A New Data Processing Method for Acoustic Emission Signals for Metalworking Fluid Classification

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ABSTRACT

The focus of this contribution is to distinguish different Metalworking Fluid (MWF) with respect to different additives used for related formulations. Acoustic Emission (AE) measurements can be easily taken as process-close measures for evaluating cutting and forming processes as well as MWFs performance. In thread forming process, AE measurements from different kinds of MWFs could be – related to the position of the tool - divided into different process phases: air, forward, and reverse phases. From a physical view, forward part contains most useful AE data. Therefore, extracting forward part data is significant for MWFs classification. In this contribution, a new data processing method is proposed to abstract the forward part data from non-related parts of the whole measurement signal. For the first time, scalogram is applied to define the boundaries in time domain. Firstly, the intact measurement signal is transformed from time domain to time-frequency domain by continuous wavelet transform (CWT) and scalogram is acquired. As boundaries among different phases are obvious in scalogram, by reverse calculation, boundaries' location in time domain could be defined and forward part data of each measurement are picked out. Afterwards, data in forward phase are divided into different samples and each sample contains data of one round. Finally, samples' features are extracted and classified by convolutional neural network (CNN). By adjusting CNN structure and hyperparameters with cross validation method, features in time domain could be distinguished well. For five kinds of testing MWF, the classification accuracy is as high as 98.11 %. For reference, oil-based, and water-based MWF classification, the results can reach to 98.94 %. Accuracy for water-based MWF distinction is 97.55 % while for oil-based MWF distinction is 98.29 %. Comparing with results using the whole AE measurements, these results improve significantly. The results show that the proposed data processing method could

extract most useful information from the whole AE measurements in time domain for MWF distinction. Besides, the proposed method also provides an effective way for data analysis in the future.

1. INTRODUCTION

Metalworking fluids (MWF) are defined as liquids which are supplied to a manufacturing process in a way that allows for increased productivity based on lubricating and cooling effects (Brinksmeier, Meyer, Huesmann-Cordes & Herrmann, 2015). Since 20th century, application of metalworking fluids grew rapidly due to the rapid growth of emerging industries such as the automotive, rail, and aerospace industries, as well as from the increased use of mechanical equipment and household appliances (Evans, Hooijman & Veer, 2020). Numerous formulations or additives like oils, emulsifiers, anti-weld agents, corrosion inhibitors, buffers, and biocides can be integrated into MWF (Anderson & Meade, 2014). Specific properties of MWF are achieved by adding specific chemical additives. To evaluate properties of MWF with diversity additives, tapping torque test etc. can be conducted. Effects of different MWF in grinding process using Acoustic Emission (AE) is presented by Liu et al. (Liu, Zhao, Bafakeeh & Marinescu, 2016). Acoustic Emission signals are also applied to evaluate performance of diversity additives in thread forming process by Wirtz et al. (Wirtz, Demmerling & Söffker, 2017) and Wei (Wei, Demmerling & Söffker, 2021). However, results in both contributions are improvable: different oil-based MWF can not be distinguished by Wirtz et al. while previously realized classification results (with respect to accuracy) show improvement potential.

Acoustic Emission events generated by rapid release of energy from materials can be linked to the onset of new damage or the progression of existing anomalies. Acoustic Emission analysis is based on passive detection of dynamic surface motion caused by elastic stress or pressure waves (Bohse, 2013). To analysis damage or anomalies, Acoustic Emission signals can be analyzed in time domain, frequency domain, and time-frequency domain. Continuous wavelet

transform (CWT) plays for a key role in time-frequency analysis for non-stationary signals. According to (Sifuzzama, Islam & Ali, 2009), wavelets reveal signal information in both time and frequency domain whereas the standard Fourier transform only reveal signal information in frequency domain. Comparing with short-time Fourier transform (STFT) which also reveal signal information in time and frequency domain, wavelets offer a better signal resolution using multi-resolution analysis.

Metalworking processes can be categorized into: forming, cutting, grinding, milling, and stamping. Thread drilling screw has cutting edges and chip cavities that generate a mating thread by removing material from the part they are driven into. On the contrary, thread forming is a manufacturing process involving the generation of internal threading by plastic deformation. Successive action of tap lobes is conducted in thread forming, each lobe causes three-dimension plastic flow and plastic flow leads to strain hardening of work material. The process of thread forming can be divided into three parts: air part (tap has no contact with workpiece), forward part (tap drills into reserved hole), and reverse part (tap leave reserved hole). Comparing with other metalworking processes, no chips are produced in threading forming. Therefore, AE signals are less effected by chips in thread forming than in other metalworking process.

Convolutional neural network (CNN) is a type of deep learning that can extract sample features and classified features automatically. Innovation of CNN is its ability to automatically learn a large number of filters in parallel specific to a training dataset under the constraints of a specific predictive modeling problem (Alzubaidi, et al., 2021). Classical layers for CNN are convolution, polling and fully connected layers (Kiranyaz, et al., 2021). In addition, nonlinear activation feature layers, dropout layers, batch normalization layers, and softmax layers are included in the CNN structure. Although CNN can extract data features automatically, data processing such as selection and filtering are also important for data classification because they help separate irrelevant data from the main data so that it is not processed further.

In this contribution, experiments applying different kinds of MWF in threading forming process are conducted. Acoustic Emission signals are acquired in the experiment and analyzed. In AE signal analysis process, for the first time, one data selection and filtering method combing data in time domain and CWT is introduced. Afterwards, selected data are segmented into different samples and features of samples are extracted and classified by CNN. Comparing with results with no data selection in Wei (Wei, Demmerling, & Söffker 2021), classification results are improved after raw AE signals are filtered.

The structure of this paper is as follows: experiment will be introduced in Section 2. Data selection method and features extraction and classification will be introduced in detail in Section 3. In Section 4, results will be shown. Lastly, conclusions are drawn in Section 5.

2. EXPERIMENT DESIGN

The experiment is designed and conducted by the Chair of Dynamics and Control and Rhenus Lub GmbH & Co KG, the measurements are taken at Rhenus Lub. Details about the test rig and measurement procedure are reported in (Demmerling & Söffker, 2020). To reduce chip effects for AE signals in metalworking process as much as possible, thread forming is chosen as metalworking process. As introduced in (Wei, Demmerling, & Söffker, 2021), Thread forming trials are carried out on a tribometer Tauro®120 (Taurox e. K., Germany). The test rig for threading consists of a test platform made of a carbon steel (1.1191) with drilled pilot holes of 5.6H7 mm, a titanium nitride-coated tapping tool for thread forming (Emuge M6-6HX InnoForm1-Z HSSE-TiN-T1). The active tap length is 8 mm with an entry taper of approximately 2 to 3 mm and speed of tap is 1000 rpm. The test rig is shown in Figure 1.
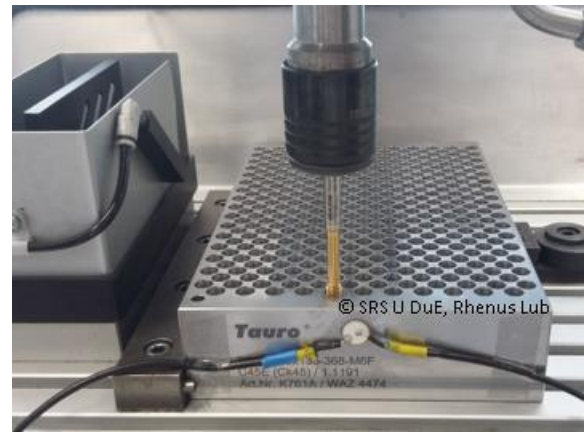

Figure 1. Test rig (Rhenus Lub, Germany) (Demmerling & Söffker, 2020)

Before threading, five different kinds of MWF are filled into the predrilled holes: reference fluid (Ref) and four different test fluids (Emulsion 1 and 2, Oil 1 and 2). Main components and additives in these five MWF are listed in Table 1. Besides the run-in of the tap at the beginning of the test procedure (32 threads with reference fluid), 16 threads are tapped with each test fluid. The test order of the fluids is shown in Table 2.

Table 1. Main component and additive in MWF

MWF	Basis	Water (%)	Oil (%)	Ester (%)	Phosphorus (ppm)
Reference	Water	95	0	1.25	50
Emulsion 1	Water	95	1.4	0	3163
Emulsion 2	Water	95	1.4	0	48
Oil 1	Oil	0	85	6.5	80
Oil 2	Oil	0	85	6.5	1600

Acoustic Emission measurement is conducted by a custom FPGA-based AE measuring system established by the Chair Dynamics and Control. A disc-shaped broadband piezoelectric transducer with 3.6 MHz corresponding resonant frequency is mounted on the workpiece using cyanoacrylic glue. During thread forming, AE signals are continuously acquired with 4 MHz sampling rate. Although several contributions have applied AE data from this experiment, as their results are still improvable, AE data are analyzed again with new approach in this contribution.

Table 2. Test order of MWF

Series	MWF	Number of threads
m1	Reference (run-in)	1-32
m2	Emulsion 1	33-40
m3	Emulsion 2	41-48
m4	Oil 1	49-56
m5	Oil 2	57-64
m6	Reference	65-72
m7	Oil 2	73-80
m8	Oil 1	81-88
m9	Emulsion 2	89-96
m10	Emulsion 1	97-104
m11	Reference	105-112

3. PROPOSED APPROACH

To distinguish AE signals acquired from different MWF in the experiment, data are processed before they are put into CNN for feature extraction and classification. Feature extraction and classification method has been introduced in (Wei, Demmerling, & Söffker 2021). In this contribution, the new data processing method will be introduced in detail.

In the experiment, as the temporal start and end of tapping are performed manually, the tapping process can be divided into air, a forward, and a reverse part. No usable AE data in air part because the tap has no contact with the platform. For this reason, data in this part should be removed. From a physical point of view, threads are mainly formed in the forward part of one measurement, therefore the relevant AE events occur in this part - data in this part should be analyzed. However, no clear boundary among air, forward and reverse part as shown in Figure 3. To find the boundary among different part in one measurement and pick up the forward part data, firstly, whole measurements are transformed into time-frequency domain by CWT and scalogram are gotten. As boundary among different parts are clear in scalogram, forward part can be isolated. Then, by reverse calculation, forward part data in time domain are picked out. Afterwards, forward part data of each measurement are segmented into different samples according to tap speed. Lastly, features in these samples are extracted and classified by CNN. Flowchart of the proposed approach is presented in Figure 2.
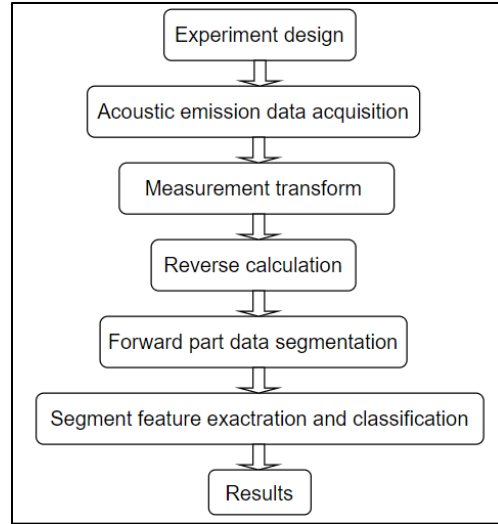

Figure 2. Flowchart of proposed approach

3.1. Data Processing

3.1.1. Raw AE signal

In the experiment, time for each threading is controlled at about 5 seconds. As the start and end time of each threading is controlled manually, consequently, time of tap stays in the air is not exactly the same. The AE signals are continuously acquired at sampling rate of 4 MHz, so most threading have about 20 M data. The length of each measurement is not constant. For example, threading-163243 contains about 19480000 data, meanwhile, threading-163429 contains about 24658000 data as shown in Figure 3. In other words, the forward part start point of each measurement is variant. Besides different start point of forward part in each measurement, no clear boundary among different parts in one whole measurement. This means that it is impossible to single out forward part data from one whole measurement just in time domain.
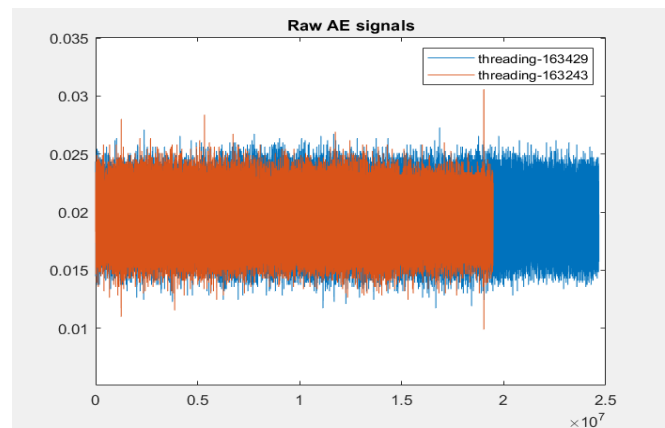

Figure 3. Raw AE data of threading

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3.1.2. Measurement Transform

To search out the forward part of each measurement, Continuous wavelet transform is performed to the raw AE signals of the whole measurement. By specifying the mother wavelet 'morlet' and scale value, pseudo-frequencies corresponding to scales and wavelet are gotten. Furthermore, CWT coefficients are acquired by specifying the frame size. Finally, scalogram of each whole measurement are acquired. As shown in Figure 4, boundaries among different parts in whole measurement are clear in scalogram. For example, in Figure 4, the forward part in this threading arises at 1.1s and last until 2.8s. Besides that, frequency distinction among different parts is also obvious: frequency in forward part and reverse part are higher than air parts. Frequency band concentrate in the range of 80-120 kHz while in reverse process, frequency band concentrate in the range of 45-75 kHz. Although frequency is obvious in scalogram, for each fluid, only 16 measurements are conducted in this experiment, so 16 samples for each class are classified. This sample number is too less for deep learning which need quality samples. Accordingly, in this contribution, scalogram is employed for finding boundaries among different part in whole measurement instead of samples to CNN.
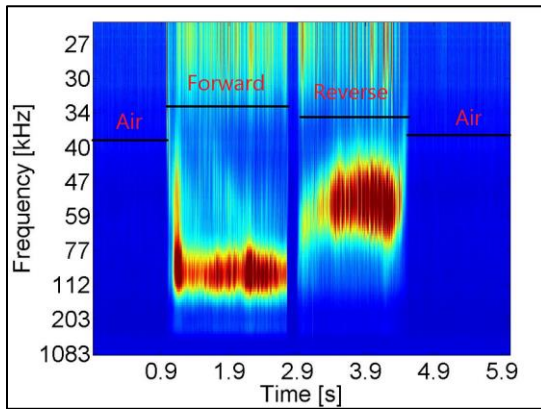

Figure 4. Scalogram of one threading (163133)

3.1.3. Reverse Calculation

While the forward part of each measurement is clear in scalogram in time axis, the forward data in time domain can be simply selected. As the sampling rate of AE signals is 4 MHz, start time multiply with 4,000,000 is the start point of forward data. Meanwhile, end time multiply with 4,000,000 is the last data point of forward part. Data in between start point and end point are forward part data. Despite the start time of each threading is different, forward part duration time are the same for all threading.

3.1.4. Segmentation

Since samples are at the core of machine learning, a large amount of training samples plays a critical role in making the machine learning models successful. To train a machine learning model, the sample number must be suitably large. Measurement segmentation is an efficient technique for increasing samples. As thread forming belong to rotating machinery process, the segmentation length is designed by tap's speed. In consideration of tap speed is 1000 rpm and sampling rate is 4 MHz, so each sample contains 240000 data. To maintain the key points of each sample, data overlaps with neighboring samples.

3.2. Feature Extraction and Classification

Convolutional neural network is employed to extract features from segments and classify them. Hyperparameters of CNN which determine the network structure and how the network is trained have significant effects on results [Yamashita, Nishio, Do & Togashi, 2018].

Each sample contains as much as 240000 data, CNN structure should be deep enough to extract their feature. Structure with respect to the number of layers used, it was observed that eight layers are most suitable. The proposed CNN structure contains: eight convolutions, eight batch normalizations, eight active functions, and eight max pooling layers are contained. Two dropout layers are added in between to reduce calculation time. Finally, one fully connected layer and softmax layer are applied to classify samples features. For hyperparameters related to training algorithms, cross validation method is applied. Several values are tried for one hyperparameter in CNN and the value that get best results is kept. Then, other hyperparameter's value are chosen by the same way. In this way, the set of hyperparameters are tuned and optimized step by step. Detailed information about cross validation is introduced in (Wei, Demmerling, & Söffker 2021).

4. RESULTS

Five different kinds of MWF are employed in the experiment. Two options are applied to distinguish these five MWF. For the first option, these five MWF are classified into five classes: reference (R), emulsion 1 (E1), emulsion 2 (E2), oil 1 (O1), and oil 2 (O2). For the second option, five MWF are firstly classified into 3 big categories: reference, emulsion-based (E), and oil-based (O). After that, emulsion-based fluid is further differentiated into emulsion 1 and 2, oil-based fluid is further decollated into oil 1 and 2. To reduce the randomness of results and check robustness of the model, the same data in each step is calculated 5 times. Detailed results are shown in Table 3.

When five MWF are differentiated in one step, accuracy is from 96.65 % to 99.43 %, average accuracy for these five times is 98.11 %. When five MWF are firstly divided into 3 categories, test accuracy is from 98.56 % to 99.04 %, average accuracy is 98.94 %. Average accuracy for emulsion 1 and emulsion is 97.55 % while average accuracy for oil 1 and oil 2 is 98.29 %. The results can be summarized as:

1) No relevant difference among each calculating time can be observed, this means the proposed model is robust.

2) The results are good regardless of whether the MWF used in the experiment is first divided into five classes or into three classes and then subdivided into detail classes.

3) Emulsions 1 and 2 can be distinguished perfectly in the fifth calculation.

Table 3. Results

MWF	Test accuracy (%)					
	1	2	3	4	5	Ave.
R./E1/E2/ O1/O2	97.70	98.28	98.85	99.43	96.65	98.11
R./E/O	99.04	99.04	99.04	99.04	98.56	98.94
E1/E2	98.56	96.40	97.84	97.96	100	97.55
O1/O2	99.28	98.65	97.12	97.84	98.56	98.29

In (Wei, Demmerling, & Söffker, 2021), these five MWF are differentiated using the second option. Results in that paper is as following: average accuracy for 3 classes is 71.27 %, average accuracy for emulsion 1 and 2 is 79.83 %, and average accuracy for oil 1 and 2 is 68.76 %. Comparing these results with the newly obtained ones it can be stated that the proposed approach (combing CWT and time domain for data processing) will significantly improve the results.

5. CONCLUSION

To validate metalworking fluid influence on AE signals in metalworking process, an experiment is designed. Before thread forming, five MWF are filled into the pre-drilled holes. During threading, AE signals are acquired. On account of threading process is conducted manually, whole threading measurement could be divided into air, forward, and reverse parts. While in air part, tap has no contact with platform, data in this part should be abandoned. From a physical point of view, threading is mainly formed in forward part and more AE events occur in this period, so forward part data should be picked out from whole measurement. However, no clear boundary among different parts from raw AE signals in time domain. In this contribution, a new data processing method is raised. Firstly, AE data of whole measurement in time domain are transformed into time-frequency domain by CWT and scalogram are obtained. Boundaries among different parts in whole measurement is very clear in scalogram. By reverse calculation, forward part data are picked up in time domain. Afterwards, the forward part data of each measurement are segmented into different samples according

to tap speed. Finally, segments features are extracted and classified by CNN.

Five MWF employed in the experiment are differentiated into two options: first option is to categorize five MWF into five classes while second option is to categorize these five MWF into three categories and then subdivide each category into detail classes. Results from both two options are good. Besides, comparing with previous work which apply the whole measurements and divide them into segments randomly, results in this contribution improve greatly. From results and calculation process, the following conclusions can be drawn:

1) Forward part of thread forming process contains more useful AE event comparing with the whole measurement.

2) For rotating machinery, segments length can be decided by tool speed.

3) Continuous wavelet transform support the analysis of AE signal.

4) Combination of time domain and time-frequency domain analysis is a good way for data processing.

For future work, experiments applying more MWF can be conducted. The proposed data processing method can be used to analyze AE signals.

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