Human-robot Collaborative Assembly and Welding: A Review and Analysis of the State of the Art

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Abstract: This paper reviews and analyzes the recent progress in human-robot collaborative (HRC) technologies that enhance assembly and welding processes. It focuses on how the HRC approach helps improve assembly and welding productivity and quality, while enabling complex process operations that cannot be accomplished by humans or robots/machines alone. It also discusses the basic elements in HRC approaches, including (1) human sensors, (2) signal processing for extraction of human intent from sensors, (3) presentation of information to the human for their reaction, obtained from environmental sensors that monitor the environment, machines, and processes, and (4) interface control, which manages how information is presented to the human, what reactions are expected from the human, and what needs to be presented next. Finally, it summarizes the state-of-the-art in the major elements and application accomplishments, identifies challenges for greater benefits, and proposes directions to address these challenges.

1. Introduction

The manufacturing industry has undergone a significant transformation in recent years with the increasing use of automation technologies, particularly robotics, which have been shown to improve production efficiency, product quality, and reduce manufacturing costs. However, robots/machines often require intelligence to adapt to complex jobs, which can be job-specific, complex, and difficult to learn. While human operators can train their mental "neural networks" and develop the required process intelligence, transferring this knowledge to machines is often not straightforward. Human-robot collaborative manufacturing (HRCM) offers a solution that combines the accuracy, repeatability, and physical strength of machines with the adaptation and quick learning abilities of humans in operating processes.

Casting, forming, machining, joining/welding, additive manufacturing, assembly, and coating are among major manufacturing processes. The latter four share a common goal of locally connecting materials together. In particular, while the connection by assembly is considered reversible, joining/welding, additive manufacturing, and coating connect materials in irreversible ways and can be considered welded. Assembly and welding are thus two major types of materials connection processes. As the final goal of manufacturing is to finish a product that integrates/connects parts together in the designed ways, welding and assembly thus play important roles in manufacturing. As our focus is assembly and welding, this paper analyzes the state-of-the-art of human-robot collaboration (HRC) in assembly and welding.

We conducted a search in Web of Science for publications in the past five years with key words <weld OR assembly> AND <human> AND <machine OR robot> AND <manufacturing> in all fields and uncovered 74 publications [1-74]. A basic function of HRCM is for a human to control a machine/robot. To this end, the human must send a signal that may be understandable by the robot. Acquisition of such signals, referred to as human signals, can be referred to as human signal sensing. The acquired signals often require certain processing to become understandable. Human signal sensing and processing of human signals are thus two basic functions in an HRC system. To integrate human intelligence, the human must also be immersive despite if the human is actually at, or away from the manufacturing. Virtual reality (VR), augmented reality (AR), and mixed reality (MR) equip humans to realize and improve immersion with AI enhanced sensing and seamless guidance.

This review paper aims to assess the current state of research in the following areas: (1) Human Sensing, which explores the use of sensors to detect various aspects of human behavior, including motor movements and intentions, and the methods used to process sensor data to extract this information. (2) Information Presented/Visualized to Humans, which investigates the types of environmental information that are presented to individuals to facilitate interaction with their surroundings, including other humans, machines, robots, and processes. (3) Immersive Technologies, which examines the hardware platforms and commercial products employed to create augmented, virtual, and mixed reality environments that enable individuals to better engage with their surroundings. (4) Intelligent Human-Machine Collaboration, which explores the ways in which humans and machines/robots can collaborate to increase intelligence and adaptability of their counterparts in complex human-robot systems. (5) Challenges and Opportunities in Human-Machine Interactions, which examines the obstacles and prospects associated with the development of more intelligent human-robot collaborative manufacturing processes.

This paper is organized as follows: Section 2 will provide a few exemplar applications to demonstrate human-robot collaboration in order to provide an overall picture. The following sections, Section 3-6, will review and analyze the details in Human Sensing, Information Presented/Visualized to Humans, Immersive Technologies, and Intelligent Human-Machine Collaboration. The Challenges and Opportunities in Human-Machine Interactions will be identified in the conclusion Section 7.

2. Human-Robot Collaboration Examples

Example 1: Robot Assistance to Human for Assembly [2]

Sanna et al. [2] presented an example of an assembly application where a human assembles parts together in the Assembling Area (close to the human) and a robot picks the next part to be assembled from a Picking Area (out of reach of the human, with many parts) and then places it in the Releasing Area (close to the human with only the next required part). The robot's assistance improves the efficiency of the human worker. A key question here is how the human instructs the robot to pick the correct part when needed. This is accomplished through the NextMind, which senses the human's intention and communicates with the AR. The AR, with a HoloLens 2 as the platform, presents options to the human to make a selection.

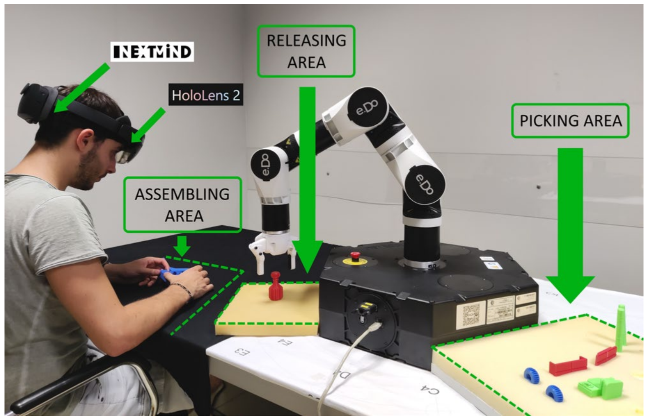


Fig. 1 Robot assistance to assembly by human operator [2].

The NextMind is a wireless device that can be worn like a headband to detect brain activity using nine electrodes located at the back of the head where the visual cortex is located. The device consists of two main components: NeuroTags and NeuroManager. NeuroTags are unique visual signatures that are identified by blinking textures and allow the user to control objects in the scene. Here "blinking textures" refer to a visual pattern that NeuroTags use to identify specific objects in the scene. These textures are created by rapidly changing the color or brightness of a pattern at specific frequencies that correspond to each unique NeuroTag. When the user focuses their attention on an object associated with a specific NeuroTag, the NextMind device detects the corresponding blinking texture and generates a response in the user's brain, which allows them to control the object. NeuroManager manages the communication between the NeuroTags and the NextMind engine, which processes signals received from the electrodes. The device can be paired with other devices that support Bluetooth and has been used in studies to compare the performance of selection using gestures versus brain-computer interfaces in augmented reality interfaces.

We above mentioned that the user makes his/her selection by focusing on the respective NeuroTag in his/her view among those displayed. The display is done using a Microsoft HoloLens 2, which is transparent without interference to the human vision/operation or can display visual information to the user when commanded. When a section is made, all corresponding parts are displayed. Two NeuroTags are associated with each part: Explore and Select. In Explore mode, the user can achieve more information about the selected component, change the representation from solid to wireframe, rotate the object, select the object, see a video about the object, and skip back to the visualization of all the section components. In Select mode, the robot is directly activated to pick the selected object. The selection mechanism is triggered by the user focusing on a NeuroTag for a given time, e.g., two seconds, and a growing circle is associated with the selection mechanism to provide more efficient feedback than the standard three green lines forming a triangle. The gaze-tracking constraint is also activated for the main menu scene so that the selection panel can always be displayed in front of the user. Finally, the calibration scene allows the user to calibrate the NextMind device, and a graphical representation denotes the quality of signals received from the electrodes.

Example 2: Human Commanded Robotic Assembly Tasks [3]

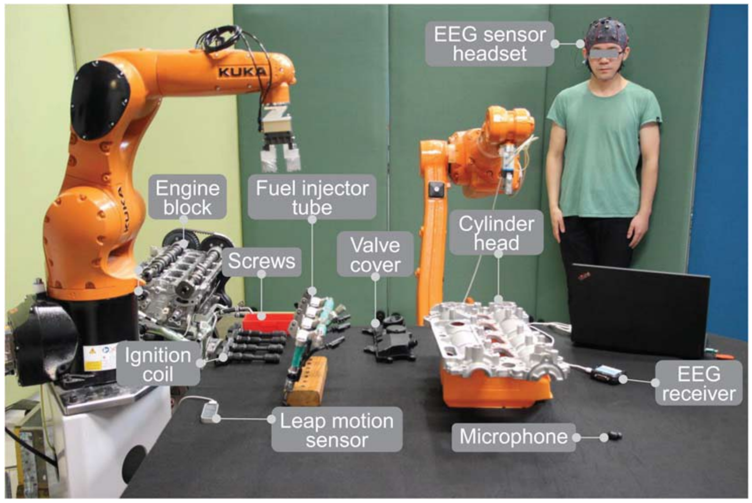


Fig. 2 Experimental system for human-robot collaborative assembly [3]

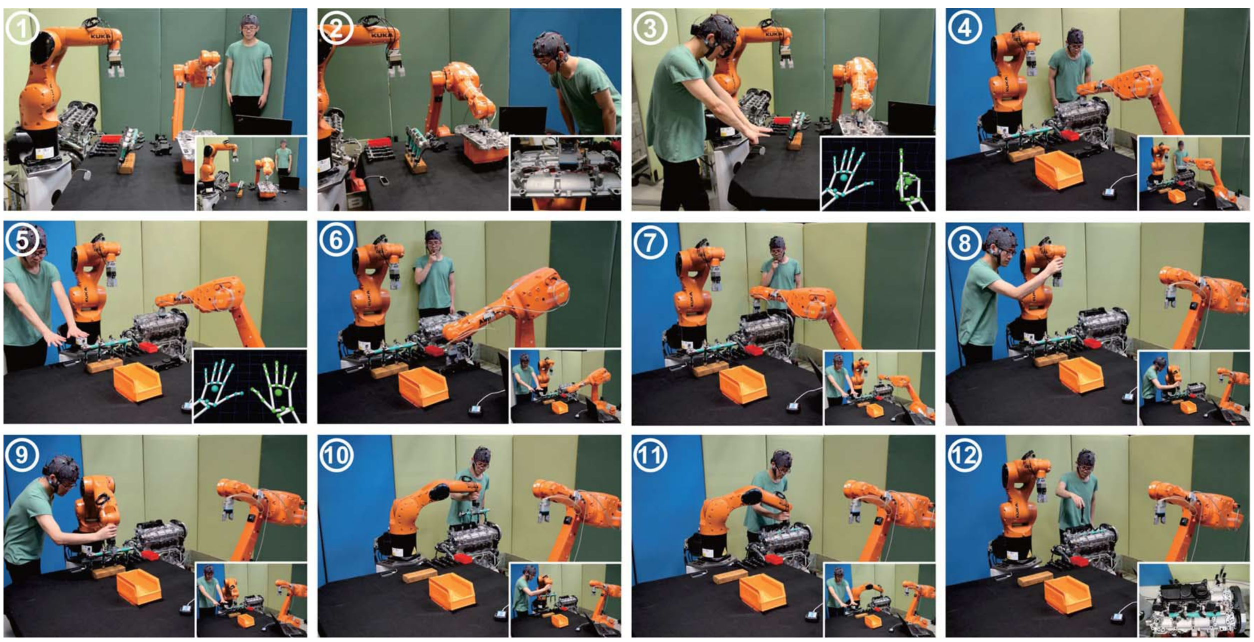


Fig. 3 Human-Robot Collaborative Assembly Process [3]

In the above example, the assembly is finished by the human and the robot assists the human. In this example, the job is done by robots commanded by human who is sensed by various sensors using the experimental system shown in Fig. 2 which is connected to a team of robot controllers via Ethernet. An external computer processes the signals from a Leap motion sensor (a kind of motion sensor that integrates cameras and infrared LEDs for being capable of observing a roughly hemispherical area to a distance of about 1 m and tracking fingers or similar items to a spatial precision of 0.01 mm), a microphone, and an EEG sensor headset. The assembly process involved first fitting a cylinder head (weighing 3.4 kg) onto the engine block, placing a valve cover on it, fastening screws, and then accurately inserting an injector fuel tube (weighing 1.8 kg) into the cylinder head's holes. Finally, the operator assembled the ignition coils.

The assembly process has 12 steps illustrated in Fig. 3: 1) Brainwave commands the first robot to place the cylinder; 2) The first robot is controlled to move to the cylinder head and fit the gripper's fingers with millimeter-level tolerance. 3) Gesture 1" is used to control the gripper to grasp the cylinder head; 4) Brainwave commands the first robot to place the cylinder head onto the engine block, and the operator checks the alignment of the cylinder head with the engine block; 5) "Gesture 2" is used to open the gripper at a specified level; 6) The assembly of the valve cover is initiated by a voice command, which instructs the first robot to move from the engine block to the valve cover using "Up," "Left," and "Down," respectively. Once the gripper fits with the component, a hand gesture (Gesture 1) is posed to close the gripper; 7) The operator issues voice commands to control the first robot to place the valve cover on the engine block, followed by fastening screws, and enables the "open" of the gripper via the hand gesture; 8) The accurate assembly of the fuel injection tube starts with sensorless haptics control. During the assembly, the detection threshold of the external force applied by the operator to the second robot can be up to 2 Nm. The admittance controller is adopted to transform the contact force into reference position and velocity with adaptive admittance parameters; 9) Fine manipulation of the second robot is achieved by adjusting the admittance parameters. Within the context, a low-speed and accurate robot motion control assists in the appropriate fit of the gripper into the fuel injection tube, followed by the close gesture of the gripper control as shown in the inset; 10) The operator forces the second robot to move the tube to the engine block and align it with the holes of the cylinder head, and the inset shows one of the haptic control operations during assembly. A relatively large force is applied to the robot for a fast motion; 11) A fine adjustment of the orientation and position of the end-effector at a low speed facilitates accurate insertion of the tube into the cylinder head's holes, followed by opening the gripper via the gesture in the inset, as well as the quality check of the insertion operation; 12) The operator assembles the ignition coils and secures the components by fastening screws, and the final assembly state of all the components is shown in the inset.

In this example, two robots are controlled by a human operator to complete a number of tasks. The human commands are detected by multiple "human sensors," and the signals are processed using advanced techniques, which will be discussed in detail later. However, the humans and robots do not operate or process a common object. In [8], the robot holds a workpiece while the human co-worker performs assembly operations on it.

Example 3: Comprehensive Use of Augmented Reality [23]

This example demonstrates a comprehensive use of AR in human control of robot trajectory, utilizing a finite state machine (FSM) as the control logic (refer to Fig. 4). The FSM has four states (states 1-4), and each state can transition in two directions - advancing to the next state or not advancing. User eye blinks, categorized into three types (normal, double, and long) and detected through EEG waveforms, control these state transitions. Normal blinks are ignored, while long and double blinks correspond to advancing and not advancing, respectively. If not advancing, the particular action depends on the particular state. Throughout all states except for state 1, the human eye blink is a reaction to what is displayed by the AR on the HoloLens.

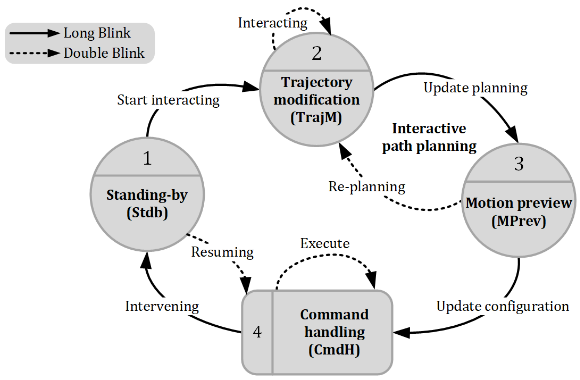


Fig. 4 FSM and HRC based robot programming [23]

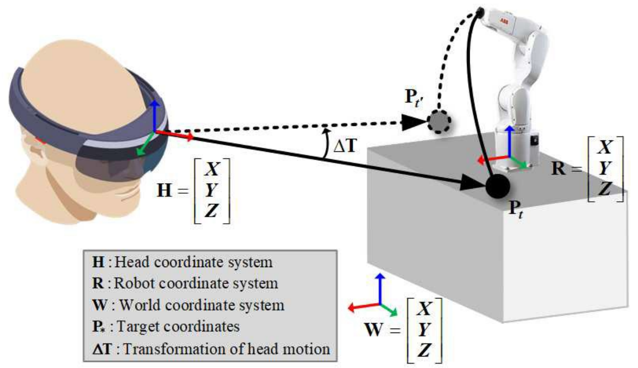


Fig. 5 Real-time adjustment of the target point by head pose [23].

In all states, if no "abnormal" eye blinks (double or long blinks) are detected, no changes are made, and the system continues to do what it is currently doing. For example, in state 1, this implies "waiting." In state 2, where the robot's trajectory is programmed, the user first interacts with the visual display in the HoloLens to determine the final target point. This can be seen in Figure 5: the user's head pose (coordinate system H) aims at the target point, and the distance from the head pose to the target point is the same as the distance between the head pose and the robot's TCP (tool center point). When a double blink is performed, the target point is fixed, and a proposed trajectory is displayed. This displayed trajectory toward the target point consists of several points in the display. In the Trajectory Modification stage, also in state 2, the user can focus on a point in the trajectory and then perform a double blink to choose it as an intermediate point in the trajectory. This point changes color to blue to confirm the selection. Each time an intermediate point is confirmed, the trajectory is updated. Then, the user can focus on additional points if needed and select them by performing a double blink each time to choose additional intermediate points. Once all the intermediate points are selected, the user performs a long blink to leave state 2 with the updated trajectory to advance to state 3. In state 3, the user is displayed with the virtual movement of the robot along the trajectory for preview. If it is unsatisfactory, a double blink sends the system back to state 2. Otherwise, the system advances to state 4. In state 4, the user waits (no abnormal blinks) or accepts the trajectory and commands the robot to execute it with a double blink or restarts the programming with a long blink to advance to state 1.

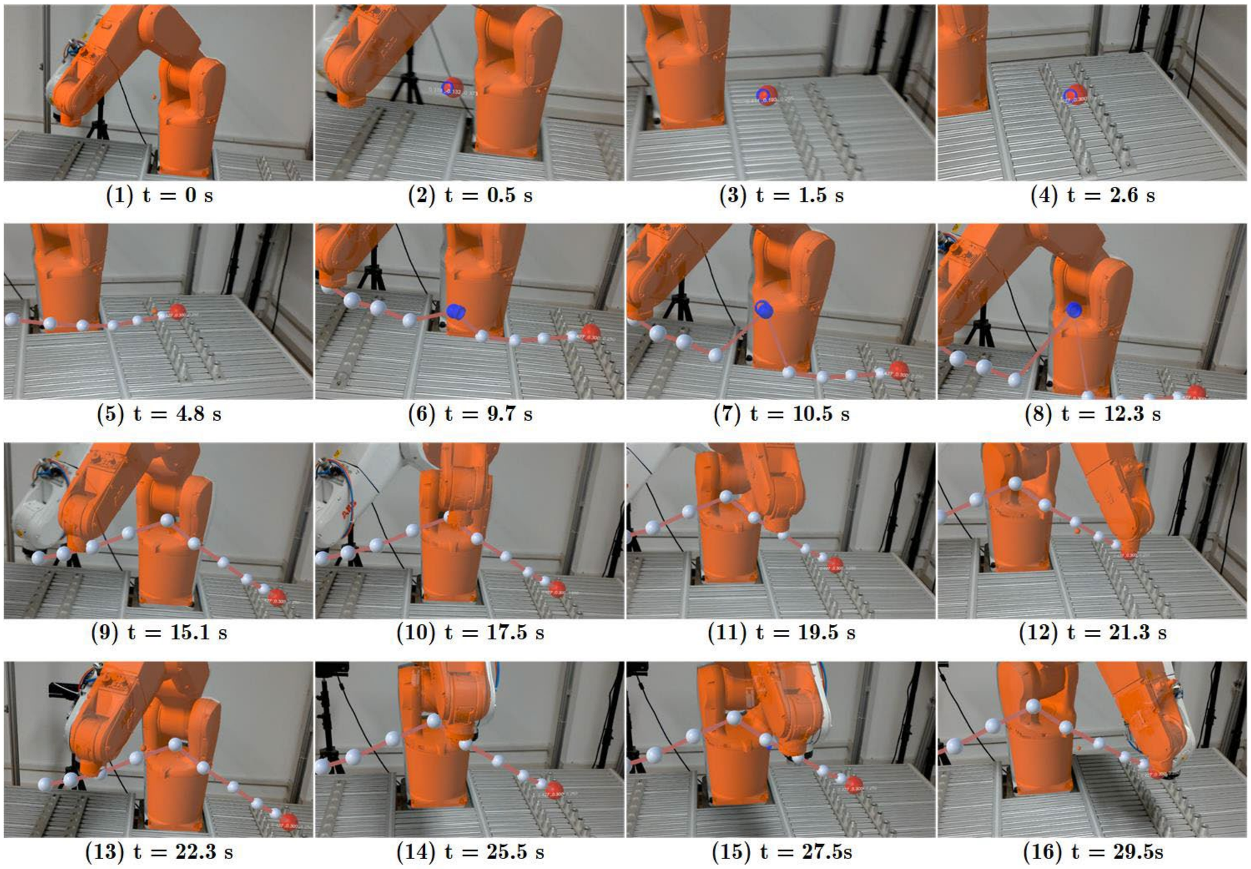
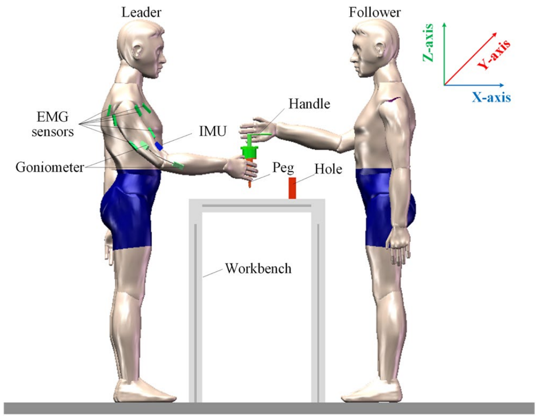


Fig. 6 Application of AR enabled robot programming [23].

Fig. 6 shows a programming for robot by user with interaction with AR through HoloLens using the displays to the user. The interaction began with a long blink by the user at t=0s, which triggered the state transition from state 1 to state 2 for the interaction where human first determine the final target point which is indicated in the HoloLens snapshot by a red sphere appeared in the user's field of view. This point moves as the head pose moves (Fig. 6(2)-(4)) and always appears in the center of the user’s view in the HoloLens display. At t=2.6s (Fig. 6(4), the user performed a double blink to fix the target. In Fig. 6(5)-(8), an intermediate point is selected and confirmed. In Fig. 6(9)-(12), the user is displayed with a preview of the robot trajectory being considered for execution. In Fig. 6(13)-(16), the robot executed the programmed trajectory.

Example 4: Coordination Learning [36]

The examples presented earlier only involve jobs that are separatable and can be assigned to different team members. Complex jobs may not be separable and require coordination among team members to effectively perform. This highlights the crucial role of coordination in certain complex manufacturing tasks that require the collaboration of robots, machines, and humans. The study in [36] studies a particular coordination that involves followers adapting their motion speed by detecting changes in external force information and working closely with the leader. To study this type of coordination, human leaders and followers are used to provide the needed data in this study [36].



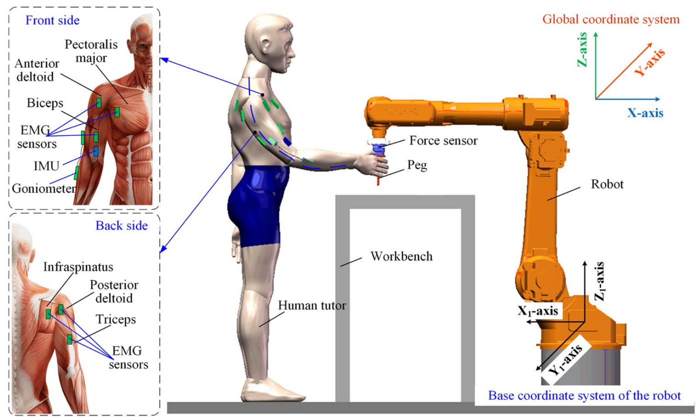


Fig. 7 Learning experimental set-up [36]

Fig. 8 Experimental set-up to generate data to train a force estimation model [36]

Fig. 7 shows the human-human experiment that is used to collect the force imposed by the leader and the speed from the follower. They are the input and output of the model to be learned. By using this model, a human leader can operate a robot and the robot can provide the right speed as a response to the force imposed by the human. This right speed from the robot is calculated using the learned model from the detected force. For the robot follower, a force sensor can be installed and the envisioned human-robot collaboration can be implemented. However, to learn this model, we need (force, speed) data. The experimental set-up in Fig. 7 can provide the speed of the follower but not the force imposed by the leader directly. As can be seen in Fig. 7, the leader has been installed with various sensors. The hope is that the force imposed by the leader can be estimated from the signals from these sensors.

To estimate the force from the sensor signals, an experimental set-up shown in Fig. 8 is used to generate sensor data and measure the corresponding force by the force sensor installed on the robot. They will be the input and output of the force estimation model. With this model, the force in the experiment shown in Fig. 7 can be estimated so that the leader-follower model can be learned. As such, the experiments shown in Fig. 8 need to be conducted first. To this end, the arm is attached with six EMG sensors that are distributed on different locations of different muscles, two goniometers, and one IMU sensor. A peg is connected to a robot arm and the human operates the peg.

Example 5: Coordinated Human-Robot Collaborative Welding [13, 90]

This example demonstrated a control, coordinated by a human and robot, for precision welding, which requires control of both the weld bead (surface appearance) and weld penetration (internal quality). This is a job that demands not only extensive training and practice to appropriately respond and adapt to observed process phenomena, but also physical strength and motor controllability to hold the welding torch steadily and move it smoothly and accurately while making necessary adjustments. However, this is challenging for both robots and human workers. Appropriately responding and adapting to observed process phenomena depends on the human's understanding of welding phenomena and process dynamics, which is acquired through training and practice. Such understanding is unstructured and difficult to explain or export. This is a major challenge in robotizing such a welding process for precision welding. On the other hand, human welders, regardless of the training, practice, ageing, disability, etc. are all subjected to different limitation in physical strength and motor controllability to provide the needed steady, smooth, and accurate movement and adjustment. Such limitation is in general not concerned for a robot but developing/equipping the intelligence and adaptation for a robot requires the knowledge about welding phenomena and process dynamics human gain through long training and practices. A human-robot collaborative approach to combine human intelligence and machine physical strengths and repetition provides an effective solution.

Fig. 9 demonstrates this welding job which is the root pass of the welding for the groove joint. For this job, the welding torch is supposed to weave transversely while moving along the central line of groove longitudinally. Ideally, the frequency and amplitude of the weaving need to be consistent during welding. This repetitive job is thus fully controlled by the robot through programming. The welding process also needs to be controlled to produce the needed weld bead and weld penetration as the bead and penetration are subjected to the influence of the welding conditions whose accurate control is considered not realistic. This requires a major welding parameter be real-time adjusted per the feedback of the welding process. In this example, the welding speed is chosen as the welding parameter that is adjusted in real-time. This is challenging for the robot to undertake as it must be based on understanding of process phenomena and process dynamics but may be better done by human. As such, fusing the actions from the robot which carries the welding torch to move forward and weave and the responses from the human which adjusts the welding speed to form a coordinated control is an appropriate solution.

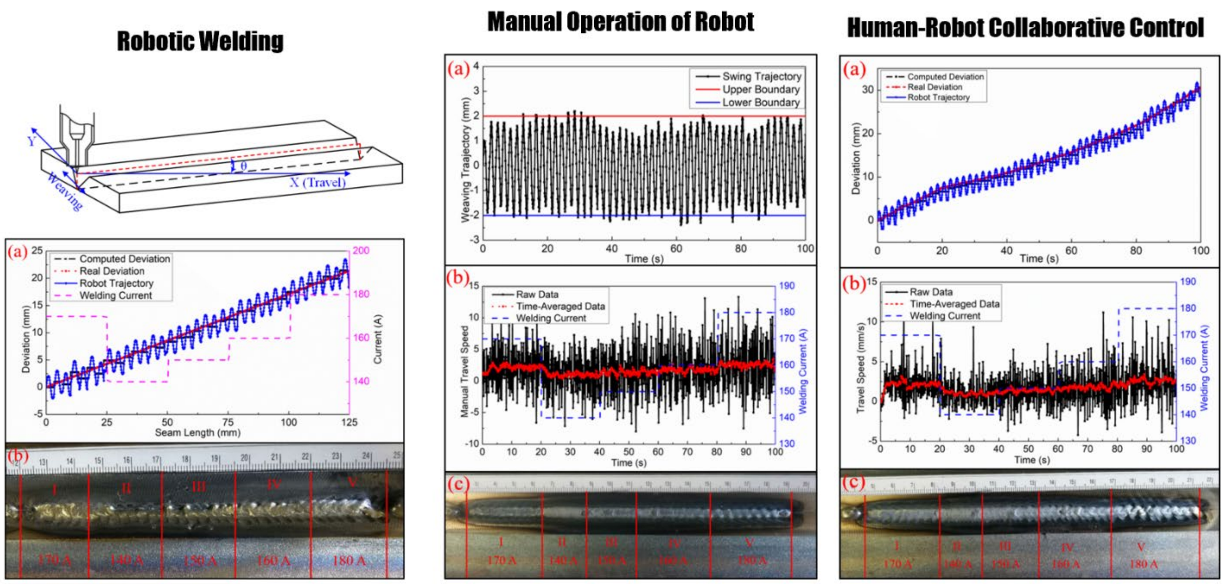


Fig. 9 Comparison of human-robot collaborative welding result with robotic and manual welding results [90]

As shown in the left of Fig. 9, the robot is purposely programmed to carry the torch to travel in a direction deviating from the central line of the groove. As the torch also weaves transversely, the groove is scanned. The arc voltage increases approximately proportionally with the arc length, the distance from the torch to the work-piece surface. The arc volage is used to estimate the lowest point (where the arc voltage is the highest) for the robot to adjust its weaving center but not the weaving frequency and amplitude. As such, robotic welding has a consistent weaving pattern while assuring the weld be made at the right position. However, the welding current is purposely changed to generate a condition, which should be caused by the deviation of welding conditions from the nominal ones, where real-time adjustment of welding speed is needed. As there is no adjustment from the robot for the welding speed, the produced weld bead (appearance) changes with the changed condition (current) and is thus not consistent as can be seen from the picture of the produced weld. In the middle of Fig. 9, the welding is done manually by a human welder. The weld appearance looks much consistent despite the changed current, but the weaving is not consistent. The weld appearance is much more consistent although the inconsistence on the weaving should also have affected the consistence of the produced weld but the adjustment of the welding speed partially compensated. The right of Fig. 9 shows the result from fused coordination from human adjustment in speed and robotic movement where the weaving and the produced weld bead are both consistent.

A human-robot collaborative system is needed to realize this coordinated process control. To this end, a system shown in Fig. 10 has been developed where a human views the welding process from the display of an augmented reality (AR) system and operates a virtual torch which is light and easy to control. The sensors of the AR system capture the movement of the virtual torch. The speed can be calculated from their signals and human operation errors and fluctuations can be corrected/filtered. The corrected/filtered speed as a better representation of the human intent is sent to the robot for execution. The robot fuses the real-time adjusted speed with its movement program to form the entire command of the robot movement. The robot also carries a camera that provides the raw information of the welding process feedback for the AR system to generate the information on the display for the human to view the welding process away from the welding site as being present (immersive). As such, human and robot are effectively coordinated to outperform over human and robot for a complex welding job.

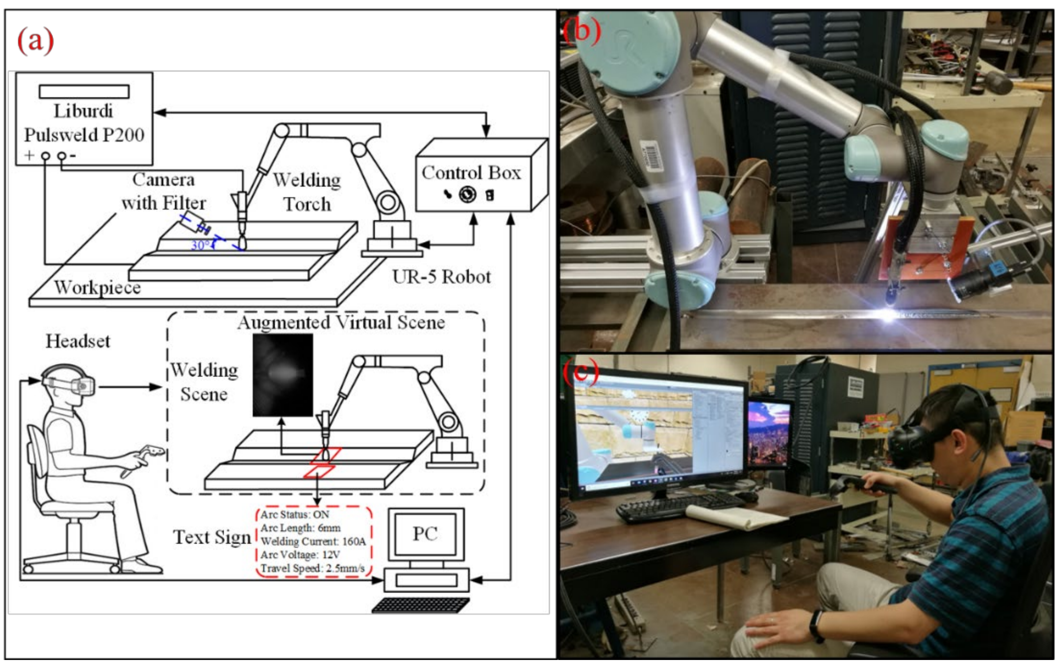


Fig. 10 Human-robot collaborative welding system [90].

Example 6: Human-Robot Collaboration for Micromanufacturing [75]

Micromanufacturing refers to the process of fabrication, alignment, attachment, packaging, and testing devices whose components span across several dimensional scales, nominally from 1 µm to 1 cm. Examples of such systems include many of the sensors in use today in consumer electronics, as well as

Micro-Opto-Electro-Mechanical Systems (MOEMS), that have active parts for processing motion, light, fluids, and so on. Due to the stringent precision requirements, automated handling of parts has long been recognized as a better way to complete micro-assemblies, in terms of both time and accuracy. A microassembly system typically consists of precision robots, one or several visual microscopes to monitor the assembly scene, and other, finer resolution sensors for final alignment steps with sub-micron accuracy that are often needed [76]. Although part handling can often be automated, calibration and bonding/processes often require human intervention, due to difficulties in compensation of unknown process conditions such as temperature, humidity, lighting, stiction, etc. These play a much more important role as disturbances at the small scales, than at the larger scales, and often prevent full automation of manufacturing. The NeXus is a custom micromanufacturing platform that contains five precision robots working in tandem to perform tasks such as additive manufacturing via Aerosol and Inkjet printing, thin-film curing via Intense Pulse Light (IPL), robotic microassembly, wirebonding and inspection, Fused-Deposition-Modeling (FDM) printing with a 6 DOF robot, electronic pick and place, and textile weaving and interconnect for wearable devices. The system is depicted in Figure 11. An operator interface consisting of a display system and joystick is used on the NeXus to bring the human operator into the micromanufacturing decision and execution processes.

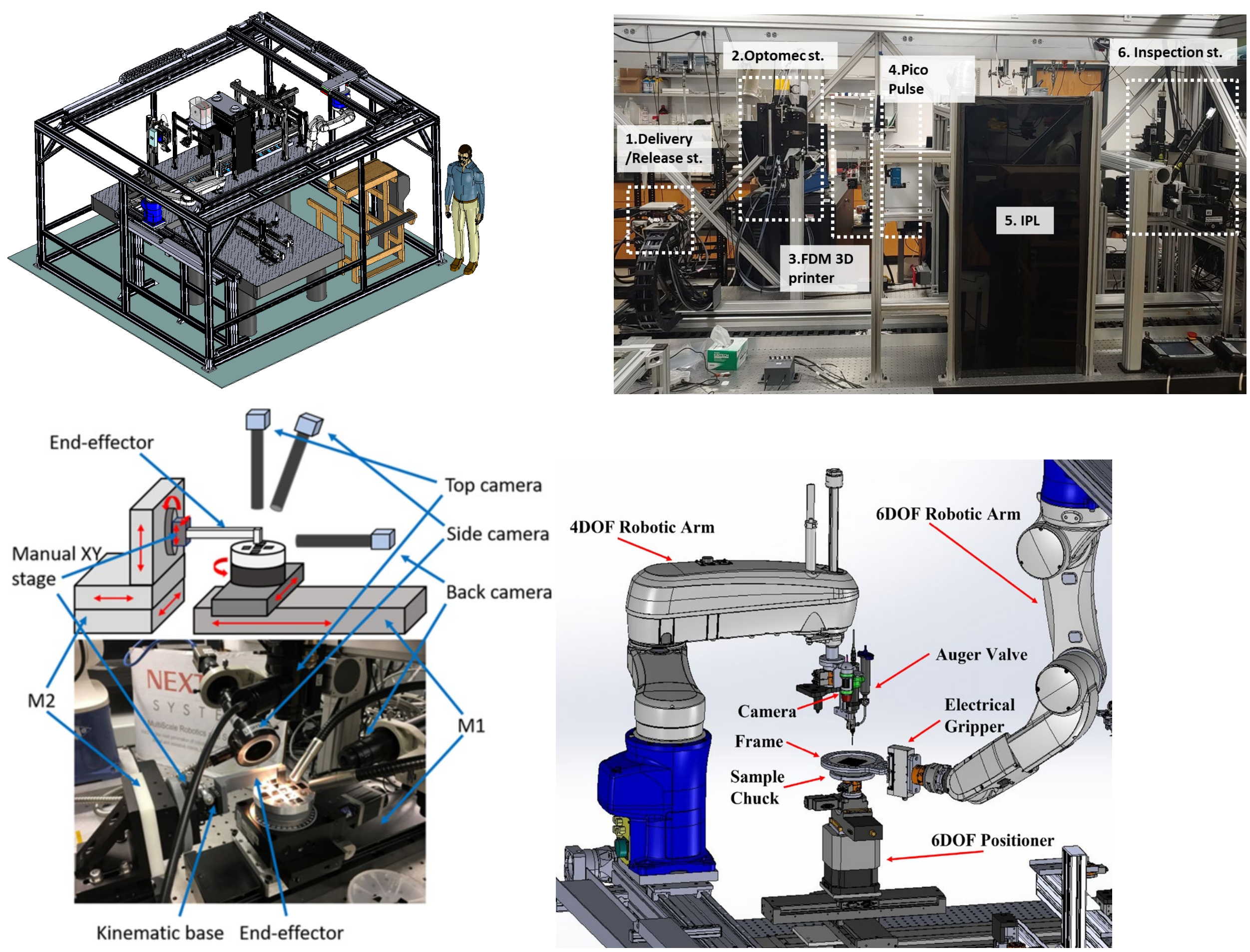


Fig. 11 NeXus robotic additive micromanufacturing system, showing overall design (top, left), automated thin-film aerosol jet printing, curing and inspection line (top, right) [75], microassembly station (bottom, left) [9], and 3 – robot collaborative fabric interconnection diagram (bottom, right) [76].

Because a high magnification is required for the microscope to see the assembly site and features of interest, tradeoffs including limited field of view, sensitivity to ambient lighting, and occlusions due to micro-gripping tools must be navigated by the operator in a semi-automated fashion. Additionally, attachment processes such as dispensing of adhesive fluids, alignment of probes for electric contact or strain testing also require human intervention to interpret visual results, and achieve situational awareness in the assembly scene, and compensate for the lack of tactile feedback.

In a study, we evaluated the performance of the user interface of our microassembly subsystem while performing assembly of a microrobot using semi-automated capabilities vs. complete teleoperation. Results clearly show that by automating 10 of the 13 assembly and packaging processes, mostly those related to alignment, assembly target identification, and motion execution, we increase assembly precision by an order of magnitude, while also slightly improving the fabrication time. The manual processes (e.g., those not automated) included difficult to perform adhesive dispensing, recovery from failed assembly, and inspection, where the operator's experience is critical. Furthermore, by automating many of the precision alignment processes, the mental workload on the operator was considerably reduced during the operation of the NeXus [9].

3. Key Elements in Human-Robot Collaborative Systems

The goal of an HRC system is to either improve manufacturing productivity, assure quality, or accomplish jobs that are not possible to achieve by either humans or robots alone. Improving productivity involves allowing humans and robots to work in close proximity on separate subtasks, and ensuring the safety of humans in such an environment is often a primary concern for HRC systems. Assuring quality requires combining the actions and decisions of humans and robots to accomplish a task.

Despite the goal, an HRC system typically has the following key components: human sensors that monitor human intent (such as commands, reactions, and actions), signal processing that interprets human intent from human sensor signals, presentation of information to the human for them to react, environmental sensors that monitor the environment, machines and processes to obtain the raw information that needs to be used as the basis for presenting to the human, and interface control that manages how the information is presented to the human, what reactions are expected from the human, and what needs to be presented next and expected. Additionally, there are humans and robots. These components form an HRC system as illustrated by Fig. 12.

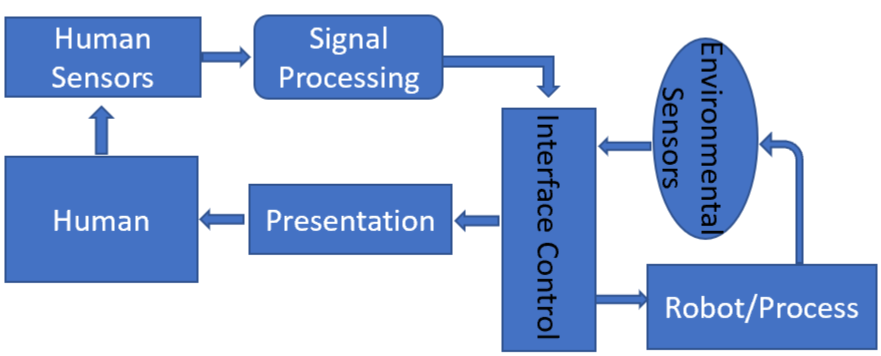


Fig. 12 Principle of HRC system

As can be seen, interface control is the core of an HRC system. It decides when to present what information to the human, in what way, what human intents to expect, and what to do next, including what to present further or what to inform the robot. The information sources it receives include processed human sensor signals and processed environmental sensor signals, but it further processes these signals using technologies such as deep learning, augmented reality, etc., to decide what to present and how to control the robot. The presentation to the human is typically realized in a way such that the human feels being at the process and within the environment. This is the immersive requirement and is better realized using VR, AR, or MR.

3.1 Human Sensors

The following sensors have been used to monitor human reactions, actions and intents: (1) External Sensors: voice sensors, and motion sensors including vision/cameras, IMUs and their combinations. They have been used for motion track including gesture, hand gesture, head pose; (2) Force Sensors: haptic control, force sensor; and (3) Internal Sensors: electroencephalogram (EEG), electrocardiograms (ECG) and electromyogram (EMG). They have been used to monitor brain and muscle activities. Table 1 lists the relevant papers with the sensors used, what the sensors are monitored and how the sensed information is used to improve the manufacturing. From Table 1, we can see:

Ref #	Sensor type	Human intent	Benefits/purposes
2;	EEG;	brain activities;	BCI to control robot.
3;	Voice, motion, force, EEG	voice, hand gesture, haptic control, motion, brain activities;	multi-sensors to allow human to control robot.
5;	motion;	hand gesture;	hand gestures to control robot.
8;	IMUs;	gesture;	work on the same job collaboratively (holding part for human to easily operate).
13;	camera, IMUs;	VR system;	human operates the robot/overcome the delay from human to robot.
15;	camera;	human movement;	monitor and supervise human activities.
22;	EEG;	brain activities;	human controls robot to stop if human feels danger.
23;	EEG, IMUs;	brain activities, head pose, AR headset;	human controls how robot should move.
27;	EMG;	muscle gesture;	human controls two arm robot to move.
34;	camera;	human model;	gesture recognition and body skeletal detection to enable human ergonomics analysis.
36;	EMG, IMUs;	estimate the human force;	learning from human collaboration through force to determine speed.
49;	motion;	human gross and fine motions;	using gross motion from Motion Capture and fine-grained motion to classify human tasks.
53;	ECG, EEG, EMG;	full monitoring of human;	developing a new class of skin-like, stretchable bioelectronics.
69;	motion	hand gesture, hand motion track;	human to operate a robot remotely for reducing task completion times, shortening the time needed for training, reducing unwanted collisions, and decreasing cognitive workload.

External sensors: Cameras have been used for monitoring and supervising human activities [15]. In collaborative scenarios, IMUs have been used to track human gesture and allow for cooperative work with robots [8]. IMUs have also been combined with cameras in virtual reality (VR) systems to enable human operation of robots and to overcome delay from human to robot [13]. Motion sensors, such as those used to track hand gestures, have been used to allow humans to control robots [5, 49]. Gross motion from motion capture and fine-grained motion have been combined to classify human tasks [49]. Hand gestures and hand motion tracking have been used to enable humans to operate robots remotely, reducing task completion times, shortening training time, reducing unwanted collisions, and decreasing cognitive workload [69].

Internal Sensors: EEG sensors have been used in several studies for brain activity monitoring in order to control robots through brain-computer interfaces (BCI) [2, 22]. EMG sensors have been used to detect muscle gestures for human control of two-arm robots [27]. EMG sensors combined with IMUs have been used to estimate human force and to enable learning from human collaboration through force to determine speed [36].

Combined Sensors: Gesture recognition and body skeletal detection have been used to enable human ergonomics analysis [34]. Full monitoring of human activities using ECG, EEG, and EMG sensors has been used in the development of a new class of skin-like, stretchable bioelectronics [53]. Overall, these sensors are used to enable humans to control robots in various ways, including voice commands, hand gestures, haptic control, motion detection, EEG, and more. Additionally, these sensors can be used to monitor and supervise human activities, enable ergonomics analysis of human movement, and improve the safety of human-robot interactions. Multi-sensor systems combining voice, hand gesture, haptic control, motion, and brain activity (EEG) have been used to enable humans to control robots in various ways [3].

In addition, in [10], the force is sensed to provide the human operator the feedback for the human to operate machine. This is not for human sensing but for environmental and process sensing for which this paper will not discuss.

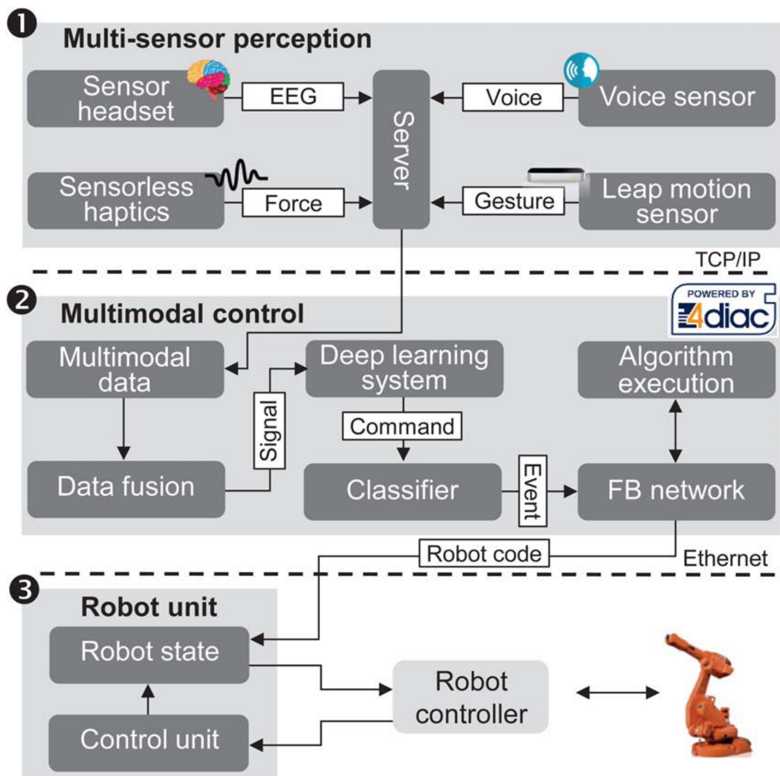


Fig. 13 System design for multimodal robot control in HRC assembly [3].

3.2 Processing of Signals from Human Sensors

Reference [3] used multiple sensors to control the robot as shown in Fig. 13. As can be seen, EEG, force, voice and gesture are monitored by headset, haptics, voice and leap motion sensor respectively for human intent in multi-sensor perception step. In step 2, the data is organized and fused to present to a deep learning system as its input. The deep learning system detects the human intent directly from the fused data. The corresponding command for the robot is classified to decide what event is needed for the robot to execute. The corresponding robot code is automatically generated by an FB network and then pasted to the robot. As the true intent of the human is considered known, the needed label to train the deep learning system is available. Also, the fused data from relevant sensors assures the sufficiency of the raw information. A deep learning model is thus learnable to find the right human intent. Without deep learning, finding true human intent from the complex inputs could be complex and reliability would be difficult to assure.

Reference [8] used a upper body gesture to control a robot. The proposed human-robot interaction (HRI) is to enable a robot to assist a human co-worker in delivering tools and parts, as well as holding objects for an assembly operation. To capture human upper body gestures, wearable IMUs are used. The captured data is segmented into static and dynamic blocks using an unsupervised sliding window method. The segmented data is then used to calculate the respective features. The features calculated from the respective data, static and dynamic data blocks, are then used to train an artificial neural network (ANN) for static, dynamic, and combined gesture classification. The classification result is then used by the Task manager to control the robot to provide the needed assistance to the human co-worker.

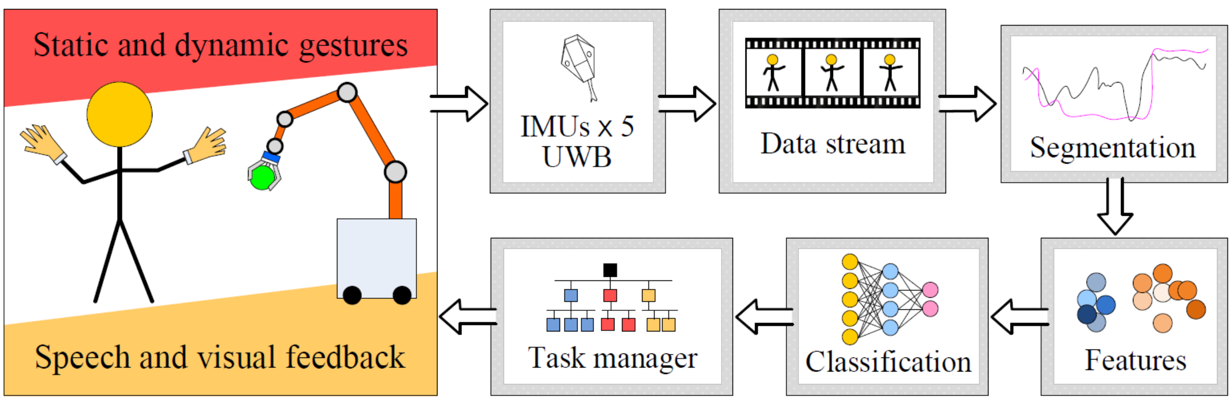


Fig. 14 Gesture based robot control for robot to assist human co-worker [8].

This study utilized wearable IMUs in multiple positions to monitor the upper body movement, as demonstrated in Fig. 15. Each IMU sensor typically records the 3-axial acceleration and 3-axial angular speed, which can be utilized to determine the translation and rotation of the sensor and, consequently, the movement of the specific body part to which the IMU is attached. However, the signals from IMU sensors are often noisy, and there are multiple IMUs in use. Therefore, while algorithms can be developed to process the sensor data directly to identify human intent, they can be highly complex and time-consuming to develop without adequate assurance of detection accuracy. An end-to-end approach with accurate labeling can result in better outcomes, with machine learning offering promising results. As such, the authors reported “the proposed solution accurately classifies static and dynamic gestures, trained with a relatively small number of patterns, and with an accuracy of about 98% for a library of 8 SGs and 4 DGs.” [8].

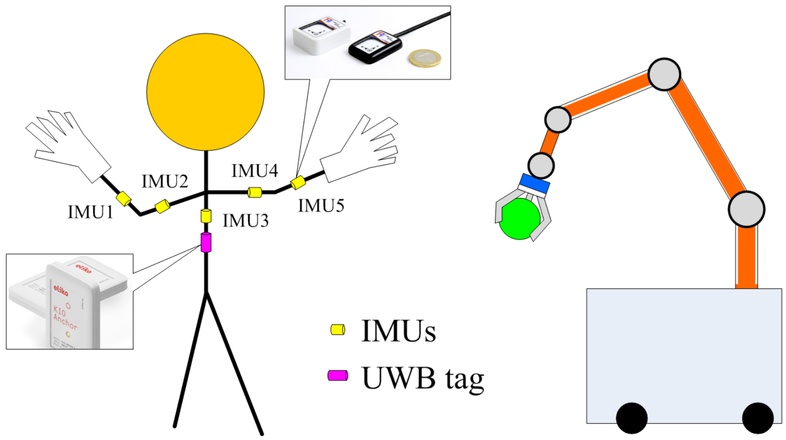


Fig. 15 Using multiple IMUs to monitor the movement of the upper body [8].

Reference [36] aimed to investigate how a follower adjusts their hand movement speed based on their perception of the force from the leader. The study first assumed that the follower's speed was solely determined by the leader's force. To establish a model with the force from the leader as the input and the follower's speed as the output, accurate labels of the follower's true speed were required. As the relationship between force and speed could be complex, the researchers trained a machine learning model, called the "Skill Imitation Model," as shown in Figure 16. The model has two layers. The first layer is a classifier that categorizes the follower's movement into slow and fast modes based on the force waveform. Then, the force data is input into its respective model to predict the speed. The first layer is an unsupervised classification, and the second layer consists of two parallel models based on Gaussian process regression. The first layer determines which of the two models to use.

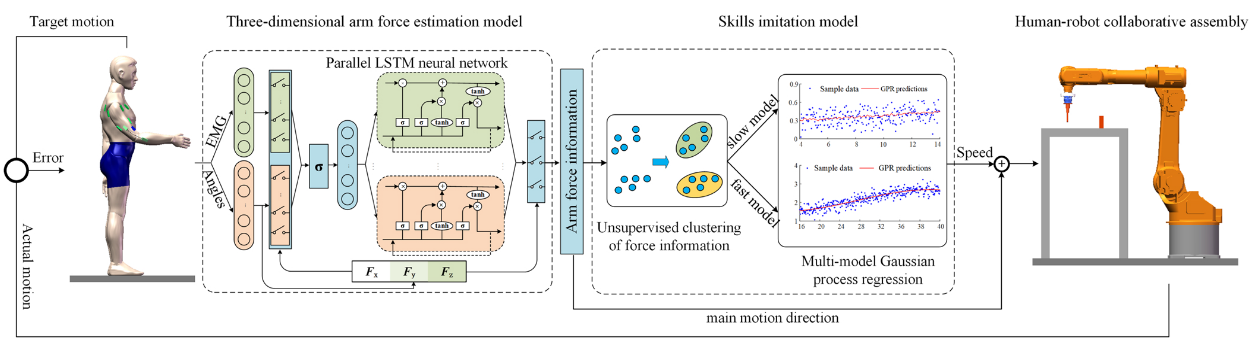


Figure 16. Deep learning for speed estimation from human sensors and its training [36].

Although there are two layers, they form a single model. The parameters in both layers must be trained together using the imported force and output label. However, as the force originates from the human, the force data is not directly obtainable but must be estimated using the "Three-Dimensional Arm Force Estimation Model," which is also shown in Figure 16. This force estimation model employs signals from the human sensors discussed in Section 2 **Example 4: Coordination Learning** as its input to predict the force. The key component of this force estimation model is two parallel LSTM neural networks. LSTM stands for Long-Short Term Memory, and LSTM neural networks are popular recurrent deep learning networks used to process dynamic data, as is the case for force estimation from human sensors. To train this model, experiments were performed using a robot as the follower so that the force could be accurately measured as the label. This model was trained separately before the "Skill Imitation Model" was trained.

Once the Three-Dimensional Arm Force Estimation Model has been trained, the signals from the human sensors can be used to calculate a target speed for the robot. The robot speed can be realized, measured, and compared to the actual human speed. The resulting error, which represents the difference between the actual and target motions, is utilized to update the parameters in the Skill Imitation Model so that this model can be trained.

3.3 Interface Control

Human sensors are supposed to work continuously. Each manufacturing job follows a certain procedure with multiple steps. The logic of the interface control must be organized to provide the human with the information needed at the particular step for human to make a particular decision, often to select among possible choices. The design of the logic is often task specific and thus should not be discussed in detail here. We thus only use two examples to illustrate below in this paper.

One example is to enable a human to program a robot using a Finite State Machine (FSM), as illustrated in Figure 4. The FSM consists of a decision tree with several (four in Figure 4) states. At each state, the FSM detects the human's response to decide what action to take next. The human's response is one of three options that are consistent across all states. However, the action taken for each response may differ depending on the current state. This approach is necessary because human sensors, particularly brain sensors, are often insufficient for deriving complex information. As a result, human's control over the robot may be limited, requiring the need for a well-designed logic system to ensure appropriate and effective control.

Another example involves relative complex communication with the human which has been introduced in Section 2.1 Example 1 [2]. In that example, the human performs the assembly operation in the Assembling Area, while the robot retrieves the next part from the Picking Area, where there are many parts that are out of reach for the human, and then transfers it to the Releasing Area, which is located near the human and only contains the next required part. As there are multiple parts, it is more than just asking the robot to pick up and release. The human will also select the next part that needs the robot to transport. To provide an intuitive selection mechanism based on visual cortex signals, a relatively complex NextMind has been developed whose core is composed of two main components: NeuroTags and NeuroManager. NeuroTags (Figure 17) are identifiable by blinking or flickering textures that allow any object in the scene to become "mind-controllable." Each NeuroTag has a unique visual signature that triggers a response in the user's brain. NeuroManager, serving as the Interface Control, manages communication between the NeuroTags and the NextMind engine, which processes the signals received from the electrodes that detect human brain activities.

Figure 17 NeuroTag example with flickering texture [2].

The communication between NeuroTags and the NextMind engine can be explained below:

1) The NeuroManager is structured into three distinct scenarios, the main menu, calibration, and project, and this paper only reviews the main menu. Upon launching, the main menu is displayed, providing the user (human) with the options for the user to choose either view the assembled or exploded

version of the clamp. To ensure that the selection panel remains visible to the user, a gaze-tracking constraint is implemented. The option is decided based on the signals received from the electrodes. Due to the ten NeuroTags per scene limit, the clamp is divided into three sections (as exampled in Figure 18 for exploded version).

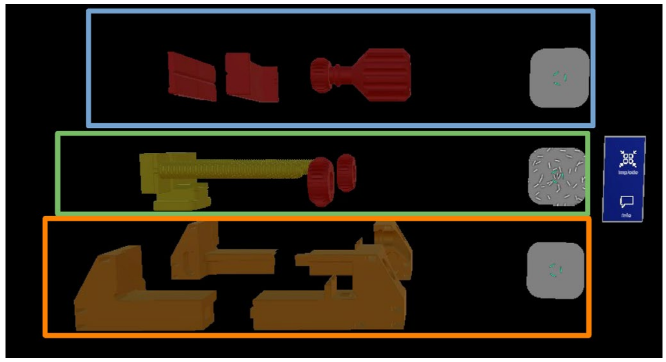


Figure 18 Three sections of exploded clamp [2].

2) Each section is assigned a NeuroTag, with two NeuroTags assigned to each component: Explore and Select (refer to Figure 19). Selecting a section leads NeuroManager to present all the corresponding parts to the user via being displayed on the HoloLens. The Select mode then activates the robot directly to pick the selected objects.

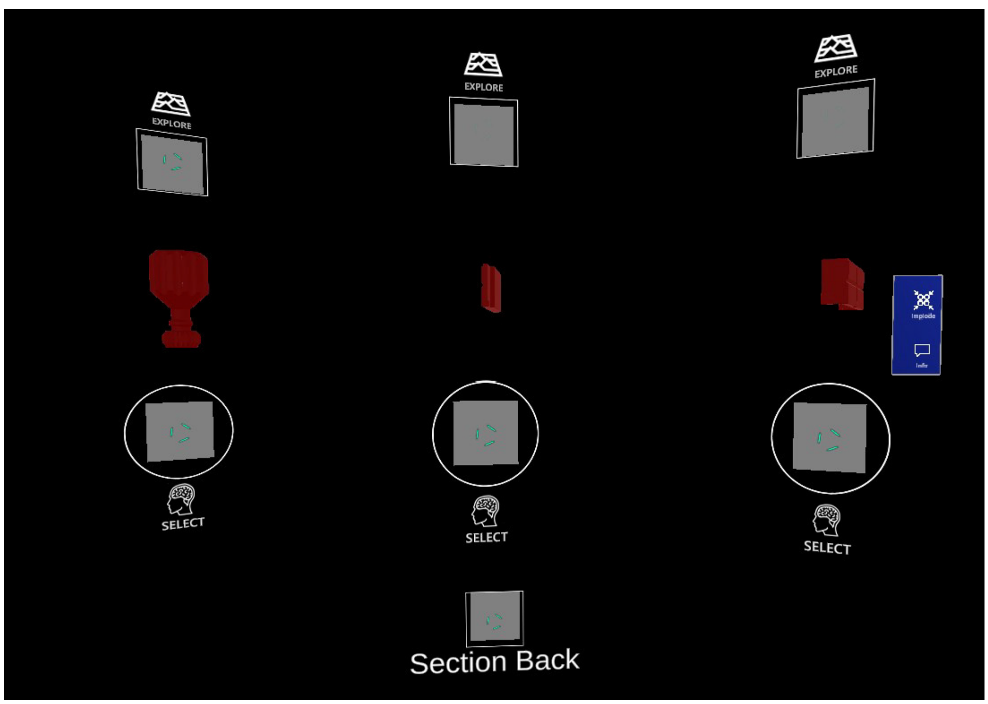


Figure 19 Display of all parts in section 1 in Fig. 18 [2].

3) To provide more effective feedback than the standard three green lines forming a triangle, a growing circle is used to associate with the selection mechanism when the user focuses on a NeuroTag. The green circle grows gradually until it reaches the size of the white circle, indicating that the user has focused on the NeuroTag for a specific period, typically two seconds, before

the NeuroTag triggers the selection (refer to Figure 20). This approach is useful in preventing unintended selections.

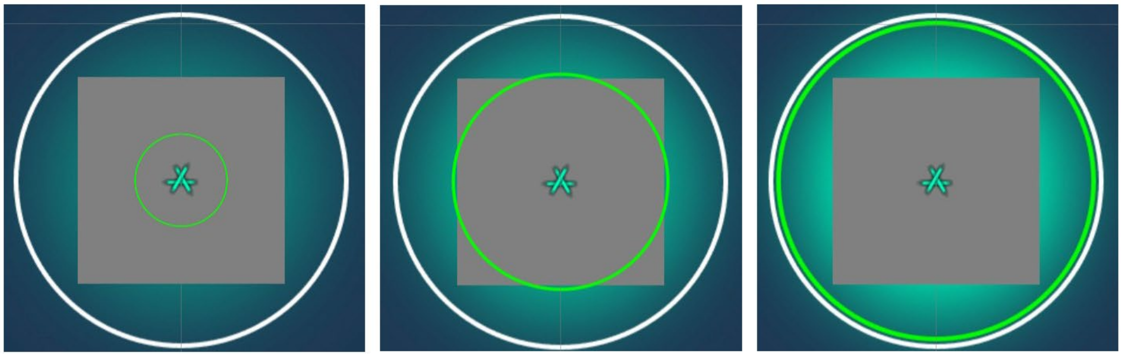


Figure 20 Effective feedback by growing a green circle grows for the user to focus and select [2].

3.4 Presentation to the Human

Environmental information, process feedback, and assistance from artificial intelligence for human to react are presented to the human in different ways using different devices. Out of them, reaction force in HRC environment provides human operators with feedback to decide how much force is needed to move the object. A projector projects an image onto a ground in HRC environment to provide humans safety alert. Computer display, GUI, and high-definition multimedia provide humans more detailed information for human to react and respond. 3D virtual interface uses three-dimensional models to represent objects and environments in a virtual space. Virtual reality headset (HTC Vive) and HoloLens are headsets for virtual reality, augmented reality and mixed reality that provide 3D immersive environment for human to react. allow users to see and interact with holographic images in their environment. Customized large AR displays use augmented reality (AR) to overlay digital information onto the physical world. In particular, high-definition multimedia [1] has provided human the needed view and details for human to perceive and interpret robot's surroundings for high precision trajectory planning for welding. HoloLens [2][23][35], Projector [4][24], and customized large AR displays [35] have provided a safe working environment for humans and robots. Computer displays [5][9][12][69], virtual reality headsets [13], and customized AR displays [35] have allowed humans to control robots using hand gestures or by selecting waypoints for path programming. Reaction force has provided feedback for remote object manipulation [10], while Unity3D game engine environment [31] has improved human learning and created immersive environments. Hololens [35][47] and Robot Operating System (ROS) [47] have been used for programming and operating robots with the assistance of AR, while GUI and computer displays [17] have guided human-robot collaboration. Display usage has also enabled humans to remotely operate robots [69], reducing task completion times, training time, unwanted collisions, and cognitive workload.

In particular, HTC Vive is a virtual reality headset developed by HTC and Valve Corporation. It uses room-scale tracking technology, which allows users to move around a physical space and have their movements tracked and translated into the virtual world. The headset features a high-resolution display with a refresh rate of 90 Hz, providing users with an immersive and realistic experience. HTC Vive is commonly used in various applications, including gaming, education, and training. Its ability to track movements in a physical space makes it an ideal tool for simulating real-world scenarios and training users in a safe environment. For example, HTC Vive has been used in medical training to simulate surgeries, allowing medical students to practice procedures before performing them on real patients [77]. It has also been used in astronaut training, allowing trainees to simulate tasks in a virtual environment that mimics the conditions of space [78]. In addition, HTC Vive has been used in human-robot interaction research to enable humans to remotely control robots in a more natural and intuitive way. By using the headset and its motion controllers, humans can control the robot's movements and interact with the environment in a more intuitive way, allowing for more efficient and effective collaboration between humans and robots [79].

Microsoft HoloLens [80-83] is a mixed reality device that uses a combination of sensors, cameras, and holographic displays to project virtual images onto the real world. It allows the user to see and interact with digital content in a physical space, creating an immersive and interactive experience. In human-robot interaction, HoloLens has been utilized to provide a safe region for the human to work with the robot [82-84] and to enable the human to control the robot [80-83]. By using HoloLens, the human can visualize the robot's perspective [81], track its movements, and provide commands through gestures and voice recognition [80, 81]. In addition, HoloLens can be used to program and operate the robot with the assistance of augmented reality [83], as well as to guide human-robot collaboration [85]. The use of HoloLens in human-robot interaction has several benefits, including increased safety, improved control and communication, and enhanced efficiency and productivity.

4. Summary: State-of-the-art, Challenges, and Future Directions

4.1 State-of-the-art

The state-of-the-art in sensor technology for human-robot collaboration involves a range of external and internal sensors. External sensors like cameras and motion sensors have been used to monitor and track human gestures and activities, enabling humans to control robots through hand gestures, voice commands, and haptic control. Internal sensors like EEG and EMG have been used to monitor brain and muscle activity, respectively, to control robots through brain-computer interfaces and detect muscle gestures for human control of robots. Combined sensor systems have been used for human ergonomics analysis and to monitor and supervise human activities. Multi-sensor systems combining voice, hand gesture, haptic control, motion, and EEG have been used to enable humans to control robots in various ways.

Signal processing techniques have been applied in various fields such as robotics and human-robot interaction. Deep learning models have been utilized to detect human intent from multiple sensors and classify corresponding robot commands for execution. Wearable IMUs have been used to monitor human upper body movement, which is then segmented and processed for gesture classification using machine learning models such as artificial neural networks. Additionally, deep learning has been employed to estimate human speed from force perception, where the force estimation model utilizes parallel LSTM neural networks. These studies highlight the importance of accurate labeling and machine learning in processing complex sensor data to detect human intent and enable effective human-robot interaction.

The state of the art in designing communication with humans involves developing logical interfaces that provide humans with the necessary information to make decisions during manufacturing jobs. Two examples are given, one using a Finite State Machine (FSM) to program a robot, and the other using NextMind technology to provide an intuitive selection mechanism based on visual cortex signals. The NextMind technology involves using NeuroTags and NeuroManager to manage communication between the NextMind engine and the user's brain activities. Effective feedback is provided using a growing circle that associates with the selection mechanism when the user focuses on a NeuroTag, preventing unintended selections. Overall, these designs aim to provide humans with efficient and effective control over robots during manufacturing jobs.

Presenting information, feedback, and assistance to humans can be achieved through various devices and technologies. Some of the state-of-the-art devices include HTC Vive, a virtual reality headset with room-scale tracking technology, which allows users to move around a physical space and have their movements tracked and translated into the virtual world. It has been used in various applications, including medical training and astronaut training. Microsoft HoloLens is a mixed reality device that projects virtual images onto the real world, allowing users to interact with digital content in a physical space. HoloLens has been utilized in human-robot interaction to provide a safe region for humans to work with robots and to enable humans to control robots through gestures and voice recognition, among others. The use of these devices has several benefits, including increased safety, improved control and communication, and enhanced efficiency and productivity.

We note that there is a fundamental difference between assembly and welding. In general, assembly involves a number of different steps or subtasks, while welding is a continuous process that requires careful control and adjustment of welding parameters based on feedback. While welding may seem relatively simple, it is actually much more complex, particularly when it comes to ensuring welding quality. This requires many years of training and practice. In contrast, assembly skills mainly determine productivity rather than quality and acceptability.

Assembly can also be decomposed into subtasks that can be finished separately, and the pace of work typically only affects productivity rather than quality and acceptability. As such, assembly is generally easier for HCR systems to realize than welding. Hence, there are far more studies in HRC assembly than in welding. We also note that per the Bureau of Labor Statistics (BLS), as of May 2020, there were approximately 1.5 million workers employed as assemblers and fabricators in the US [86]. On the other hand, the BLS reports that there were approximately 404,800 welding, soldering, and brazing workers employed in the US as of May 2020 [87]. These figures suggest that, out of every three HRC assembly and welding papers, there should be one HRC welding paper. However, out of the 74 papers we uncovered, example 5 is probably the only one focusing on welding operations. The difficulty in realizing HRC welding is likely the reason for this.

For the papers uncovered, almost all of them for assembly do not involve real-time collaboration from human and robots to accomplish a same job that is not accomplishable by either a human or a robot, except for [8] where a robot holds a workpiece while the human co-worker performs assembly operations. However, in this case, the work decouplable among human and robot and the collaboration is still not in real time and does not involve real-time changes.

In summary, various advanced tools, including human sensors, AI-based signal processing, advanced RV, AR, and MR technologies to enable providing human with immersive environment and intelligent assistance, etc. have been developed. However, the examples presented for HRC assembly show that HRC provides only marginal improvements in productivity rather than fundamental solutions. While the presentation to humans appears to be advanced, intelligent, and reliable, human sensors are less ideal and reliable requiring comprehensive processing and deep learning to extract accurate human intent. Reliably interfacing human intent with machines remains a challenging task. Additionally, in most case studies, the roles of humans are not adaptive and may easily be replaced by better solutions except for adaptive robot programming with human assistance through HRC interface. For welding, limited studies have been done.

4.2 Challenges and Future Directions

The challenge lies in achieving a more comprehensive, reliable, and quantitative understanding of human intent in real-time to effectively communicate with machines/robots. This allows humans to provide adaptive input to the robots rather than merely selecting a job from a pre-determined library or modifying the robot's trajectory planning outside of real-time. This challenge arises primarily because all human sensors are external, while critical human intents are often internal and difficult to accurately measure and monitor using external sensors, making reliability a significant challenge.

It is important to emphasize that achieving a more comprehensive, reliable, and quantitative understanding of human intent in real-time requires a fundamental grasp of human operations. In general, we must determine the raw information that the human operators sense from their "outside world" as input and the output they generate to control their "outside world." This involves mapping a portion of their external environment (input to their model) to another portion of their external environment (output of their model). While this mapping is complex and often unknown, deep learning offers a powerful tool for approximating it using suitable models. With the advancement of deep learning techniques and algorithms, success primarily hinges on whether the model inputs contain sufficient raw information about the model outputs.

It is evident that the necessary fundamental understanding is application dependent. Such comprehension can be particularly challenging for distinct manufacturing jobs, such as welding, which require extensive training. For instance, consider the case of a skilled human welder successfully controlling weld penetration [88]. While it is commonly believed that the welder responds to the weld pool, this notion is incomplete. The study in [88] revealed that weld penetration depends on the history of the weld pool. Consequently, the skilled welder's raw information must encompass the history of the weld pool rather than just its present state. To predict welder intent, a deep learning model should be a recurrent network, such as a RNN (recurrent neural network), rather than a simple convolutional neural network (CNN) [88]. Further investigation delved into the factors influencing the phenomena observed by human welders [89]. The study determined that the weld pool observed at a given time is influenced by the history of the weld penetration, rather than solely the current state of the penetration. Armed with the findings from these two studies, we can select more appropriate deep learning models to comprehend and predict human welder intent during weld penetration control. Different applications may necessitate different yet conceptually similar fundamental studies.

Another challenge lies in acquiring the requisite data for learning human behaviors, such as training deep learning models. In assembly scenarios, the data exchanged among collaborators may involve forces, tactile sensations, and more, which are more challenging to present immersively than visual scenes. However, in welding, the primary data exchanged among collaborators pertains to the weld pool and arc, both of which can be represented using images and videos. Advanced tools like Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) have been developed to enable immersion. Nonetheless, effective methods are still needed to capture what demonstrating welders see without affecting their operational skills. A potential approach involves operating robots with collaborating welders, allowing the robots to carry cameras while performing tasks. This method enables the collection of genuine demonstration data and may guide the development of Human-Robot Collaboration (HRC) welding and the programming of a robot team with the requisite intelligence and collaborative skills.

Given the challenges associated with HRC assembly for practical applications, it is prudent to focus on bottleneck applications for in-depth study. This approach holds the potential to uncover the most efficient HRC solutions.

CRediT authorship contribution statement

Yue Cao: Investigation, Writing – original draft. Quan Zhou: Conceptualization, Funding acquisition. Wei Yuan: Conceptualization, Funding acquisition. Qiang Ye: Conceptualization, Funding acquisition. Dan Popa: Conceptualization, Funding acquisition, Writing – original draft. YuMing Zhang: Conceptualization, Funding acquisition, Investigation, Writing – original draft, Writing – review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to better assure readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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References

1. Ong, S.K., Nee, A.Y.C., Yew, A.W.W. and Thanigaivel, N.K., 2020. AR-assisted robot welding programming. *Advances in Manufacturing*, *8*, pp.40-48.
2. Sanna, A., Manuri, F., Fiorenza, J. and De Pace, F., 2022. BARI: An Affordable Brain-Augmented Reality Interface to Support Human–Robot Collaboration in Assembly Tasks. *Information*, *13*(10), p.460.
3. Liu, S., Wang, L. and Vincent Wang, X., 2022. Multimodal data-driven robot control for human–robot collaborative assembly. *Journal of Manufacturing Science and Engineering*, *144*(5), p.051012.
4. Hietanen, A., Pieters, R., Lanz, M., Latokartano, J. and Kämäräinen, J.K., 2020. AR-based interaction for human-robot collaborative manufacturing. *Robotics and Computer-Integrated Manufacturing*, *63*, p.101891.
5. Garcia, M.A.R., Rojas, R., Gualtieri, L., Rauch, E. and Matt, D., 2019. A human-in-the-loop cyber-physical system for collaborative assembly in smart manufacturing. *Procedia CIRP*, *81*, pp.600-605.
6. Tannous, M., Miraglia, M., Inglese, F., Giorgini, L., Ricciardi, F., Pelliccia, R., Milazzo, M. and Stefanini, C., 2020. Haptic-based touch detection for collaborative robots in welding applications. *Robotics and Computer-Integrated Manufacturing*, *64*, p.101952.
7. Joo, T. and Shin, D., 2019. Formalizing human–machine interactions for adaptive automation in smart manufacturing. *IEEE Transactions on Human-Machine Systems*, *49*(6), pp.529-539.

8. Neto, P., Simão, M., Mendes, N. and Safeea, M., 2019. Gesture-based human-robot interaction for human assistance in manufacturing. *The International Journal of Advanced Manufacturing Technology*, *101*, pp.119-135.
9. Wei, D., Hall, M.B., Sherehiy, A. and Popa, D.O., 2020. Design and Evaluation of Human–Machine Interface for NEXUS: A Custom Microassembly System. *Journal of Micro and Nano-Manufacturing*, *8*(4).
10. Roozbahani, H. and Handroos, H., 2019. A novel haptic interface and universal control strategy for international thermonuclear experimental reactor (ITER) welding/machining assembly robot. *Robotics and Computer-Integrated Manufacturing*, *57*, pp.255-270.
11. Maderna, R., Pozzi, M., Zanchettin, A.M., Rocco, P. and Prattichizzo, D., 2022. Flexible scheduling and tactile communication for human–robot collaboration. *Robotics and Computer-Integrated Manufacturing*, *73*, p.102233.
12. Peng, Y.C., Chen, S., Jivani, D., Wason, J., Lawler, W., Saunders, G., J. Radke, R., Trinkle, J., Nath, S. and T. Wen, J., 2021. Sensor-guided assembly of segmented structures with industrial robots. *Applied Sciences*, *11*(6), p.2669.
13. Wang, Q., Jiao, W., Yu, R., Johnson, M.T. and Zhang, Y., 2019. Modeling of human welders' operations in virtual reality human–robot interaction. *IEEE Robotics and automation letters*, *4*(3), pp.2958-2964.
14. Wei, D., Hall, M.B., Sherehiy, A. and Popa, D.O., 2020. Design and Evaluation of Human–Machine Interface for NEXUS: A Custom Microassembly System. *Journal of Micro and Nano-Manufacturing*, *8*(4). PROCEEDINGS OF THE ASME 2020 15TH INTERNATIONAL MANUFACTURING SCIENCE AND ENGINEERING CONFERENCE (MSEC2020), VOL 2B Article Number: V002T08A018 Published: 2020
15. Lucci, N., Monguzzi, A., Zanchettin, A.M. and Rocco, P., 2022. Workflow modelling for human–robot collaborative assembly operations. *Robotics and Computer-Integrated Manufacturing*, *78*, p.102384.
16. Rahman, S.M., 2019, May. Cognitive cyber-physical system (C-CPS) for human-robot collaborative manufacturing. In *2019 14th Annual conference system of systems engineering (SoSE)* (pp. 125-130). IEEE.
17. Aliev, K., Antonelli, D. and Bruno, G., 2019. Task-based programming and sequence planning for human-robot collaborative assembly. *IFAC-PapersOnLine*, *52*(13), pp.1638-1643.
18. Tuli, T.B., Kohl, L., Chala, S.A., Manns, M. and Ansari, F., 2021, September. Knowledge-based digital twin for predicting interactions in human-robot collaboration. In *2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)* (pp. 1-8). IEEE.
19. Fang, H., Wen, J., Yang, X., Wang, P. and Li, Y., 2022, May. Assisted Human-Robot Interaction for Industry Application Based Augmented Reality. In *Virtual, Augmented and Mixed Reality: Applications in Education, Aviation and Industry: 14th International Conference, VAMR 2022, Held as Part of the 24th HCI International Conference, HCII 2022, Virtual Event, June 26–July 1, 2022, Proceedings, Part II* (pp. 291-301). Cham: Springer International Publishing.
20. Hjorth, S. and Chrysostomou, D., 2022. Human–robot collaboration in industrial environments: A literature review on non-destructive disassembly. *Robotics and Computer-Integrated Manufacturing*, *73*, p.102208.
21. Li, D., Chen, H., Sheng, Y. and Yang, L., 2019. Dual-station intelligent welding robot system based on CCD. *Measurement Science and Technology*, *30*(4), p.045401.
22. Buerkle, A., Bamber, T., Lohse, N. and Ferreira, P., 2021. Feasibility of detecting potential emergencies in symbiotic human-robot collaboration with a mobile EEG. *Robotics and Computer-Integrated Manufacturing*, *72*, p.102179.
23. Ji, Z., Liu, Q., Xu, W. et al., 2023. A closed-loop brain-computer interface with augmented reality feedback for industrial human-robot collaboration. Int J Adv Manuf Technol 124, 3083–3098 (2023). https://doi.org/10.1007/s00170-021-07937-z
24. Monakhov, D., Latokartano, J., Lanz, M., Pieters, R. and Kämäräinen, J.K., 2021, December. Mobile and adaptive User interface for human robot collaboration in assembly tasks. In *2021 20th International Conference on Advanced Robotics (ICAR)* (pp. 812-817). IEEE.

25. Kaplanoglu, E., Nasab, A., Erdemir, E., Young, M. and Dayton, N., 2021, October. Hand gesture based motion control of collaborative robot in assembly line. In *2021 International Conference on Engineering and Emerging Technologies (ICEET)* (pp. 1-4). IEEE.
26. Gujre, V.S. and Anand, R., 2020. Machine learning algorithms for failure prediction and yield improvement during electric resistance welded tube manufacturing. *Journal of Experimental & Theoretical Artificial Intelligence*, *32*(4), pp.601-622.
27. Herfs, W., Storms, S. and Petrovic, O., 2019. An approach on simplifying the commissioning of collaborative assembly workstations based on product-lifecycle-management and intuitive robot programming. In *Intelligent Human Systems Integration 2019: Proceedings of the 2nd International Conference on Intelligent Human Systems Integration (IHSI 2019): Integrating People and Intelligent Systems, February 7-10, 2019, San Diego, California, USA* (pp. 43-49). Springer International Publishing.
28. Prati, E., Peruzzini, M., Pellicciari, M. and Raffaeli, R., 2021. How to include User eXperience in the design of Human-Robot Interaction. *Robotics and Computer-Integrated Manufacturing*, *68*, p.102072.
29. Li, X., Wu, P., Lin, Z. and Zhao, Q., 2020, November. Design and Evaluation of Human-computer Interface for Auxiliary Aircraft Assembly. In *2020 Chinese Automation Congress (CAC)* (pp. 1825-1828). IEEE.
30. Li, Y. and Kesavadas, T., 2018, November. Welding robotic co-worker using brain computer interface. In *ASME International Mechanical Engineering Congress and Exposition* (Vol. 52019, p. V002T02A097). American Society of Mechanical Engineers.
31. Papanastasiou, S., Kousi, N., Karagiannis, P., Gkournelos, C., Papavasileiou, A., Dimoulas, K., Baris, K., Koukas, S., Michalos, G. and Makris, S., 2019. Towards seamless human robot collaboration: integrating multimodal interaction. *The International Journal of Advanced Manufacturing Technology*, *105*, pp.3881-3897.
32. Tannous, M., Bologna, F. and Stefanini, C., 2020. Load cell torques and force data collection during tele-operated robotic gas tungsten arc welding in presence of collisions. *Data in Brief*, *31*, p.105981.
33. Schubert, M., Wambera, L., Mudrievska, O., Nieweglowski, K., Wagner, J., Partzsch, J., Mayr, C., Ellinger, F. and Bock, K., 2020, September. Flexible and stretchable redistribution layer with embedded chips for human-machine interface. In *2020 IEEE 8th Electronics System-Integration Technology Conference (ESTC)* (pp. 1-5). IEEE.
34. El Makrini, I., Mathijssen, G., Verhaegen, S., Verstraten, T. and Vanderborght, B., 2022. A virtual element-based postural optimization method for improved ergonomics during human-robot collaboration. *IEEE Transactions on Automation Science and Engineering*, *19*(3), pp.1772-1783.
35. Aivaliotis, S., Lotsaris, K., Gkournelos, C., Fourtakas, N., Koukas, S., Kousi, N. and Makris, S., 2023. An augmented reality software suite enabling seamless human robot interaction. *International Journal of Computer Integrated Manufacturing*, *36*(1), pp.3-29.
36. Zhang, T., Sun, H., Zou, Y. and Chu, H., 2022. An electromyography signals-based human-robot collaboration method for human skill learning and imitation. Journal of Manufacturing Systems, 64, pp.330-343.
37. Tavares, P., Costa, C.M., Rocha, L., Malaca, P., Costa, P., Moreira, A.P., Sousa, A. and Veiga, G., 2019. Collaborative welding system using BIM for robotic reprogramming and spatial augmented reality. *Automation in Construction*, *106*, p.102825.
38. Henrichs, C., Zhao, F. and Mutlu, B., 2021, August. Designing Interface Aids to Assist Collaborative Robot Operators in Attention Management. In *2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN)* (pp. 264-271). IEEE.
39. Ateş, G., Stølen, M.F. and Kyrkjebø, E., 2022, March. Force and gesture-based motion control of human-robot cooperative lifting using imus. In *2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (pp. 688-692). IEEE.
40. Anwer, S., Waris, A., Sultan, H., Butt, S.I., Zafar, M.H., Sarwar, M., Niazi, I.K., Shafique, M. and Pujari, A.N., 2020. Eye and voice-controlled human machine interface system for wheelchairs using image gradient approach. *Sensors*, *20*(19), p.5510.
41. Nair, P.U., 2021. Optimizing OCTG Thread Manufacturing Operation Using Automation. *Journal of Advanced Manufacturing Systems*, *20*(01), pp.205-225.

42. Mourtzis, D., Angelopoulos, J. and Siatras, V., 2020. Cycle time estimation model for hybrid assembly stations based on digital twin. In *Advances in Production Management Systems. The Path to Digital Transformation and Innovation of Production Management Systems: IFIP WG 5.7 International Conference, APMS 2020, Novi Sad, Serbia, August 30–September 3, 2020, Proceedings, Part I* (pp. 169-175). Springer International Publishing.
43. Eswaran, M., Gulivindala, A.K., Inkulu, A.K. and Raju Bahubalendruni, M.V.A., 2023. Augmented reality-based guidance in product assembly and maintenance/repair perspective:: A state of the art review on challenges and opportunities.
44. Krauß, M., Leutert, F., Scholz, M.R., Fritscher, M., Heß, R., Lilge, C. and Schilling, K., 2021. Digital manufacturing for smart small satellites systems. *Procedia Computer Science*, *180*, pp.150-161.
45. Kolla, S.S.V.K., Sanchez, A. and Plapper, P., 2021. Comparing software frameworks of Augmented Reality solutions for manufacturing. *Procedia Manufacturing*, *55*, pp.312-318.
46. Wang, S.M., Tu, R.Q. and Gunawan, H., 2021, June. Assembly error-mating measurement and compensation method for machining production line. In *2021 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4. 0&IoT)* (pp. 77-82). IEEE.
47. Shamaine, C.X.E., Qiao, Y., Henry, J., McNevin, K. and Murray, N., 2020, September. RoSTAR: ROS-based telerobotic control via augmented reality. In *2020 IEEE 22nd International Workshop on Multimedia Signal Processing (MMSP)* (pp. 1-6). IEEE.
48. Xie, L., Chen, P., Chen, S., Yu, K. and Sun, H., 2019. Low-cost and highly sensitive wearable sensor based on napkin for health monitoring. *Sensors*, *19*(15), p.3427.
49. Kubota, A., Iqbal, T., Shah, J.A. and Riek, L.D., 2019, May. Activity recognition in manufacturing: The roles of motion capture and sEMG+ inertial wearables in detecting fine vs. gross motion. In *2019 International Conference on Robotics and Automation (ICRA)* (pp. 6533-6539). IEEE.
50. Tan, Q., Tong, Y., Wu, S. and Li, D., 2019. Anthropocentric approach for smart assembly: Integration and collaboration. *Journal of Robotics*, *2019*.
51. Singh, A., Kalaichelvi, V. and Karthikeyan, R., 2020. Application of convolutional neural network for classification and tracking of weld seam shapes for TAL Brabo manipulator. *Materials Today: Proceedings*, *28*, pp.491-497.
52. Zhu, Z., Liu, C. and Xu, X., 2019. Visualisation of the digital twin data in manufacturing by using augmented reality. *Procedia Cirp*, *81*, pp.898-903.
53. Mahmood, M., Kwon, Y.T., Kim, Y.S., Kim, J. and Yeo, W.H., 2020, June. Smart and Connected Physiological Monitoring Enabled by Stretchable Bioelectronics and Deep-Learning Algorithm. In *2020 IEEE 70th Electronic Components and Technology Conference (ECTC)* (pp. 979-984). IEEE.
54. Kazanzides, P., Vagvolgyi, B.P., Pryor, W., Deguet, A., Leonard, S. and Whitcomb, L.L., 2021. Teleoperation and Visualization Interfaces for Remote Intervention in Space. *Frontiers in Robotics and AI*, *8*, p.747917.
55. Jambhulkar, S., Liu, S., Vala, P., Xu, W., Ravichandran, D., Zhu, Y., Bi, K., Nian, Q., Chen, X. and Song, K., 2021. Aligned Ti3C2T x MXene for 3D Micropatterning via Additive Manufacturing. *ACS nano*, *15*(7), pp.12057-12068.
56. Colceriu, C., Leichtmann, B., Brell-Cokcan, S., Jonas, W. and Nitsch, V., 2022, August. From Task Analysis to Wireframe Design: An Approach to User-Centered Design of a GUI for Mobile HRI at Assembly Workplaces. In *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)* (pp. 876-883). IEEE.
57. Colceriu, C., Leichtmann, B., Brell-Cokcan, S., Jonas, W. and Nitsch, V., 2022, August. From Task Analysis to Wireframe Design: An Approach to User-Centered Design of a GUI for Mobile HRI at Assembly Workplaces. In *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)* (pp. 876-883). IEEE.
58. Jiang, C., Li, Q., Fan, S., Guo, Q., Bi, S., Wang, X., Cao, X., Liu, Y. and Song, J., 2020. Hyaline and stretchable haptic interfaces based on serpentine-shaped silver nanofiber networks. *Nano Energy*, *73*, p.104782.

59. Cao, J., Liang, F., Li, H., Li, X., Fan, Y., Hu, C., Yu, J., Xu, J., Yin, Y., Li, F. and Xu, D., 2022. Ultra-robust stretchable electrode for e-skin: In situ assembly using a nanofiber scaffold and liquid metal to mimic water-to-net interaction. *InfoMat*, *4*(4), p.e12302.
60. Loch, F., Fahimipirehgalin, M., Czerniak, J.N., Mertens, A., Villani, V., Sabattini, L., Fantuzzi, C. and Vogel-Heuser, B., 2019. An adaptive virtual training system based on universal design. *IFAC-PapersOnLine*, *51*(34), pp.335-340.
61. Hu, X., Arista, R., Zheng, X., Lentes, J., Sorvari, J., Lu, J., Ubis, F. and Kiritsis, D., 2022. Ontology-based system to support industrial system design for aircraft assembly. *IFAC-PapersOnLine*, *55*(2), pp.175-180.
62. Wang, S.M., Lee, C.Y., Gunawan, H. and Yeh, C.C., 2022. On-line error-matching measurement and compensation method for a precision machining production line. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *9*(2), pp.493-505.
63. Chiang, C.H., Wang, C., Barth, K., Rahimpour, S., Trumpis, M., Duraivel, S., Rachinskiy, I., Dubey, A., Wingel, K.E., Wong, M. and Witham, N.S., 2021. Flexible, high-resolution thin-film electrodes for human and animal neural research. *Journal of neural engineering*, *18*(4), p.045009.
64. Tao, W., Linyan, W., Yanping, L., Nuo, G. and Weiran, Z., 2019. Learning Advanced Brain Computer Interface Technology: Comparing CSP Algorithm and WPA Algorithm for EEG Feature Extraction. *International Journal of Technology and Human Interaction (IJTHI)*, *15*(3), pp.14-27.
65. Minnetti, E., Chiariotti, P., Paone, N., Garcia, G., Vicente, H., Violini, L. and Castellini, P., 2020. A smartphone integrated hand-held gap and flush measurement system for in line quality control of car body assembly. *Sensors*, *20*(11), p.3300.
66. Mincă, E., Filipescu, A., Cernega, D., Șolea, R., Filipescu, A., Ionescu, D. and Simion, G., 2022. Digital Twin for a Multifunctional Technology of Flexible Assembly on a Mechatronics Line with Integrated Robotic Systems and Mobile Visual Sensor—Challenges towards Industry 5.0. *Sensors*, *22*(21), p.8153.
67. Simões, B., Amicis, R.D., Segura, A., Martín, M. and Ipiña, I., 2021. A cross reality wire assembly training system for workers with disabilities. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *15*, pp.429-440.
68. Lin, R., Li, Y., Mao, X., Zhou, W. and Liu, R., 2019. Hybrid 3D printing all-in-one heterogenous rigidity assemblies for soft electronics. *Advanced Materials Technologies*, *4*(12), p.1900614.
69. Su, Y., Chen, X., Zhou, T., Pretty, C. and Chase, G., 2022. Mixed reality-integrated 3D/2D vision mapping for intuitive teleoperation of mobile manipulator. *Robotics and Computer-Integrated Manufacturing*, *77*, p.102332.
70. Huang, T.T. and Wu, W., 2020. Inkjet-printed wearable nanosystems for self-powered technologies. *Advanced Materials Interfaces*, *7*(12), p.2000015.
71. Huang, Y., Wu, H., Xiao, L., Duan, Y., Zhu, H., Bian, J., Ye, D. and Yin, Z., 2019. Assembly and applications of 3D conformal electronics on curvilinear surfaces. *Materials Horizons*, *6*(4), pp.642-683.
72. Xing, S.L., Xiao, Y., Huo, J.P., Lin, L.C., Shen, D.Z., Liu, L., 2021. Nanowelding and Electrical Performance Tuning of Pt-TiO2 Induced by Femtosecond Laser. CHINESE JOURNAL OF LASERS-ZHONGGUO JIGUANG Volume: 48 Issue: 8 Article Number: 0802004 DOI: 10.3788/CJL202148.0802004 Published: APR 2021
73. Andriamiseza, F., Bordignon, D., Payré, B., Vaysse, L. and Fitremann, J., 2022. 3D printing of biocompatible low molecular weight gels: Imbricated structures with sacrificial and persistent N-alkyl-d-galactonamides. *Journal of Colloid and Interface Science*, *617*, pp.156-170.
74. Wei, C., Yu, C., Li, S., Meng, J., Li, T., Cheng, J., Pan, F. and Li, J., 2022. Easy-to-operate co-flow step emulsification device for droplet digital polymerase chain reaction. *Analytical Chemistry*, *94*(9), pp.3939-3947.
75. Wei, Danming, Ruoshi Zhang, Ji-Tzuoh Lin, Dilan Ratnayake, Olalekan O. Olowo, Andrew S. Nimon, Moath Alqatamin, Andriy Sherehiy, and Dan O. Popa. "Automated Fabrication of Tactile Sensors Using a Custom Additive Manufacturing Platform." In 2022 International Conference on Manipulation, Automation and Robotics at Small Scales (MARSS), pp. 1-6. IEEE, 2022.

76. Wei, Danming, Sushmita Challa, Mohammad S. Islam, Jasmin Beharic, Cindy K. Harnett, and Dan O. Popa. "Multi-Robot Collaboration for Electronic Textile Fabrication." In 2022 International Conference on Manipulation, Automation and Robotics at Small Scales (MARSS), pp. 1-6. IEEE, 2022.
77. Al-Jibouri, S. A., & Cheng, A. (2018). Developing Virtual Reality Medical Simulation Scenarios with HTC Vive for Medical Training. International Journal of Emerging Technologies in Learning (iJET), 13(01), 153-162.
78. Shull, P. B., & Damann-Hauser, N. (2019). Virtual reality training for space missions. In Space Safety and Human Performance (pp. 107-125). Butterworth-Heinemann.
79. Li, W., & Ahn, C. R. (2018). VR-based teleoperation system using HTC Vive for intuitive robot control. International Journal of Control, Automation and Systems, 16(1), 166-176.
80. Huang, J., & Ma, Y. (2020). Intelligent human-robot interaction based on augmented reality technology. In Proceedings of the 2nd International Conference on Robotics, Control and Automation (pp. 330-334).
81. Thakur, A., Singh, R., & Kaur, H. (2020). Vision based robot control using HoloLens. In International Conference on Communication, Computing and Networking (pp. 259-269).
82. Yilmaz, F., & Fjeld, M. (2019). Enabling intuitive robot programming through augmented reality and digital twin technologies. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (p. 600).
83. Zhang, Y., Hu, H., & Li, W. (2020). A Hololens-based augmented reality system for remote programming and operation of robots. Sensors, 20(21), 5967.
84. Lin, H., & Kuo, C. (2018). A portable projection-based augmented reality system for robotic arm operation. IEEE Transactions on Industrial Electronics, 66(9), 7415-7424.
85. Wood, L., & Aha, D. W. (2015). A visual language for human-robot teaming. In Proceedings of the 2015 AAAI Fall Symposium Series.
86. Bureau of Labor Statistics, 2021. Occupational employment and wages, May 2020: 51-2000 assemblers and fabricators. https://www.bls.gov/oes/current/oes512000.htm.
87. Bureau of Labor Statistics, 2021. Occupational employment and wages, May 2020: 51-4121 welding, soldering, and brazing workers. https://www.bls.gov/oes/current/oes514121.htm.
88. Yu, R., Kershaw, J., Wang, P. and Zhang, Y., 2022. How to accurately monitor the weld penetration from dynamic weld pool serial images using CNN-LSTM deep learning model?. IEEE Robotics and Automation Letters, 7(3), pp.6519-6525.
89. Mucllari, E., Yu, R., Cao, Y., Ye, Q. and Zhang, Y., 2023. Do We Need a New Foundation to Use Deep Learning to Monitor Weld Penetration?. IEEE Robotics and Automation Letters, 8(6): 3669 – 3676, DOI 10.1109/LRA.2023.3270038.
90. Qiyue Wang, Yongchao Cheng, Wenhua Jiao, Michael T. Johnson, YuMing Zhang, 2019. Virtual Reality Human-Robot Collaborative Welding: A Case Study of Weaving Gas Tungsten Arc Welding. Journal of Manufacturing Processes, Volume 48, December 2019, Pages 210-217, https://doi.org/10.1016/j.jmapro.2019.10.016