The Application of Deep Learning Techniques in Advanced Robotics for Aerospace Manufacturing: Enhancing Efficiency and Competitiveness in the USA

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1. Introduction

With looming competition from countries that are rapidly expanding their manufacturing and automation efforts, a sense of urgency has emerged around advancing robotics for aerospace manufacturing in the USA. This effort would both directly address the shortage of skilled workers for aerospace manufacturing and indirectly bolster the existing workforce across many manufacturing industries. Recent advances in deep learning, particularly in computer vision, natural language processing, and reinforcement learning, open the door for new robotic applications previously thought unattainable. Unfortunately, many of these breakthroughs are not being actively pursued within the robotics community [1]. The effectiveness with which the USA responds to these changes will have ramifications that extend well into the future. This report details a robust research agenda applying recent advances in deep learning to robotics problems relevant to aerospace manufacturing.

The goal is to advance robotics and machine intelligence within the manufacturing context, facilitating automation with present and future deep learning capabilities. Four significant domains of inquiry are identified, each requiring distinct and complementary robotics efforts. For each domain of inquiry, an overview of the research opportunity is provided, along with specific robot tasks, potential applications, bottom-up and top-down challenges, and illustrative uses of existing tech. The urgency of aerospace manufacturing (am) is discussed first, followed by an overview of complementary research domains that could reinvigorate robotics research in am. An agenda prioritizing efforts within each domain is outlined, detailing initial and ongoing work within each. Finally, the anticipated opportunities and impact are discussed.

1.1. Background and Significance

The new era of Industrial Revolution 4.0 has forced organizations worldwide to move toward smart factories or production plants in order to enhance the performance and operation of their manufacturing systems and production facilities. This shift would propel their performance beyond one or only couple of dimensions such as cost, throughput, quality or efficiency, and take full advantage of cyber-physical technologies. To be able to stay competitive, significantly efficient, flexible and robust venues and solutions for cyber-physical manufacturing systems must be devised. The intelligent automatic pilot and operation of aerospace and envisaged high-speed rail systems above vine globally relevant transportation venues requires a smart, intelligent and robust integrated approach. Universal flexible robotic manipulators capable of promptly and effectively adapting to different tasks and environment conditions utilizing Artificial Intelligence technologies and taking into consideration uncertainties, disturbances and constraints in their spatial and end-user requirements constitute the core of such solution [2]. So, the significant attention is devoted to modeling, presentation (real-time digital twin modeling) and visualization, simulation, design, control and robust/optimal automatic guidance of flexible robotic manipulators applied for (but not limited to) aerospace components.

This special session is planned to address recent investigations focused on deep learning and AI-enabled control strategies for flexible robotic application in aerospace industry. This session invites works on the novel and effective design and control of flexible robotic manipulators building on deep learning models (e.g. Feed forward neural Network, Convolutional Neural Network, Recurrent Neural Network) and AI technologies (e.g. Generalized Neural Networks, Fuzzy Logic, Neuro-Fuzzy, Knowledge based systems) or combination of those. Additionally, analysis, modeling, implementation of innovative strategy out of the essence of different disciplines such as Robotics, Aerospace Engineering, Mechanics and Aeronautics with regard to Neural/Digital Twin Modelling and Control using AI technologies is considered relevant. The presentation of industrial application cases is encouraged [3].

1.2. Research Objectives

The specific objective of this research is to study the feasibility and the potential effectiveness of deep learning techniques in the realm of advanced robotics and to develop and benchmarking these techniques in an aerospace manufacturing context. Aerospace (including aircraft, spacecraft, and satellites) design and production is an especially important sector for the economy of the United States (US). After a recession in 2020, the US aerospace sector is expected to rebound quickly. Automation of the aerospace manufacturing sector has lagged behind other manufacturing sectors since many aerospace components are large, high-value, complex structures with strict mechanical and thermal tolerances. As these structures are conventionally machined separately, there is a need to investigate the potential of advanced robotics with deep learning to automate multiple processes such as milling, drilling, inspection, and so on, on one robotic platform. A new research initiative is required, through which new solutions can be developed or matured. A key need is a laboratory that has both advanced robotics and deep learning capabilities in-house [3]. While there are labs with one or the other, such as labs that have developed advanced robotic platforms but don't have the necessary controls, vision, or simulation capabilities, few labs have both.

The deep learning techniques to be studied will be convolutional neural networks (CNN) and recurrent neural networks (RNN). CNN will be studied for visual perception tasks such as image segmentation and image classification. RNN with long short-term memory (LSTM) units will be studied for tasks that have a temporal component such as trajectory prediction and control. These deep learning techniques will be integrated into either a mobile or stationary robot manufactured in-house. It is expected that significant advances will be made in the area of deep learning-based perception and control, and that several peer-reviewed publications in high-impact journals or conferences will result. In addition to scientific advancements, it is expected that several developments related to advanced robotics will have a high industrial relevance [4]. Such developments will include new advanced robotic platforms with a variety of perception and end-effector options such as passive compliant grippers, machine vision, etc. Furthermore, new applications of advanced robotics will be developed for aerospace, biomedical, and agriculture-related contexts.

1.3. Scope and Limitations

The focus of this research is on pursuing the application of deep learning techniques in a smart robotics system for improving production efficiency and manufacturing competitiveness in the aerospace domain of the USA. Improving production efficiency and manufacturing competitiveness has been a thrust area in the aerospace domain for decades. Though complex and capital-intensive, many innovative processing methods have been developed and adopted in the aerospace sector to improve manufacturing efficiency. In addition to seeking advanced processing methods, other areas, such as advanced manufacturing equipment, including robotics, inspection, and smart instrumentation & control, are also being investigated to improve production efficiency [3]. Commercially, it is believed that the efficient use of advanced robotics in complex aerospace manufacturing will improve the USA competitiveness.

Today robotics is more often associated with division of labor and automation of labor-intensive tasks in manufacturing and assembly. The automation made possible by robotics has led to remarkable benefits in manufacturing productivity and quality. Central to the envisioned sophistication of robotics for complex processing and assembly is the ability of the robots to possess some degree of perception and intelligence with regard to their environment. Considering the complexity of the operations and environment, in addition to the development of advanced sensors, control algorithm and mechanism consideration, the development of learning techniques, for example, neural networks will be essential. The aerospace aircraft and transport vehicles are extremely complex from the view point of design, geometric configuration, number of components, construction methodology; therefore, the surface contour of these components is often non-planar and free form.

2. Fundamentals of Deep Learning

This section begins with a brief introduction to deep learning and follows with deeper consideration of its fundamentals. Four topics are selected to present the fundamentals of deep learning—deep feedforward neural networks, convolutional neural networks, recurrent neural networks, and deep reinforcement learning. Artificial neural networks consist of processing units organized into layers. A processing unit receives inputs, calculates a function of the inputs, and produces an output. The function usually consists of the linear transformation of its inputs followed by a non-linear activation function. The output of a processing unit is usually connected to the inputs of the units in the following layer. Despite this simple architecture, deep feedforward neural networks are universal approximators of continuous functions, provided they are sufficiently large [5]. However, it is extremely difficult to train networks with more than one hidden layer [3].

Deep convolutional neural networks are neural networks that exploit the spatial structure in their inputs; they use convolutional layers to reduce the number of parameters and exploit the translational invariance in their inputs. Convolutional layers were inspired by cortical neurons in the visual cortex; these neurons respond only to stimuli with a receptive field. The pioneering works in neural networks with convolutional layers (CNNs) applied them to the task of image recognition. Widespread interest in convolutional layers surged around 2012 when Krizhevsky used them to dominate in the ImageNet image recognition competition, achieving super-human recognition on notable image recognition benchmarks. CNNs have become well established as a highly effective deep learning model for a diversity of image-based applications.

2.1. Neural Networks

Neural networks can be thought of as black boxes, which are good for a wide variety of tasks, but no one is sure how they work. However, each piece can be examined to build a better understanding of how the structure of neural networks function. A neural network is a system of nodes working together to fill in a basically given structure. This section first explains the essential characteristics of a neural network and describes how neural networks fill in the structure. Then it examines how neural networks change based on input and output data as well as how they train and generalize, increasing their utility. The section concludes with a discussion of different structures employed by neural networks and their advantages or displeasures for various tasks [3].

One of the most enduring concepts of intelligence is the comparison of human thinking to machine processing. Neural networks are structures of “neurons” based on the capability of the human brain to create natural and experiential relationships within data or events [5]. Likewise, neural networks are a form of machine processing of parallel information usually represented by numeric values. A neural network initially has little or no knowledge about the dataset it attempts to relate. Instead, a neural network fills in a structure basically given (the architecture) while numbers representing data fill in the assigned values of that structure (the weights). The weights can be thought of as relationships between represented data in the case of a neural network without interaction abilities, or predefined “knowledge” as in the case of systems with “expert” information.

2.2. Convolutional Neural Networks

Deep learning techniques, particularly feedforward neural networks known as convolutional neural networks (CNNs), have been emerging in the manufacturing community. This discussion focuses on basic concepts of CNNs and outlines their uses in manufacturing. Different types of data objects encountered in manufacturing can be represented in a flexible manner using tensors and graphs. CNNs use convolution operations to extract informative features to predict emergent properties and phenomena and/or to identify anomalies. CNNs can exploit color as a key source of information, enabling the use of modern computer vision hardware [6].

As a class of feedforward neural networks, CNNs are distinguished by their use of convolution operations in constructing processing layers that extract and combine features for classification. Different from general artificial neural networks or multilayer perceptrons, CNNs consider the locality of interactions among nodes and share weights for the same set of receptive fields. Through these innovative approaches, it is possible to capture complex features required for classification while keeping the number of weights to be learned relatively small. These features can be extracted hierarchically, in which low-level features such as edges or textures are first detected and then combined to build higher-level but more complex features such as shapes or objects [7].

2.3. Recurrent Neural Networks

Recurrent neural networks (RNNs) are connectionist models for processing sequential data by passing information selectively across sequence steps without attention mechanisms. A standard RNN consists of a layer of hidden units which are connected to themselves and to input and output units, feeding activations one step at a time. After each input, a new hidden activation is executed as a function of the current input and the previous hidden state. This representation of past inputs is maintained in the hidden units, allowing for modeling input and output consisting of sequences. RNNs are especially suited for sequential data, addressing limitations of standard feedforward networks [8]. In feedforward networks, after each example is processed, the network loses its entire state, which is unacceptable when examples are temporally or spatially related. Further, feedforward networks assume independence among training and test examples as well as examples being vectors of fixed length. RNNs address this by processing sequences one element at a time while maintaining hidden activations representing the entire input sequence.

Standard RNNs have connections feeding back from hidden units to themselves, leading to hidden unit activations being computed as a function of the current input and the previous hidden activations. This sets up a recurrent state that allows holding information across sequence steps. The model can be applied to sequences of arbitrary length, avoiding a priori segmenting inputs or outputs into fixed-length pieces. In addition to standard RNNs, there are a variety of alternative or supplementary mechanisms for processing sequential data, including feedforward models with delays, fixed-architecture networks, hierarchical models, and models whose parameters change over time [9].

2.4. Deep Reinforcement Learning

[10] [3]

Deep Reinforcement Learning (DRL) is a promising field of artificial intelligence that applies deep learning and reinforcement learning methodologies to develop decision-making agents and accomplish desired tasks. A fundamental goal is to learn a policy that enhances cumulative reward by facilitating interaction with an environment. Broadly executed and studied DRL applications include playing games, robotic systems, unmanned aerial vehicle systems, the Internet of things, stock market investment, smart grid development, and wind farm control.

Currently, DRL remains a vastly open area of research. Despite increasing interest, extensive proficiency is required beyond coding ability. It is desirable to have a thorough understanding of DRL principles and mechanisms. An introduction to DRL is herein elaborated upon, including reinforcement learning, deep reinforcement learning, and some contemporary methodologies addressing significant problems for agents. For each branch of DRL, representative implementations aimed at promoting comprehension and improvement are investigated and remarked upon.

3. Advanced Robotics in Aerospace Manufacturing

Advanced Robotics (AR) systems are widely used in various manufacturing processes for aerospace and automotive industries, such as applications in the assembly of large components like aircraft wings, fuselages, and other structural components [2]. Often, there are rigid body parts with difficult geometry and complex handling systems (conventional machinery and Fixturing and Handling) that can greatly influence the assembly precision and productivity. Other manufacturing techniques can also benefit from AR, e.g., material removal processes such as drilling, riveting, milling, etc. As for large parts, collaborative AR systems with collaborative robots or cooperative multi-robots for concurrent and synchronous tasks are a trend to improve the current productivity [3]. With the impressive development concerning programming and perception technologies, different types of robotic arms and end-effectors are actively being used in AR systems. The advantage of multi-robot systems is that a simple assembly operation can be done by sharing the task into different robots and concurrent actions.

Nevertheless, handling operations of these AR systems (robotic arms) usually involve parts with a large scale, heavy weight, and complex shapes (i.e. a lot of undercuts and hidden areas). It is very difficult to define the poses for the robot arms, especially for flexible or heavy parts with more than one attachment point or with large tolerances in the relative poses of the assembly components. Difficulties also arise due to uncertainty in the boundary of the parts (e.g. for casted parts), flexibility of LR and/or parts, or complex parts' geometry (complex shapes with undercuts). Therefore, conventional handling systems (Fixturing and Handling systems) cannot be applied directly, and handling operations must be done using the parts' own geometrical features. Thus, the perception of flexible assembly poses is of primary concern in AR systems applied to complex or massive part assembly. Vision feedback is needed for observing the assembly structures concerning the robot arms. Competitiveness remains a big problem in this area, especially in the USA, mostly due to the high maintenance cost of robot arms. As to the perception system, many existing solutions are too expensive for frequently used systems with the above-determined parameters like assembly robotics. Bench-mounted laser sensors or robots with vision systems are often situations that would not easily satisfy the current performance. A trade-off between the computing time of the mobile manipulators and the software solutions for determining the interfaces and controlling the movement of the arms would often yield unsatisfactory results for critical situations (i.e., robustness, fast reaction time, strict safety requirements).

3.1. Robotic Arms and End-Effectors

A robotic arm is an electromechanical system constructively manufactured to mimic the structure and flexibility of an arm, capable of carrying and moving different objects. The invention of the robotic arm helped free human beings from performing harsh, unsafe, hard, and repetitive activities. Robotic arms are widely used in automotive and heavy industries by running simple repetitive tasks such as welding, painting, boring, and picking and placing heavy units [2]. A simple robotic arm consists of joints, links, an actuator, and an end-effector. The joints in robotic arms can be classified as revolute and prismatic joints. A robotic arm with revolute joints is called a rotary robot (RR) arm and the robotic arm with prismatic joints is called a linear robot (LR) arm. The robotic arm consists of serial rigid links connected in series by joints to perform specific tasks. Depending on the number of degrees of freedom (DoF), they are classified as 1-DoF, 2-DoF, 3-DoF, 4-DoF, etc. A 3-DoF arm can rotate in three different axis directions and move perpendicularly in three different planes (XY, YZ, and XZ), 5-DoF robotic arms are universal arms. Presently robotic arms are used in flexible moves, picking and placing light, heavy and delicate objects, inspection, polishing, grinding, washing, in simple writing to complex documents, painting and decoration of rough surfaces, etc. [11]. The end-effector is a device that provides the interaction between the robot and the external environment and facilitates better operations for the robotic system. The design of the end-effector greatly influences the performance of a robotic system. It can be designed to perform several operations like pick and place, avoid obstacles while being transferred, polishing, grinding, etc. Design of a robotic gripper-based end-effector for pick and place operation is proposed in this paper. The gripper relies on the three-finger and two-finger claws, pincer and under hooks, which are palm structures consisting of three protrusions. The three fingers, each having a torsion spring, assist their rotation. A simple palm structure with a tooth height evenly specified is designed for the two-finger claw without springs to minimize expensive parts. It proposed an under hook designed to prevent excessive widths and heights of the objects, which may decrease the reliability of the pick and place operations. Designs obtained using the optimization method can conduct stable manipulation with more successful rate in a wider field of object sizes compared with conventional designs.

3.2. Sensors and Perception Systems

Sensors and perception systems are fundamental components of robotic systems that provide robots with the capability to perceive the world around them. Acting as the "eyes" of the robots, sensors furnish them with spatial awareness and knowledge of their environment, which helps distinguish objects of interest from others, avoiding potential accidents in populated environments. Sensors can be deployed in robotic systems in a simple or complex organizational structure depending on the mission design and desired performance, and they can fulfill several functions related to data acquisition and analysis intended for subsequent actions [12]. Several perception systems have been incorporated into robotic systems operating in aerospace manufacturing processes.

The need for human augmentation (HA) systems supportive of human and robotic collaboration has become increasingly critical in aerospace manufacturing due to the high mix, low volume, and customized nature of products [13]. The more-strict weight and fuel consumption constraints than other industries result in a high demand for assembly automation and, ultimately, robotization. However, a fully automated production approach is broadly deemed infeasible owing to the excessive variations of components and the lack of infrastructure preparedness in factories transitioning from traditional mechanics to robotics, such as the spatial density of robots being lower than typical machine tools and the need for co-existence with large numbers of manual workers. Therefore, a HA-safe robotic assistant for assembly manufacturing is proposed, in which a mobile robot equipped with perception sensors holds the overall system position, completes fine manipulation situational-awareness tasks, and provides augmented reality (AR) visual aids to assembly workers.

3.3. Motion Planning and Control

Robotic automation and smart manufacturing have been emerging as the new generation of manufacturing technologies for the advanced manufacturing of aerospace components. Automated processes in aerospace engineering include the automated low-cost design of complex structures and their subsequent automated manufacturing via robotic assembly of composite parts, machining operations, etc. Advanced robotic approaches involve the design of a robotic launcher with a negotiable compliant control, stereo vision multi-camera systems for work space mapping and object recognition, specialized active-grippers fitted to a robotic arm for composite preform handling, a dexterous hand equipped with voice recognition for human-robot industrial applications, and similar [2]. The trajectory of motion between two or more states in the search space is analyzed in terms of position, orientation, time, and velocity. Motion planning attempts to break the motion into discrete moves and search a path through the free space. To identify a feasible trajectory, it is always necessary to synthesize a model that identifies the physical kinematics of the manipulator. Kinematic modeling deals with the position and the orientation of the end-effector concerning the world frame, while dynamic modeling describes the forces and torques generated at the actuator level. Based on the direct and inverse kinematics offers provided the geometric equations in analytical and vector form and developed the algorithm in pseudo-code format [14]. Control is defined as the processes that stabilize a controlled variable to prevent unwanted disturbances from affecting the controlled variable. Control of robotic manipulators involves controlling the position, velocity, and acceleration of its joints and tasks. The joint-controlled robot manipulator is defined as a multi-joint single end-effector robot. As the first step of the control design procedure, to transfer the manipulator joint co-ordinate variables into Cartesian co-ordinate variables, forward kinematics is analyzed. Multiply the respective transformation matrices sequentially to get the transformation matrix of the last link concerning the world frame and formulate the position and orientation equations of the manipulator in terms of the joint angles. The task Jacobian matrix and manipulator Jacobian matrix in the joint space are expressed in terms of the manipulator D-H parameters.

4. Integration of Deep Learning and Robotics

Deep learning methods have gained prominence within the field of robotics, especially in computer vision and perception tasks. High-performance deep learning models are touted as providing new opportunities for improving robotic operations. Recent robotic operations, such as grasping and manipulation, are enabling a natural integration of deep learning techniques with robotics. Vision has been incorporated into many robotic systems, with recent developments involving deep learning architectures. The implementation of perception modules in robotics has a long history, notably on problems such as object identification, localization, and working on RGB-D data sets.

Several essential topics such as sensor fusion and data preprocessing for deep learning-based robotics tasks are elements of interest. Sensor fusion techniques are essential to enrich the data being processed and improve the robustness of the networks. Data preprocessing is also important for robotics systems as the vision data acquired in real environments are normally noisy and need to be filtered or normalized to feed into the networks [3]. Supervised learning applied to perform robotics tasks is another topic of interest. Supervised learning is the type of learning in which a query example is accompanied by an expected response, or label. The last topic of interest is focused on autonomous control through deep reinforcement learning. Reinforcement learning is a family of machine learning methods that enables an agent to interact with an environment and learn over time with the aim to maximize a reward [15]. This approach is essential for applications such as mobile robotic navigation.

4.1. Sensor Fusion and Data Preprocessing

Robotic systems featuring artificial intelligence (AI) and deep learning techniques require the utilization of a number of sensors in order to fuse and process the massive amounts of sensory information they require for effective decision-making. Sensor fusion refers to the combination of data acquired through purposeful activity from several sensors that provide significant information to enhance the understanding of a phenomenon. This can be implemented using AI methods to create a uniform wheelchair such as overall motion perception, location, and environment reconstruction [16]. This section discusses the techniques for sensor fusion, in conjunction with preprocessing its data, implemented within this thesis robotic framework. In the case of the robotic arm, cameras and IMUs are combined to perceive the spatial robot joint states, in addition to lip-sensing cameras for grasp quality estimation, while a camera and Li-DAR are fused to portray the surrounding environment map within the wheeled robot. Finally, after considering the possible low-level implementations for the utilized sensor fusion algorithms, it is discussed how AI methodologies are applied to intelligently utilize this plethora of integrated sensors and several sensory modalities. Such intelligence is crucial for the learning and performance enhancement of AI-driven automatons and robots [7].

4.2. Supervised Learning for Robotics Tasks

For robotics tasks related to advanced robotics in aerospace manufacturing, deep learning techniques associated with supervised learning are being examined in this section. Supervised learning, which can be used to train a model on a specific manufacturing function when enough labeled data exists, is focused on (1) robustness to model perturbation, (2) robustness to challenging object characteristics, and (3) accurate estimation of model performance [3]. In this sense, the supervised learning techniques outside of the deep learning domain are reviewed first. Next, the deep learning approaches developed recently for manufacturing functions and compatible with supervised learning techniques are presented.

The deep learning approaches consist of (1) Object Shape Configuration Selector for Part Insertion, (2) Automated Neural Network Hyper-Parameter Selection/Training Tool for State

Estimation, and (3) Deep Functional Part-Geometric Modeling for Product Robust Quality Improvement. They are already applied to or currently being developed for a solid product in the aerospace industry [2]. To enhance their robustness or accuracy in the design stage of automation, the aforementioned objectives are pursued based on the one or two concepts in the deep learning domain. Some studies on the effort to commercialize the corresponding product or techniques will also be presented.

4.3. Reinforcement Learning for Autonomous Control

Recent years have seen a shift of attention from supervised learning to reinforcement learning (RL) to achieve autonomous control in robotics [15]. The essence of RL is an iterative learning process. A control policy is learned to maximize a reward signal that indicates the performance of the decisions made; thus reinforcement signals guide the search of the most appropriate controller similar to the way people learn to play basketball or chess by obtaining rewards (e.g., success, win) or penalties (e.g., failure, lose). In robotics, this control policy learned through RL can then be used for on-line autonomous decision making for robots and manipulators with a wide variety of applications, including autonomous vehicles, manipulations, walking patterns, bicycles, humanoids, and flying vehicles [2]. Because this approach is a natural way to achieve autonomy and intelligence in machines, RL is a promising candidate for advancing autonomous capabilities.

5. Case Studies and Applications

Automation of aerospace manufacturing demands smart application of robotic systems. With the advances in the machine vision and robotics, there is a need to enhance the overall efficiency and competitiveness of aerospace manufacturing in the USA via a deep learning-driven robotics and automation approach. In this paper, different aspects of deep learning-driven robotics and automation are explored with a special focus on the applications and case studies in the aerospace manufacturing scenarios. Case Studies and Applications of Deep Learning-driven Robotics in Aerospace Manufacturing [17]. Automation of aerospace manufacturing demands smart application of robotic systems. With the more and more complicated components and structures to be inspected, there is a pressing need to develop fully automated inspection systems instead of manual inspections (e.g. fluorescence penetrant test). With the advances in the machine vision and robotics, such an inspection system can be developed by integrating a multi-vision machine system and a robot. The basic idea for the robotic ultrasonic testing (RUT) system is to design and develop the commercial robot systems, multi-vision machine systems, combined computer processing systems, and industrial PCs to perform contour-following inspection for critical aerospace components and structures [3]. Data and information are elaborately processed on-line and fed back to the robotic systems, so that a precise inspection path and rig can be generated to perform, on the one hand, a time-efficient and safe-test, and on the other hand, prevent the impairment of the components to be inspected. The basic concepts and principles are outlined, and real-life commissioning cases in aerospace manufacturing and machining industries are given to illustrate the effectiveness of the approaches. With the more and more complicated structures of aerospace components, such as intricate contoured surfaces, special materials (e.g. composites, alloys, and super alloys), and complicated manufacturing processes (e.g. welding, casting, and machining), there is a pressing need to develop precision automation in the manufacture process. A deep learning-based vision is applied to a robot cell in order to enhance the precision in the assembly process. A base robot select and present several knobs on the assembly line to a subordinate Novinter robot that performs assembly. The robot is equipped with two cameras and a calibration camera that is used to refine the 3D position of the knob. Besides a description of the system, images acquired by the robots at different positions are used to illustrate the robustness of the implemented vision system in the different views of the knob. The knobs are presented to the vision system as a bounding box and therefore a 2D image matching is performed on the images. The knot is then assembled on the wire harness, and the assembly position is targeted to the middle of the knob. This target is transformed into a set of commands for a motron servo of demeanour of a compact size and lightweight. Hence, the overall assembly precision is enhanced by 1.118 mm, and it is guaranteed that the knob will engage to the wire harness in a safe manner preventing mechanical damages. In view of commercial and competitive models of robotics, the robotic assembly cell modularity architecture is presented as a set of individual modules that can operate independently or integrated together.

5.1. Automated Inspection Systems

Automated inspection systems are smart and automated systems designed to detect defects on products coming from production lines. Systems using deep learning techniques can be classified as automated inspection systems consisting of a conveyor, a camera to acquire images, and a computing unit on which the deep learning model is trained and runs. The deep learning model inspects products by determining whether they are defective or acceptable. This type of defect detection system can be implemented with a cycle time of one second or less, enabling a substantial increase in the lot's inspection speed along with maintaining a high detection performance. Therefore, the competitiveness of the relevant industries can be increased by a thorough application of this technology [18].

For illustration purposes, an automated inspection system using a convolutional neural network (CNN) for defect detection on a crop product is described here. The focus is on the system design and operation rather than the technical aspect of the deep learning model itself. The methodology and the learnings from implementing automated inspection systems not existent in the literature are summarized to give helpful hints to organizations considering to employ deep learning techniques in their inspection processes [13]. Automated inspection systems can enhance the aerospace manufacturing business by improving the quality of manufactured products while reducing cost and enhancing process efficiency. Both moral obligations and legal requirements necessitate a high degree of quality in aerospace manufacturing. However, maintaining a high-quality level usually comes at the expense of low process efficiency. Therefore, the policies within a company, or the modes in which one company competes against another, can be either high target quality, fast production speed, or low cost.

5.2. Precision Assembly Processes

Precision assembly is one of the key manufacturing processes in aerospace that require micrometer-level accuracy and submillimeter tolerance. In aerospace component manufacturing, precision assembly with fixtures/stoppers is the most prevalent method. Because of the constraints on components around assembly locations, traditional assembly workflow programming methods are not ideal. There are concerns regarding robustness, simplicity, ease of use, and cycle time optimization [19]. Therefore, a deep learning-based assembly workflow optimization framework generating assembly workflows with modification locations, sequences, and working poses has been developed. Schematic assembly structures are extracted from CAD models to represent attachment relationships and to guide deep learning model training. The trained models predict modification parameters in a component pair with a similar assembly structure during component matching.

Both ideal and perturbed assembly structures have been tested by the path planner on the two-generation dataset. The utility of deep learning-based assembly workflow generation helps lock-in deep learning-based design thinking, which reduces the time and complexity. The proposed assembly workflow generation method is based on deep learning techniques, which makes it adaptable to various component designs. Generative design techniques can be integrated into CAD model-based assembly design evaluation and modification strategies, utilizing CAD models with newer component designs [20].

5.3. Real-time Adaptive Control Systems

In the context of smart factories and Industry 4.0, there is a growing interest in using real-time adaptive control systems in mechanical manufacturing and assembly operations. Deep learning-driven adaptive control systems are exceptional at understanding the factors that cause variability in manufacturing processes. These systems can dynamically adjust the manufacturing process in real time based on incoming external and environmental stimuli . This allows manufacturers to achieve a greater tolerance of operation in the presence of unexpected deviations and disturbances. But how can the assembly/adaptive control systems be made so smart that they can efficiently deal with large redundancies and unpredictable variability/situations? The answer comes from advanced data acquisition techniques and state-of-the-art artificial intelligence (AI) approaches [2]. The understanding of mechanical and manufacturing processes can be enhanced and transferred to a control system so that it can learn the process and adapt its control actions accordingly.

6. Challenges and Future Directions

The application of deep learning techniques in advanced robotics for aerospace manufacturing presents several challenges that need to be addressed. Firstly, there is a need for high-quality data to train deep neural networks (DNNs) that are used for motion planning, control, and decision-making [3]. Alternatively, the possibility of acquiring training data using hardware prototypes is also addressed. However, designing and conducting experiments using hardware prototypes can be a time-consuming and costly endeavor. Future works should focus on developing and implementing techniques based on cloud robotics that address the issues and limitations of both sides while leveraging their benefits.

A second challenge is the interpretability and explainability of the decisions generated by a deep learning model [2]. After providing the prediction of the model, it is essential to provide additional information that highlights the reasons behind each prediction, allowing validation that the DNNs are not learning trivial correlations not representative of the real-world problem. This literature aims to highlight the areas of improvement for future work in the aerospace domain.

A third challenge is the safety of the actions outputted by the deep learning model in a new context. DNNs with high generalization capabilities (i.e., capable of providing reliable outputs in contexts that are significantly different from those encountered during training) must be developed. Data augmentation techniques can be used to design a more robust training dataset or generative models capable of producing realistic synthetic data. However, this remains a major challenge in the aerospace domain, where flight conditions (hardware, environment, and disturbances) can be radically different despite compromised operational conditions.

Finally, ethical considerations regarding aerial missions (e.g., privacy and security) and the social acceptance of advanced robotics deploying deep learning techniques should be mentioned. Safety assurance and risk assessment methodologies for design and operation should be developed, and scenarios should be studied to demonstrate the potential advantages of deploying DNNs in advanced robotics.

6.1. Data Quality and Quantity

The successful application of deep learning techniques for robotics in aerospace manufacturing in the USA is challenged by both data quality and data quantity. These challenges are paramount for deep learning techniques to successfully address the application needs. While challenges related to data quality and data quantity have been studied separately, they are discussed together here as they are intimately intertwined. First, the data quality challenges, including the type of data for training and execution, data collected from the physical world, and the data processing task itself, are analyzed in detail. Then, the data quantity challenges, including the cost and time to generate data collections, and considerations for human and physical dimensional data, are discussed in detail [20]. Finally, a future outlook on potential solutions to address both data quality and data quantity challenges is provided considering technological and process advances within the robotics, deep learning, simulation, and digital twin domains.

Robotics is an important application area for deep learning techniques, where the input data often contain high-bandwidth signals from the physical world, such as images, point clouds, audio, 6D poses, etc. With advancements in sensor technologies, high-dimensional and high-volume data signals from the environment can be collected, leading to better performance and capabilities for robotic systems. Nevertheless, the training and execution data at the network level must conform to a specific type and dimension, which usually requires further processing tasks, such as perspective conversion, background removal, simplification, augmentation, etc. Therefore, while the raw data available for robotics may be plentiful, the signals that can directly feed into the networks are often severely restricted. These complicated processing tasks introduce challenges for data quality as they entail many manual steps that can compromise the performance of trained networks if improperly done [21].

6.2. Interpretability and Explainability

A formidable challenge for AI engineers is to make their models interpretable. AI systems are often perceived as black boxes. Even more than other machine learning techniques, the performance of neuro-network based decision systems is poorly understood [22]. Technically, it is difficult to relate the performance of deep learning models to network parameters and architecture. Operationally, it is difficult to present explanations of deep learning system performance in an intelligible manner. Unfortunately, the lack of transparency is a major shortcoming, particularly in safety-critical applications like self-driving cars or in medical diagnostics and treatment, where trust in a model's predictions is a pre-condition to its successful operation. In accordance with the IEEE 7001 standard, ethic principles of transparency, accountability, and responsibility have been formulated. However, presently, even though model accountability may be provable, model interpretability is far from guaranteed.

The AI techniques and their interpretations should receive much attention in the future development of AI-based robotics for aerospace manufacturing systems since the advancement and understanding of these AI techniques and their interpretations greatly affect the ethics, responsibility and performance robustness of these AI systems [23]. For applying deep learning techniques in autonomous robotics for aerospace manufacturing systems, in addition to ensuring their good performance and reliability, similar attention should be paid to the deep learning model interpretability. Because the aerospace manufacturing systems involve high value-added objectives with high requirements in safety, completion accuracy and time, and complying with strict release time, adopting bias and wrong deep learning robot controls without understanding their causes will result in great losses.

6.3. Safety and Ethical Considerations

Safety and ethical considerations must not be overlooked when developing and deploying deep-learning-driven robotics for aerospace manufacturing. Advanced robotics systems deploying emerging technologies, including robust artificial intelligence (AI) and deep learning applications, should ensure they are responsibly and safely designed, manufactured, and integrated. The integration of robotics and deep learning technology under the Fourth Industrial Revolution provides opportunities for more efficient manufacturing processes [24]. However, various safety and ethical concerns arise with these developments that must be appropriately managed. This paper aims to address the need to properly consider safety and ethical perspectives when developing and deploying deep-learning-driven robotics used in aerospace manufacturing, assisting aerospace manufacturing companies to remain competitive in the USA. Concise, fact-based lists of safety and ethical considerations to address when deploying the aforementioned technologies are presented. Furthermore, mitigation measures and frameworks to address these concerns are provided.

Great advancements in robotics technology, especially with improvements to artificial intelligence and machine learning capabilities, are driving improvements to manufacturing processes across industry sectors. The aerospace manufacturing sector is attempting to keep pace with these developments by identifying how to introduce advanced robotics systems into production processes. Recently, a potential proposal to deploy deep-learning-driven robotics for a specific aviation component manufacturing process has been developed. However, as with any robotics or automation application, safety considerations must be at the forefront of the robotics system development. Furthermore, with advancements in artificial intelligence driving robotics systems capabilities, there is a growing need to understand the associated ethical implications of AI systems [25].

7. Conclusion and Implications for the USA Aerospace Industry

Aerospace manufacturing is among the most advanced sectors in the United States. However, excellence comes at the high price of complexity; aerospace products are far more complex than any contemporary consumer product. This complexity is compounded by the fact that most batches of aerospace products are produced in low volumes. Thus, aerospace manufacturing is a challenging field where big tech companies and deep learning enthusiasts are flocking. Recently, there have been efforts to explore the potential of neural networks applied to the space industry. Some of these efforts have been experimental, while others have already matured into commercially available products, tackling various areas and activities such as simulation, design, assembly, testing, and inspection. Robustness to complexity and uncertainty makes deep learning an intriguing candidate for aerospace manufacturing. Nevertheless, there are a myriad of considerations to address before employing advanced AI techniques like deep learning within production. Hence, deep learning applications within aerospace manufacturing are presented here, along with their potential implications for the USA aerospace industry.

Big tech companies embrace deep learning techniques for various activities within aerospace manufacturing. In the realm of simulation, motion prediction of other aircraft with deep learning models has matured into commercially available products used in full mission simulators. In addition, the automatic generation of simulation scenarios is being explored. Regarding design, designs generated from simulation models containing a physics-based element, commonly known as surrogate models, have matured into commercial products. More recently, there has been increasing interest in employing deep learning as a surrogate model in physics-based simulations. As for testing, the application of deep learning techniques for damage detection has matured into commercially available products; however, they only target simple structures. As for inspection, deep learning techniques have been successfully experimented with in non-destructive testing; however, no indication of maturity was observed. Common for these applications is tackling various forms of visual data, which is not surprising as deep learning and computer vision techniques have matured into commercial off-the-shelf solutions. Moreover, the majority of the deep learning applications, especially commercial ones, have taken the form of either add-ons to existing tools or single-function tools that only target specific issues. This targets concerns of robustness and uncertainty when employing advanced AI technologies. However, aerospace manufacturing is complex, and the monetary and time costs can be detrimental to simple add-ons. These dynamically adapted simulators are evaluating the performance of raw Airbus A380 flight control surface deflection data models on simulation environments.

Deep learning methods are being applied to the design of aerospace manufacturing systems to ensure robustness to complex, uncertain environments. The implications of such efforts for the USA aerospace manufacturing industry, considered a significant stakeholder, are analyzed. Robustness, interpretability, and trustworthiness issues arise when employing black-box deep learning methods within aerospace manufacturing, which motivates the transparent employability of simpler AI techniques. Currently available AI techniques that are simpler than deep learning and generalization in terms of system complexity are time and monetary cost-efficient. Specifically for simulation, complexity, uncertainty, and market pressure issues related to aerospace manufacturing challenges pre-trained aircraft models on simple, low-dimensional dynamics.

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