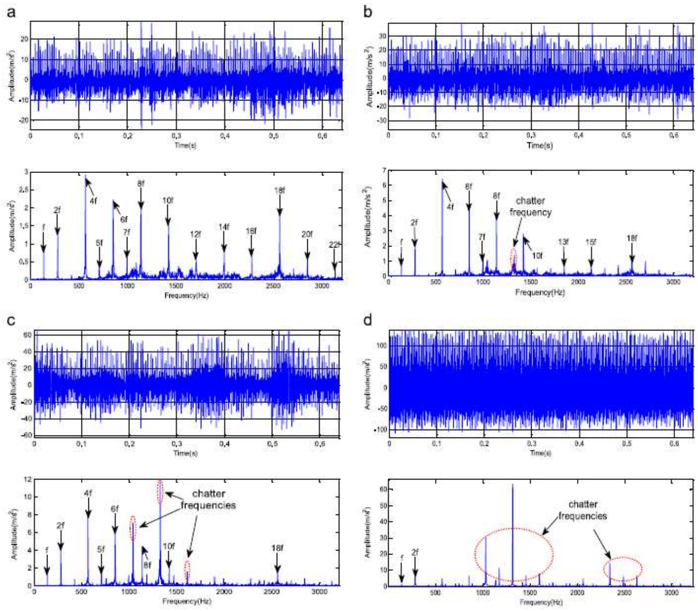

Figure 3. Vibration signal in the time domain and frequency domain a) stable cutting case with a depth of cut 1mm, b) unstable cutting case with a depth of cut 2mm c) unstable cutting case with a depth of cut 3mm d) unstable cutting case with a depth of cut 5mm [18]

In this study, in order to label the data as stable (no chatter) and unstable (chatter formation), the collected acoustic data were examined separately as in the studies of Zhang et al. [17] and Cao et al. [18]. It was observed that in stationary signals, the rotational frequency and harmonic frequency dominates. Thus, data encountered in such a case is labeled stable. However, when chatter frequencies instead of rotational frequencies were observed, the data was labeled as unstable. Then, the data tagged were given to the model in order to train the CNN based estimation model. In this study, CNN which has been gaining popularity in the field of autonomous vehicles, computer vision, and image classification, was preferred to identify chatter formation.

2 Methodology

The proposed method of machining state monitoring consists of the following three steps, including signal acquisition, preprocessing of acoustic emission signal, and chatter detection model training.

2.1 Signal acquisition

In order to monitor state of machining, accelerometer, AE sensor, dynamometer, amperemeter can be utilized to collect signals such as vibration, acoustic, cutting force and electrical current respectively. In this paper, acoustic emission signals were captured by an AE sensor. The experiments were conducted on a DMG-MORI® 5 axis milling machine which is able to operate up to 12000 rpm in order to machine slots on an aluminum 7075 workpiece as shown in Fig 4. A three-flute tungsten-carbide cutting tool with a diameter of 10 mm and length of 72 mm was used for the slot milling operations and 0.08 mm/tooth were used as feed parameter. During the experiments, the process parameters which were used are shown in Table 1.

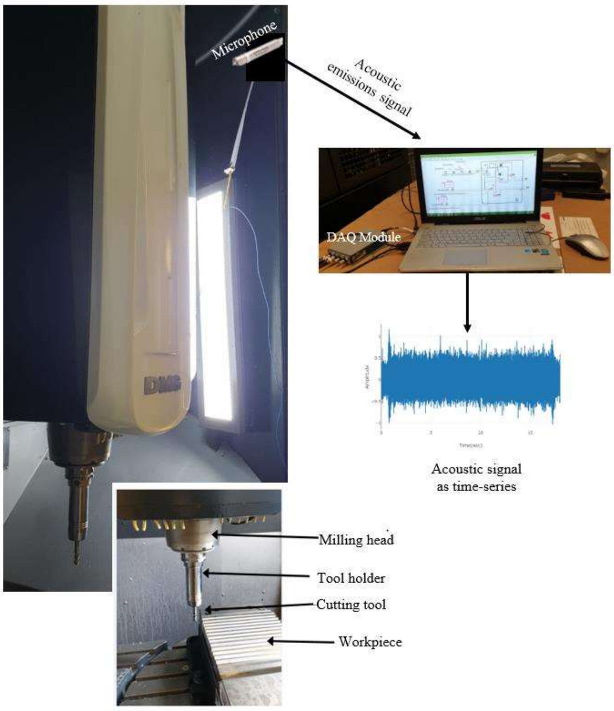

Figure 4. The machine tool and data acquisition setup

Test No:	Depth of cut (mm)	Spindle speed (rpm)
1	2	3150
2	2	3430
3	2	3760
4	3	3760
5	8	3760
6	3	4200
7	8	4730
8	3	4730
9	3	5400
10	8	5400
11	3	6300
12	8	6300
13	3	7500
14	8	7500
15	3	9500
16	6	9500
17	8	9500
18	10	11000
19	6	11000
20	1	11000
21	1	9500
22	1	7500
23	1	5400
24	1	4730
25	1	3760
26	1	6300

Table 1. Process parameters used in experiments

Acoustic data is sampled at 12800 Hz and all samples were used without any down-sampling operation in order to maintain a high-resolution sampling. No filtering is used during acquisition to keep the raw data for future processing. Each slot has its own data stored in a separate log file. The block diagram of the data acquisition algorithm is provided in Fig. 5.

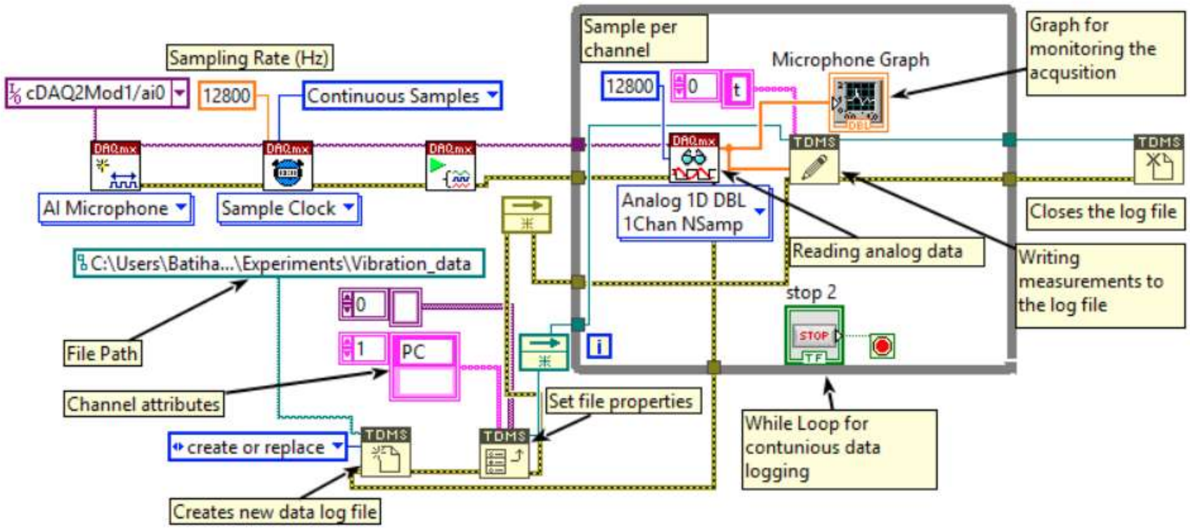

Figure 5: Block diagram of the data acquisition system developed in LabVIEW.

2.2 Preprocessing of AE signal

The collected AE data is the form of time-series. For cleaning and converting to another form requires preprocessing operations. Therefore, a python script was created to process the raw data captured via LabVIEW. Via this script, the time before machining starts and the time after machining ends removed the original data. The remaining part of the data is split into one-second intervals to increase the number of samples and to correctly capture chatter. In the unstable slot milling process, it is observed that the chatter frequency gradually dominates over the data in the frequency domain as shown in Fig 6. However, when it is a stable slot milling process, chatter frequencies are not observed, and the rotation frequency continues to dominate as shown in Fig 7. These observations were used to assign a label to each sample. Before introducing the spectrograms to the CNN, by using STFT method, each sample is converted into spectrogram which is a time versus frequency representation of the time-series signal. In total, 147 spectrogram data were passed to the CNN model.

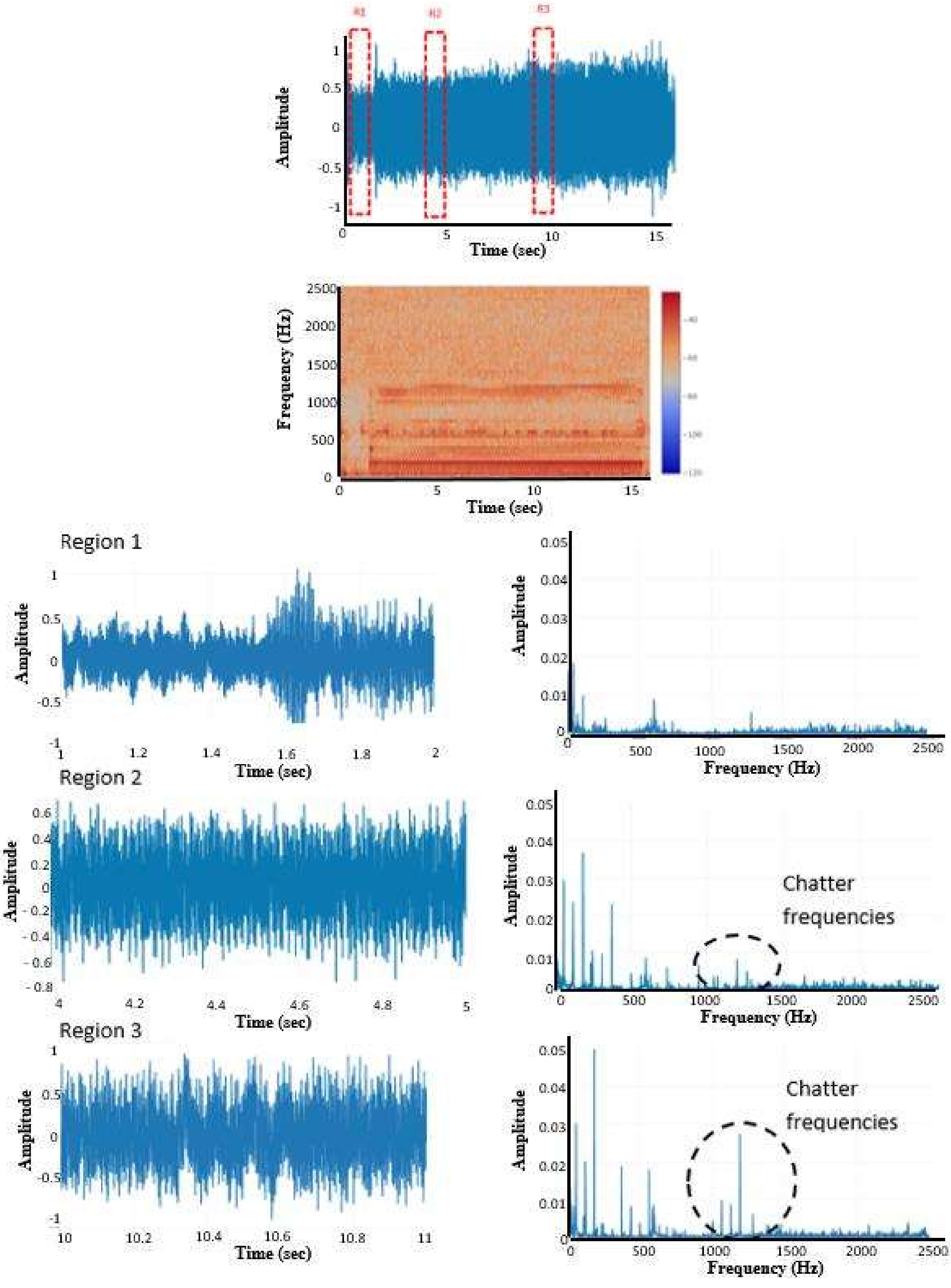

Figure 6. Unstable cutting AE signals (spindle speed 3760 rpm, feed rate 902.4 mm/min, doc 3 mm)

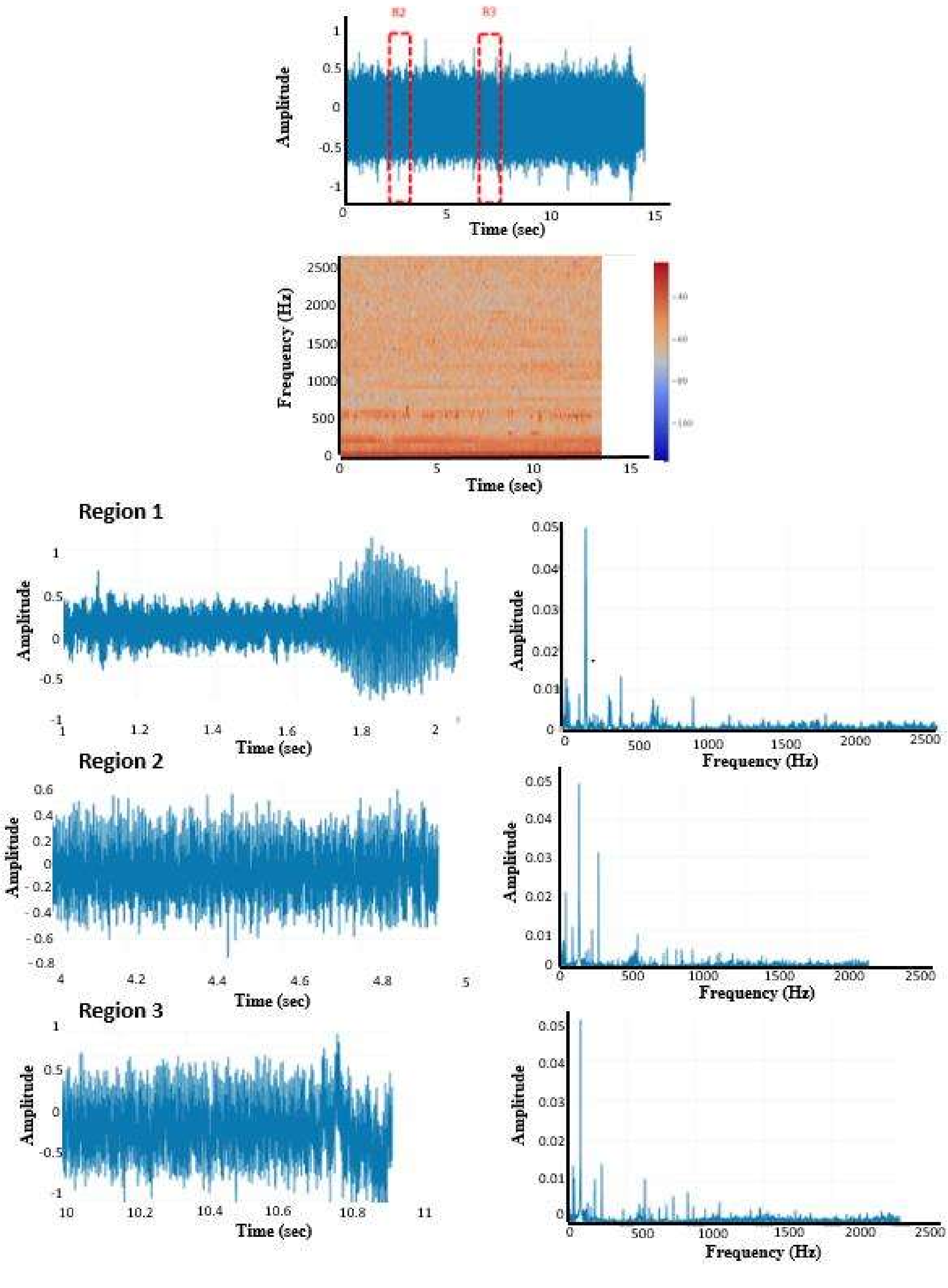

Figure 7. Stable cutting AE signals (spindle speed 3150 rpm, feed rate 750 mm/min, doc 2 mm)

2.3. Prediction model for chatter detection

Convolutional neural networks gain popularity when AlexNet cut the error by half in ImageNet competition [19]. This shows that CNNs are good for working with images because of that spatial relationship in images makes convolution operator powerful. In this work, vibration data are converted to spectrogram which is 2D time versus frequency representation of time-series signal. Therefore, it would be beneficial to use CNNs in this work. However, spectrograms are correlated on time axis but not on the frequency axis and 2D convolution operator assumes that data is correlated on both x and y-axis. Therefore, rather than taking 2D convolution or 2D max-pooling, 1D version of each is selected.

The first layer consists of 10 convolutional filters with kernel size 5. These 10 filters have passed through a max-pooling layer with kernel size 4 and Rectified Linear Unit (ReLU). The second layer has the same configuration as the first layer. These two layers are added in successive order to act as a feature extractor. These automated feature extracting properties of deep learning models form the main difference between classical machine learning and deep learning. After that, 3 fully connected layers are connected in successive order to be able to classify the vibration samples as chatter or not. ReLU activation function is chosen to make the model non-linear. In addition, after the first and second fully connected layer, dropout with 0.9 drop rate is applied to avert overfitting.

3 Results

The CNN based prediction model was developed in order to determine stable or unstable cutting condition during milling operation. Several CNN architectures were investigated to find the optimal structure. In addition, several hyper parameter settings are applied. Selected architecture design and hyper parameters setup play crucial role because of the lack of data. Specifically, dropout rates on fully-connected layers affect the performances. Experiments shows that lower dropout rates make the model performs unsatisfactorily. Therefore, 0.9 dropout rate is selected. In addition to the dropout rate, experiments were conducted with the following parameters:

Experiments are conducted with the following setup:

- number of epochs: 670
- batch size: 20
- learning rate: 1e-4
- train-test ratio: 0.75 which splits all samples into 110 training, 37 test samples.

The learning curve of the prediction model is shown in Fig. 8. In early epoch (0-120) CNN predicts all test samples as 0 or 1. Therefore, test accuracy is alternating between the mean of 0-labeled and mean of 1-labeled samples. After that, training loss starts to decrease and alternation between label mean stops. At the end of the training process (670^{th} epoch), 0.95 accuracy for training samples and 0.92 accuracy for test samples are obtained.

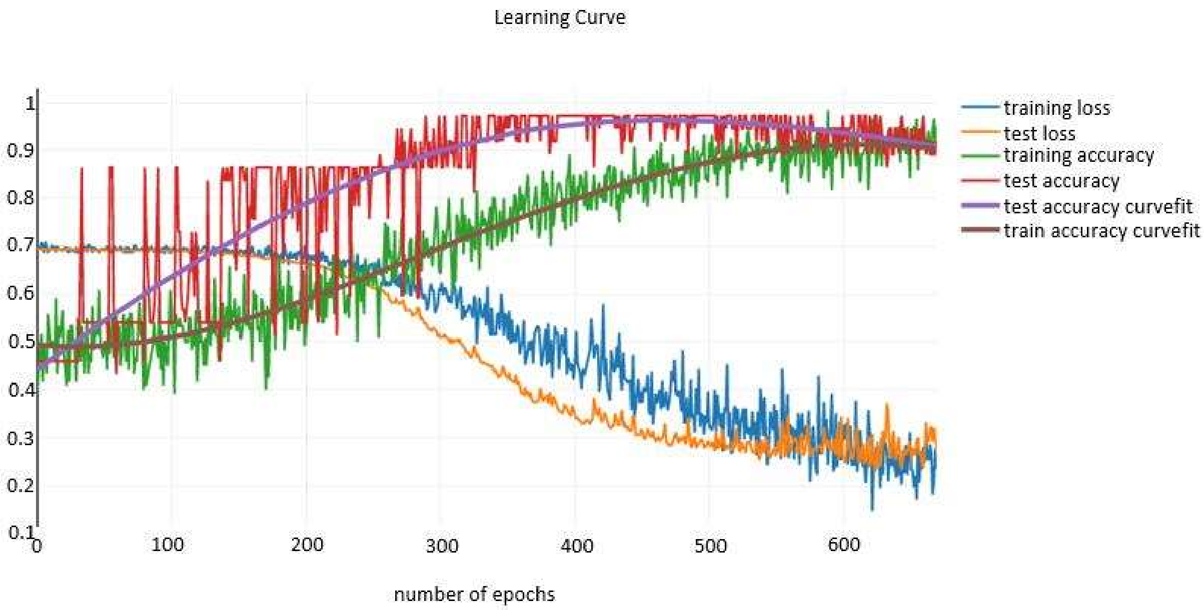

Figure 8. The learning curve of the prediction model

Confusion matrix for the developed chatter detection model is shown in Fig. 9. These matrices show true-positives (TP), false-negatives (FN), false-positives (FP) and true-negatives (TN) separately. In training dataset; 50 samples are predicted as stable out of 51 stable samples and 54 samples are predicted as unstable out of 59 unstable samples. In test dataset; 14 samples are predicted as stable out of 17 stable samples and all unstable samples are predicted correctly. These results indicate that chatter detection prediction model generates satisfactory results.

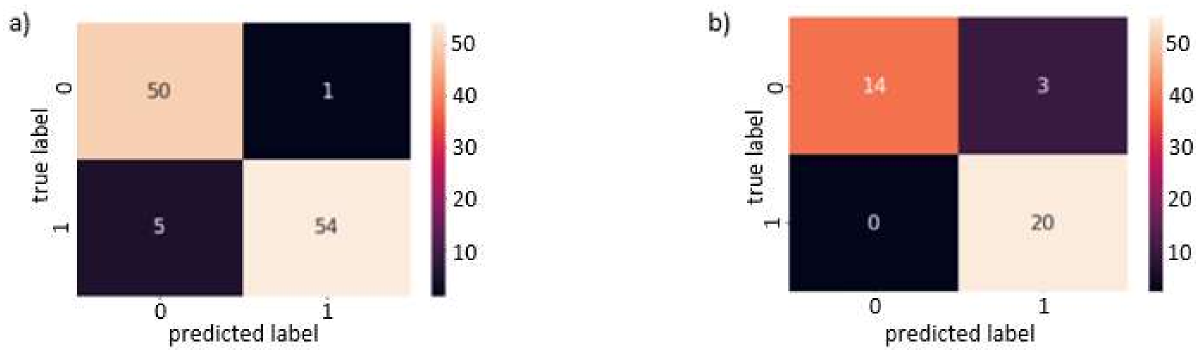

Figure 9. Confusion matrix a) for training predictions b) for test predictions

Receiver Operating Characteristic Area Under Curve (ROC-AUC) is shown in Fig. 10. Area under the curve is obtained as 0.98 which has a maximum value of 1.0. Hence, this ROC-AUC indicates that separation of probability distributions of the predictions is nearly ideal which means that predictions are perfectly distinguishable between stable and unstable.

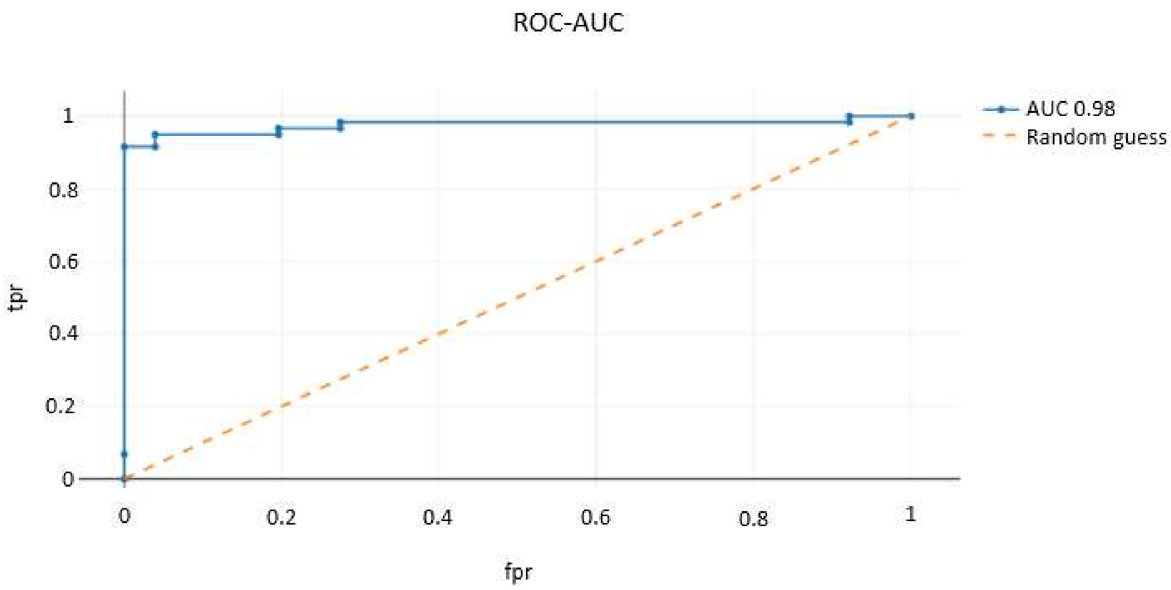

Figure 10. Receiver Operating Characteristic Area Under Curve (ROC-AUC)

4 Conclusion

This paper presents a CNN based prediction model for chatter detection in CNC milling machines. STFT method was applied to the AE signals collected using accelerometer. Thereby, the time-series data converted into spectrograms because a CNN based model generally use spectrograms. Then, the spectrograms were labeled as stable and unstable in order to train CNN based prediction model for chatter detection. The CNN based estimation model developed in this study predicts stable and unstable situations with 92% accuracy. In this way, surface roughness and cutting tool breakage caused by chatter in machining processes can be prevented.

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