Original Article

Development Of Artificial Intelligence Algorithm For Automated Cnc Machining Process For Unmanned Production

Dr. Pravin Prakash Pande[1*], Dr Yugesh Anil Kharche Kharche[2]

[1*]Associate Professor, Department of Mechanical engineering, Padmashri Dr. V. B. Kolte College of Engineering Malkapur
[2]Assistant Professor, Department of Mechanical engineering, Padmashri Dr. V. B. Kolte College of Engineering Malkapur

***Corresponding Author:** Dr. Pravin Prakash Pande

*Associate Professor, Department of Mechanical engineering, Padmashri Dr. V. B. Kolte College of Engineering Malkapur
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Abstract

Today, the world is growing in the direction of robotics, automation and automated automation theme. As a traditional automation, Computer Numerical Control (CNC) machining is the most prominent and accurate option for production division. However, Covid-19 pandemic and frequent lockdowns proved that, at a certain level, unmanned manufacturing is required to avoid an economic crisis. Industries like pharmaceutical manufacturing are important and cannot stop the production in the situations like pandemic. Hence, this paper presents the artificial intelligence algorithm which can communicate with the CNC G-code and M-code to provide geometrical and/or machine processing instructions.

Keywords: G-code, M-code, CNC, machining, production automation

1. INTRODUCTION

Smart production is heading. It assures a potential of mass-producing extremely customized merchandise by way of responsive, independent production procedures at an affordable expense. Of maximum importance, intelligent production needs end-to-end incorporation of intra-business, as well as inter-business production procedures and programs [1]. Mass modification as well as customization is the vital significance of Industry 4.0. Although additive manufacturing (AM) solutions have the ability to individualize complete products, they are not able to be utilized for mass development. Industries are reluctant concerning the thought of AM approaches to execute industrial productions [2]. The part of humans in production circumstances has progressed from human operators running, activating and unloading machines in the industry 2.0 to even more decision-oriented actions, including systems administration in the industry 3.0 as well as 4.0 eras [3]. The low-code program is a set of tools for coders and nonprogrammers. It allows rapid creation as well as execution of industry applications with minimal effort and hard work to compose in a code language and so needs the minimum, practical efforts for the setup and arrangement of environments, and training and enactment [4]. For an instance, the arc-welding procedure at the center of WAAM systems has particular limitations to the standard of precision attainable in the deposition procedure. Besides that, the precision of a deposited region is delimited by means of the diameter of the wire utilized. Arc ignition and extinguishment operations also tweaked to vital variances in deposited bead geometries [5]. So, automation by CNC needs to be figured out.

The process as well as regulation of production units have transformed considerably in the latest years. The typical central strategy for managing individual operations has gone through many essential procedures of advancement to reach its present standard of commercial utility [6]. Complex intellectual computing as well as deep learning strategies have initiated to discover application in manufacturing platforms for robotic visual assessments, error diagnosis, and maintenance. Certainly, there are effective attempts to incorporate fortification learning strategies into material managing units, as well as production scheduling. Industries expecting to enhance real-time information and facts into workable possibilities seek possibilities to incorporate AI solutions with customary Functional Research plans, the principles and solutions of the Internet of Things (IoT), cyber-physical systems. [7].

2. LITERATURE REVIEW

According to the author, the innovative incorporation of robotics as well as AI constructs a fusion of cutting-edge prospects in technological know-how. Economical outcome of robotic innovations and AI have generated self-driving cars, smart digital solutions that operate for people, which eventually place robots expand. AI gets predicted on needing extensive applications, just like machine learning that mechanizes analytic strategy development with the aid of algorithms. Algorithms enable robots to process with humanitarian help [8].

Lately, commercial artificial intelligence (IAI) has fascinated widespread focus and so has powered the release of Industry 4.0. As a branch of artificial intelligence, deep learning (DL) is broadly applied to resolve data-driven commercial challenges in real-world tasks, including smart grid, autonomous driving, and facial recognition [9]. According to the author, in artificial intelligence as well as machine learning, statistics and utility predicaments are extremely essential. If we can cast off the utility circumstance into a model, use Information and facts, blended with the appropriate algorithm, then data dependable applications will be superb for network information reliability has turn into among the crucial concerns of Internet advancement and approval whether artificial intelligence can be effectively implemented to the reliable arena, including Many considerable elements: versatility, interpretability as well as enforceability of algorithmic training [10].

According to author(s), the primary research gap is the complex concern with today's industrial development is the resource-constrained characteristics of IoT-based manageable gadgets. To solve these kinds of difficulties, author's analysis provides in 3 unique approaches [11]. Author(s) suggested a deep neural network (DNN) soft-sensor that analyzes the scanned surface to the employed engraving file and then carries out an automatic quality control procedure by learning features by using exposure to training data. The DNN sensor designed accomplished a fully automated classification accuracy level of 98.4% [12]. Deep learning (DL) techniques, routinely formulated from artificial neural networks (ANNs), have got the capability to cope with process nonlinearities by means of making positive aspects of multiple-layer nonlinear mappings that are capable of addressing remarkably challenging systems [13]. For computers designated to the administration of manufacturing plants, one of the most crucial jobs is to identify and detect product flaws. The initial stage in this process is to attain the data required for operation evaluation. The foremost inspection systems used a modest number of data producing processes and sensing elements [14]. Author suggested a crash detection perspective (CollisionNet) influenced by a deep learning system. Author devised a deep neural network model to train robot crash signals and discover any event of a crash. This data-driven procedure unifies feature extraction by high-dimensional impulses and the decision processes [15].

3. RESEARCH METHODOLOGY

Machining is the major art of manufacturing companies in terms of producing good quality product; this process involves the machine parameters, lubricants and the environment. Due to the ecological pollution, the government regulations encourage manufacturing industry to implement machining techniques that are environmentally friendly in their operations along with automation of processes [16]. The proposed methodology assumes the MQL machining process by CNC automation. The scenario considered here is to use the G-code of CNC, which will be driven by the proposed algorithm. The input will be given as coordinates of 3D printed design, which further will be transformed as a coordinate plot. Following Fig.1 shows the plot transformation which further can be fed to G-code to trace geometrical layout.

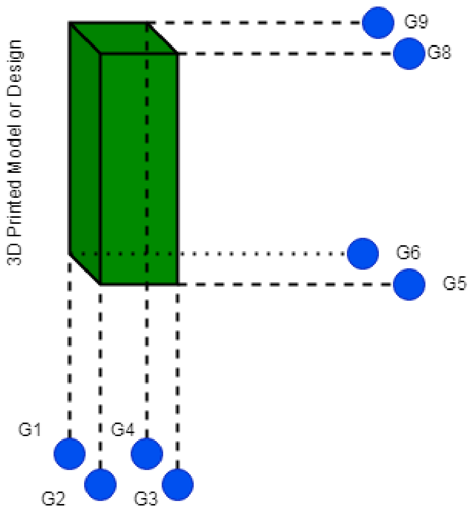

Fig. 1: Proposed plot transformation algorithm representation

The 3D printed model or design coordinates will be collected by the proposed deep learning algorithm and will form an image plot. Further, image plots are augmented using multiple angle plot transformation to get the best suited and visible coordinates. The transformation example is as follows:

Proposed deep learning algorithm: deep Machining

Input: 3D printing object image if 3D object image != 'null'

Record X-axis coordinates, Y-axis coordinates, z-axis coordinates using PyCNC

Store x-coord[], y-coord[], z-coord[]

if x-coord[] || y-coord[] || z-coord[] == 'null'

Set invalid Image()
else
Set validImage()
Get validImage()
Store imageArray[] //for all captured angles
Set Max_pooling()
Set Stride()
startTrainingImageSet()
Get optimumVisibilityImage()
Record coordinatesArray [G1,G2,G3,…,Gn]
Set commandArray[]
Set executionTime()//As per G-code time per node/task execution of job will be set
RunJob()
if coordinatesArray[]== 'null'
End

4. RESULT ANALYSIS

Assume G-code G1 X 10 Y30 F100, which means the tool, goes linear to desired coordinates: X=10 mm, Y=30 mm with the velocity of 100 millimeters per second. Further, with an output of the proposed algorithm PyCNC package will interpret the G-code and the task will keep running without any attention till coordinates array shows value 'null'. Based of pilot run, following table 1 shows the proposed algorithm performance.

Table 1: Proposed deepMachining algorithm performance

Srn.	Object	Accuracy	Algorithm Execution Time (s)	Tolerance
1.	3D	92.41	92	0.581
2.	2D	90.85	85	0.498

With reference to algorithmic performance, the accuracy is optimum and can be used for automation of CNC commands. The algorithm execution time can further be lowered by balancing the stride and max pooling. If we lower the epoch, the accuracy will be lowered. Tolerance values are acceptable, as this will not cause code errors during the training of transformed images.

5. CONCLUSION

The PyCNC can be a bridge for CNC G-code, which further can be a great solution for command automation for machining process. The 3D printing coordinates can be transformed as 1D image coordinates, which can be fed to the G-code. The applicability of the proposed algorithm can generalize any task based on 1D design and can replicate 3D design too, which is the unmanned job execution. The image augmentation can be achieved to capture precise coordinates by multiple image development and comparison to lower the error index. As a future development, M-code can be simulated to assist full automation of CNC commands.

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