Towards intelligent control system for computer numerical control machines

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Abstract. Advances in deep learning have led to impressive results in recent years. The new technologies such as convolutional neural networks, reinforcement learning and generative adversarial networks have shown a real promise for industrial and real-life applications. In this paper, the results of the experimental research on designing, training and implementation of the intelligent control system for the computer numerical control (CNC) machine were presented. The results indicate that using the generative adversarial technique in conjunction with reinforcement learning is possible to design and train the control systems for the machine tools. Building intelligent models in the absence of large datasets of labelled data is a crucial task. One of the key points of this experimental study is the training of a model of the control system using a set of unmarked data. This is achieved by using a reinforcement learning technique. A designed model can be deployed on the physical machine tools like a computer numerical control machine. At the presented research the laser engraver CNC machine is used. In this paper, the architecture of the computer intelligent control system for the laser engraver and the process of its training are described. The proposed model can be applied to different types of CNC machines.

1. Introduction

Intelligent manufacturing is a core technology of the new industrial revolution. Although the strategic priorities are different for each country, the core technologies converge at the cyber-physical system (CPS) [1]. CPSs are the main component of intelligent manufacturing systems. The common CPS system architecture is composed of hardware (equipment layer), layer of sensing, communication layer and control layer [2]. But the most fundamental and important manufacturing equipment and the most important physical resource are CNC machine tools. CNC machines are used in more and more demanding and changing environments. Today, CNC machines deployed across various industries are mostly doing repetitive tasks. The overall task performance hinges on the accuracy of their control systems. To this end, endowing these machines with a greater level of intelligence to autonomously acquire skills is desirable. Being able to adapt to new input data, or even to the uncertain manufacturing conditions to the machine itself can be crucial in many applications. The main challenge is to design adaptable, yet robust, control systems in the face of inherent difficulties in modelling all possible system behaviours and the necessity of behaviour generalization. In other words, in order to realize intelligent manufacturing, it is important to an intelligent model of CNC machine tool.

Another challenge in industrial machinery is to prevent the tool wear or even the tool breakage. Preventing the tool wear of CNC machines has a great significance, tool breakage is often caused huge losses because some types of working tools, such as lasers or 3D printer heaters, are quite expensive. Therefore, designing a control system, capable to perform the task in a short time and to keep high
productivity, is a crucial task. Modern CNC machines perform the control commands in a sequential manner. A simple control system lets them obtain high productivity. Therefore, designing an intelligent control system for minimizing the time of the fabrication process with preserving the efficiency of the industrial process is a very difficult problem. Being able to find the right complexity balance when designing an intelligent system can be very challenging.

There are different types of CNC machines. In the framework of this experimental research, the laser engraver CNC machine is considered. The aim of the research is to design, to investigate and to deploy a computer intelligent control system for the laser engraver. Computer intelligent control (CIC) system aims for reducing working tool (laser) wear, by minimizing the time of the fabrication process. The challenge is that there is a gap between CNC control techniques which is well studied and based on linear deterministic algorithms and modern deep learning technologies. Summarizing this information, the crucial problem is to generate the sequence of commands which obtain an optimal trajectory of the laser module. To address this problem, the model for generating control commands for the initial image is proposed. Advances in deep generative learning have led to impressive results in recent years [3-5], but this approach is related to the use of the deep neural network (DNN) and the availability of very large scale training datasets. Unfortunately, large scale public labelled datasets on similar task are not available. To overcome this drawback, it is proposed to use reinforcement learning technologies.

2. Related works

In the neural network community, there have been real promise attempts at learning feed-forward technologies for image generation [6-10]. These models demonstrate impressive image generation capabilities. The presented experimental study employs adversarial training techniques, first used for generative modelling [11] and domain adaptation [12]. Generative Adversarial Networks (GANs) [11] were originally used for image generation but have now been successfully applied to model audio, text and motor behaviours [13]. But the most interesting extension in our context is their use in domain transfer, where images from one domain (e.g., segmentation) were mapped to another (e.g., pixels). Models such as pix2pix [14], CycleGAN [15] and AIGN [16] are in this category. Also, the current research was inspired by the SPIRAL project [17].

3. An intelligent control system for CNC machine

3.1. Overview

The principal scheme of the 2D laser engraver is depicted in figure 1. There are structural parts of the CNC machine: the working tool (laser); the base plate with two axes, which provide a working tool movement and a set of sensors. The grayscale bitmap image is used as an input data for CNC machine.

A typical mode of operation of the machine is the sequential burning of points in the material. It’s possible to achieve a high efficiency of the fabrication process by using a vector image as an input, but in case of using a bitmap image, the time of the burning process increases significantly. The main idea of this experimental study is to create a model for generating a sequence of commands for the initial image to control the working tool. The model takes bitmap image as input and iteratively produces
plausible samples or reconstructions via graphics program synthesis (or via a physical tool like a laser engraver). The next stage of the experimental study is to deploy the model on the physical equipment.

3.2. Deep model design and training

The basic concept of the generating model being developed is shown in figure 2. At the initial stage of learning a deep model G, data from a random distribution is used to adjust the weights in an adversarial manner [11]. At the final stage of training, the generator G is tuned using real images.

![Figure 2. The sequential process of bitmap image generation.](image)

The key point of the generation process is that generator G produces a set of samples or commands for the working tool (laser). The first row in figure 2 depicts an unconditional implementation given random noise. Other rows depict conditional generation given a handwritten character or a bitmap image.

A scheme of the generator G is depicted in figure 3. Recurrent neural network R generates control commands \((c_1, c_2, c_3, ..., c_N)\) that are used by the visualization subsystem V to draw the samples \((g_1, g_2, g_3, ..., g_N)\). A sample \(g_i\) as been generated is used as an input for the next level of the recurrent neural network. Thus, the model G generates a set of samples \((g_1, g_2, g_3, ..., g_N)\) and control commands \((c_1, c_2, c_3, ..., c_N)\). Each control command \(c_i, i = 1, N\) is defined by its parameters \(c_i = (c_i^1, c_i^2)\), where \(c_i^1\) – the coordinates of the end-point; \(c_i^2\) – a stroke size. At the training stage of the experimental study, the visualizing subsystem V is implemented as a python module. But during the evaluation process, V is a physical CNC machine.

![Figure 3. A structure of the generative model G.](image)

In order to optimize the generative model G, the adversarial training process was implemented [17]. In the framework of this process, the generator G tries to confuse a discriminator model D (figure 4). But the last one is optimized to distinguish between the samples generated by G and the samples from the real dataset.
During the training process the generator tries to draw images from some target distribution $p_{data}$ by using a command set $(c_1, c_2, c_3, ..., c_N)$ and external visual subsystem $V$. Thus, the task is to model a distribution $p_{data} \approx V(p_c)$, where distribution $p_c$ is modelled by the recurrent network $R$. The generative network $R$ (figure 3) is defined as a network that predicts a distribution of control commands $r = r(a_i|s_i; \theta), i = 1, N$, where $a_i$ is a set of commands; $s_i$ is the internal state of the network $R$ and $\theta$ is a set of learnable parameters of $R$. A sample from generative distribution $p_g$ is computed as $V(c_1, c_2, c_3, ..., c_N)$ by given a sequence of commands $a_i, i = 1, N$. The adversarial training process is defined by training objectives in form (1) and (2).

$$\mathcal{L}_D = -\mathbb{E}_{x \sim p_{data}}[D(x)] + \mathbb{E}_{x \sim p_g}[D(x)] + R$$  \hspace{1cm} (1)$$

The objective for discriminator $D$ contains a regularization term $R$ for constraining $D$ to stay in the set of Lipschitz continuous functions [18]. Since the generator $G$ is characterized by an objective:

$$\mathcal{L}_G = -\mathbb{E}_{x \sim p_g}[D(x)]$$  \hspace{1cm} (2)$$

During the training process an SGD is used. At the initial stage of the training, random noise is used as an input. During the conditional training stage (training with a given image $x_{target}$ as an input), the distribution $p_G$ is modelled in a form $p_g = V(p_c(c|x_{target}))$.

4. Experiments
The validation of the intelligent control system is performed on MNIST dataset [19]. MNIST contains 70,000 images of hand-written digits, of which 10,000 examples are for testing.

The learning process of the model consists of two stages: unconditional training by using the data from a random distribution and condition training on the MNIST dataset. The results of the first stage are depicted in figure 5a. Figure 5b presents the generations produced during the second stage.
In this research, the straight lines have been used as drawing primitives. Therefore, the reconstructions of the digits (figure 5b) produced by the intelligent control system are quite rough, but the possibility of building an intelligent control system was demonstrated.

5. Conclusion and future work

The presented experimental results can be applied not only to control the laser engraver, but also for any 2D CNC machine. There are various options for deploying a trained model. The first option (deferred execution) involves the deployment of a deep generating model on a computer to generate a G-code that is transferred to the physical machine tool. The second option (real-time control) involves the deployment of an intelligent control system in real-time, that is, the commands generated by the model directly control the visualization process in real-time.

As a promising direction for further research, it is necessary to note the possibility of increasing the complexity of individual generated commands, that is, training a generator model that will be able to produce control commands with a wide range of parameters, including line thickness and color of the primitive, shape of the geometric primitive (a replacement of straight line segments by Bezier curves).

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