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Wire EDM Monitoring for Zero-Defect Manufacturing based on Advanced Sensor Signal Processing

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Abstract

In the framework of zero-defect manufacturing, an advanced sensor monitoring procedure aimed at detecting the process conditions leading to surface defects in Wire Electrical Discharge Machining (WEDM) is proposed. WEDM experimental tests were carried out with the employment of a multiple sensor monitoring system to acquire voltage and current signals in the gap between workpiece and wire electrode at the high sampling rate of 100 MHz. In order to extract from the acquired signals the most relevant features that can be useful in the identification of abnormal process conditions, an advanced sensor signal processing methodology based on signal feature extraction for the construction of sensor fusion pattern vectors is proposed and implemented.

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1. Introduction

In the last years, wire electrical discharge machining (WEDM) has become a key non-traditional manufacturing process, widely used in several industrial sectors including aerospace and automotive [1]. WEDM allows to obtain precise, complex and irregular shapes with high accuracy and fine resultant surface finish on materials which are considered difficult-to-machine through traditional processes. Currently, it is used to machine a wide variety of electrically conductive materials from metals, alloys, sintered materials, cemented carbides, etc. [2]. However, the achievement of zero-defect WEDM manufacturing still represents a challenge, even with skilled operators and state-of-the-art CNC machines, mainly due to the large number of variables and the stochastic nature of the process mechanisms involved [3].

Different methodologies to model WEDM through suitable mathematical techniques have been proposed with the aim to determine the relationships between process performance and controllable input parameters [2–4]. Nevertheless, the selection of the machining parameters for optimal WEDM process

performance in terms of higher material removal efficiency or product accuracy is still not fully solved. As a result, process monitoring and control has become a key research area in the field of WEDM [1,5].

In this paper, WEDM sensor monitoring based on advanced signal processing is implemented with the aim to detect the process conditions related to common surface defects such as lines and marks generated during WEDM. The study is performed through the employment of a multiple sensor monitoring system able to acquire voltage and current signals in the gap between the workpiece and the wire electrode at the very high sampling rate of 100 MHz. An advanced signal processing methodology based on sensor fusion to combine the relevant features extracted from current and voltage signals is proposed and implemented to generate sensor fusion pattern feature vectors effective for the detection of abnormal process conditions responsible for surface defects.

The research activity has been developed within the EC FP7 large scale project IFaCOM - Intelligent Fault Correction and self Optimizing Manufacturing Systems, in collaboration among the University of Naples Federico II, GF Machining

Solutions and the Swiss Federal Institute of Technology.

2. Wire EDM Monitoring for Zero-Defect Manufacturing

In the perspective of zero-defect manufacturing, one of the most significant part quality characteristics to be addressed in WEDM is the presence of lines and marks on the machine surface after the finishing pass. The most likely cause of such defects on the WEDM processed surface can be related to the occurrence of abnormal sparks like short circuits and arcs. To assess this assumption, a WEDM experimental campaign was conducted with the employment of a sensor monitoring system to investigate the relationship between selected current and voltage sensor signal features and the produced output, i.e. the finished surface. The final aim of this approach is to capture the influence exerted on the WEDM process by variations in the setting of process parameters and by unknown/unmodeled factors so as to realize an on-line intelligent fault diagnosis system able to predict the occurrence of undesired conditions, such as those leading to surface lines and marks, through the extraction, selection and fusion of relevant features from the in-process detected voltage and current signals to feed to cognitive pattern recognition paradigms.

In this approach, the sensor signal features play a key role in the prediction of undesired process conditions. The research methodology for the definition, extraction and selection of relevant signal features involves the following tasks:

- Identification of signal features of potential interest;
- Definition of suitable procedures to extract the features;
- Code development for automatic feature extraction from experimental voltage and current signals;
- Identification of symptoms/indicators of faults such as the occurrence of lines and marks on the machined surface.

Within this framework, the aim of the research activity presented in this paper is focused on the first three tasks, with particular reference to the definition and implementation of an appropriate methodology to extract the relevant features from current and voltage sensor signals. The main challenge is related to the difficulties encountered when dealing with real WEDM sensor signals which may significantly differ from the theoretical ones described in the literature [6].

3. Experimental setup

The WEDM experimental campaign was performed on a GF Agie Charmilles FI 440 ccS machine. WEDM cuts were realized on a workpiece consisting of a steel plate with a thickness of 20 mm. A wire electrode, made of AC Brass 900, with a 0.25 mm diameter was employed. To perform the study, different workpieces were cut both under normal and abnormal conditions. The latter were intentionally determined by introducing disturbances into the WEDM process in order to provoke short circuits. The sensor signal acquisition was carried out only during the surfacing, i.e. the last of the three workpiece machining phases: roughing, trimming and finishing. The sensor monitoring system consisted of two current sensors and one voltage probe employed to acquire, respectively, upper and lower current signals as well as voltage signals during the process (Table 1).

4. Identification of relevant sensor signal features

The sensor signals acquired during the WEDM experimental campaign consisted in voltage and current signals detected during 11 machining tests. Regarding current, three sensorial data types were collected: lower head current, upper head current and total current (sum of lower and upper currents). In the analysis presented in this paper, only the total current signals were taken into account for data processing.

The sampling rate for voltage and current signal acquisition was as high as 100 MHz. Each experimental test, and thus each signal, had a duration of 10 ms, so that each voltage and current signal is made of 1'000'000 data points.

A list of potentially relevant features to be extracted from the voltage and the current signals for use in the WEDM fault diagnosis system is summarized in Table 2. The list was defined on the basis of literature review, brainstorming and discussion with technicians from GF Machining Solutions.

5. Sensor signal processing for feature extraction

The sensor signal feature extraction procedures applied to the WEDM sensor signal data can be classified as follows:

- Feature extraction from current signals
- Feature extraction from voltage signals
- Sensor fusion feature extraction from combined current and voltage signals

As a matter of fact, some of the features of interest can only be extracted by taking into consideration both current and voltage data simultaneously. Sensor fusion technology was therefore employed to combine information provided by voltage data with information provided by current data in an integrated approach. The features extracted from the two signal types were then used to construct sensor fusion pattern vectors where each element corresponds to a feature (Fig. 1).

Table 1. Overview of the sensor monitoring system.

Sensor type	Objective
Voltage probe mounted on machine	Measure the voltage in the gap between wire electrode and workpiece.
Pearson Current Monitor Model 6585	Measure the current variations in the discharge zone. Two current sensors are employed to measure the upper and lower head currents (1A=1V).

Table 2. Relevant features to be extracted from voltage and current signals.

No.	Feature
1	Average spark frequency
2	Average gap voltage
3	Short circuit ratio
4	Short circuit duration
5	Average ignition delay time
6	Open circuit ratio
7	Average discharge energy
8	Average short circuit current
9	Average peak discharge current
10	Average discharge current pulse duration

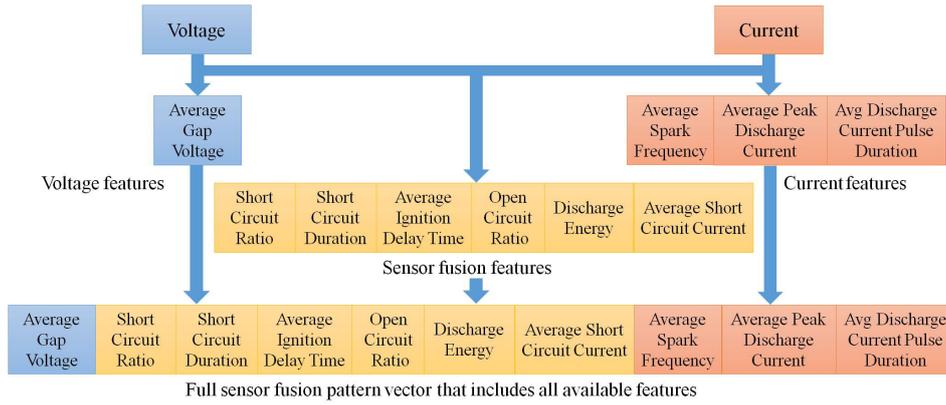


Fig. 1. Sensor fusion pattern vector construction.

In the Electrical Discharge Machining (EDM) process, voltage and current signals characteristic parameters have the standard shapes and designations reported in Fig. 2 [6-7]. These shapes change in some degree in the WEDM process under study, as shown in Fig. 3, thus making the feature extraction procedure the more complex.

5.1. Average spark frequency

The sparking frequency can be defined as the total number of sparks, N_s , divided by the total machining time, t_t . A variation of the sparking frequency can help spotting abnormal conditions before the occurrence of events such as short circuits [6]. The sparking frequency was calculated based on the current signal as the total number of sparks divided by the signal duration (10 ms). To identify the sparks in the current signal and neglect the non relevant low peaks, the search was filtered based on thresholds for minimum distance between peaks and minimum peak value (Fig. 4).

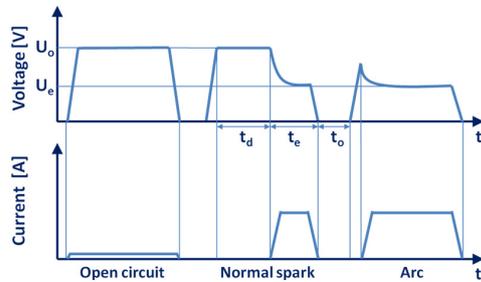


Fig. 2. Schematic shapes of EDM current and voltage signals.

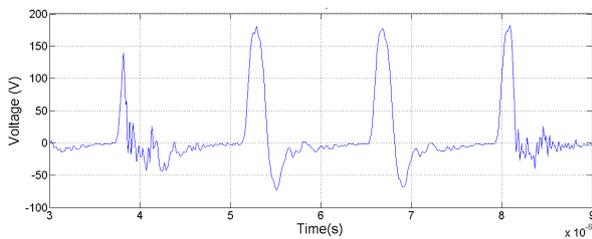


Fig. 3. Actual shapes of the acquired WEDM voltage signals.

5.2. Open circuit ratio

As mentioned above, some of the features for WEDM sensor monitoring can only be extracted by combined processing of both current and voltage signal data in a sensor fusion approach. This applies to the open circuit ratio feature defined as the number of open circuits over the total number of pulses in a signal. An open circuit occurs when a voltage pulse does not generate a current spark because the dielectric perforation is not verified, for example as a consequence of too large a gap between workpiece and wire electrode. In point of fact, to identify an open circuit, sensorial data from voltage and current signals are processed in an integrated manner. First, voltage signal data is analysed for voltage peak detection (Fig. 5). Then, current signal data is evaluated to determine whether each voltage peak represents an open circuit or an ordinary voltage peak: an open circuit is revealed when a voltage peak is not followed by a current peak (Fig. 5). The number of open circuits divided by the total number of pulses yields the open circuit ratio sensor fusion feature.

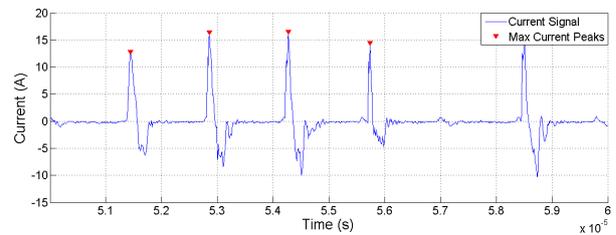


Fig. 4. Filtered search of current peaks.

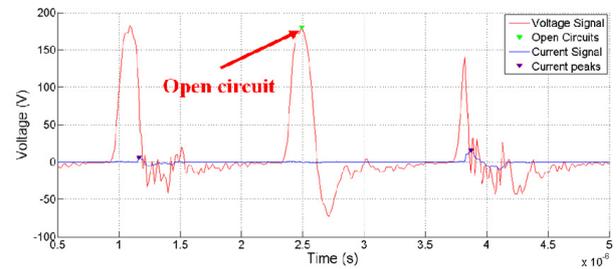


Fig. 5. Open circuit peaks are voltage peaks not followed by a current peak.

5.3. Short circuit ratio

The occurrence of short circuits, due to contact between wire electrode and workpiece, represents an undesired phenomenon in WEDM since it can lead to surface defects in the final workpiece or even to wire breakage [7,9].

The short circuit ratio, defined by the number of short circuit pulses over the total number of pulses in a signal, was extracted through a sensor fusion feature extraction procedure using information from both voltage and current signals. Short circuit pulses were pinpointed as the pulses with peak value below a specified voltage threshold, expressed as a percentage of the average open circuit voltage peak values (Fig. 6). The proper voltage threshold was established with reference to a known signal where short circuit occurrence was ascertained. The short circuit voltage peak values were estimated and compared with the open circuit voltage peak values to obtain a threshold expressed as percentage of the average of the open circuit voltage peaks (in this case study ~14%).

5.4. Short circuit duration

To measure the duration of the occurrence of short circuits, only the cases in which there are at least two consecutive short circuit peaks were taken into account. In these cases, the feature extraction procedure searches for the last consecutive short circuit peak and calculates the time distance between last and first short circuit peaks. This time distance is the short circuit duration provided as output by the procedure. In Fig. 7, the vertical red lines represent the first and the last short circuit peaks and the short circuit duration is the distance on the time axis between these two lines (in this case 0.0035 s).

5.5. Average short circuit current

The average current, defined by the EDM glossary [8], is the average value of all the minimum valleys and maximum peaks of amperage in the spark gap, as read on the ammeter.

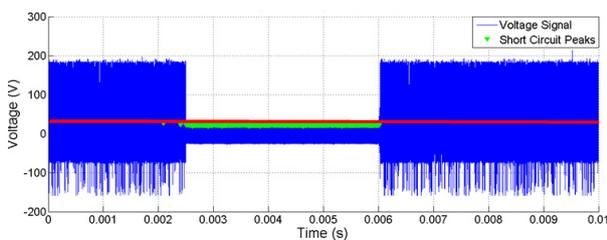


Fig. 6. Short circuit voltage peaks: the threshold is indicated as a red line.

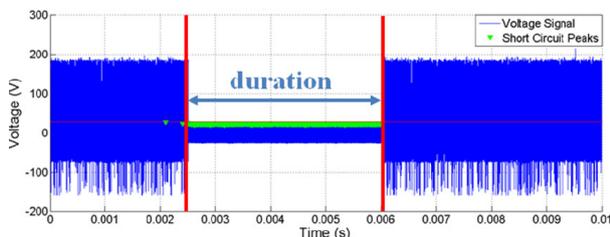


Fig. 7. Short circuit duration feature extraction procedure.

The average short circuit current was calculated as the mean between all maximum peak current values and all minimum valley current values over the entire duration of short circuit occurrence, following the procedure below:

1. Detection of maximum current peaks ($>$ threshold) in the short circuit carried out by setting a minimum threshold.
2. Detection of minimum current valleys ($<$ threshold) in the short circuit carried out by setting a maximum threshold.
3. Short circuit current calculation: for each pulse, the short circuit current was calculated as the mean between the peak and valley values.
4. Average short circuit current evaluation: this feature was calculated as the mean of all short circuit current values.

5.6. Average ignition delay time

The ignition delay time is the time which elapses between the application of the voltage pulse across the gap and the resulting discharge, i.e. until the current is established (t_d in Fig. 2). In the literature, diverse methods have been proposed to measure the ignition delay time for employment as process sensing parameter [7].

However, the voltage signals acquired during the WEDM process under study are very different from the theoretical plot of Fig. 8: the plateau before the current spark initiates, characterized by constant voltage U_0 , is not present in the actual signal and highly variable voltage pulse shapes and peak values occur. In this case, therefore, the ignition delay time is hard to measure with the methods proposed in the literature. Nonetheless, the additional information provided by the current signal can valuably support the measurement.

Thus, a more accurate detection of the ignition delay time feature can be performed by gathering information from both the voltage signal and the current signal according to a sensor fusion approach.

Because of the specific shape of the experimental WEDM voltage signal data, which do not have a constant $V = U_0$ plateau as shown in Fig. 8, it is difficult to determine the start point of the ignition delay time t_d . On the other hand, it is possible to accurately detect its end point that corresponds to the start of the current spark.

Therefore, the best measurable proxy of the ignition delay time was identified as the time from the start of the voltage pulse to the start of the current spark, t'_d , given by the sum of the time required by the voltage to rise from zero to its maximum value (also known as “rise time”) and the ignition delay time, t_d , as defined in the literature (Fig. 9).

Finally, the average of all the t'_d values was calculated to extract the proxy of the average ignition delay time feature.

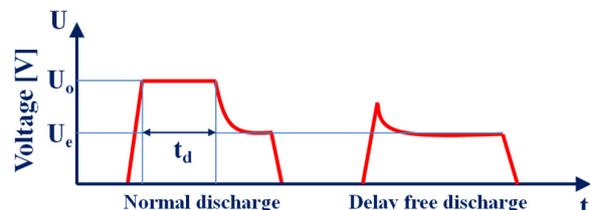


Fig. 8. Theoretical definition of ignition delay time, t_d .

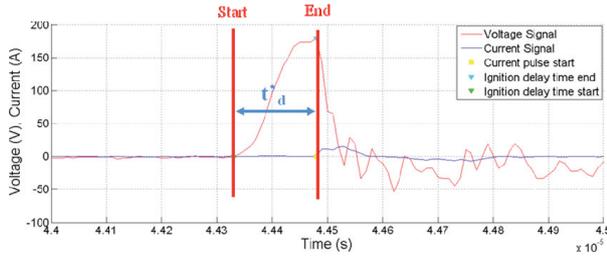


Fig. 9. Proxy of the ignition delay time, t'_d , given by the sum of the rise time and the ignition delay time.



Fig. 10. Frequency distribution of t'_d .

The ignition delay time can be employed for the classification of the different types of discharges [7]. As a matter of fact, the frequency distribution of the t'_d feature calculated for one of the 11 experimental test signals showed three different groups of values, probably indicating the presence of three different discharge typologies (Fig. 10). This aspect requires further investigation to achieve a suitable classification of the discharges such as normal sparks, arcs and so on.

5.7. Average peak discharge current

The peak current is the maximum intensity of the current passing through the electrodes for a given pulse. The average peak discharge current is the mean of the peak discharge current values measured in a period of time [10-11]. This feature was extracted from the current signal as shown in Fig. 11. According to [11], an increase in the spark energy setting increases the peak discharge current.

5.8. Average discharge current pulse duration

The average discharge current pulse duration can be used to distinguish between different types of discharges. It was evaluated for all the current pulses as the distance between current pulse end time and current pulse start time identified as shown in Fig. 12.

5.9. Average discharge energy

The discharge energy is a key feature in WEDM processes. As a matter of fact, it has been shown that an increase of the discharge energy, due to increased discharge power or discharge duration, leads to a higher gap distance that should be kept under control to maintain the stability of the WEDM process [12-14]. Differently, the deionization of the discharge

zone would be affected, resulting in either low or uncontrolled material removal rate.

The discharge energy E_i of discharge i can be obtained as:

$$E_i = \int_0^{t_{ei}} I_{pi} U_i dt \quad (2)$$

where t_{ei} is the duration of discharge i , U_i is the discharge voltage and I_{pi} is the peak current of discharge i [12].

This equation assumes that the discharge voltage stays constant during the current discharge. However, by observing the voltage and current signals acquired during the WEDM experimental tests, it can be noticed that the typical behaviour is the one shown in Fig. 13, where the discharge voltage does not keep constant during the current discharge.

Therefore, a constant voltage reference value, equal to 50 V, was assumed for the discharge voltage U_i . The use of this reference value is acceptable because the relative variation of the discharge energy is much more relevant than its absolute value for the purpose of this study. Accordingly, the discharge energy was calculated as follows: the average discharge current value of each current spark was multiplied by the current spark duration and by the voltage reference value to obtain the discharge energy of each single spark. Then, in order to obtain the average discharge energy feature, the mean of the discharge energy values for all sparks was calculated as output of the feature extraction procedure.

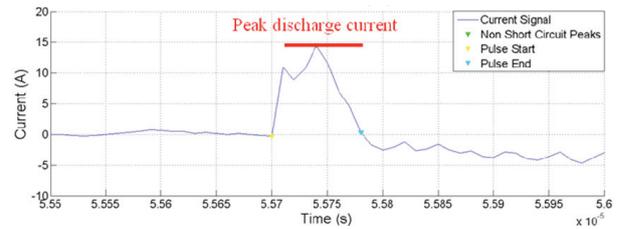


Fig. 11. Peak discharge current feature extraction.

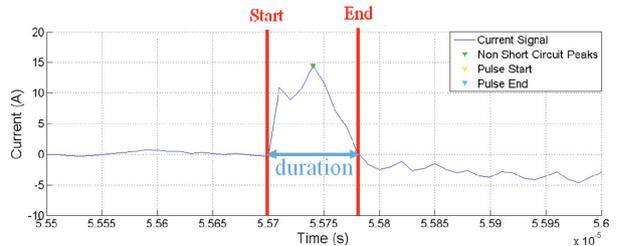


Fig. 12. Discharge current pulse duration feature extraction.

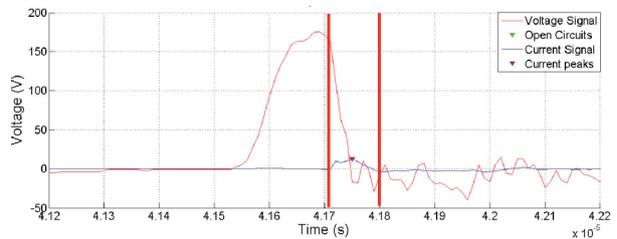


Fig. 13. Voltage (red) is not constant during the current spark (blue).

5.10. Average gap voltage

Unstable machining conditions are determined by the rapid decrease of the average gap voltage, which is the average of a number of measured values of gap voltage in a period of time [8,9,14]. This feature was calculated as the mean of the voltage peak values detected in the entire signal.

6. Real-time fault diagnosis code development

The final aim of the sensor signal feature extraction from voltage and current signals was to develop a valid code to be implemented for real-time on-line WEDM fault diagnosis.

The feature extraction code was developed in two phases. In the first one, MATLAB® was employed to extract the sensor signal features. This tool offers optimized functions useful in the feature extraction procedure and avoids the difficulties which are typical of programming languages like C++ (need to provide the declaration of variable types, memory leak, etc.), thus making the initial programming phase simpler and faster. The MATLAB® functions and visualization tools offered a convenient and valuable support to verify the effectiveness and correctness of the written algorithms. The second phase, providing for C++ code development, was comfortably carried out starting from the optimised MATLAB® code. The C++ implementation was smoothly validated by comparing its results with those previously obtained in MATLAB®. In this way, any programming error not immediately visible in C++ could be readily identified and eliminated.

7. Conclusions and future developments

This research work was focused on the development of an effective signal processing methodology to extract voltage and current sensor signal features to be utilised for WEDM process monitoring. Experimental sensor signals acquired during WEDM tests appear to be significantly different from the theoretical signal shapes found in the literature [6], making the extraction of relevant features from real signals a quite demanding task. As an example, the voltage value is not constant during a current spark in open contrast with what is assumed in most literature definitions. New assumptions were made and appropriate adaptations of the theoretical definitions were applied to gather the relevant information from the available signals. In some cases, selected reference values were adopted, as in the case of the reference voltage value employed to calculate the average discharge energy. In other cases, a suitable proxy of the desired feature was taken into consideration, as in the case of the ignition delay time. A potential improvement of this methodology is the realization of a pulse classification algorithm based on the evaluation of critical signal features such as the ignition delay time.

All the features extracted directly from the voltage and current signals or through sensor fusion of both signal types were collected in a single sensor fusion pattern vector (SFPV). In a future development, different configurations of SFPVs will be assessed to identify the features that best contribute with pertinent knowledge on process behaviour in

view of the prediction of output product quality. To do this, data on the quality of the final workpiece surface (e.g. presence or absence of lines and marks on the machined surface) obtained by the WEDM for each of the examined voltage and current signals is necessary, as such information represents the indispensable output quality parameter to rate the success or failure of the process. To appraise the performance of the differently constructed SFPVs, the latter will be correlated to the output quality parameters using diverse cognitive paradigms such as artificial neural networks, fuzzy logic and hybrid techniques like neuro-fuzzy systems.

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