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Online workpiece height estimation for reciprocated traveling wire EDM based on support vector machine

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Abstract

The reciprocated traveling wire EDM is a unique type of wire EDM machine, in which the wire electrode is not discarded after passing the discharge gap but being re-winded on the wire drum instead. It is of specific features such as ultra-thick workpiece cutting and reuse of wire electrode. While cutting variable height workpieces with constant machining parameters, this type of WEDM faces the same challenges as western style WEDM, either the risk of wire breakage or the low cutting speed. Due to the intermittent discharge process and the varying machining characteristics, online estimation of workpiece height becomes even more difficult for this type of WEDM.

This paper proposes a method of online workpiece height estimation based on support vector machine (SVM), an effective machine learning method. The inputs of the SVM model are effective discharge frequency, pulse interval, programmed feed rate and actual feed rate and the output is the estimated height. The algorithm is integrated in a newly developed computer numerical control (CNC) system for reciprocated traveling WEDM, with a sampling circuit collecting current and voltage signals from the discharge gap and an adaptive control unit which adjusts the machining parameters according to the workpiece height estimation.

The data for training the SVM were produced by cutting stair-shaped workpieces to build the SVM model. Then verification was carried out by cutting through workpieces with variable height cross sections. The results demonstrated the effectiveness of the proposed method. The estimation error was less than 2 mm and the machining time was reduced by more than 30%.

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1. Introduction

Wire electrical discharge machining (WEDM) has the advantages of high machining accuracy, high machining efficiency and the ability to process hard-to-cut materials. It has been widely applied to machine molds and dies, cutting tools, parts with complex shapes and micro-scale parts[1]. The reciprocated traveling wire EDM (RT-WEDM) is a unique type of wire EDM machine, in which the wire electrode is not discarded after passing the discharge gap but it is re-winded on the wire drum instead. It is of specific features such as ultra-thick workpiece cutting (thicker than 500 mm, even 1000 mm) and reuse of wire electrode. While cutting variable height workpieces with constant machining parameters, this type of WEDM faces the same challenges as the unidirectional feed WEDM does: (1) If the height increases, the length of the electrical discharging area along the wire also increases. Therefore, the electrical discharge energy becomes insufficient to maintain the same feed rate, which leads to low working efficiency and more short circuits. (2) Contrarily, if the height decreases, the electrical discharge energy density and corresponding thermal load added upon the working segment gets higher and higher, resulting in a greater risk of wire breakage.

Approaches such as adaptive control and workpiece height estimation were commonly used to cope with the problem. Some reported adaptive control methods were used without the knowledge of the actual workpiece height. Such methods try to modify the machining parameters when discharging process becomes unstable due to the workpiece height change. Whereas

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the other adaptive control methods are combined with height estimation methods, which estimate the current workpiece height by sensed signals, and then adjust the machining parameters accordingly by referring to process databases which are set up in advance. Portillo et al[2] proposed an artificial neural networks (ANN) method to diagnose degraded behaviors in WEDM when cutting workpieces with different heights. The authors used peak discharge current, ignition delay time and the pulse energy as the inputs of the ANN model, and consequently lower rate of wire breakage and higher machining efficiency was reported. Lee et al[3] developed an adaptive control system for WEDM that uses a gain self-tuning fuzzy control algorithm to suppress the increasing of abnormal sparks when the workpiece height changes suddenly and the cutting speed was improved by the control strategy. Rajurkar et al[4] developed a WEDM adaptive control system to monitor and control the normal discharge frequency. The system uses a non-linear discrete model relating cutting speed with spark frequency to estimate the workpiece height. The error of the workpiece height identification is 1 mm and the response time is 1 second. S. C. Dou and X. C. Xi, et al[5,6] built workpiece height estimation models by using support vector regression and least squares support vector machine (LS-SVM) with online correction. The models take gap voltage, pulse interval, discharge frequency and feed rate as inputs and can estimate the workpiece height with errors less than 1.5 mm.

The researches mentioned above were dedicated to the unidirectional feed WEDM. Due to the intermittent discharge process and the varying machining characteristics, they cannot be applied to the RT-WEDM directly. The ideas, however, are inspiring for solving the variant-height workpiece cutting problem for RT-WEDM.

Since most RT-WEDM machine manufacturers have their process databases for workpieces with different heights, good performance can be ensured if the workpiece height is estimated and the databases are queried. The height estimation problem is a typical non-linear regression problem. Traditional modelling techniques are incompetent since the direct relation between the machining status and the workpiece height is unknown. While machine learning methods are suitable for such problems. With carefully selected features, the estimation model can be built through sample data training without the knowledge of the physical or statistical relation between the inputs and output. Among commonly used machine learning algorithms, support vector machine (SVM) is one the most efficient and practicable ones. It is of the advantages of global optimal solution, low generalization error and relatively simple training process.

This paper proposes a method of online workpiece height estimation based on machine learning for the RT-WEDM. The regression version of SVM, called the support vector regression (SVR) is used therein. A discrete adaptive control system was built upon the estimation method to modify the variant-height workpiece cutting process. Section 2 briefly explains the SVR algorithm. Section 3 introduces the experiment setup. The processes of feature selection and modelling are discussed in detail in section 4. Section 5 covers the adaptive control system. And conclusions are drawn in section 6.

2. Support Vector Regression Algorithm

The support vector machine algorithm was first developed based on statistical learning theory by Vapnik and it was intended for classification[7]. And SVR, the regression version of SVM, was proposed before long[8].

Assume that samples are denoted as $(\boldsymbol{x}_i, y_i)$, where the $\boldsymbol{x}_i$ is the feature vector in the feature space and its corresponding output value is y_i. The SVR tries to find a hyperplane that all sample data are located near it with a tolerance ε. The hyperplane can be expressed as

$$y_i - \boldsymbol{\omega} \cdot \boldsymbol{x}_i - b = 0 \tag{1}$$

And to train a SVR model is to solve the following optimization problem[9]:

$$\max\{\frac{2}{\|\boldsymbol{\omega}\|}\} \tag{2}$$

Subject to

$$|y_i - \boldsymbol{\omega} \cdot \boldsymbol{x}_i - b| \le \varepsilon \tag{3}$$

The dot product plus intercept $\boldsymbol{\omega} \cdot \boldsymbol{x}_i + b$ is the prediction for that sample, and ε is an error threshold.

For non-linear problems, the SVR algorithm uses a kernel trick to map the samples into a higher-dimensional space, where the problem becomes linear[10]. The kernel trick introduces kernel functions $k(\boldsymbol{x}_i, \boldsymbol{x}_j)$ as expressed in equation 4 in order to calculate the dot products in the original space, which reduces the computational load.

$$k(\boldsymbol{\omega}, \boldsymbol{x}_i) = \varphi(\boldsymbol{\omega}) \cdot \varphi(\boldsymbol{x}_i) \tag{4}$$

And $\varphi(\bullet)$ is the mapping process.

The SVR algorithm has been proved having low generalization error and is also widely used to build prediction models that otherwise are difficult to build[11,12].

3. Experiment setup

The experimental work in this study were conducted on a Suzhou Baoma BM400C-C reciprocated traveling wire EDM machine, shown in Fig. 1. A smart CNC system for RT-WEDM, based on embedded hardware and the state of the art software technologies, was built to replace the original control cabinet. An embedded discharge status monitoring unit was developed to recognize different discharge statuses, including normal discharges, idle pulses and short circuits. Fig. 2 illustrates one of the circuits in the CNC system, which is integrated with the monitoring unit.

Machining parameters that can be adjusted by the control system are pulse duration, pulse interval, peak current, programmed feed rate and wire traveling speed. The work fluid pressure can be changed manually during machining. The available levels of these parameters are listed in Table 1. In most industrial applications, molybdenum wire electrodes are utilized for RT-WEDM and tool steel is one of the most commonly machined materials. Therefore, molybdenum electrodes and tool steel workpieces are used in the experiments.