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Metalworking Fluid Classification Based on Acoustic Emission Signals and Convolutional Neural Network

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ABSTRACT

Acoustic emission (AE) which describes the transient stress waves generated by the rapid release of energy from solid sources has been widely used in nondestructive testing (NDT) of materials and structures especially in health monitoring. As a class of deep neural networks, convolutional neural network (CNN) has applications in many fields. Several investigations have been conducted on the application of CNN in feature learning and fault diagnosis and prognosis. Metalworking fluids (MWF) play a significant role in manufacturing processes. By reducing friction between tool and workpiece, the heat generation in metalworking process is affected. Thread forming is a transformative manufacturing process for generating threads in ductile materials. As the thread geometry is manufactured by cold forming of the material, lubricating properties of the MWF strongly effect tool wear and workpiece quality. Up to now, there are only a few papers on MWF classification using the process variables like torque or released AE. In this contribution, a novel approach combining AE signals and CNN is raised for MWF classification. A tribometer is used to carry out thread forming trials under well-controlled experimental conditions. AE measurements are conducted in context of thread forming. The AE signals are divided into suitable samples and CNN is applied as classifier. The results of MWF classification show that the new approach could distinguish different types of MWF.

1. INTRODUCTION

Metalworking fluids (MWF) are used in many manufacturing processes such as milling, drilling, or threading to lubricate the contact zone between tool and work piece. Five different vegetable oils were applied for 45 steel milling and the results shown that cottonseed and palm oils perform better than castor, soybean, and peanut oils by measuring temperature (Dong, Li, Zhou, Bai, Gao, Duan, Li, Lv, & Zhang, 2021). Modified vegetable oils were employed for turning and drilling of AA 6061 aluminum and AISI 304L stainless steel and their machinability and rheological properties were investigated (Jeevan, Jayaram, Afzal, Ashrith, Soudaga, & Mujtaba, 2021). Yeast-based MWF was used for milling process of Ti6Al4V titanium alloy and the results showed that it performed similar or better compared to a mineral oil-based reference MWF (Damm, Bezuidenhout, Uheida, Dicks, Hadasha, & Hassen, 2021). In the process of tapping, the surfactant structure effect on film forming ability of emulsion was studied (Benedicto, Rubio, Carou, & Santacruz, 2020). A novel developed biodegradable MWF was designed and its performance was measured during turning of AISI 420 material (Nune & Chaganti, 2020). In thread forming processes when threads are formed by taps into pilot holes, MWF prevent the tool from welding with the work piece material by reducing friction and temperature at the forming lobes. Types and different characteristics of MWF affect thread quality (Fromentin, Bierla, Minfray, & Poulachon, 2020) and tool wear (Ghuge & Mahalle, 2016). Acoustic emission (AE) technique has already been used as a tool for condition monitoring during machining (Jemielniak & Arrazola, 2008; Bhuiyan, Choudhury, &. Nukman, 2012; Kosaraju, Anne, & Popuri, 2013; Srinivasan, Bhinge, & Dornfeld, 2016）. Meanwhile, AE signals can also be applied for distinction of MWF during threading (Wirtz, Demmering, & Söffker, 2017) besides the well-known tapping torque test according to ASTM D5619 and advanced approaches (Demmerling & Söffker, 2020). K-means clustering was applied to classify the AE energy in different frequency bands which was a feature to distinguish different MWF qualities (Wirtz et al. 2017). Convolutional neural network (CNN) is a neural network with a convolution operation instead of matrix multiplication in at least one of the layers. Compare with other neural networks, the innovation of convolutional neural network is based on the ability to automatically learn a large number of filters in parallel to the trained model under the constraints of specific predictive modeling problem, such as image classification (Brownlee, 2018.). Convolutional neural network is well known and are applied on many fields, however, there are only a few references for distinguish MWF applying CNN as classifier.

In this contribution, the second author serves as the domain expert from the MWF chemistry side, the other two authors apply and develop machine learning approaches. According to the authors knowledge this contribution is the first work combining the MWF classification task using AE signal and machine learning. Although many machine learning and deep learning approaches could be applied for MWF classification, in this contribution CNN is chosen to apply on AE signals. In the proposed approach, the complexity of the used example realizes a challenging diagnostic task within the prognostics and health management (PHM) framework. The hope is in the long run to distinguish aging processes within the metalworking fluid.

The structure of this paper is organized as follows. A brief introduction of CNN is given in section 2. In section 3, the experimental process is presented. Data processing, CNN architecture, and related hyperparameters tuning process applied for MWF classification as well as results are shown in section 4. In section 5, the findings are summarized and a conclusion is given.

2. CONVOLUTIONAL NEURAL NETWORK

In the early 1960s, David Hubel and Torsten Wiesel improved the concept of receptive fields. In 1975 and 1980, Kunihiko Fukushima furthered the theory basis by raising the concept of ‘cognitron’ and ‘neocognitron’ which are the biological theory of CNN. In 1986, Rumelhart et al. raised back propagation (BP). Yann Lecun et al. applied the BP algorithm to train neural network and proposed LeNet-5 (Lecun, Bottou, Bengio & Haffner, 1998) which is the prototype of contemporary convolutional neural network. In 2012, Alex raised the new deep structure and dropout method in CNN (Krizhevsky, Sutskever & Hinton, 2012) by which they raised the test accuracy to 84.6 %, which aroused people’s interest and started a new epoch of CNN. From 2012, many CNN models were developed, such as LeNet, AlexNet, VGG, GoogLeNet, ResNet which are widely applied in many fields.

Convolutional neural network is a type of deep learning model for processing data that has a grid pattern and it is designed to automatically and adaptively learn spatial hierarchies for features, from low-to high-level patterns. It is suitable for inputs that are locally or temporally correlated such as time-series (1D structure), images (2D structure), or videos (3D structure) (Schielke, 2018). In the proposed approach, the time domain AE signals are applied as CNN input.

The classic building blocks for CNN are: convolution, pooling, and fully connected (FC) layers. The convolution and pooling layers perform feature extraction, whereas the fully connected layer maps the extracted features into final output (Yamashita, Nishio, Do & Togashi, 2018).

The fundamental block for CNN is convolution layer which is composed of a stack of mathematical operation called convolution. In convolution operation, the element-wise product between each element of the kernel and the input tensor is calculated and summed to obtain feature map. In convolution layer, the convolution operation is repeated, applying multiple kernels to form an arbitrary numbers of feature maps which represent different characteristics of the input tensors (Brownlee, 2019).

Usually, the output of the convolution layer is then passed through a nonlinear activation function which is used to increase the expression ability of neural network model. There are several common nonlinear activation functions like sigmoid, tanh, rectified linear unit (ReLU) etc.

After multiple stages of convolutional and nonlinear layers to reduce the computational requirements progressively through the network as well as minimizing the likelihood of overfitting, pooling layers are used. There are 4 types of pooling: max pooling, average pooling, global max pooling, and global average pooling.

The output feature maps of the final convolution or pooling layer are transformed into a one-dimensional (1D) array of numbers (or vector) and connected to one or more fully connected layers, in which every input is connected to every output by a learnable weight. The features generated by the final convolutional and pooling layer correspond to a portion of the input image as its receptive field does not cover the entire spatial dimension of the image, thus, fully connected layer is mandatory in CNN (Basha, Pulabaigari, & Mukherje, 2020).

Besides the classic building blocks in CNN, according to the task, another activation function would be applied to the last FC layer. For classification task, softmax would be used to normalize output values to target class probabilities.

3. DESIGN OF EXPERIMENT

Thread forming trials are carried out on a tribometer Tauro®120 (Taurox e. K., Germany, Figure). 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) and different test fluids. The active tap length is 8 mm with an entry taper of approximately 2 to 3 mm. In the present tests, no rigid tapping is used. The spindle is fixed at a weight compensated suspension. During threading, the spindle is turned into the nut blank through the thread flanks of the tap. The axial force only works at the entry taper until the first thread flanks have caught material.

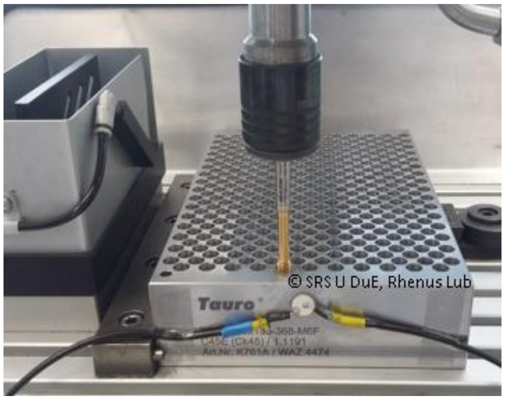

Figure 1. Tribometer Tauro®120 and the experimental setup

Before testing, platform and tap are cleaned in an ultrasonic bath for 15 min. using a cleaning solvent (1:1 mixture of naphta and isopropyl alcohol) and dried in a drying oven at 50 °C for 15 min. During testing, the tap is cleaned in a cleaning station with brushes and air blow system to remove chips and fluid residues after every thread. Between different fluids the tap is manually cleaned with the cleaning solvent.

The test rig for measuring AE during threading consists of a custom FPGA-based AE measurement system. A disc-shaped broadband piezoelectric transducer (diameter 10 mm, thickness 0.55 mm) with corresponding resonant frequency of 3.6 MHz is mounted on the workpiece using cyanoacrylic glue. The AE signals are continuously acquired during the forming of every thread at a sampling rate of 4 MHz. In total 112 threads of 28 mm depth are formed at a speed of 20 m/min using the reference fluid (ReF) and four different test fluids (Emulsion 1 and 2, Oil 1 and 2). Besides the run-in of the tap at the beginning of the test procedure (32 threads with reference fluid), eight threads are tapped with each test fluid. The pilot holes are filled with fluid before starting the automatic test procedure of the tribometer. Between the test fluids, the tap is cleaned with solvent to remove the substances adhering on the forming lobes of the tap. The test order of the fluids is shown in Table 1.

Table 1. 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

The fluids differ in the concentration of phosphorus listed in Table 2.

Table 2. Phosphorus contents in test MWF

MWF	Emulsion 1	Emulsion 2	Oil 1	Oil 2
w-% [1e-3]	316	5	8	160

4. CNN APPLIED ON MWF CLASSIFICATION

In the proposed approach, AE signals acquired during threading are classified by CNN to check the distinguishability of the test fluids. The flowchart of proposed approach is shown in Figure 2.

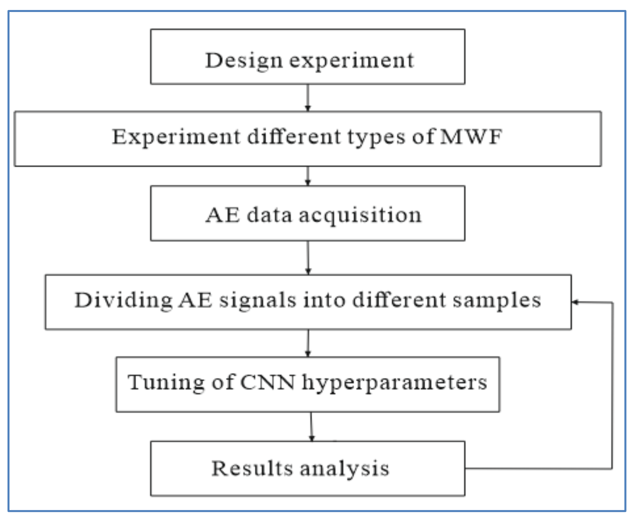

Figure 2. Flowchart of proposed approach

4.1. AE Signal Processing

In calculation process, firstly all thread data of one series are applied as CNN input. To reduce the impact of hole location and calculation time, the middle threading AE signals of each series are used. For example, series m2 contains eight threads, namely, the position of the threads is from position 33 to 40. For data processing, only the measurements from position 35 to 38 are taken into account. In order to balance the samples' number in every class, different numbers of threads are applied in m1. All these threads are chosen from the middle of series m1.

The AE waveforms continuously are acquired at a sampling rate of 4 MHz. The forming of a single thread lasts about 5 seconds and contains about 20 M data. The original signal of thread 35 is shown in Figure 3-a. The raw data of every thread is divided into different samples. To maintain the key points of each sample, data overlaps with neighboring samples. In this experiment, different data (3400, 6800, 13600, and 27200 data for each sample) are used as CNN input. After comparing the results, 13600 as best data/sample combination is chosen as the CNN input. The overlap of adjacent samples is 0.5. One sample and AE event in thread 35 are shown in Figure 3-b and Figure 3-c separately.

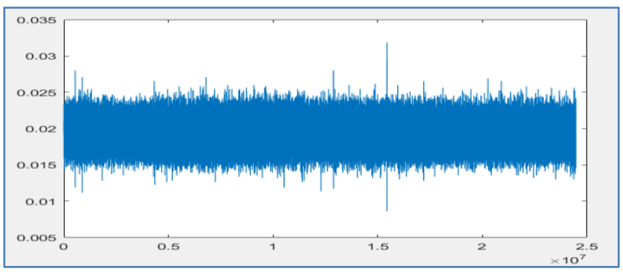

Figure 3-a. Original AE signal of thread no. 35

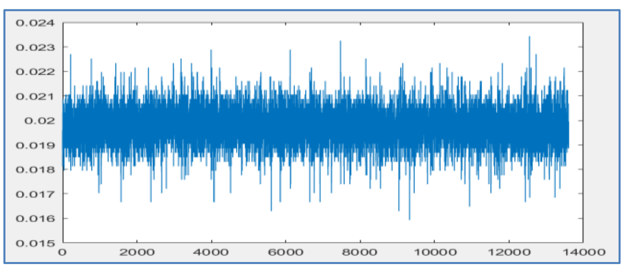

Figure 3-b. One sample of thread no. 35

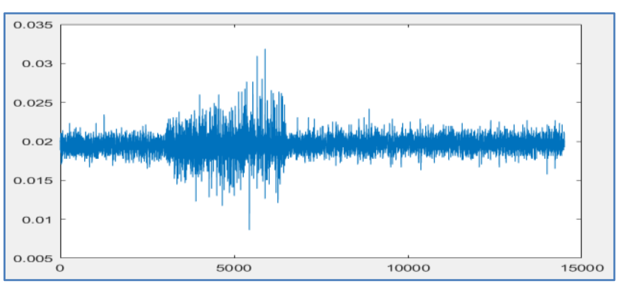

Figure 3-c. One AE event in thread no. 35

4.2. CNN Hyperparameters Tuning

Hyperparameters which are set before training are variables determining the neural network structure and have to be defined by training. If hyperparameters are well tuned, the model could minimize a predefined loss function and give better results.

For the proposed CNN model, a systematic approach for hyperparameter tuning is cross-validation between different sets of hyperparameters (Montavon, Orr, & Mueller, 2012). In detail, several CNNs are trained differing only in the value of one hyperparameter. After comparing the performance of these CNNs, the best setting for this hyperparameter can be chosen. This optimized value is used for every future CNN. Afterwards, another hyperparameter is examined. In this way, the set of hyperparameters are tuned and optimized step by step. Since there are many tunable hyperparameters, only those are examined that yield the best performance improvement.

According to the contribution of Montavon et al. (2012), L2-normazation and dropout layer are added in the proposed CNN model and the detailed hyperparameters value of proposed CNN model are shown in Table 3.

Table 3. Hyperparameters for proposed CNN model

Hyperparameters		Value
Initial learning rate		0.01
Batch size		1380
Maximal number of epochs		40
L2-regularization factor		0.001
Drop probability		0.5
Receptive input size	conv1	1 x 109 x 1
	conv2	1 x 67 x 1
	conv3	1 x 29 x 1
	conv4	1 x 15 x 1

For the activation function layer, ReLU function is chosen as the non-linear activation function. For the pooling layer, max pooling function is selected. A deep neural network is constructed in Matlab by concatenating its layers into a 'layer'-object which describes the network's architecture. In Figure 4, the 'layer'-graph of the proposed approach is shown. It can be described as a 4-layer CNN with one FC layer as it is composed of 4 convolutional layers and one FC layer. Additionally, batch-normalization layers, ReLU non-linearities, max-pooling layers, and a dropout layer are used.

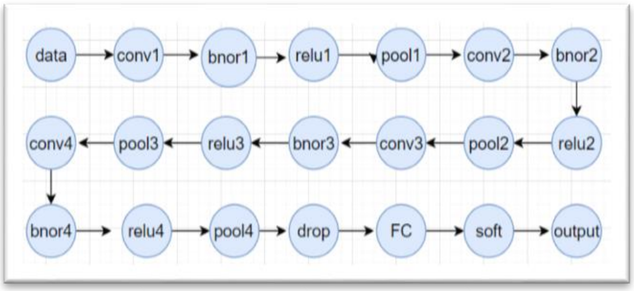

Figure 4. Architecture overview of CNN

4.3. Classification and Results

In the experiment, five different types of MWF are applied for thread forming: reference, emulsion 1, emulsion 2, oil 1, oil 2. For reference, AE signals' data are taken from 3 series: m1, m6, and m11. For the other 4 MWF, AE signals' data come from 2 series as shown in Table 1.

The MWF classification process is divided into 3 steps. For the first step: samples are divided into reference, emulsion-based (emulsion 1 and 2), oil-based (oil 1 and 2) roughly. For the second step: divide emulsion-based samples into two classes: emulsion 1 and emulsion 2. For the third step: divide oil-based samples into two classes: oil 1 and oil 2. For each step, the proportion between training data and test data is the same. In order to verify the robustness of the model, the same data in each step is calculated 5 times.

Step 1: These five kinds of MWF are divided into 3 classes: reference, emulsion-based, and oil-based. For reference, data from m1 is employed. For the emulsion-based dataset, AE signal data in m2, m3, m9, and m10 is categorized into one class. For oil-based MWFs, the AE data in m4, m5, m7, and m8 is categorized in one class.

Step 2: To distinguish emulsion 1 (E1) and emulsion 2 (E2) in detail, samples acquired from m2 and m10 is mixed as one class. Samples gotten from m3 and m9 is put into the second class.

Step 3: To distinguish oil 1 (O1) and oil 2 (O2), samples obtained from m4 and m8 is mixed as class 1, samples gotten from m5 and m7 is blended as class 2.

Table 4: Results of MWF classification process

Step	MWF type	Test accuracy (%)				
		1	2	3	4	5
1	Ref./Oil/ Emulsion	70.17	71.20	71.84	70.18	72.95
2	E1/ E2	80.71	78.47	79.09	81.00	79.87
3	O1/ O2	70.21	73.87	61.71	70.48	67.54

From Table 4, the following conclusion could be drawn:

1. Comparing the results of 5 times, the test accuracy of step 1 and step 2 are similar to each other. However, the results in step 3 are more different for each time, especially, in third time the test accuracy is much low than other times.
2. The average test accuracy for step 1, step 2, and step 3 are 71.27 %, 79.83 % and 68.76 %. This means, the result in step 2 is better than in other steps. Test accuracy in step 3 is the worst.
3. From the results of step 2 and step 3, the following assumption can be drawn: compared with oil-based MWF, emulsion-based MWF are easier to distinguish by the proposed CNN model.

The following additional observation can be stated:

1. The length of the data sample affects the results.
2. Hyperparameters tuning is required to improve results.
3. Additional to the dependencies to be classified, it could be overserved that also the thread's position effect the results.

5. CONCLUSION

In this contribution, an experiment is designed for acquiring the AE signals in the process of thread forming in which five different types of MWFs are applied in the blank thread holes. AE signals in time domain are divided into different samples and the overlap of adjacent samples are applied to maintain the key points of each sample. These samples' features are extracted and classified by CNN in which the hyperparameters are tuned by cross-validation. The proposed approach in this contribution is a combination of AE signals and CNN for MWF classification.

The process of MWF classification is separated from rough to detailed. For MWF rough classification, the test accuracy is medium. However, the proposed approach performs well in emulsion-based MWF distinction, but it is not so good for the distinction of oil-based MWF.

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