Automatic characterization of WEDM single craters through CNN based object detection

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Abstract: The identification and characterization of single craters are critical for the understanding and optimization of the wire electrical discharge machining (WEDM) process. Recent efforts have been made to study the influence that process parameters have on the geometry of the craters. These efforts collect geometrical data from the single craters through microscope imaging and manual labeling, a method that is time-consuming and labor-intensive. In this work, an automated crater identification and characterization approach based on state-of-the-art object detection algorithms is presented. In particular, the model You Only Look Once (YOLO) – a convolutional neural network-based object detection technique – is used to fit tight bounding boxes enclosing the craters of superficial microscope images. In addition, the model Detectron2 is used for instance segmentation of individual crops of the craters. The models are trained on a custom-made database of microscope images of WEDM single craters. The geometrical characteristics of the single craters are extracted from the segmentation masks and tight bounding boxes.

Key words: wire electric discharge machining, machine learning, image processing, computer vision, object detection, instance segmentation.

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1. Introduction

Wire Electrical Discharge Machining (WEDM) is a non-traditional machining process for conductive materials. In WEDM, the material is removed by using sequential electrical discharges that take place between the electrodes. Each discharge generates a plasma channel that can reach temperatures above 10000 K. The workpiece material is molten locally in the area where the discharge happens. After the collapse of the plasma channel, the molten material is flushed away and a crater originates in the place where the discharge took place.

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The physics of the process is not yet fully understood since it involves a complex interaction between different areas of physics as non-equilibrium plasma, high-temperature thermodynamics, and turbulent hydrodynamics with several fluids, among others.

Crater formation is the basic element of material removal in WEDM. Accordingly, the characterization of single craters depending on process parameters is a topic of interest from a process modelling perspective. In this direction, Esteves et al.[1] performed a study in which they analyzed geometrical variations of the craters depending on the discharge energy and wire diameter. Among their findings, they observed elongation of the shapes of the craters along the unwinding direction that was accentuated for high energies and thinner wires. In this study, the data was obtained by taking individual images of the single craters for subsequent processing. Such a process is time-consuming and limits the number of single crater samples available.

To solve these issues, a toolset composed of two algorithms, YOLOv5[2] and Detectron2[3], is proposed. It recognizes single crates of superficial microscope images and produces tight crops and pixel masks for each of them, enabling a precise dimensional characterization. In this way, the number of samples available for posterior statistical analysis is increased by orders of magnitude.

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2. Tools for object detection and semantic segmentation

Since its development in 2015, the YOLO model[4] has become increasingly popular due to its combination of high speed and accuracy. Specifically, YOLO is a real-time object detection algorithm that employs a single convolutional neural network to both detect and classify objects in an input image. This is achieved by dividing the image into a grid composed of cells of equal dimensions. For each of these cells, the model detects whether an object is present. If this is affirmative, the model assigns bounding boxes and confidence scores for each object.

Alongside YOLOv5, Detectron2 is implemented. This Facebook AI Research (FAIR) vision library employs several state-of-the-art object detection models, in particular, the Mask R-CNN algorithm[5]. This algorithm is a CNN that, at first, proposes and selects regions of interest from an image (where objects could be) and successively extracts features from each of them such as object masks.

3. Methods

3.1 Data collection

The data used to train and test the model has been obtained through the generation of single spark discharges by using a GF-AgieCharmilles CUT P350 WEDM machine. This process was done by passing the wire with different energy settings near a flat prepared steel surface and making sure that the size was appropriate to ensure a large number of spaced single discharges.

The craters were photographed and stitched into a single image by using an optical Keyence digital microscope. This method allows obtaining images of thousands of unlabeled single craters in a short amount of time.

Finally, the stitched images were cropped in pictures of 1000x1000 pixels and stored in a database for later labelling and processing.

3.2 Training and data preprocessing

For training of YOLOv5 model, a manually labelled dataset of tightly bounded craters of 155 images is used that made up a total of 614 different single craters. During the labelling, only clear single craters were marked and overlapped craters were ignored.

For training of Detectron2 algorithm, a dataset composed of 357 instances of different craters under different lighting conditions is used. For the labelling, to avoid ambiguities and minimize the effect of focus-related distortions, a single crater contour is defined as the polygon containing all the pixels that are clearly not part of the original steel surface.

For both models, typical data augmentation techniques (e.g. horizontal flip, 90° rotation, noise, blur, saturation) are used to increase the pool of available samples.

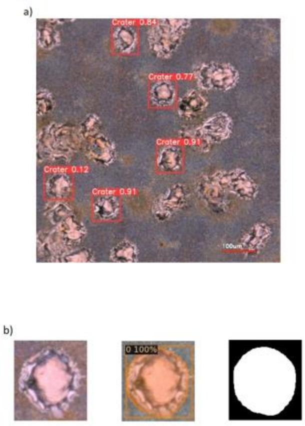

Fig. 1. Two steps of crater detection and characterization.
a) Example of the tight bounding boxes provided by YOLOv5. Note that only single craters are detected and overlaps are ignored.
b) Example of the semantic segmentation of a single crater (previously detected and isolated with YOLOv5) by using Detectron2. The resulting mask contains all the 2D dimensional information of the crater that can be used for posterior processing.

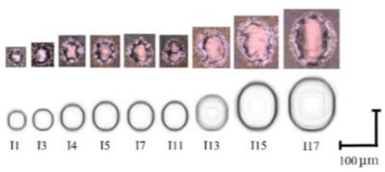

Fig. 2. Graphical characterization of the craters' 2D geometry for different energy levels I1 to I17 of the machine on 0.15mm wire diameter. On the top row, microscope images of typical single craters are shown. In the bottom row, the superposition of the contours of at least 500 craters per energy level. The contours were extracted through automatic instance segmentation by using YOLOv5 and Detectron2.

3.3 Results

Both models perform with high accuracy only with a relatively small amount of data (in the context of computer vision) provided for the training. The YOLOv5 model obtains a precision of 0.93, i.e. it detects 93% of the human-labeled craters of a test set. The YOLOv5 obtains a recall of 0.74, which means that of the detected craters, 74% are only true single craters. However, most of the false positives provided by YOLOv5 are craters with unrealistic dimensions. These false positives can be filtered out by limiting the height-to-width ratio of the bounding box between 0.5 and 2. This eliminates most of the false positives yielding a recall of 0.9. The Detectron2 model obtains an AP50 of 90% and AP75 of 77% for the instance segmentation task. However, for craters with highly irregular borders with many sharp edges, the model is incapable of getting the fine details of the borders, returning a mask with smoothed borders.

One of the risks of these models is the possible appearance of biases due to the inaccuracies of the model. For example, if the model systematically ignores craters of a given shape that can influence a posterior statistical analysis. From a preliminary study, this is not the case. The normal distributions of the dimensions (width, height, and width-to-height ratio) of the false-negative single craters are statistically indistinguishable from the normal distributions of the dimensions of the true-positive single craters.

4. Conclusions

The problem of identification and dimensional characterization of single craters in the WEDM process is discussed. In particular, the model YOLOv5 is used to identify and fit tight bounding boxes around each single crater from superficial microscope images, while Detectron2 assigns a mask consisting of the coordinates of the contour to every crater detected through YOLOv5 (see Fig. 1 and Fig. 2). Both models successfully enable to increase by several orders of magnitude the amount of available geometrically characterized single crater samples in WEDM.

References

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