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Predicting the sparks occurrence in electrochemical discharge machining by machine learning using convolutional neural networks

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Abstract

This study investigates the use of convolutional neural networks (CNNs) to define sparks from the high-speed video feed of the electrochemical discharge machining (ECDM) process. The visual data is used to monitor the spark activity in the electrolyte. The recognition of the sparks in optical data can potentially improve the prediction of material removal in ECDM since the majority of machining is caused by the sparking. The massive dataset size is a challenge to study the optical data frame by frame. The CNN model in this study generated a time series for the presence of sparks based on the image feed in sequential order. The CNN based machine learning model in this study is found to be more consistent than the manual labeling of the images. This model is used to analyze the image data and predict the presence of the sparks over 95% accuracy.

Keywords: Convolutional Neural Network; Deep learning; ECDM; High-speed camera imaging; Machine Learning

1. Introduction

Brittle materials like ceramics and complex materials like composites are difficult to be machined by traditional methods [1]. Electrical machining methods are well known for their outstanding performance in machining such materials [2]. Electrochemical discharge machining (ECDM) is particularly suitable for machining such difficult to machine materials [3]. The material removal in ECDM is due to the heat generated by the sparks occurring between the tool and its surrounding gas film. A layer of gas film is formed around the tool due to electrolysis and locally insulates it from the electrolyte. Sparking happens when the applied voltage is above critical voltage. Thermal machining happens if the workmaterial is kept in the vicinity of the sparks. Since the work material is not required to be a part of the electrical circuit, ECDM is well suited for machining non-conducting materials. ECDM process conditions can affect its performance and surface quality [4]. Thus, a proper monitoring and control is required to improve ECDM performance.

Detection of sparks during electrical machining is important to classify the discharges such as sparks, arcs; understand the process stability; and also for adaptive process control [5]. Current is the main feedback signal used to monitor sparking process [6, 7]. Since the current flow in ECDM is a complex combination of electrolysis and sparking, it influences the gas film formation process and affects the sparking [8]. Few recent studies have used optical signals from high-speed camera to characterize the gas film formation process and ECDM sparks [9, 10]. However, individual sparking has not yet been studied with a high-speed camera.

There are many non-linearly correlated factors that affect the ECDM process, making its analysis complex. This complexity of the machining process results in a challenge in signal processing. Some recent studies are applying artificial neural networks (ANNs) to ECDM [11]. They focus on predicting the material removal in composite machining [12, 13]. ANN has been used to classify the pulses from the current signal in ECDM [14]. However, ANNs have not yet been applied for optical sensing in ECDM.

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A major challenge in the studying the sparks using optical signals is the hinderance of spark visibility caused by the bubbles and gas film around the spark. Also, the spark glow is reflected or deflected by the gas bubbles. Moreover, sparks could be partially or completely covered by the tool or gas film, making it hard to identify the sparks and distinguish them from noise light sources.

This study aims to analyze the optical image data from a high-speed camera with machine learning using a neural network (NN). There are many models in the NN, including Perceptron, Feed Forward Neural Network, Multilayer Perceptron, Convolutional Neural Network, Radial Basis Functional Neural Network, Recurrent Neural Network[15]. These networks differ based on the layers used in them. The data used in this study is an RGB image feed from a high-speed camera. RGB imaging data warrants using a convolutional neural network (CNN) as its convolution layers are best suited for feature extraction from image data for further layers in the network. In this study, the CNN is applied to automatically generate a time series of sparking using a video feed. The outcoming data can further be compared and analyzed with the time-series data from the current sensor. This study is an initial attempt to use machine learning based optical monitoring of ECDM. Such a study has a huge potential for automated spark monitoring, classification and adaptive control of the ECDM process in future based on optical signals in an industrial setting.

2. Research Method

2.1. Experimental Procedure

Figure 1 shows the in-house built ECDM setup used in this study. The setup uses a DC power supply that provides power supply in 0 -120 V range with 3A max current. The experimental conditions used in this study are given in Table 1.

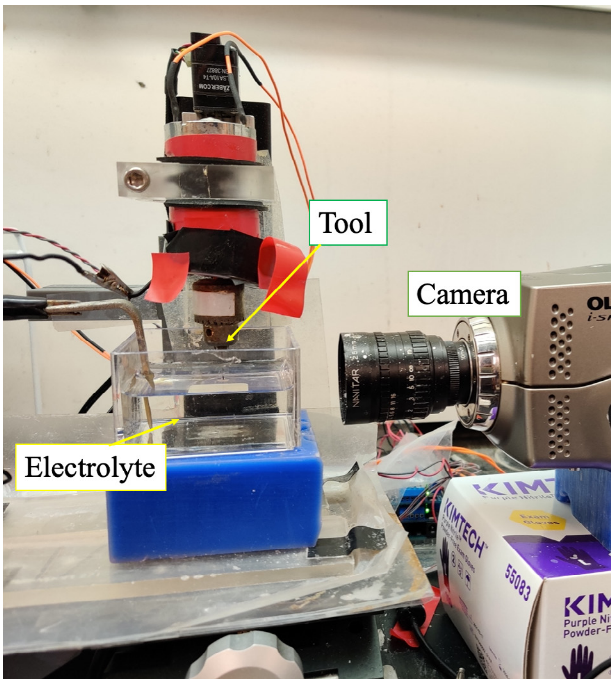


Figure 1 Experimental setup

Table 1 Experiment Parameters

Parameters	Values
Tool	Tungsten Carbide 500 µm cylinder
Electrolyte	1M NaOH
Applied voltage	55 V DC
Optical capture rate	1000 frames per second
Capture duration	2-3 seconds

An Olympus i-Speed 2 high-speed camera at 1000 frames per second was used in this study to monitor and record the occurrence of ECDM sparks. A blue light source was used to illuminate the electrolyte and tool for better image quality. Multiple sample sets are collected for at least 2 seconds (i.e., 2000 frames or above) which is later developed into the learning sets and testing sets for CNN.

2.2. Analysis Model

A 9-layer neural network model as illustrated in Figure 2 is used in this study. Two convolution layers of 32 and 64 nodes, respectively, have been used in conjunction with 2D max-pooling layers. After this step, the data is flattened and passed to dense layer network of 4 layers with 16, 8, 4, and 2 nodes. The 2 nodes in last dense layer represent the outputs “spark” or “no spark”. The sequence of layers is listed in Table 2.

This choice of layers has been decided after testing multiple combinations of layers and nodes per layer like 1-4 Convolution layers, presence or absence of batch normalization, 3-5 dense layers, etc. The below combination of layers and nodes per layer works best to achieve fast and correct learning from training data without overfitting or underfitting the data. The model is built using the keras library in python.

Table 2 Convolutional neural network layers

Sr. No.	Layer type	Output matrix size
-	Input	140 ×140 ×3
1	2D Convolutional	138 ×138 ×32
2	2D Maxpooling	69 ×69 ×32
3	2D Convolutional	67 ×67 ×64
4	2D Maxpooling	33 ×33 ×64
5	Flatten	69696
6	Dense	16
7	Dense	8
8	Dense	4
9	Dense	2

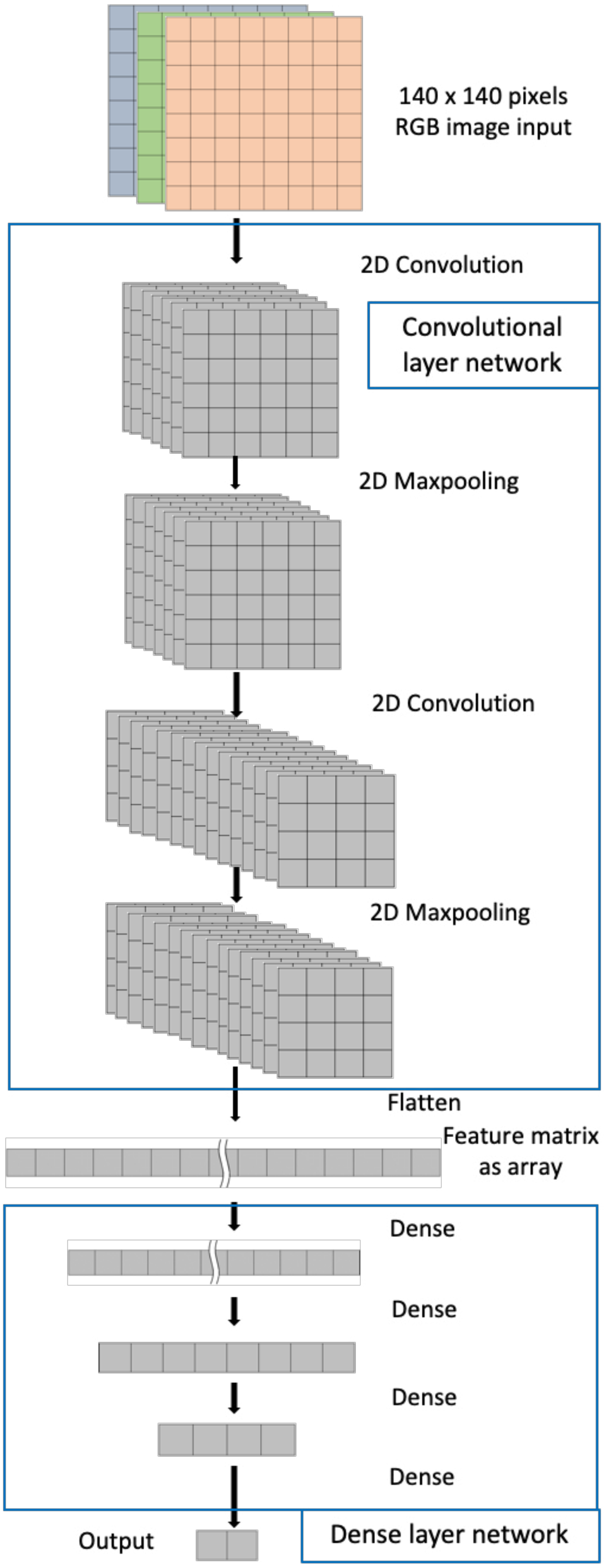
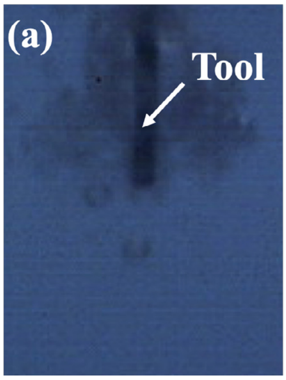


Figure 2 Visual representations of layers of neural network used

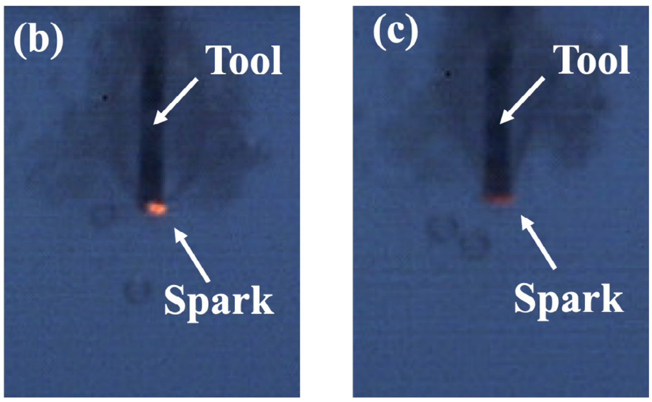
3. Results and Discussion

3.1. Preprocessing and defining a spark

Before the model can be built and trained, it is necessary to label the training images set whether each image is a spark or not. A sample size of 2000 images has been labeled for training, and further training data is generated from data augmentation that generate more data based on existing data. In this method existing images, when they undergo image shifts, flip, rotation, and other similar transformations, become new images (new set of pixels) while still maintaining the same labels ("spark" or "no-spark"). One of the important points in this study was defining a spark. In some cases, as shown in Figure 3(a) and (b), the image clearly shows whether a spark is present or not. However, in most other cases, the intensity of the spark is low. Also sparks can occur on the rear side of the tool that is not directly visible. In such cases, only the glow of the spark can be seen around the tool, as shown in Figure 3 (c). Thus, an effort has been taken to thoroughly analyze the training images and label them as accurately as possible.



(i) Spark is absent



(ii) Spark at differ location affects the illuminance

Figure 3 (a) shows a case of no spark. (b) and (c) shows a case of spark. In (b), the spark is in front of the tool towards the camera. In (c), the spark is behind the tool, away from the camera; hence, it is dim.

3.2. Results

It is necessary to have as much data as possible to train the model accurately. A sample size of at least around 3000 images is recommended to achieve an accuracy of over 90%. The model is trained using a total of 5285 samples after data augmentation and another 1321 samples were used for testing. The model has been trained over 12 epochs (iterations) to converge to the best weights and biases for the neural network. Figure 4 shows the training and testing accuracy of the model when detecting the presence and absence of the spark. As can be seen from the plot, the training and testing accuracies increase over the epochs and stabilize at around 97%.

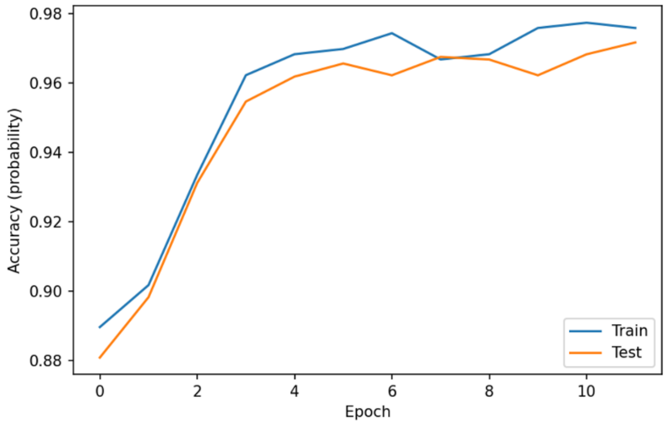


Figure 4 Training and testing accuracy over training runs (epoch).

The loss function is a unitless value representing the total error between prediction and the actual output value. The goal of training a machine learning model is to minimize the loss function. The decreasing trend of loss function over epochs in this study can be seen in Figure 5.

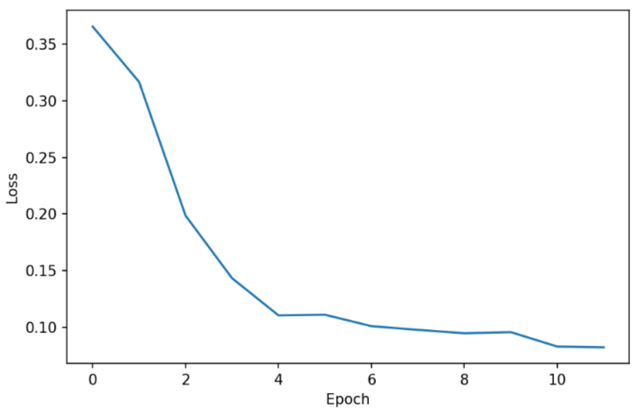


Figure 5 Loss function vs. epochs.

This study uses machine learning to convert the optical feed to time series of digital data. If the image array data is passed as the same sequence in time, the output of the CNN model is a time series of sparks. Figure 6 shows such a plot of a 50 frame (0.05 second) window. The prediction rate is very close to the accuracy in the training, as 48 out of the 50 predictions made by the model for this window are accurate.

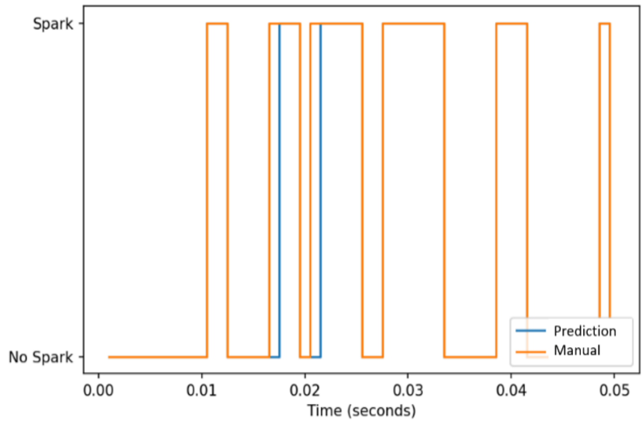


Figure 6 Time series of prediction and manual.

3.3. Validation

Tests with 5 more random sets of 200 contiguous samples with known output were used to verify the model further. The model predicted the presence or absence of spark; the output of the CNN model was compared to the known labels for the samples. Table 3 shows the results of the testing.

Table 3 Model testing

Test (200 samples)	Mispredictions in 200 samples (spark instead of no spark or otherwise)	Percentage correctness
1	11	94.5
2	5	97.5
3	2	99
4	15	92.5
5	5	97.5

It is found that the model prediction correctness is close to the accuracy found in training within the allowable tolerance. The misprediction from data can come from the noise in data and limited computing power. However, the result shows a similar result accuracy predicting the testing data, which is close to 97%.

To further analyze the validation results, the output of a random 200 sample set was observed as shown in Figure 7 and compared with manual labels. Four predictions of the CNN model were found to be mismatched with the manual labels. Two of them (Figure 8) had mismatched because the spark was very faint. The remaining two frames (Figure 9) were wrongly labeled while preparing the training and testing sets. These inaccuracies were human error due to handling large data, which the CNN model corrected.

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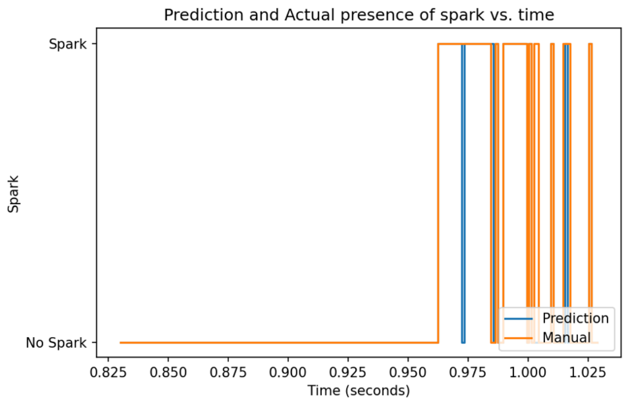

Figure 7 Analyzing set of 200 samples for misprediction

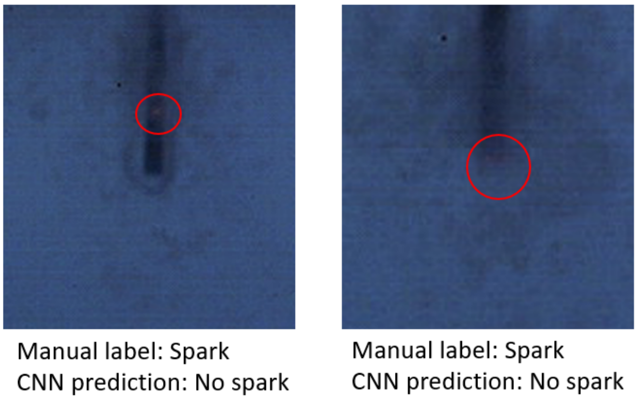

Figure 8 Examples of cases where the spark is faint leading to a misprediction

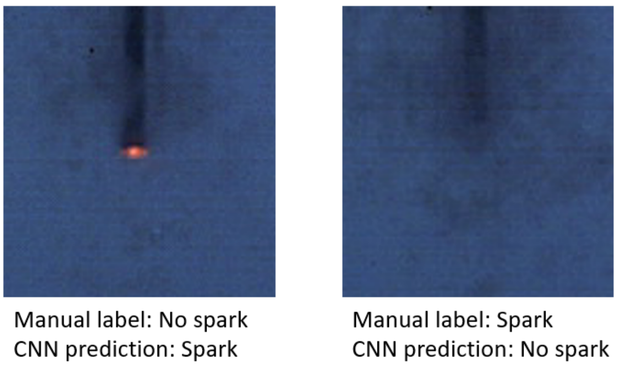

Figure 9 Cases of error in manual labelling but the machine still predicted the spark accurately

4. Conclusion

Machine learning was applied to study the image recognition of sparking in ECDM. The learning model is a 9-layer CNN. In the training and testing, a 97% accuracy is achieved. Furthermore, random sets of data were tested with the developed model resulting in a similar accuracy. The model also corrected the human error in manual labeling. Thus, these results show that the CNN model used in this study is valid in defining the sparks in an ECDM process.

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