euspen's 23rd International Conference & Exhibition, Copenhagen, DK, June 2023
www.euspen.eu

An unsupervised learning method for pulse classification in electrical discharge machining

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Abstract
Surface roughness (Ra) and material removal rate (MRR) of electrical discharge machining (EDM) are significantly associated with electric discharge pulses. The tool wear rate and compensation, which are crucial for precise control, are affected by varied pulse energies, which affect different pulse energies. As a result, EDM pulse categorisation is critical for theoretical analysis and servo systems. For divers machining techniques, current EDM power systems often use a combination of RC, LC, and transistorised pulse generators. Therefore, it is difficult to annotate the transitional condition between open and short pulses with voltage thresholds. Furthermore, because the discharge state is sensitive to the inter-electrode gap circumstances, the classification technique in current EDM should be able to adjust to the changeable pulse time. The current work proposes a data-driven model that is pulse duration naturally suited and free of voltage threshold for pulse categorisation. Dynamic Time Warping (DWT) is a technique that estimates the similarity of distinct pulses, notwithstanding their duration and peak voltage, without predefined time and voltage criteria After establishing a similarity matrix for each pulse, an unsupervised learning model with no specified pulse categories is developed to autonomously cluster pulses. After establishing a similarity matrix for each pulse, an unsupervised learning model with no specified pulse categories is developed to autonomously cluster pulses. In addition, this effort would contribute to a greater comprehension of the EDM process and provide additional insight into EDM pulses.

EDM, pulse classification, machine learning, unsupervised learning

1. Introduction

Electrical discharge machining (EDM)[1] is an important unconventional machining technology that can process difficult-to-cut materials such as titanium alloys, nickel-based alloys, and silicon carbide, and has been widely used in aerospace and mold manufacturing. The processing performance of EDM such as surface roughness (Ra) [2–4] and material removal rate (MRR) [2,5] is strongly associated with electric discharge pulses. Additionally, different pulses result in distinct pulse energies and tool effects. While the tool wear rate (TWR) and compensation are vital for the exact operation of the servo system, they are also essential.

Pulse classification by thresholds of voltage [6] is a very popular method for pulse feature extraction. These thresholds, which are mostly concluded by experience knowledge, are laborious to set as the processing parameters changed. Machine learning is an effective approach to classification [7]. There are two kinds of machine learning algorithms: supervised learning[8] and unsupervised learning [9]. For EDM pulse classification, supervised learning means some pulses were labelled by expert knowledge previously, e.g. open, spark, short, and partially short, and train the algorithm to learn to tag the remaining pulses correctly; unsupervised learning is a technique that can assign the unclassified pulses into several clusters, the unsupervised learning algorithm discovers information on its own.

For various manufacturing techniques, the power supply of modern EDM often employs a combination of RC, LC, and transistorised pulse generators. It is difficult to characterise the transitional state between open and short pulses. In addition, because of the discharge condition of RC-based power supplies, the pulse duration is not constant, causing an adaptation of the classification technique to the variable time span. For various manufacturing techniques, the power supply of modern EDM often employs a combination of RC, LC, and transistorised pulse generators. It is difficult to characterise the transitional state between open and short pulses. In addition, because of the

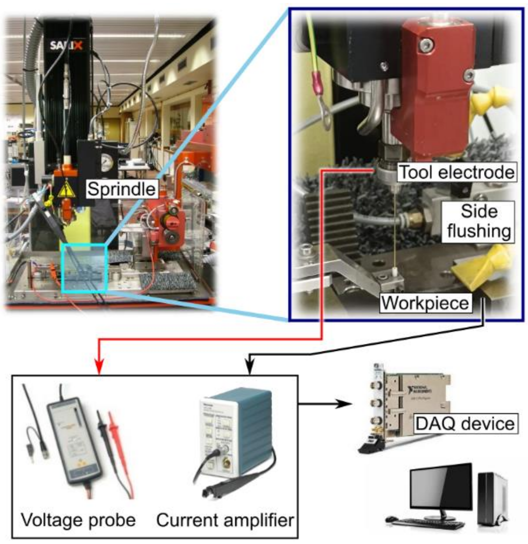

Fig. 1 Experimental setup and data acquisition system

discharge condition of RC-based power supplies, the pulse duration is not constant, causing an adaptation of the classification technique to the variable time span. In the present study, the similarity of different pulses was calculated by Dynamic time warping (DWT) [10], which is intensively used in pattern recognition[11,12]. DWT is a non-linear method that measures the similarity between two time series by warping them in the time domain, which allows it to handle time series that may be out of phase or have different temporal sampling rates. In contrast, other convolution methods either require time series to have the same length and temporal resolution, which may not be practical or feasible in some applications, or simply adjust the data by padding it with zeros, which can lead to data inconsistencies.

In this study, the similarity of distinct pulses, regardless of their duration and peak voltage, is evaluated using the DWT without predefined time and voltage thresholds. The pulses were classified into several clusters using hierarchical clustering, with a matrix of similarity for each cluster. This effort would contribute to a greater comprehension of the EDM process and provide additional insight into EDM pulses.

2. Experimental setup and pulse data acquisition

Experiments of micro-EDM drilling and the pulse data recording are carried out on a SARIX EDM machine and NI data acquisitions system (DAQ), as shown in Fig. 1. This system allows for monitoring and recording the electric pulse signals during the EDM process. WC rods of 0.3 mm in diameter were used as tool electrode and STAVAX (stainless steel) plates were used as the workpiece.

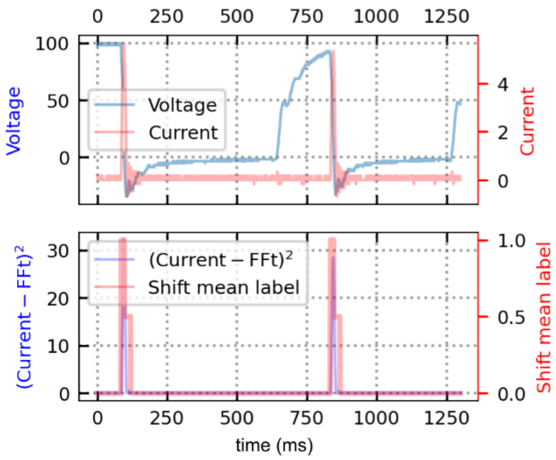

Fig. 2 Electric discharge cycle definition

3. Results and discussion

3.1 Pulse cycle definition

Pulse cycle definition in electro-discharge machining (EDM) is important as it determines the timing and sequence of electrical pulses that remove material from a workpiece. The parameters of cycle definition such as pulse duration, peak current, and pulse frequency are crucial in controlling the material removal rate, surface finish and overall efficiency of EDM process. It is therefore essential to optimise the cycle definition for the desired outcome.

In this work, the pulse cycle was characterised by the shift mean and Fast Fourier Transform (FFT). In particular, the FFT was used to remove the noise from the electric signal, and then the shift mean value was calculated continuously inside a moving time window. The beginning and end points of an electric discharge cycle were labelled when the shift mean value underwent a considerable change, as indicated in Fig. 2. In this case, a pulse cycle begins when the shift mean label transitions from 0 to 1, and ends when the shift mean label transitions from 1 or 0.5 to 0.

Figure 3 depicts the defining findings for the pulse cycle. The FFT + shift mean method may effectively distinguish pulses from continuous time series data, regardless of their duration

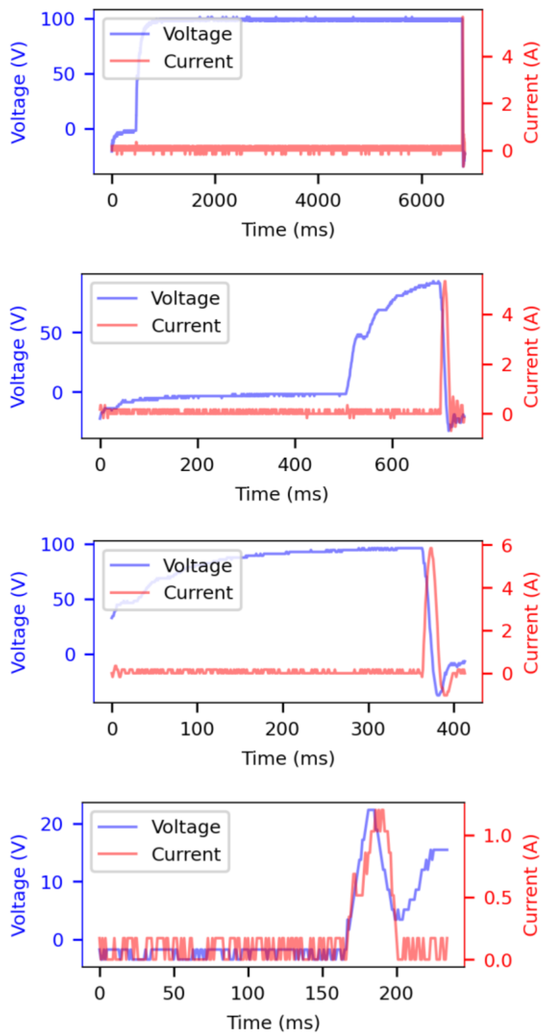

Fig. 3 Typical EDM pulses

or peak value. Figure 3 depicts the defining findings for the pulse cycle. The FFT + shift mean method may effectively distinguish pulses from continuous time series data, regardless of their duration or peak value. In fact, this method employs a relative threshold value in the y direction, which is the time direction, as opposed to an absolute threshold value in the x direction, which is the voltage/current amplitude value. This allows for greater flexibility when the pulse duration is not constant, and the discharge peak value varies greatly.

3.2 Dynamic time warping

Dynamic Time Warping (DTW) is a technique for comparing and aligning two data sets (often time series) that are not precisely synchronised. It's a technique for determining the optimal matching and warping distance (similarity) between two sequences. For sequence $Q = \{q_1, q_2, \dots, q_n\}$ and $C = \{c_1, c_2, \dots, c_m\}$, $d(q_i, c_c)$ is the Euclidean distance between the q_i and c_j, and allocate all the points in Q and C.to construct

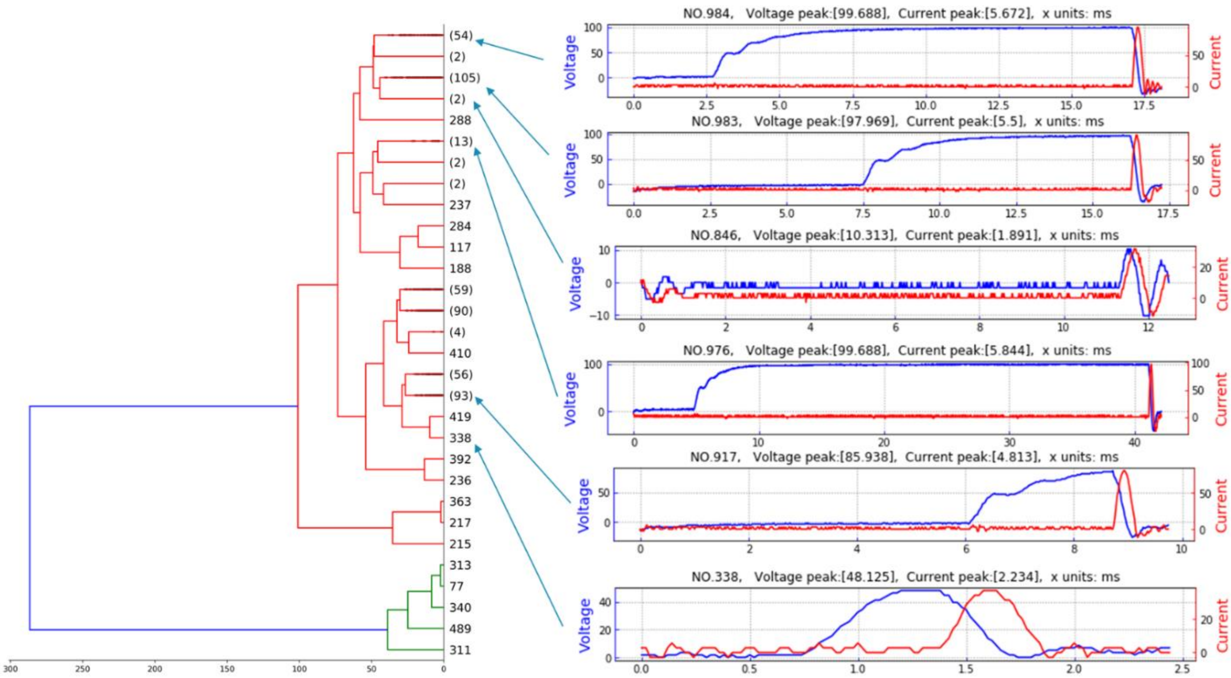

Fig. 4 Electric discharge cycle definition

the matrix $A_{m\times n}$ where the $a_{ij} = d(q_i, c_j) \in A_{m\times n}$ is the warping path. Hence, the $DTW(Q,C)$ is aiming to find the overall minimal summing warping path:

$$DTW(Q,C) = \min\left\{\sum_{t=1}^{K} \frac{(a_{ij})_t}{K}\right\} \quad (1)$$

where $K = \max(m,n)$ is the longer data length of Q and C.

A typical DTW alignment and the corresponding warping path is shown in Fig. 5. The pulse NO.22, pulse NO. 78 and pulse NO.338 can make a good alignment despite their different amplitudes and durations. Table 2 and Table 2 illustrate the pair wise DTW distances of voltage and current

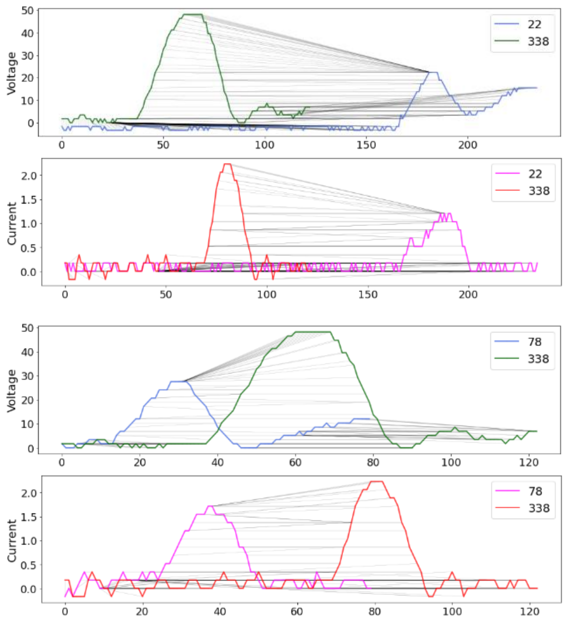

Fig. 5 Dynamic time warping for EDM pulses: Pulse NO. 22 vs Pulse NO. 338 and Pulse NO. 78 vs Pulse NO. 338

for pulses No. 22, No. 78, and No. 338 as an illustration. In this case, the $DTW(Voltage_{22}, Voltage_{338}) = 1220.367 < DTW(Voltage_{22}, Voltage_{78} = 515.690$, denotes that the Pulse NO. 22 is more similar to Pulse NO. 78 than Pulse 338.

As a result, by constructing a DTW distance matrix for all observable pulses with pair wise DTW distance, the relative similarity between each pair of pulses can be determined.

Table 1 Pair wise DTW distance of voltage for pulses [22, 78, 338]

	Pulse NO. 22	Pulse NO. 78	Pulse NO. 338
Pulse NO. 22	0	515.690	1220.367
Pulse NO. 78	515.690	0	537.968
Pulse NO. 338	1220.367	537.968	0

Table 2 Pair wise DTW distance of current for pulses [22, 78, 338]

	Pulse NO. 22	Pulse NO. 78	Pulse NO. 338
Pulse NO. 22	0	19.779	24.245
Pulse NO. 78	19.779	0	11.519
Pulse NO. 338	24.245	11.519	0

3.3 Hierarchical clustering

Hierarchical clustering, also known as hierarchical cluster analysis, is a technique that clusters related objects. The endpoint consists of a collection of clusters, where each cluster is distinct from the others and the items within each cluster are generally comparable. In this study, the DWT distance between pulses NO.1 and NO. 6 (voltage and current, respectively) is [6203.44, 356.87], however, the DWT distance between NO.1 and NO. 22 is [482536.59, 332.60], which is much more than that between NO.1 and NO. 6. In addition, the DWT distance between NO 22 and NO 312 is [1,099,93, 13.75]. Consequently, the NO. 22 pulse is more similar to the NO. 312 pulse than the NO. 1 pulse, and the NO. 338 pulse is more similar to the NO. 22 pulse than the NO. 22 pulse.

Multiple clusters can be constructed when calculating the pair wise similarity of all items. By modifying the cluster method's parameters, the number of clusters can be changed. The pair wise DTW distance matrix can be utilised to develop a linking criterion that determines how similarity between two clusters is calculated. In hierarchical clustering, several linkage criteria, including single linkage, complete linkage, average linkage, and Ward's linkage, are widely applied. Single linkage clustering employs the minimal similarity between any two data points from the two clusters being merged as the measure of cluster similarity. This technique produces clusters with an extended form. Complete linkage clustering employs the highest similarity between any two data points from the two clusters being merged as the measure of cluster similarity. In addition, this technique typically yields clusters with compact forms. As the measure of similarity between clusters, average linkage clustering employs the average similarity between all pairs of data points from the two clusters being merged. As a measure of similarity, Ward's linkage clustering use the variance increase induced by combining two clusters.

As a result, using the pair wise similarity matrix and linkage criterion, the algorithm will proceed to iteratively merge or split the clusters until a stopping criterion is met. Once the clustering is done, the dendrogram is a tree-like diagram that shows the hierarchical relationship between the clusters and pulses as shown in Fig. 4.

Moreover, in the context of hierarchical clustering, active learning can be used to iteratively refine the clustering results by allowing the expert to provide feedback on the clusters. The expert can provide labels for the clusters, such as normal or abnormal, and the model can use this feedback to adjust the similarity matrix and linkage criterion for the next iteration of clustering. This process can be repeated until the expert is satisfied with the clustering results. By incorporating expert knowledge via active learning, the model's accuracy in identifying normal and abnormal discharge pulses can be improved, and it can be a more valuable tool for the expert in gaining a deeper understanding of EDM.

4. Conclusion

In conclusion, this study provides a data-driven model that is naturally suitable for pulse duration and voltage threshold-free for pulse categorisation. Dynamic Time Warping (DWT) is a technique for estimating the similarity between distinct pulses, regardless of their duration and peak voltage, and without predefined time and voltage criteria. After constructing a similarity matrix for each pulse, an unsupervised learning model is constructed to cluster pulses autonomously. This framework is able to cluster pulses based on their similarity requiring no predefined pulse classifications.

Furthermore, the use of active learning with expert knowledge allows the model to be refined and improve its accuracy in identifying normal and abnormal pulses. This can be a useful tool for experts to analyse EDM data and gain a deeper understanding of the EDM process. Additionally, this effort can provide additional insights into EDM pulses and contribute to a greater comprehension of the EDM process. Overall, the proposed data-driven model can be a valuable tool for the analysis of EDM pulses and can assist in the optimization of the EDM process.

In the meantime, DTW can serve as an advanced tool for process monitoring and control in various manufacturing applications. For instance, in the production of small and large cups, the processing time for each cup would differ but they would have similar manufacturing steps. DTW could be employed to analyze the time-series data generated by the manufacturing process for each cup and compare the differences between the processing times.

By utilizing DTW in this way, manufacturers can gain insights into the production process for each cup and identify any anomalies or deviations from the standard process. This information could then be used to diagnose and correct any issues in the manufacturing process, regardless of the varying production times. Moreover, DTW can be used for more complex manufacturing processes where multiple steps are involved. DTW can compare time-series data from each step and detect any deviations from the expected process. This enables manufacturers to monitor and control the production process in real-time, preventing any issues or defects from arising.

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