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Digital Twin for Machining Tool Condition Prediction

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Abstract

Digital twin introduces new opportunities for predictive maintenance of manufacturing machines which can consider the influence of working condition on cutting tool and contribute to the understanding and application of the predicted results. This paper presents a data-driven model for digital twin, together with a hybrid model prediction method based on deep learning that creates a prediction technique for enhanced machining tool condition prediction. First, a five-dimensional digital twin model is introduced that highlights the performance of the data analytics in model construction. Next, a deep learning technique, termed Deep Stacked GRU (DSGRU), is demonstrated that enables system identification and prediction. Experimental studies using vibration data measured on milling machine tool have shown the effectiveness of the presented digital twin model for tool wear prediction.

Keywords: tool system; digital twin; deep learning

1. Introduction

Intelligent manufacturing is gradually emerging in the current technological development, which has transformed mass production to customized production. Intelligent manufacturing is a manufacturing paradigm [1] that optimizes the allocation of resources, with characteristics of real-time analysis, intelligence, refinement and agile perception of the real-time status of the market and customers.

Manufacturing mode is developing from digital manufacturing to digital-networked manufacturing and ultimately to the new-generation intelligent manufacturing [2]. During this process, the manufacturing becomes more intelligence, networking and digitalization. That change proposes the challenges to fault diagnosis and prognosis which expect the new one to consider the influence of operating environment on prediction, enhance the accuracy of prediction results and customize the production. In the past few decades, a great deal of researches has been done in fault diagnosis and prognosis.

In the past fault diagnosis and prognosis, it is usually based on signal analysis and does not involve big data, mostly relying on expert experience, manual experience and field inspection. Cyber-Physical System (CPS) as an essential part of information-handling technology, it is a new service-oriented technology to support fault diagnosis and prognosis, alarm management, cloud storage and reuse of data for complex mechanical equipment under different operating conditions. It can build the high precision and real equipment or machine digital model in five-dimensional mode by using Digital Twin technology.

In order to improve the reliability, availability and safety of the equipment or machine, it is of great significance to develop fault prediction based on digital twin in the whole life cycle of the machine. Research on digital-based fault diagnosis and prognosis is still at its infancy. There are still the following problems:(1) establishment of model: it has a significant issue about the influence of working condition or operating environment for tool system;(2) data storage: there is no enough space to save heterogeneous data;(3) feedback on predicted

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results: the predicted results cannot be better understood, such as the cutting amount of the cutter.

To address the aforementioned challenges, this paper proposed a systematic development method for cyber-physical tool system [4]. To build a high-precision model, a tool system depend on digital twin is first developed. The Digital Twin of tool system integrates physical objects [5], virtual model, data fusion, embedded sensors, intelligent algorithms and database [4]. For the sake of solving the problem of low accuracy of fault prediction, we proposed the deep learning applied for the tool system model which will help to forecast the condition of tool system. It extracts features and tags from the collected signals which will be put into the neural network for training. Then the training model with the minimum error is obtained. Last, the subsequent measured data is put into the trained model to get the prediction label. In this way we can obtain the fault prediction of the tool system.

The rest of this paper is constructed as follows. The state of the art about digital twin and tool system fault prediction technique is reviewed in Section 2. Then, the systematic framework of the tool system is described in Section 3, which describes digital twin reference model for tool maintenance prediction in detail and analyses the data from the digital model sensors. Next, an experimental study on the tool system fault diagnosis and prognosis test is performed to validate the performance of data-driven digital model and the application of remote operation and maintenance in Section 4. Finally, conclusions and the future works are drawn in Section 5.

2. State of the art

2.1. The development of Digital Twin

With the development of manufacturing towards automation, integration, intelligent mode, there has been an increasing concern about Digital Twin and its evolution as illustrated in Fig. 1. The concept of "twin" is originally derived from NASA's Apollo Project when the aircraft's twin body is a real physical system [6]. Nowadays, twin models can help astronauts and staffs make decisions under the emergency situations. Then, the concept of Digital Twin is firstly proposed for the formation of a product lifecycle management center in 2002 [7]. Internet of Things allows the Digital Twin model to support new intelligent services to connect and interact with the physical object [8,9]. These capabilities enable the manufacturers to realize and drive new business models such as real-time simulation and fault prediction [10].

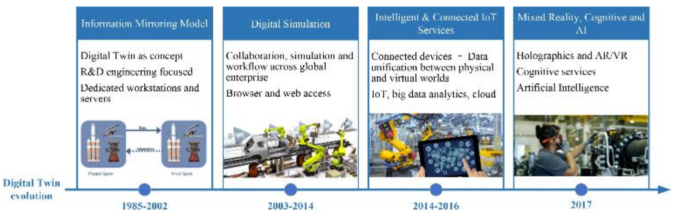

Fig. 1. Evolution of Digital Twin technology.

In terms of Digital Twin applications, there are some enterprises visualizing and implementing in real life, such as General Electric, PTC, NASA, Siemens and so on.

Currently, some studies of digital twin have developed [11-16]. From the above researches and studies, it can be found that much works have been done in the manufacture of machine tools based on digital twin which has involved technology including big data analysis, Internet of Things, Cyber-Physical systems and cloud computing. In terms of diagnosis and prognosis of fault, advantages of the digital twin are that it is possible to process information from complex or different sources and monitor the real working conditions, and the prediction results can be placed in the digital model to show the accuracy of cutting amount or the better feed of the tool system [17].

With the development of technology, the approaches about fault prognosis of tool system are also improved. There are some currently studies about data-driven approaches to prognosis. A new method for motor bearings condition monitoring and fault diagnosis is used to undersample vibration signals [18]. The method of predicting and detecting cutting tool failure in a process computer is proposed by the group method of data handling (GMDH) [19]. Such diagnosis and prognosis methods which are based on statistical process have been proposed [20-23]. The model and method presented above are all about model based prognosis approach.

Existing fault prognosis methods have some special advantages. However, there are some disadvantages: 1) system with the certain is often too stochastic to model, 2) the method highly relies on expert knowledge and the significant number of rules is required, 3) the model is lack of scheme to update the model with new test data.

Thus, a Digital Twin reference model is investigated hereby to support the study of fault diagnosis and prognosis. The big data is used for analyzing and processing the information from the sensors, and the computer control machine accepts the digital signals and guide the physical machines to next steps through CPS. The model of fault prediction algorithm is provided by deep learning. This method is combined data-driven and model based approach. It is possible to establish an effective virtual and real interaction model, which can truly reflect the movement form and material structure of physical objects in the virtual world. Furthermore, the predicted results are easy to demonstrate visually in three dimensions which can help operators to understand the prognosis results.

3. The systematic framework of the tool system

3.1. The synthetic nature of digital twin model

Digital Twin is essentially a unique living model of the physical system with the support of enabling technologies including multi-physics simulation, machine learning, AR/VR and cloud service, etc. It allows the continuous adaption to the changes in the environment or operations and delivers the best business outcomes. It offers a great potential to optimize operations and maintenance, as well as further accelerate the speed of new product developed process.

In Fig. 2, we present a new ontology based the digital twin technology information from existing literature and researches, which demonstrates a tool system digital twin model in terms of six technology characteristics, four service applications, four advantages and three enabling factors used to drive the establish of tool system digital twin model.

The characteristics of digital twin model consist of various aspects of technology (cyber-physical systems, IoT/IoS，AI，unique identifier), resource allocation (energy efficiency) and processes (cloud manufacturing, various data, communication and physical-virtual interaction). Cyber-Physical systems as a new generation of systems with computational and physical capabilities can build a good bridge between humans and the digital information world [24]. Internet of things (IoT/IoS) processes large amounts of data of various types through different sensors (such as radio frequency identification, infrared induction and global positioning, etc.) to realize the functions of risk identification, fault location and safety management [25]. From a security viewpoint, the new proposed digital twin model of tool system has some services (Process control/Process monitoring, Fault diagnosis and prognosis, Alarm management, Shorten MTBF).

Digital Twin achieves human-machine communication and can interact with the environment and physical entities in real time. It has a unique identifier which is only connected to the tool system. The technology is embedded with AI (ontologies, machine learning and deep learning, etc.) in the digital twin model.According to the digital twin model's feedback mechanism, it can effectively help to correct errors in tool system design stage. Digital Twin makes the tool system model, motion, and fault visibility, and can accurately locate whether the feed system or the tool failure.

The enabling factors in Fig. 2 are given as education, data and rule of conduct. Innovative education makes people put forward higher requirements for intelligent manufacturing and opens a larger vision. A large amount of data processing needs to be supported by more accurate data processing technology. The rule of conduct ensures the accuracy and continuity of the digital twin model when it is built.

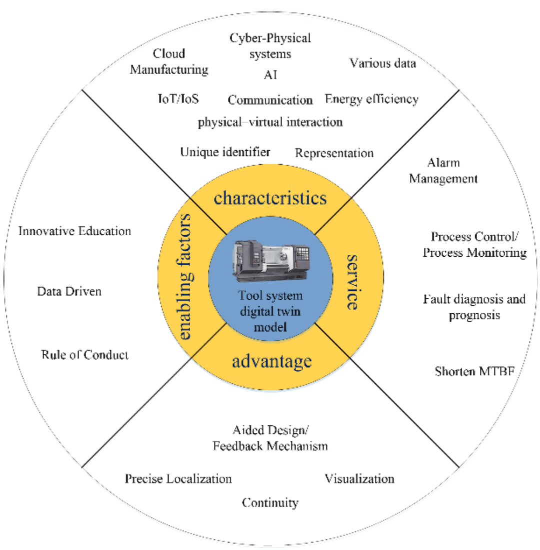

Fig. 2. Characteristics, service, advantage and enabling factors defining tool system digital twin model.

3.2. Digital twin establishment process

In the past, most studies on digital twin have been limited in the three-dimensional models, only considered entity model, virtual model and their connections. Compared with the mentioned above model, this paper proposes a new model called five-dimensional digital twin model of tool system which has a more accurate model, a more active monitoring and prediction calculation method, and can express the predicted results more easily. The main construction process of the tool system is to construct a digital model through various data mapping of various stages in the physical entity. The new model based on the previous three - dimensional research has a data space and service system.

Entity tool system is the foundation of the digital twin tool system which is composed of the various functional subsystems (mechanical system, control system, auxiliary system and sensory devices) and working status, operation conditions. Virtual tool system is a high fidelity mapping of the entity tool system.

The data space mainly consists of design parameters, process data, manufacturing process data and feedback process data in the five-dimensional digital twin model. It promotes the development of tool system service, and makes the whole service system more intelligent and accurate.

In this architecture, the service system includes alarm management, process control, fault diagnosis and prognosis and the maintenance which can shorten MTBF.

The connections between the systems are shown in Fig. 3. The virtual-entity interaction model is connected by information mapped. In a broad sense, information mapping is to transform physical space information into digital space, where data and information collected or perceived from physical space are finally stored in the Internet of things cloud computing platform. Through the user experiences in the service system, feedback on the product and continue to optimize the product production and design.

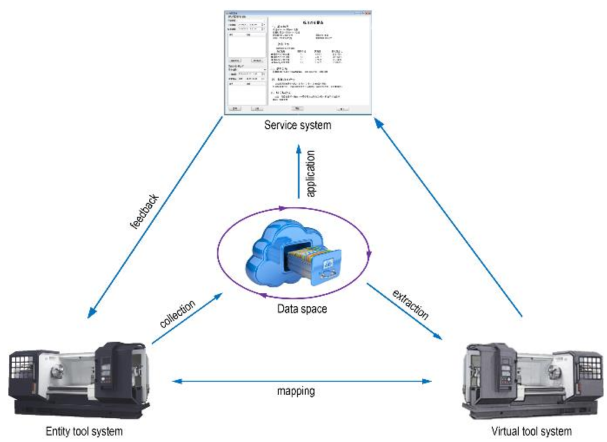

Fig. 3. Five-dimensional Digital Twin model of tool system.

3.3. Data Analytics Process of Tool System

By mining knowledge from aggregated data, deep learning techniques play a key role in automatically learning from data, identifying patterns, and making decisions. Different levels of data analytics can be produced including descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. Descriptive analytics aims to summarize what happens by capturing the product's conditions, environment and operational parameters. When the product performance is reduced or the equipment failure happens, diagnostic analytics examine the root cause and report the reason it happens. Predictive analytics utilizes statistical models to make predictions about the possibility of future production or equipment degradation with available historical data.

Considering the difficulty of direct observation of tool condition, observation model actually builds a multivariate regression prediction function between the in-process measurements and tool wear condition. Bi-Directional GRU is employed to construct observation model to predict the tool wear condition based on extracted local features, which can be expressed as:

$$\bar{h} = [\vec{h}, \overleftarrow{h}] \quad (1)$$

where $\vec{h}$ denotes to the hidden state vector of the last units in GRU during the left-to-right propagation and $\overleftarrow{h}$ for the right-to-left propagation.

The information in the middle range of the sequence might be lost in Bi-Directional GRU. A weighted features averaging layer is introduced into Di-Directional GRU. The weighted feature averaging layer mainly contains a fully-connected layer. As the input of weighted averaging feature layer, the averaged features are calculated using sequential features and equal to the average value of sequential features. The weighted averaging feature vector can be given as:

$$\bar{v} = [\bar{v}_1, \bar{v}_2, \ldots, \bar{v}_T] \quad (2)$$

$$\bar{v}_i = \sum_{w=1}^{T} w_k v_{ik} \quad (3)$$

$$w_k = e^{r(k)} / \sum_{j=1}^{T} e^{r(j)} \quad (4)$$

$$r(j) = \min(j-1, T-j) \quad (5)$$

where $\bar{v}_i$ represents each element in weight feature averaging vector, k denotes the time index and w_k represents the weight. In our model, two kinds of inputs including one concatenated vector from Bi-Directional GRU and one coding of weighted averaging feature are fed into a regression layer to predict the tool wear condition, which can be expressed as:

$$\tilde{x}_t = W[\bar{h}, \bar{c}] + b \quad (6)$$

where $\tilde{x}_t$ denotes to the predicted tool wear value, $\bar{h}$ is the output vector of Bi-Directional GRU and $\bar{c}$ represent the coding of weighted feature averaging vector. W and b denote the weight matrix and bias vector, respectively. Ultimately, back propagation is conducted to update the parameters layer by layer.

System model describes the underlying tool wear growth behaviour evolving with time. In this paper, the transition of system state is regarded as an autoregression process of time-series data. GRU network receives one scalar which represents the current tool wear condition and produces the other scalar which represents latter tool wear condition. Then a fully-connected layer is added to the GRU neural network for prediction. This procedure can be defined as:

$$x_{t+n} = Wg\left(x_t\right) + b \quad (7)$$

where x_t denotes the predicted tool wear value at current moment. x_{t+n} denotes the predicted tool wear value after n time steps. $g(\cdot)$ denotes the mapping operation controlled by GRU neural network. By measuring the error between x_{t+n} and actual tool wear value in time step $t+n$, the model parameters including weight vector W and bias b and can be updated to achieve the optimal predictive performance of GRU neural network.

4. Experimental studies

4.1. Experimental Setup

To experimentally evaluate the performance of presented model, a high speed CNC machine was run under dry milling operations. The schematic diagram of the experimental platform is shown in Fig. 4. In order to acquire the data related to this CNC machine's operation, a Kistler quartz 3-component platform dynamometer mounted between the work piece and the machining table is employed to measure cutting forces. Three Kistler piezo accelerometers were mounted on the work pieces to measure the machine tool vibration in the x, y and z directions, respectively. AE signals were collected from the dynamometer. The data acquisition system NI PCI1200 was adopted to perform in-process measurements. Seven different signals are acquired by these corresponding seven sensors were used in our experiments as listed in Table 1. The examples of raw signals are shown in Fig. 5.

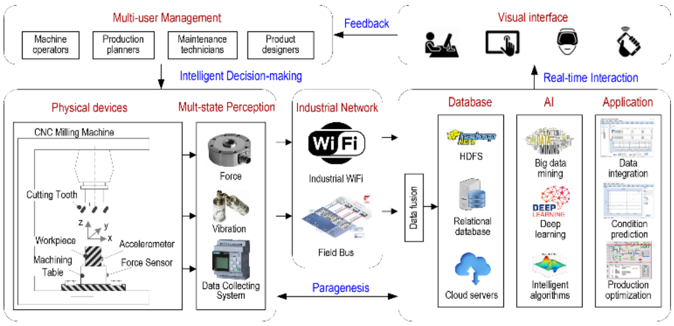

Fig. 4. Schematic diagram of the experimental setup for tool wear prediction.

Table 1. Sensor channels and Signal types.

Channels	Signal types
Channel 1	F_x: force(N) in X dimension
Channel 2	F_y: force(N) in Y dimension
Channel 3	F_z: force(N) in Z dimension
Channel 4	V_x: vibration(g) in X dimension
Channel 5	V_y: vibration(g) in Y dimension
Channel 6	V_z: vibration(g) in Z dimension
Channel 7	AE: acoustic emission(V)

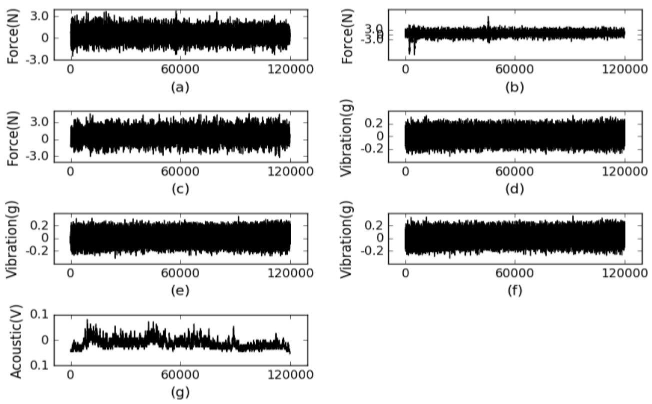

Fig. 5. Example of collected multisensory signals.

Table 2. List of extracted features.

Domain	Feature	Equation
Statistical	RMS	$y_{rms} = \sqrt{\left(1/n\sum_{i=1}^{n} y_i^2\right)}$
	Variance	$\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2$
	Maximum	$max(y)$
	Skewness	$E\left[\left((y\text{-}\mu)/\sigma\right)^6\right]$
	Kurtosis	$E\left[\left((y\text{-}\mu)/\sigma\right)^4\right]$
	Peak to Peak	$max(y)\text{-}min(y)$
Frequency	Spectral Skewness	$\sum_{i=1}^{k}\left(\left(f_i - \bar{f}\right)/\sigma\right)^3 S(f_i)$
	Spectral Kurtosis	$\sum_{i=1}^{k}\left(\left(f_i - \bar{f}\right)/\sigma\right)^4 S(f_i)$
	Spectral powder	$\sum_{i=1}^{k}\left(f_i\right)^3 S(f_i)$
Time-frequency	Wavelet Energy	$\sum_{i=1}^{k} wt_{\phi}^2(i)/N$

4.2. Data Preparation

Three tool life tests named C1, C4 and C6 were carried out in the experimental rig. Each test data contains 315 data samples, while each sample has a corresponding flank wear. For training/testing splitting, a three-fold setting is adopted such that two tests are used as the training domain and the other one is used as the testing domain. And the sample rate of the force and vibration in this experiment collected was 50KHz as same as the digital twin applied. This splitting is denoted as C1. The details about training/testing splitting are shown in Table 3. Our task is defined as the prediction of tool wear width based on the multisensory input. To facilitate the training, the target value of training data is firstly scaled into the range of [0, 1]. Additionally, the predicted value of testing data will be inverse transformed and then compared to ground-truth values.

In order to feed the time series features into presented approach, the raw signal was split into 20 segments to construct the sequence features to transfer each sample into a matrix whose shape is (20,7). Secondly, ten features mentioned in Table 2 are extracted from raw signal. After that, for each time segment, there are 70 feature values within a feature vector. Ultimately, the shape of an intact feature matrix is (20, 70).

Table 3. The setup of training and testing data.

Symbol	Training Domain	Testing Domain
C1	C4, C6	C1
C4	C1, C6	C4
C6	C1, C4	C6

4.3. Performance Analysis

In order to verify the effectiveness of the tool fault simulation by the digital twin of the tool system, the deep learning about data analysis method is applied to the fault diagnosis prediction. The prediction method at this stage is a new deep stacked GRU model.

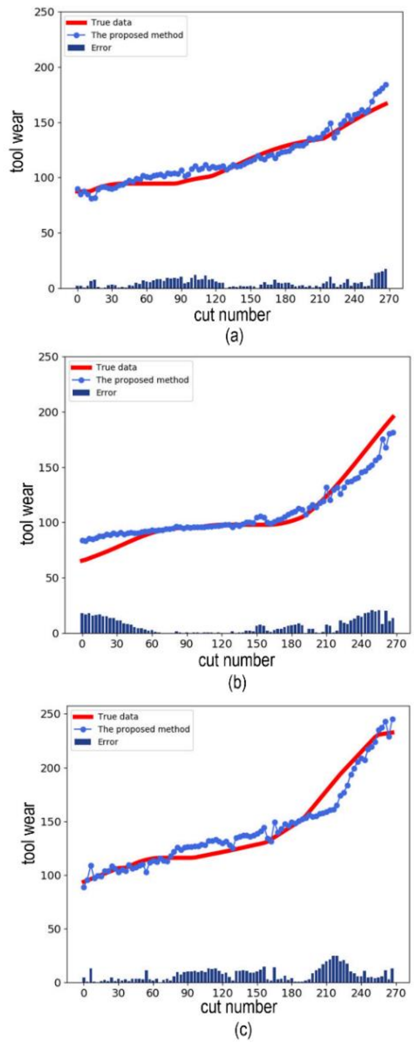

Fig.6. The 30-step-ahead prediction results of five different models for testing dataset, a) C1, b) C2, c) C3.

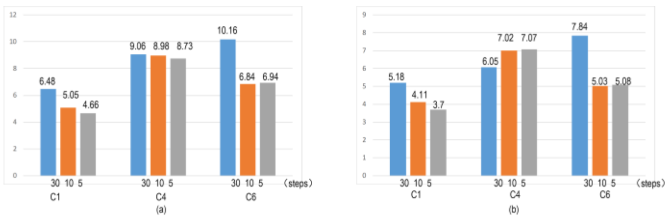

Fig.7. Performance analysis of different algorithms under different steps-ahead Prediction a) RMSE, b) MAE.

With the setup of training and testing dataset as shown in Table 3, the long term of 30 steps-ahead prediction is firstly carried out. The predicted results of this model and the prediction error in terms of absolute difference between actual values and predicted values are shown in Figs. 6. Two additional evaluation schemes are also carried out including 10 steps-ahead and 5 steps-ahead predictions. To quantitatively demonstrate the difference of this method, two performance indexes including MAE and RMSE are calculated and summarized in Figs. 7. It shows that two-step hybrid prediction scheme implemented by deep stacked GRU model can improve the prediction accuracy and robustness.

5. Conclusions and future works

As an enabling tool for convergence between a physical system and its digital representation, Digital Twin integrates physical knowledge and data driven intelligence into one model, providing a new perspective for fault diagnosis and performance degradation prognosis. Based on the results obtained in this study, the following conclusions can be drawn.

1) Based on the traditional CNC, tool system, machining process simulation, real-time machining data, data analysis and intelligent algorithms are integrated through diverse types of networks.
2) The accuracy of the numerical model of the tool system is developed by deep learning and the accuracy of fault prediction is greatly improved.
3) The experiment verifies the accuracy and efficiency of the model and proves that the intelligent algorithm in the digital twin can predict the fault of the equipment.

In future, Digital Twin will be widely used in manufacturing industry, promoting intelligent, integrated and high-speed. Intelligent algorithm applied in Digital Twin can ensure the prediction accuracy.

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