Transfer learning for the design of a digital twins-based automatic relay production line

Rui Yang1,2, Qinglong Mo1*, Zijuan Huang2, Yu Zhang1

1. Guangdong Institute of Intelligent Manufacturing, Guangdong Key Laboratory of Modern Control Technology, Guangzhou 510070, China
2. Cloud Computing Center Chinese Academy of Sciences, Dongguan 523808, China

ql.mo@giim.ac.com

Abstract. At present, the world is experiencing a new round of scientific and technological revolution and industrial transformation. It has entered a historic intersection with the transformation and upgrading of the manufacturing industry, bringing new opportunities to the industry. Digital twins are considered as an effective way to realize the interaction and integration of the manufacturing physical world and the information world, attracting great attention from the relevant academic and business sectors at home and abroad. Specifically, they use virtual models and simulation technology to design industrial production lines and predict the future operation of equipment, which contributes to the efficient operation of intelligent production processes. Nonetheless, the key learning problem of accurate modeling should be solved, so as to adapt to the random and dynamic changes in industrial equipment design. Transfer learning, an innovative learning paradigm in machine learning, is developed to solve challenging learning problems with only a few or no labelled samples in the target field.

1. Introduction

With the integration and application of a new generation of information technology and manufacturing, countries throughout the world have introduced specific advanced manufacturing development strategies. For instance, China proposes to “accelerate the construction of a manufacturing power, boost the development of advanced manufacturing, and promote the deep integration of the Internet, big data, artificial intelligence and the real economy.” It can be translated into the goal of promoting the in-depth integration of a new generation of information technology and artificial intelligence technology with the manufacturing industry, enhancing the transformation and upgrading of the real economy, and vigorously developing intelligent manufacturing.

The production line design is the basis of manufacturing design, which is helpful to research the rapid learning and accurate modeling method of production equipment design[1]. The design of a fully automatic production line faces the challenge of interaction and inclusiveness between the physical world and the information world; therefore, it is necessary to realize iterative simulation and virtual construction of manufacturing design, thereby providing a reliable, rapid learning and accurate design equipment model for intelligent industrial design[2]. There are key points and difficulties in the research of intelligent manufacturing[3]. However, such tasks are difficult for most current machine learning algorithms, especially for deep learning models with strong competitiveness in the design of fully automated production lines[4]. In most cases, a large number of new samples are needed so as to update the model for new tasks.
2. Digital twins-based automatic relay production line

A digital twins-based automatic relay production line is depicted in Fig. 1, which consists of such functions as automatic assembly, detection and marking. A digital twin entity model is constructed to verify all elements of production, multi-domain, multi-level, multi-dimensional and component/scenario/process/process, the mapping mechanism and optimization iteration of twin data and production line features, as well as the digital twin design simulation process [5].

Notably, key science and key technology applied in digital twins are shown in Fig. 2. When the full-factor model of the intelligent production process is constructed for the automatic production line, it needs to realize the rapid learning and design of industrial equipment, as well as the accurate mapping of virtual and real design, resulting in a variety of the production line data and their complex sources[6]. It is difficult to monitor data equipment, product quality, energy consumption and other production line processes. Hence, the relationship between the original design and transfer learning is researched, and the simulation solution methods are integrated to build a simulation solution interface for modelling and data fusion. This will help to develop high-confidence and effective simulation solutions for production line design.

![Fig. 1 Digital twins-based automatic relay production line](image1)

![Fig. 2 Key science and key technology in digital twins](image2)

A full-element multi-dimensional dynamic model of the digital twins-based intelligent production line is constructed, followed by the assembly and fusion of the entity model. Afterward, the virtual and real consistency of the digital twins-based model is verified.
3. Single sample learning algorithm in transfer learning

3.1. Overview
In single-sample learning, only one sample is given for each class. In this case, most machine learning algorithms have poor performance, especially deep learning. The model may be over-fitting on a single sample, and a small change in the test data may pose a negative influence on the breeding structure[7]. Therefore, a single-sample classification task is converted to a verification task[8]. Specifically, when a test sample is given, it is matched by the model with the labelled examples in the support set[9]. Then the predicted label of the test sample is identified as the class to which the sample with the highest matching score belongs.

3.2. Twin neural network
The digital twins-based automatic relay production line as shown in Fig. 1 is completed. The typical architecture of twin nerves is shown in Fig.3.

The twin neural network was first proposed by Bromley and others to solve the task of signature verification. It is composed of a pair of identical neural networks, the outputs of which are connected by a loss function. The symmetrical network structure ensures that the two samples compared are mapped to the same hidden space. In addition, the distance of the samples in the hidden space is measured by the loss function as well. The motivation of the twin neural network is to endow the model with certain discrimination ability.

The inputs and output of the twin neural network are represented by X(1) and X(2), and P(x(1), x(2)), respectively. In the network, the L layer can be any one of a linear layer, a convolutional layer, a pooling layer or any of other nonlinear layers connected in turn. The output of Layer l in the i-th neural network is denoted by h(i,l). In the training phase, for each pair of inputs (x(1), x(2)) from the support set, if x(1) and x(2) belong to the same class, then the output y is set to 1; otherwise, it is equal to 0. The loss function is defined as:

$$l(x(1), x(2)) = y \log(P(x(1), x(2))) + (1 - y) \log(1 - P(x(1), x(2)))$$

(1)
In the testing phase, it is only necessary to match the test sample with each sample in the support set for determining the support set sample with the greatest confidence. Finally, the relevant tags are obtained as prediction results.

4. Conclusion

Based on the results and discussions presented above, the conclusions are drawn as below:

(1) According to the concept of digital twins, the automatic production line design model is further divided into the entity model, data model and simulation learning model.

(2) The state identification mechanism of the design process based on twin data is proposed to clarify the mapping relationship between real-time data and production design.

(3) A simulation learning model is established, the single-sample learning algorithm is introduced, and the simulation boundary conditions for the twin neural network are illustrated from the perspectives of the entity model and the data model. It is found that the practice of industrial design migration learning is responsible for the integration of the simulation process.

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