ORIGINAL ARTICLE

Intelligent Sensing Unit for Estimation Roughness of Electrical Discharge Machining

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Abstract: Estimating the quality of an electrical discharge machining (EDM) workpiece is challenging when attempting to extract features from the stochastic and time-consuming processes. To solve this problem, an intelligent sensing unit for EDM (ISU-EDM) is proposed to extract key machining features for estimating workpiece roughness. During machining, the ISU-EDM simultaneously samples the signals of both the discharge current and voltage, while automatically segmenting the signals according to tool location and discharge effectiveness. Furthermore, the machining features could be extracted from the segmented data by a genetic-algorithm-based distribution fitting method. After applying the features to an automated virtual metrology system, experimental results show that the mean absolute percentage error of roughness estimation is less than 15%.

Keywords: electrical discharge machining, discharge machining features, genetic algorithm, feature distribution fitting

Introduction

The increasingly high efficiency of manufacturing technologies has been accompanied by a trend towards the micronization on components and molds. However, small-scale machining raises challenges in terms of tool breakage and residual stress, such as in the use of high-speed milling and cutting to produce micro-holes and micro-slots. In particular, removing materials such as tungsten carbide is challenging for typical machining technologies [1] and is currently accomplished using electrical discharge machining (EDM). EDM removes material from a workpiece through a series of rapidly recurring current discharges between two electrodes, i.e. the tool and workpiece electrodes. In EDM, the lack of direct contact between the tool and the workpiece prevents issues related to tool rigidity and workpiece deformation [2]. In addition, micro-scale components and molds can be produced by designing specific electrodes and controlling the discharging energies.

Compared to other micro-machining methods, such as micro-milling and micro-drilling of workpieces, micro-level EDM has benefits of low cost, non-cutting force, high-dimensional precision, and the ability to build three-dimensional microstructures. However, problems of processing efficiency and electrode consumption raise challenges including long processing times and complicated tool compensation while using EDM to machine the complex structures of the workpieces.

Previous studies have indicated that the metal removal rate (MRR), the surface roughness (Ra), and electrode wear ratio are directly affected by the materials used for both the electrode and workpiece, as well as the EDM parameters. Furthermore, the parameters of voltage, current, speed and pulse on/off time would also effect MRR and Ra [3][4][5]. In addition, electrical discharge by a turning tool performs better in chip cleaning and discharge efficiency than a fixed tool [10]. In micro-EDM, the workpiece's dimensional accuracy and roughness can be respectively improved through the use of short discharge pulse and a small diameter tool. The conductive material of the micro-hole can be machined with micro-EDM techniques despite workpiece hardness due to the contactless machining. However, the diameter of the drilled hole may be enlarged by the bending of the long and thin tool due to the reflection force of electrical discharge. Several studies have presented methods to monitor discharge current and voltage, to measure the status of material removal and to compensate for tool profile errors during machining [11][12][13].

Furthermore, the variation of discharge waveform and defective tool-electrodes (or tools) could result in workpiece roughness and error. If the on/off times of discharge waveform are between 90/120 – 50/70 ns of a micro-EDM process, the sampling rate for estimating workpiece quality should be high enough to detect the effective waveforms of discharge voltage and current. In addition, typical processing times for micro-level workpieces range from minutes to hours, with GB or TB of waveform data generated in the EDM processes. Automated virtual metrology (AVM) has been applied in the manufacturing of semiconductors, solar cells, and TFT-LCD panels. Using the virtual metrology method with the process-data quality index and the metrology-data quality index, AVM provides an efficient means of assessing product quality and determining process variation [6].

This paper develops an intelligent sensing unit for EDM (ISU-EDM) to collect effective discharge waveforms and extract the machining features in the micro-EDM process. The ISU-EDM features can then serve as the inputs of the AVM system to estimate workpiece quality, such as surface roughness.

Problem Definition

Monitoring variation in the micro-EDM process requires uninterrupted collection of discharge waveform and tool profile data during the EDM process. When the on time of discharge waveform is 50 ns, the sampling rate would be greater than 20 MHz according to the Nyquist theorem. Hence, the first problem is:

- How to obtain complete discharge waveform data from the EDM machine?

Meanwhile, the two-channel (16 bit resolution) data collection of a workpiece for an hour could exceed 144 GB. Therefore, the second problem is:

- How to extract effective discharge data from large data sets?

In addition, the discharge machining process is a stochastic process since the discharge positions vary with the workpiece and tool profiles. This means that the final quality, e.g., the bottom roughness of a hole, can be machined from different depths with different discharge power levels. Thus, the final problem is:

- How to intelligently extract key features from effective discharge data?

The following section presents the proposed ISE-EDM architecture and method.

Proposed Architecture and METHOD

To extract the machining features for estimating quality of a micro-EDM processed workpiece, this section presents how the ISU-EDM system collects and segments data, extracts features, builds and applies the model neural network and regression models, selects key features, and suggests actions as shown in Fig. 1.

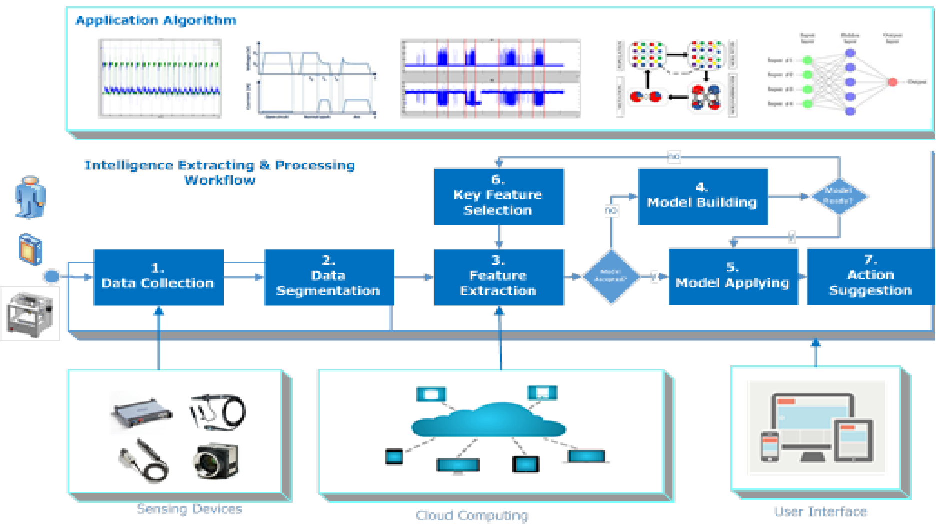


Figure 1. ISU-EDM system workflow.

Data collection

Figure 2 shows the process of collecting the current signals, voltage and the position of the Z axis using the ISU-EDM system. The current and voltage probes are connected to the discharge power line between the tool and workpiece to detect discharge waveforms during machining.

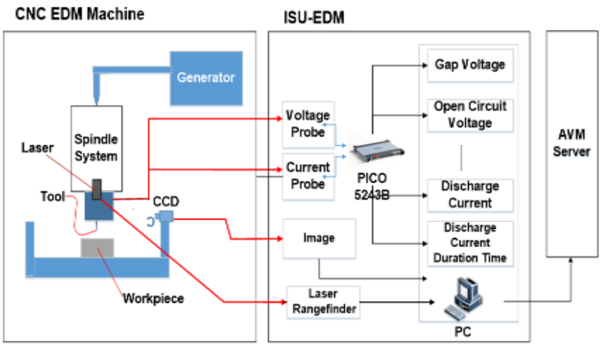


Figure 2. System architecture.

A laser rangefinder is attached to the spindle to determine the actual position of the tool end. In addition, a micro-scope CCD is installed on the edge of the workspace to measure the tool profile and length. The probe signals are collected by a scope with a high-sampling rate (PICO5243B; 2 Channels, 50 MHz), and the rangefinder data is collected through the ISU-EDM USB ports. The AVM server estimates workpiece quality based on the features derived from the ISU-EDM.

Data segmentation

The variation of workpiece bottom roughness and dimensional precision is mainly determined by discharge power level and tool profile of the last 10 µm of the EDM process. However, the actual tool discharge location varies with the discharge current between the tool and workpiece. To locate the tool position, a laser rangefinder records the actual locations of the Z-axis during machining, as shown in Fig. 3. The actual locations are used to segment the collected current and voltage data.

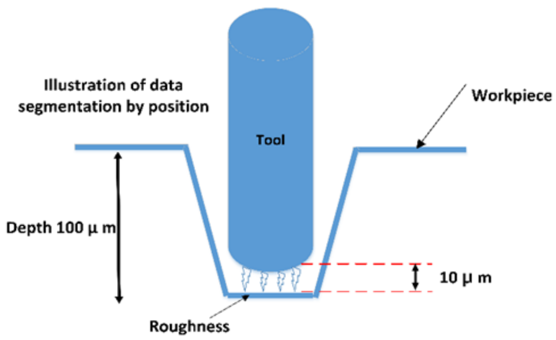


Figure 3. Data segmentation by tool location.

An effective discharge waveform includes effective current and voltage signals. Figure 4 illustrates an effective discharge waveform starting with a sufficiently high voltage and low current for charging, then followed by a sufficiently high current and low voltage for discharging, in which the T_{on} and T_{off} are respectively the on and off time durations of discharge currents.

Figure 5(a) shows the original discharge waveforms collected from an actual micro-EDM process, in which waveforms 1, 2, and 3 are effective discharge waveforms (where the upper and lower portions are the discharge current and voltage waveforms). The other sections of the original waveforms such as the short circuit waveforms should be removed.

To remove the ineffective waveforms, this study develops a rolling segmentation method that can scan all of the collected waveforms with a moving window. While using the moving window to retrieve waveform data from a section of the data file, a ring memory is used to temporally store the data with a data pointer, which indicates the current location of the stored data in the ring memory. The rolling segmentation method then captures the effective waveforms from the ring memory, and appends them to an effective queue. The window then moves on to the next section to retrieve and store additional waveforms into the ring memory with the pointer. Figure 5(b) illustrates the merged discharge waveforms with the rolling segmentation method.

Features extraction

After deriving the effective discharge waveforms, the ISU-EDM extracts nine EDM features to reduce data size. As shown in Fig 6, the features are extracted from the current and voltage signals. The voltage related features include the average ignition delay and short circuit ratio. The average spark frequency, average peak discharge current, and average discharge current pulse duration are obtained from current signals. Finally, the four features, i.e., short circuit duration, open circuit ratio, average discharge power and average short circuit current are fused from both voltage and current waveforms [5].

The nine features in Fig. 6 are described in detail as follows:

1. Average ignition delay time (AIDT): the average of durations between the time that the open-circuit voltage is sufficiently high to ignite and the start time of discharging.
2. Short circuit ratio (SCR): the short circuit pulse divided by discharge pulse; a short pulse is an open circuit voltage which remains continually below a threshold in a discharge pulse cycle.

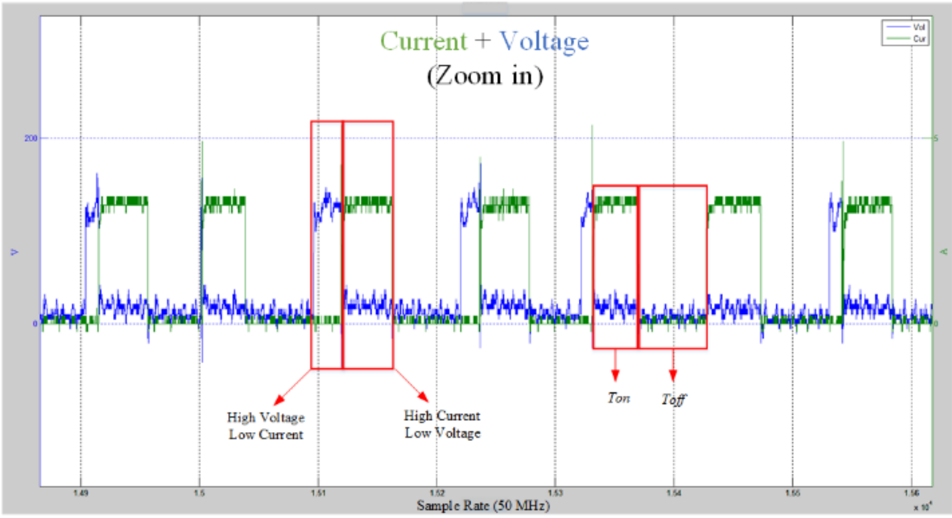
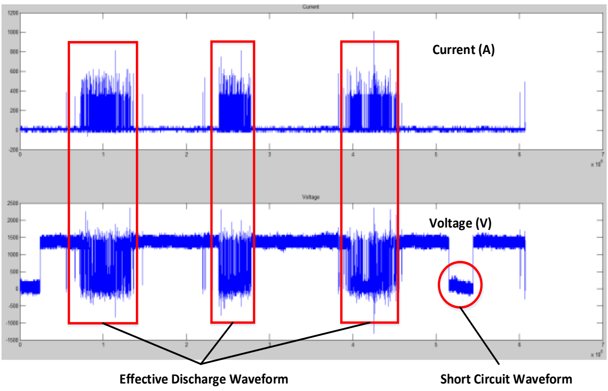
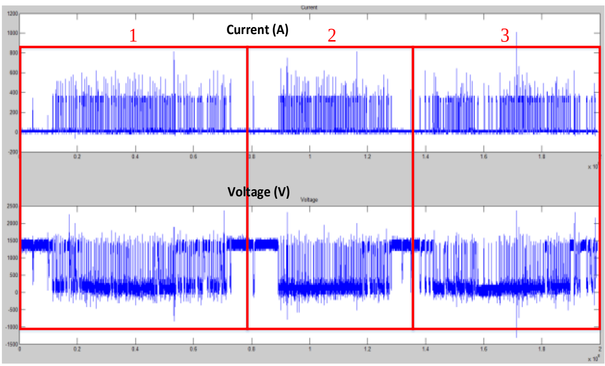


Figure 4. Effective discharge waveforms.



(a) Original discharge waveforms.



(b) Merged discharge waveforms

Figure 5. Segment the collected discharge waveforms.

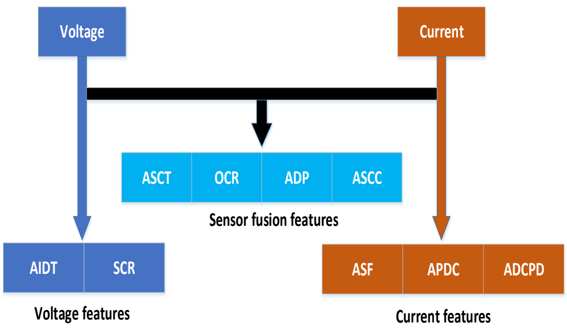


Figure 6. EDM features.

3. Average spark frequency (ASF): in a pulse cycle, a peak current is higher than the minimum peak threshold. Average spark frequency is defined as the current spark count during a given time segment, e.g. one second.
4. Average peak discharge current (APDC): peak discharge current is the maximum current that passes through the tool to the workpiece in a pulse cycle. Average peak discharge current is the average of all peak currents during a time segment.
5. Average discharge current pulse duration (ADCPD): current pulse duration is the period between the start and end times of a discharge pulse cycle. Average discharge current pulse duration represents the mean of current pulse durations in a time frame.
6. Average short circuit time (ASCT): the short circuit time is the average time between the first short circuit peak and the last one in which multiple short circuits occur in a discharge pulse cycle (at least two pulses).
7. Open circuit ratio (OCR): when an ignition voltage fails to induce a discharge current at the end of the voltage peak in a pulse cycle, this cycle is called an open circuit. The open circuit ratio is the total count of open circuits in a time duration.
8. Average discharge power (ADP): EDM process stability ensures machining quality, and the average discharge power of the i^{th} discharge is defined as follows.

$$E_i = \int_0^{t_{ei}} I_{pi} U_i dt \tag{1}$$

t_{ei} : discharge duration;
U_i : discharge voltage;
I_{pi}: discharge peak current.

9. Average short circuit current (ASCC): the mean of

the short currents in a time duration.

Key feature selection

The nine EDM features are derived from the corresponding machining ranges of the precision items, e.g., roughness, diameter, and roundness. For example, the bottom roughness of a hole could be affected by the discharge power in the machining range of the last 10 µm from the bottom of the hole. This indicates that a many-to-one relationship exists between the EDM features and surface roughness.

To select the key features to represent the effective discharge features, a genetic-algorithm-based distribution fitting method is proposed to adjust the feasible parameters (mean and standard deviation) of various distributions such as Normal, Weibull, and Gamma distributions. In Fig. 7, the three distributions indicate that the open circuit ratio features are well-fitting.

Table 1. Correlation coefficients between Ra and the features.

No. \ A	2 A	3 A	4 A
1	AI8DT2 (.47)	ASCT2 (-.489)	AIDT2 (-.395)
2	ASCT1 (-.337)	ADCPD1 (-.469)	ASCT1 (-.385)
3	ADCPD2 (.317)	ASCT1 (-.392)	ASCT2 (-.355)
4	AIDT1 (-.285)	ADP2 (.312)	AIDT1 (-.349)
5	SCR1 (-.28)	AIDT2 (-.31)	ADCPD2 (-.318)
6	OCR1 (-.273)	ADP2 (-.308)	ASF2 (-.302)
7	ADP2 (.211)	ADCPD1 (-.277)	ADCPD1 (-.272)

Case Study

The case study estimates the bottom roughness (Ra) of holes using the ISU-EDM and AVM systems. In this case, three discharge current conditions (2A, 3A, and 4A) are applied to create 48 holes with a depth of 100 µm and a diameter of 3 mm in a die steel (NAK80). A portion of the sample data is used to build the estimation model, while the remaining data is used to validate estimation model performance.

Key feature selection

For each hole, the effective discharge waveforms such as current and voltage data are collected and merged using the rolling segmentation method. Table 1 shows the higher correlation coefficients between bottom roughness (Ra) and the features, in which the features are extracted from the effective waveforms.

For example, the seven features listed in the table are the significant features of condition 2A, and the correlation coefficients of AIDT2 and ASCT1 are respectively 0.47 and -0.337. The number attached to the feature is the mean or standard deviation. Hence, AIDT2 and ASCT1 respectively represent the standard deviation of AIDT and the mean of ASCT. According to Table 1, features including AIDT2, ASCT1, ASCPD2, ADP2, and ASCT2 can be derived with the key feature set serving as the input of the AVM system for estimating roughness.

Roughness estimation

To evaluate the estimation performance of the key features, the actual roughness of each sample is assumed to be accessible in time and is used to refresh the estimation model before estimating the next sample using the AVM system. Figure 8 shows the errors between estimation values and actual values. The red stars denote the actual roughness values while the black and blue lines represent the estimation results respectively using the neural network and regression models. The machining condition of samples 1-8 and samples 9-16 is 2A, while that of samples 17-24 and 25-28 are respectively 3A and 4A. We can find that roughness values and variations increase with discharge current.

It can be inferred from Fig. 8 that the maximum estimation error of condition 2A is less than 0.5 µm, while the mean estimation error of condition 3A is 0.8 µm. The estimation errors of the last two samples of condition 4A can be reduced to 1 µm after using the top two samples to refresh the estimation model. This result indicates that the developed estimation model can adapt to various machining conditions after being refreshed with the corresponding samples.

The significant errors between the real values and estimation values for machining condition 4A are due to some of the associated features serving as the input for roughness estimation. Many studies have pointed out that the tool profile also affects the roughness, roundness, and diameter of the finished workpiece. In this case, the holes are machined by cylindrical tools, in which the wear length, the wear diameter, and the tool material will generate precision variation in the finished hole. Therefore, future work will investigate tool profile estimation .

If the estimation model is built with samples of various conditions, i.e., 2A and 3A, then the remaining samples are tested with the model. When the model is not refreshed with the testing samples, it is called a free run. Figure 9 shows the free run mode results of using 16 samples for modeling. The maximum estimation error of

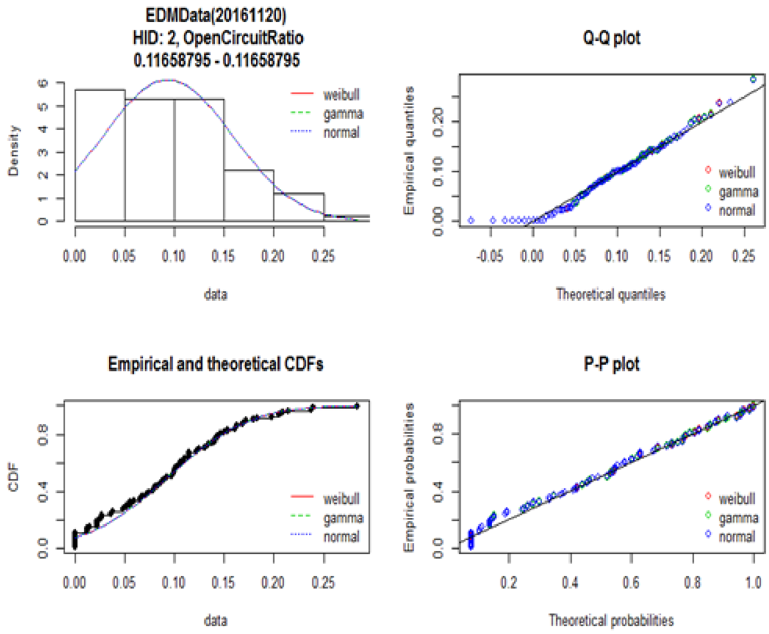


Figure 7. Distribution fitting of a feature (open circuit ratio).

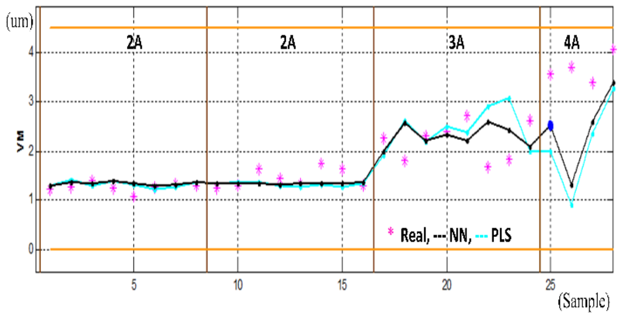


Figure 8. Roughness estimation by stepwise refreshing.

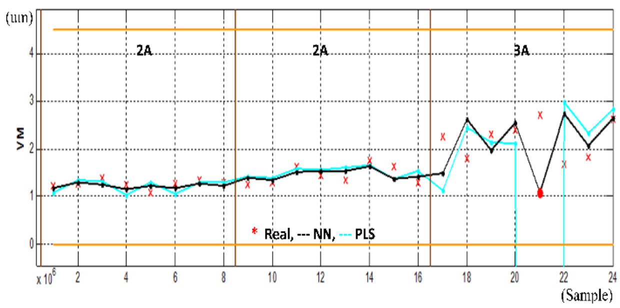


Figure 9. Roughness estimation by free run.

samples 1-16 (2A) is less than 0.2 μm, while the mean estimation error of samples 17-24 (3A) is less than 0.9 μm. If sample 21 is excluded, the mean estimation error is 0.65 μm.

After checking the sampled features, the estimation errors of sample 21 are caused by the low values of ADP1 and ADP2. In general, a low average discharge power may induce low machining variation and produce low roughness under the same machining conditions. As the experimental process moves from conditions 2A to 3A using a single machining tool, tool wear increases. Hence, the obvious estimation error of sample 21 also indicates the need to include tool wear features to correctly estimate workpiece precision.

Conclusion

Improving estimation accuracy by selecting the smallest number of the most effective features is a big challenge for the non-linear relation between EDM features and machining quality. The proposed ISU-EDM system collects the discharge current and voltage, segments and extracts the key features, and serves as the input of the AVM system to estimate workpiece surface roughness. In addition, the ISU-EDM system can integrate different sensing channels, synchronize various sensing sources, and reduce signal noise during signal processing. In terms of feature processing, the ISU-EDM system can also segment effective discharge waveforms, extract features from the effective waveforms, and then select key features using the genetic-algorithm-based distribution fitting method. Experimental results indicate that the proposed ISU-EDM system can effectively enhance the AVM system to estimate the roughness and dimensional precision of workpieces with key features.

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