Smart manufacturing control system based on deep reinforcement learning

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Abstract. The base of smart manufacturing contains two main components: cyber-physical systems and the Internet-of-Things (IoT). But the progress in machine learning, Big Data and deep learning technologies have a great impact on all areas of the modern economy, including information technology, industry. The capabilities of deep learning models associated with the ability of intelligent systems to make decisions significantly transform the key paradigms of intelligent production systems. The gap between the principles of human decision-making and intelligent systems is constantly closing. New approaches to decision-making based on deep models allow bringing the benefits of human control into production processes, and, at the same time, getting rid of errors associated with the human factor. The paper proposes an architecture for building multipurpose manufacturing systems based on deep machine learning models and reinforcement learning technologies.

1. Introduction

The research presented in this paper is interdisciplinary in nature. First, it offers a deep model architecture that allows control actions to be generated sequentially. The similar nature of the generation of control actions is inherent in humans. Secondly, the architecture of the control system for intelligent production is investigated, possible options for implementation are analyzed, the main theses of the construction of intelligent production for a wide variety of purposes. Combining smart manufacturing technologies with the latest advances in deep learning can improve the efficiency of smart manufacturing control systems.

The basic principles of building human-cyber-physical systems (HCPs) and cyber-physical systems (CPs) are presented in the works of many researchers: in [1] discussed the basic terminology of the subject area under consideration and the main differences between smart manufacturing and intelligent manufacturing; in [2] the evolutionary footprint of intelligent manufacturing is reviewed from the perspective of HCPs; in [3] discussed the principles of building CPs from an Industry 4.0 perspective.

Along with the development of intelligent manufacturing technologies, there is a rapid growth in theoretical and applied research in the field of deep learning, generative adversarial network (GAN), and effective methods of deep model training. The combination of the latest achievements from the considered areas allows us to conclude that the prerequisites for the transition to a qualitatively new level of smart manufacturing and intelligent manufacturing have been created. This work proposes the architecture of smart manufacture by example, proposes the main patterns of interaction of the control
system of production equipment with actuators. The proposed architectures were tested on a CNC machine for engraving with a laser module.

2. Background and related work
There is a lot of existing work on smart manufacturing and intelligent manufacturing, circular economy, predictive maintenance, quality control and zero-defect manufacturing. The review of related work will thus be narrowed down to the most interesting and referenced papers since 2015. In [x00], the main structural elements of cyber-physical systems are shown, their role in the industry of the future is described, the place of CNC machine tools in intelligent production systems is shown. The various architectures of production systems, which are the core of the fourth industrial revolution (Industry 4.0), is described in [4]. The principles of building a CNC machine control system based on deep learning and reinforcement learning are shown in [5]. In [6], the principles of training a deep model using competitive learning technologies are considered: the developed neural network is used as a control system of a CNC machine. Research aimed at solving problems in the field of smart manufacturing is presented in [7-10].

The construction of intelligent production management systems that are significantly superior in efficiency to existing Smart Manufacturing technologies has become possible thanks to the development of deep learning, reinforcement learning and adversarial networks technologies. Deep neural networks have shown high efficiency in the tasks of classification [11-13], object detection [14-16] and segmentation [17-19]. Generative adversarial networks [20] has demonstrated promising prospects in image synthesis [21-24]. The problems solved by GANs are not limited by tasks related to the synthesis of new graphic content. In the framework of the probabilistic approach to the design and training of GAN, the problem of generating samples from the target distribution is solved. The many proposed applications of GAN were summarized in [25], devoted to the problem of cross-domain adaptation. In this research, an application of GAN technologies for the synthesis of control commands for the intelligent control system for laser engraver is proposed.

3. Proposed smart manufacturing architecture
Intelligent control is understood as such a sequence of commands to the executive device (machine tool), which leads to the solution of the problem and is as close as possible to the sequence of actions that a person would perform in solving this problem.

3.1. The structure and principles of operation of the executive device
An executive device means a computer numerical control machine (CNC), the schematic diagram of which is shown in figure 1.

![Figure 1. CNC machine structure: laser engraver scheme.](image)

The two-axis CNC machine is controlled by a microcontroller that executes the G-code. The sequence of G-code commands is formed in advance on the computer and loaded onto the microcontroller. The machine is drawing the image (obviously, it is drawing the image in grayscale format). The microcontroller, moving the working tool (2, figure 1) along the axis Ox (3, figure 1) and
Oy (1, figure 1) axes, draws the original image. A pencil, laser module, filament, cutter, etc. can be used as a working tool. The machine in figure 1 draws the image line by line, while the image consists of dots or lines. Figure 2 shows the source image and the result obtained by CNC.

![Figure 2](image-url)

Figure 2. The original image and the resulting synthesized image: a) input image; b) synthesized image; c) enlarged fragment of the original image; d) enlarged fragment of the synthesized image.

In the practical applications, the following problems come to the fore:

- The operating time of the machine. Existing modifications of machine tools require a significant amount of time to build an image, therefore, most often machines are used that allow synthesizing an image of a small format.
- The quality of the synthesized image. Figure 2(d) shows what effect the technological characteristics of the working tool have on the quality of the synthesized image. In most implementations, such machines synthesize dotted images. In rare cases, there are methods for synthesizing images using line segments rather than points. The choice of the template (points or segments) strongly depends on the characteristics of the original image.

3.2. The control system and proposed format of the control commands

The main idea of the research is to analyze the feasibility, prove the feasibility and develop a prototype of an intelligent control system for synthesizing images through a single control command or a sequence of control commands. At the same time, the control commands are intended for a two-axis CNC machine with a wide range of working tools (further presentation of the research progress is made for this executive device).

Having analyzed the actions of a person when drawing an image, we find that the nature of his actions differs significantly from the sequential point-by-point reproduction of the target image inherent in machine methods. Simplified, you can imagine the process of drawing by a person as a sequential application of simple graphic primitives. This process can be formalized as a sequence of drawing individual points or segments. For an actuator, this is optimal from the point of view of control, but this is too rough an approximation to the human method of image synthesis.

Therefore, curves will be used in the work as the graphic primitives that make up the target image, and specifically their simplest form – Bezier curves. Bezier curves are convenient for control systems since they are a type of graphic primitive that is constructed algorithmically, that is, they are vector curves. It should also be noted that when using Bezier curves, different variations are available, specified by the order of the Bezier curve. Figure 3 shows Bezier curves of different orders.
Another advantage of using Bezier curves is the simplicity and strict sequence of their construction:

\[ P(t) = tP_1 + (1-t)P_2 \]  \hspace{1cm} (1)
\[ P(t) = t^2P_1 + 2t(1-t)P_2 + (1-t)^2P_3 \]  \hspace{1cm} (2)
\[ P(t) = t^3P_1 + 3t^2(1-t)P_2 + 3t(1-t)^2P_3 + (1-t)^3P_4 \]  \hspace{1cm} (3)
\[ P(t) = t^4P_1 + 4t^3(1-t)P_2 + 6t^2(1-t)^2P_3 + 4t(1-t)^3P_4 + (1-t)^4P_5 \]  \hspace{1cm} (4)

Expressions (1) – (4) present equations for constructing Bezier curves from the first to fourth order, respectively. \( P \) – the coordinate value (x or y); \( P_i, i=1,5 \) – control points which define the Bezier curve. The advance of Bezier curves for machine learning is that a complex curve (3-order Bezier curve) is constructed from four points. Four points on the plane are presented as a vector of length 8, that is, this is the output (tensor) of the neural network.

### 3.3. Control system architecture

The proposed control system is discussed in detail in [26]. As a result of an experimental study of the processes of interaction between an intelligent control system and an executive device (laser engraver), this work proposes an architecture of an intelligent production system that can be applied to production systems for various purposes.

Figure 4 shows a diagram of the production process and the place of the developed intelligent control system in this process.

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**Figure 3.** Bezier curves of various orders and its control points: a) 2-order curve; b) 3-order curve; c) 4-order curve; d) 5-order curve.
During the design of an intelligent control system, an important aspect of its functioning was revealed (figure 5).

Figure 5 shows that the control system is weakly connected to the control object, that is, it can be easily separated from the control object (actuator). When using a deep model or even multiple deep models as the core of the control system, high-performance GPU or TPU hardware may be required, so it is recommended to place the control system in the cloud. Through cloud architecture, many executive devices can be controlled at the same time.
4. Experimental result
In [26] the detailed experiment conditions are described. After training deep generative model which is a core of the control system, the proposed architectures can be realised on the real actuators. The result of the manufacturing process is shown in figure 6.

![Figure 6](image-url)

**Figure 6.** The examples of synthesized images at the different stages of the training process.

The actuator (laser engraver) repeats control commands and performs visualization by burning material. Additionally, the proposed architecture (figure 5) can be applied to various executive devices or groups of devices. The sequential manner of control, implemented in the proposed control system, makes it possible to control not only production equipment, but can be applied in the field of unmanned vehicles, unmanned aerial vehicles and in other areas where control actions are required that are comparable to human actions.

5. Conclusion
As part of this experimental study, an intelligent generative model of sequential synthesis of control commands was developed. Second, the possibility of generating control commands for a CNC machine like human actions was shown.

Further, the proposed intelligent control system is deployed on the laser engraver. When using the developed control system, a reduction in the material processing time of the CNC machine is achieved compared to the use of the GRBL software.

Finally, the ideas and results from efforts like those presented in this paper are necessary for many smart manufactures to reach intelligent and sustainable manufacturing/production and stay competitive and profitable.

References
[1] Yao X, Zhou J, Zhang J and Boër C 2017 From Intelligent Manufacturing to Smart Manufacturing for Industry 4.0 Driven by Next Generation Artificial Intelligence and Further 5th Int. Conf. on Enterprise Systems 311-8
[2] Zhou Y, Yu F, Chen J and Kuo Y 2020 Cyber-Physical-Social Systems: A State-of-the-Art Survey, Challenges and Opportunities *IEEE Communications Surveys & Tutorials* **22**(1) 389-425
[3] Wan J, Li X, Dai H, Kusiak H, Martínez-García M and Li D 2021 Artificial-Intelligence-Driven Customized Manufacturing Factory: Key Technologies, Applications, and Challenges *Proc. of the IEEE* **109**(4) 377-98
[4] Lee J, Bagheri B and Kao H 2015 A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems *Manufacturing Letters* **3** 18-23
[5] Nikolaev E I 2019 Towards intelligent control system for computer numerical control machines *IOP Conf. Ser.: Materials Science and Engineering* **537**(3) 032085
[6] Nikolaev E I, Zakharov V V and Zakharova N I 2019 Style Transfer for CNC Machine Input Data Preprocessing *IOP Conf. Ser.: Materials Science and Engineering* **582**(1) 012013
[7] Grangel-Gonzalez I, Halilaj L, Coskun G, Auer S, Collarana D and Hoffmeister M 2016 Towards a semantic administrative shell for industry 4.0 components *IEEE 10th Int. Conf. on Semantic*
Datta S K, Da Costa, Harri J and Bonnet C 2016 Integrating connected vehicles in Internet of Things ecosystems: Challenges and solutions *IEEE 17th int. symp. on a world of wireless, mobile and multimedia networks* 1-6

Chen B T, Wan J F, Celesti A, Li D, Abbas H and Zhang Q 2018 Edge computing in IoT-based manufacturing *IEEE Communications Magazine* **56**(9) 103-9

Wang S, Wan J F, Zhang D, Li D and Zhang C 2016 Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination Computing Networks **101** 158-68

Simonyan K and Zisserman A 2015 Very deep convolutional networks for large-scale image recognition *3rd Int. Conf. on Learning Representation*

Perez L and Jason W 2017 The effectiveness of data augmentation in image classification using deep learning *arXiv preprint arXiv:1712.04621*

Wang F, Mengqing J, Chen Q, Shuo Y, Chenxi L, Honggang Z, Xiaogang W and Xiaouo T 2017 Residual Attention Network for Image Classification *IEEE Conf. on Comp. Vision and Pattern Recognition (CVPR)* 6450-8

Chen X, Ma H, Wan J, Li B and Xia T 2017 Multi-view 3d object detection network for autonomous driving *IEEE Conf. on Comp. Vision and Pattern Recognition (CVPR)* 6526-34

Redmon J, Divvala S, Girshick R and Farhadi A 2016 You only look once: Unified, real-time object detection *IEEE Conf. on Comp. Vision and Pattern Recognition (CVPR)* 779-88

Yang F, Choi W and Lin Y 2016 Exploit all the layers: Fast and accurate cnn object detector with scale dependent pooling and cascaded rejection classifiers *IEEE Conf. on Comp. Vision and Pattern Recognition (CVPR)* 2129-37

Lin G, Shen C, Hengel A and Reid I 2016 Efficient piecewise training of deep structured models for semantic segmentation *Conf. on Comp. Vision and Pattern Recognition (CVPR)* 3194-203

Harley A W, Konstantinos G D and Iasonas K 2017 Segmentation-Aware Convolutional Networks Using Local Attention Masks *IEEE Int. Conf. on Computing Vision (ICCV)* 5048-57

Ronneberger O, Fischer P and Brox T 2015 U-Net: Convolutional Networks for Biomedical Image Segmentation *Proc. of the Int. Conf. on Medical Image Computing and Computer-Assisted Intervention* **9351** 234-41

Goodfellow I, Pouget-Abadie J, Mirza M, Xu B and Bengio Y 2014 Generative adversarial nets *Proc. of the 27th Int. Conf. on Neural Inf. Proc. Systems* (Cambridge, MA, USA) MIT Press 2672-80

Isola P, Zhu J-Y, Zhou T and Efros A 2017 Image-to-Image Translation with Conditional Adversarial Networks *Proc. of the IEEE Conf. on Comp. Vision and Pattern Recognition (CVPR)* 5967-76

Salimans T, Goodfellow I, Zaremba W and Cheung V 2016 Improved techniques for training GANs *Proc. of the 30th Int. Conf. on Neural Information Processing Systems* 2234-42

Tung F, Harley A, Seto W and Fraczkadaki K 2017 Adversarial inverse graphics networks: Learning 2d-to-3d lifting and image-to-image translation from unpaired supervision *Proc. of the Int. Conf. on Computing Vision* 4364-72

Gulrajani I, Ahmed F, Arjovsky M, Dumoulin V and Courville A 2017 Improved training of wasserstein GANs *Proc. of the 31st Int. Conf. on Neural Information Processing Systems* 5769-79

Ganin Y, Lempitsky V 2015 Unsupervised domain adaptation by backpropagation *Proc. of the 32nd Int. Conf. on Machine Learning* **37** 1180-9

Nikolaev E I 2019 Laser Engraver Control System based on Reinforcement Adversarial Learning *Proc. of the Int. Russian Automation Conf.* (Sochi, Russia) 1-5