Towards AI-Assisted Smart Training Platform for Future Manufacturing Workforce

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***Abstract*—With the fast development of Industry 4.0, the ways in which manufacturing workers handle machines, materials, and products also change drastically. Such changes post several demanding challenges to the training of future workforce. First, personalized manufacturing will lead to small batch and fast changing tasks. The training procedure must demonstrate agility. Second, new interfaces to interact with human or robots will change the training procedure. Last but not least, in addition to handling the physical objects, a worker also needs to be trained to digest and respond to rich data generated at the manufacturing site. To respond to these challenges, in this paper we describe the design of an AI-assisted training platform for manufacturing workforce. The platform will collect rich data from both machines and workers. It will capture and analyze both macro and micro movement of trainees with the help of AI algorithms. At the same time, training for interaction with robot/cobot will also be covered. Mixed reality will be used to create in-situ experiences for the trainee.**

I. Introduction

With the fast development and experimental deployment of Industry 4.0, the ways in which workers operate machines and interact on the shop floor continue to change. For example, self-driving vehicles have been used at factories for material transportation [1]. Since these vehicles can be dynamically deployed in a factory, workers have to be trained to work with and benefit from the enhanced facility. As another example, multiple companies have been developing augmented reality (AR) based techniques [2] to help field workers improve their efficiency in locating items and repairing damages. These new techniques have an increasing penetration rate in the manufacturing industry.

Compared to the flourishing research and adoption of smart manufacturing techniques, the development of corresponding training facilities and programs falls behind in several ways. As described in the "Skills gap and future of work study" report by Deloitte and the Manufacturing Institute [3], 'despite manufacturers' focus on internal training programs, the pace of change still exceeds the extent and capacity of the training programs'. With the proliferation of personalized manufacturing, the workforce need to receive continuous reskilling and upskilling. However, the fast paced changes in shop floor tasks make it not-cost-effective to send the workers to a centralized location for training. Therefore, in-house training and learning courses, along with on-the-job training, are the preferred training methods.

Since the diversity of the training programs will be very high, the required resources and efforts to develop such programs need to be low to compensate its diversity. To satisfy this requirement, in this paper we describe the design of an adaptive and agile training platform. The platform will use multiple types of sensing techniques to collect rich data about the interactions between worker and machine/robot, worker and product, and worker and worker. The data will be stored at and analyzed by the system. Near-real time feedback or recommendations on subsequent training steps will be presented to the worker through mixed reality equipment. Note that this procedure is not a single circle loop. On the contrary, the worker's responses to the feedback or recommendations will be fed to the learning algorithms again. We expect the procedure to continuously improve the intelligence and accuracy of our system. The following figure illustrates the structure of the proposed system.

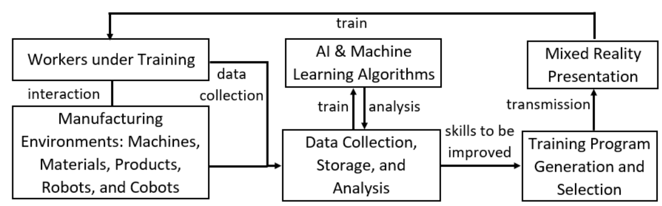

Fig. 1. Structure of the proposed training platform.

The contributions of the system, if succeed, are as follows. First, the proposed training platform is an integration of mechanical engineering, sensing, AI, and VR/AR. Different from existing systems that focus on using AR to train assembling tasks [4], our platform evaluates the performance of a worker during all phases of a manufacturing task. Second, our sensing devices will capture both macro and micro movement of the worker and the impacts of her/his operations on the machine and materials. Since all sensing procedures are non-intrusive, they are transparent to the worker without invading their privacy. Third, in addition to improving human/machine interaction capability, our system can also train future manufacturing workforce to collaborate with other workers or robot/cobot through mixed reality.

The remainder of the paper is organized as follows. In Section II we will introduce the enabling techniques of the proposed platform, present the details of each component, and discuss the challenges to implement the platform. In Section III we conclude the paper.

II. Proposed Training Platform

A. Enabling Techniques for the Training Platform

To build the proposed platform, we need the capability to capture, analyze, and visualize a large amount of both structured and unstructured data under near real time restrictions. To accomplish the task, we need to systematically integrate the advances in the following techniques.

II.A.1 Non-intrusive Sensing

Attaching sensors to a worker under training could impact her/his performance. Therefore, in this platform, we propose to adopt non-intrusive sensing techniques through the integration of high definition camera and wireless sensing. We know that the propagation of wireless signals can be affected by dynamics in an environment (e.g. a person walks by or a robot moves its arm). In the past ten years, the fast development of Multi-Input Multi-Output (MIMO) radio and millimeter wave (e.g. 5G) allows us to accurately measure such changes and map them to corresponding activities. It can accurately identify both macro movement (e.g. human walking [5]) and micro movement (e.g. hand gesture [6]). As an advantage of non-intrusive sensing, it does not require line of sight, thus enabling it to detect activities behind objects such as a wall. Fig. 2 shows the extracted point cloud and human skeleton with wireless signals when two workers jointly hold a box. These sensing data, together with the sensing results harvested from machines and robots, will provide abundant input for subsequent learning and decision making procedures.

Fig. 2. Wireless sensing results of worker interaction. (left) real life scenario, (right) wireless sensing results with point cloud and skeleton.

II.A.2 Artificial Intelligence and Machine Learning for Manufacturing

The training of future manufacturing workforce might post new demands in AI that are different from those in smart manufacturing tasks. For example, the self driving vehicles (SDV) on factory floor usually depend on image processing and object identification to plan moving trajectory and avoid collision. Our platform focuses on training workers to collaborate with these SDVs instead of improving their driving algorithms. Below we describe a few examples.

Example 1. Classification and Correction of User Behaviors: Current VR/AR based manufacturing training is often one directional. The worker under training wears a goggle and follows instructions to accomplish the task. The system does not provide feedback to the worker on whether or not she/he accomplishes the step correctly and how to improve it. In our platform, we can capture the details of such operations, compare them to those of an expert, and provide suggestions for improvement. In this way, the worker will be trained throughout the task instead of only on the task outcome.

Example 2. Analyzing and Assisting Soft Skills: Based on the Skills Gap report [3], in addition to the skills of handling equipment or products, future manufacturing workers will also need to have the soft skills such as programing a 3D printer on site. Our platform will be equipped with AI capability in this domain through analyzing previous programs by various workers. Using machine learning algorithms, we can identify missing components in a program and recommend changes to the worker. The platform can also execute a simulation of the program and project the working procedure and the final product to the user through mixed reality.

II.A.3 Augmented and Virtual Reality

The development and advances in augmented and virtual reality provide a new method for data presentation, user interaction, and knowledge discovery. In the past few years, lightweight wearable devices such as HoloLens, Oculus Quest, and HTC Vive make the new technology accessible to most researchers and many end users. There have been multiple experimental efforts to integrate AR/VR with smart manufacturing. For example, both BAE and Honeywell have used Microsoft's HoloLens to design mixed reality programs to improve user experiences and reduce learning curves for new skills. These programs turn a traditional manual based or video watching based training to the experiences that allow people to "go through the actions, with authentic sights and sounds".

Another widely adopted use case for AR/VR is for situational awareness at factory floor. Imagine an engineer walks into a working site. As her focus moves from one device to another, a window illustrating status data of the machines will automatically pop up onto the goggle that the engineer wears. Any abnormal data that needs immediate attention will be shown in bright colors.

B. Modules of the Proposed Training Platform

In this part, we will describe the detailed design of several modules in the training platform. We are especially interested in the role that AI can play in the components.

II.B.1 AI for Human/Machine Interaction

This module focuses on the training activities for the operation of a machine/product by a worker. When a trainee is first introduced to a machine, a mixed reality presentation of the operations of the machine will be shown on her goggle. Then step-by-step mixed reality based instructions will be illustrated. During the whole procedure, we will collect sensing data from both the machine under operation and the trainee. We can attach sensors that measure various parameters of the machine to characterize the operations of the trainee. For example, through measuring the vibration and power consumption, we can detect the abnormal state of an electric drive system [7]. Specifically, we can detect the current distortion, torque ripple, and speed ripple in the motor. The data can be compared with both the normal value ranges and the data previously collected from an experienced operator. We can provide recommendation for subsequent training activities based on analysis of the sensing results.

A similar approach can be applied to the non-intrusive sensor data that we collect from human actions. For example, previous research has shown that human factors in operations have a direct impact on product quality and defect rate [8]. Therefore, we need to monitor not only the manufacturing/assembly final product, but also the procedures. In our platform, we propose to use high frequency wireless signals (e.g. 6GHz) to measure the human actions. With the high frequency and short wavelength, we can detect fine granularity movement of human body and link them to the manufacturing tasks. AI algorithms can then be applied to derive out deviations from the expected operations.

The AI and ML algorithms that we plan to develop in this component are as follows. For the monitoring of machine states, we propose to use statistical learning models. For an individual parameter, we will experiment with neural networks (NN) and recurrent neural networks (RNN) with a Gated Recurrent Unit (GRU) when we consider that the parameter values form a time series following non-linear relationships. In the model, a single RNN layer is built by stacking GRU cells such that the output of one cell is the input of its adjacent cell. Since RNN could incur relatively heavy computation load, we will accomplish the training part off line by collecting and analyzing the system states during normal operations. To capture the relationship among multiple parameters, the vector autoregressive (VAR) model will be used. Considering the diversity of the manufacturing tasks, we need to decompose a task into the combination of basic operations of a machine. In this way, we need to train the model for only those fundamental operations of a machine. We can then treat a manufacturing task as the combination of these basic operations.

The classification and recommendation for human behavior is more challenging since even the same person may do the same movement slightly different each time. In our platform, we propose to use convolutional neural network to identify different human behaviors based on the wireless sensing results. We can use variances in reflected signals as a label to segment the human movement into basic actions. Once the actions are identified, we can compare them to the actions of an experienced worker to detect any deviations.

II.B.2 AI for Human/Robot Interaction

The challenge in human/robot interactions at the manufacturing sites comes from the fact that both sides have intelligence and are moving. Therefore, the trainee must adapt to the intellectual level and behaviors of the other party. For example, when two engineers work together on a task, they usually continuously communicate with each other to smoothen the collaboration. This procedure, however, must be accomplished in a different way when the engineer is working with a self driving cobot that can move at the speed up to 2 m/s. The AI algorithms in this component of the training platform do not focus on the design of a smarter robotic arm, but the design and improvement to the training programs for the engineers.

Communication of Intents between Human and Robots: The first task of this component is to design AI algorithms to evaluate and improve intent communication between human and robot. Different from a human/human collaboration environment in which people continuously express their intents through different methods, communication between human and robots has always been a challenge. From the robot's perspective, the teaching-learning-prediction model with extreme learning machine [9] has been used to predict a user's intention. Previous research uses either light or micro movement of a robot to express its intent. The shortcoming of the approach, however, is the assumption that such signals can be effectively captured and correctly interpreted by a user.

In our platform, with the adoption of AR and VR, we have a more effective method to communicate the intent of a robot to the user. Through gaze tracking, we can accurately predict the focus of a user. We can then project not only the moving intent of the robot but also how that movement will impact the user onto her mixed reality screen. Through the changes in gaze, we can also verify that the user has captured the information. The user can then instruct the robot to either hold or execute the intent based on her progress in the task.

Activity Selection to Improve Collaboration: The second task that AI algorithms will assist in the training of human/robot collaboration is selection of training activities. During the training procedure, either party may make mistakes. For example, during a hand-over operation, the user may misinterpret the signal from the robot and underestimate the weight of a part. Similarly, during a collaborative assembly task, the user may mis-instruct the robot and cause delay of the delivery. Another reason that we need to select additional training activities for a user is the software update for a robot and the user may need to re-adapt to the changes. During these procedures, our platform will capture and analyze both the successful collaboration and the failures in oder to make recommendations.

While the failures may be shown in different formats, the goal of the algorithms is to identify the common root or factors that lead to such failures so that our platform can recommend subsequent training programs for improvement. There are several families of algorithms worth exploring. The convolutional neural network (CNN) can integrate feature learning and defect diagnosis in one model. The types of mistakes can be derived out from the correction efforts (e.g. return and switch of selected parts from the robot). Since CNN was originally designed for image processing, mapping the input data to a two-dimensional space will generate better results. Deep Belief Network has fast inference as well as the advantage of encoding high order network structures by stacking multiple layers of Restricted Boltzmann Machines. Therefore, it will demonstrate advantages in analyzing more complicated tasks. For both models, auto encoder can be used for unsupervised feature learning, and the learned features will be fed into the platform for model training and classification.

II.B.3 Integrating AI with AR/VR Mechanisms

As we describe in earlier sections, to provide fast adaptation and reduce training cost, AR and VR will be widely used in the training platform. Such techniques need to be tightly integrated with AI algorithms to maximize their impacts on workforce training. As the first example, instance segmentation using the Mask R-CNN [10] and markerless AR can be integrated to present the three dimensional mapping of an object onto its surrounding environment. It is a deep learning network that adds a convolutional layer to the Faster R-CNN for instance segmentation. It can run at near-real-time for region division and object identification.

Another place that AR/VR and AI mechanisms can be integrated is the digital twin model. The digitization of machinery and production systems in the manufacturing industry led to the development of the digital twin concept. It facilitates the means to monitor, understand, and optimize the functions of various types of machines. To make sure that the model accurately captures the properties of a physical device, deep learning based approaches have been adopted to characterize the running states and deterioration of a machine. Since sensors and actuators installed on the physical machine will seamlessly sample and transmit data to the digital system, changes in the physical device or deviation between the digital model and the real machine can be quickly captured. The VR/AR device can then provide the information to the user under training and request for adjustment. While the former type of changes usually demands maintenance decisions by a user, the latter type needs the user to adjust the parameter of the digital model. Our platform can be used to provide training in both categories.

The third place at which AI and mixed reality can integrate is the training of programming skills for robots/ automation. Based on [3], 40% of US manufacturers consider robot programming as needed skills for future manufacturing workforce. Although nowadays the robot programming environment has already achieved modular design and drag-n-drop style [11], workforce training in this domain still needs a lot of efforts. With mixed reality technique, after a program is generated by a user, its simulated execution procedure and the final product can be illustrated to the user. In this way, the worker under training can immediately see the results of the program before it is actually executed on a physical device. Since the product of a manufacturing task could have complicated 3D structure, mixed reality based illustration is appropriate for the task.

C. Challenges

To implement the proposed training platform, we need to overcome the following challenges. First, the diversity of potential applications is very high. Therefore, the platform must provide easy-to-use interfaces and semi-automatic education material generation capability so that training materials can be developed in a cost-effective way. At the same time, we need to provide a set of APIs that allow other developers to easily insert both structured and unstructured data into the analysis and learning algorithms. These properties will enable wide deployment of the platform in manufacturing industry.

The second challenge that we face is to decompose a series of user actions into basic operations so that they can be compared with the experienced workers' operations. Human actions can be quite different even when they are trying to accomplish the same task. At the same time, a person could add a lot of unrelated micro movement into a task (e.g. touch his hair or nose). These noises do not directly contribute to the training procedures. Therefore, our algorithms must be able to detect and filter out such operations. Our team members working in kinesiology will apply their expertise to help the system decompose a complicated action into multiple operations.

The third challenge that we face is automatic parameter choices or adjustment for different AI algorithms. Previous research shows that the values of parameters in AI and ML algorithms could have severe impacts on the accuracy and efficiency. When the platform is applied to a new application scenario, although the potential choices of AI algorithms could be zoomed in to a few candidates quickly, the tuning procedure of parameters could demand quite some efforts. Our platform will learn from previously established models to guide the parameter choice procedures.

III. Conclusion

In this paper we describe the design of a training platform for future manufacturing workforce. Our platform will integrate sensing, learning, analyzing, and presentation into one system. Through sensors installed on physical devices and non-intrusive activity recognition, we can collect rich data about a user's training operations. Machine learning based approaches will then be adopted to analyze her/his actions and identify skills that need improvement. Training program will then be recommended. This procedure will repeat until the user satisfies all training requirements.

With the fast development and adoption of technology in manufacturing industry, many companies have noticed a widening gap between the jobs that need to be filled and the skilled talent pool capable of filling them. Therefore, the development of an adaptable and easy-to-deploy training platform that allows end users to customize and implement their training programs with a low cost is essential for the sustainable development in this domain. Our proposal explores needed efforts in this direction.

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