Journal of Manufacturing Systems 61 (2021) 696–711

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Systematic literature review on augmented reality in smart manufacturing: Collaboration between human and computational intelligence

Dawi Karomati Baroroh [a], Chih-Hsing Chu [a,*], Lihui Wang [b]

[a] Department of Industrial Engineering & Engineering Management, National Tsing Hua University, Hsinchu, Taiwan
[b] Department of Production Engineering, KTH Royal Institute of Technology, Stockholm, Sweden

A R T I C L E I N F O

Keywords:
Industry 4.0
Augmented reality
Computational intelligence
Smart manufacturing

A B S T R A C T

Smart manufacturing offers a high level of adaptability and autonomy to meet the ever-increasing demands of product mass customization. Although digitalization has been used on the shop floor of modern factory for decades, some manufacturing operations remain manual and humans can perform these better than machines. Under such circumstances, a feasible solution is to have human operators collaborate with computational intelligence (CI) in real time through augmented reality (AR). This study conducts a systematic review of the recent literature on AR applications developed for smart manufacturing. A classification framework consisting of four facets, namely interaction device, manufacturing operation, functional approach, and intelligence source, is proposed to analyze the related studies. The analysis shows how AR has been used to facilitate various manufacturing operations with intelligence. Important findings are derived from a viewpoint different from that of the previous reviews on this subject. The perspective here is on how AR can work as a collaboration interface between human and CI. The outcome of this work is expected to provide guidelines for implementing AR assisted functions with practical applications in smart manufacturing in the near future.

1. Introduction

Owing to the recent advances in information technologies (IT) and operation technologies (OT), the manufacturing industry has entered the era of Industry 4.0. Empowered by artificial intelligence (AI) and the Industrial Internet of Things (IIoT), the traditional manufacturing technologies have become “smart” in handling the ever-increasing complexity of tasks on the shop floor [1,2]. Implementing smart manufacturing that offers high production flexibility and efficiency, albeit with acceptable costs, is imperative to meeting the fast-growing consumer demands for mass customized products [3–5]. Although AI enables manufacturing systems to operate with a high degree of autonomy and intelligence, there exist certain tasks, which are either impractical or impossible to accomplish without human intervention. Under these circumstances, the purpose of introducing AI or automation technologies is to facilitate the manual operations, rather than to completely replace human involvement. AI may not perform better in tasks involving huge data or fuzzy conditions, for which, humans who can utilize their cognitive capabilities (e.g. the five senses) or implicit knowledge to quickly respond, are more suitable. A more feasible approach is to let humans and machines work with each other, in a complementary fashion, similar to the idea of “humans in the loop” (HIL) [6] or Human-Cyber-Physical System (HCPS) [7]. A conceptual view of HCPS in implementing Industry 4.0 is shown in Fig. 1.

Fig. 1 shows the progress of the industrial revolution from 1.0–4.0. The 1st, 2nd, and 3rd industrial revolutions occurred with the technical advance of power mechanical, electromechanical, and information systems, respectively. The essence of Industry 4.0 is to realize cyber-physical systems that seamlessly integrate real-world objects and cyberspace to provide adaptability and autonomy. As mentioned in the paper, a number of operations in the current manufacturing environment simply cannot be replaced by intelligent systems and continue to be manually operated. A feasible solution is to let humans collaborate with cyber-physical systems by playing the role of “master” in these operations. The idea of human-cyber-physical systems is thus proposed to characterize and realize such collaboration in the future, namely the 5th industrial revolution.

Integrating augmented reality (AR) with intelligent functions is considered a good strategy to realize HIL in smart manufacturing. AR serves as a ubiquitous interface that strengthens the interactions between a human operator and the manufacturing environment. The operator can assess the ambient intelligence through the AR interface

* Corresponding author.
E-mail address: chchu@ie.nthu.edu.tw (C.-H. Chu).

https://doi.org/10.1016/j.jmsy.2020.10.017
Received 11 July 2020; Received in revised form 27 October 2020; Accepted 29 October 2020
Available online 19 November 2020
0278-6125/© 2020 The Society of Manufacturing Engineers. Published by Elsevier Ltd. All rights reserved.

and properly respond to the manufacturing tasks in real-time. The instructive information thus obtained enhances the quality of the human decision making, which eventually results in a better outcome of the task performed.

"AR applications for smart manufacturing" has been a fast-growing research area in the recent years. The key here is to identify manufacturing tasks that can potentially benefit from collaboration between human and CI in an AR environment. Operations that can be automated well should be implemented wholly without the AR. However, the parts of manual tasks have to be distinguished between those that can be better handled by a human and a machine. The interactions between these parts are essential for successful incorporation of AR into human-machine collaboration. It is advantageous to compile and analyze how past studies have dealt with these problems and the rationale behind their solutions. Hence, this study aims to present the state-of-the-art AR applications for smart manufacturing enabled by intelligent functions, with a focus on (i) what problems are to be solved, (ii) how intelligence is to be generated, and (iii) which devices are to be used. We have conducted a rigorous systematic literature review (SLR) that ensures the reproducibility and scalability of the study, as well as objectivity of the results. This approach is particularly applicable to research topics undergoing a fast development. The remainder of this paper is organized as follows. Section 1 introduces the objective of this study. Section 2 describes the methodology and data sources utilized in the SLR. Section 3 summarizes the key results according to a classification framework. Section 4 describes important findings and observations from the classification results. The last section presents conclusions and suggestions for future work.

2. Methodology

The systematic literature review (SLR) approach is used to investigate the state-of-the-art AR applications developed for smart manufacturing. This approach aims to search, screen, synthesize, and analyze the studies relevant to a specific research field following the five steps shown in Fig. 2, namely planning, scoping, searching, assessing, and analyzing.

2.1. Planning step

In the planning step, Scopus (www.scopus.com) was chosen as the main academic database to be explored. Owing to the evolving nature of the topic, a manual search of the online documentation was performed as well. This work adopted Mendeley (www.mendeley.com) as the reference management software, as it offers a strong user community and technical support. Its useful design features include an integrated PDF viewer and automatic citation add-in for Microsoft Word documents.

2.2. Scoping step

In this step, a classification framework for the SLR based on the main research question was outlined. The framework was constructed from an iterative process between brainstorming and literature search. The research question was formulated as "What are the state-of-the-art AR applications in terms of technologies, functions, and limitations to support manual operations in smart manufacturing?" This framework offers a practical guidance to analyze the explored literature on four aspects, i.e. interaction device, manufacturing operation, functional approach, and intelligence source. As shown in Fig. 3, each aspect contains a list of possible options, which are explained subsequently.

(1) **Interaction device**: This is the hardware with which humans interact with AR application programs. It can be one of the following:

- Head mounted display (HMD): a device worn on a human head or as part of a helmet.
- Hand held display (HHD): a mobile phone, smartphone, or tablet computer.
- Monitor: a separate display screen connected to a computer.
- Projector: a device for projecting visual annotations to real objects.
- Auditory/Tactile/Olfactory devices: devices giving non-visual feedback to the user.

(2) **Manufacturing operation**: It is the specific operation/problem that AR aims to facilitate or solve. This research defines manufacturing as the production of products for use or sale using a shop floor or factory level system that contains man, machine, and process. AR applications aim to facilitate all manual operations in this context, such as assembly/disassembly, process simulation, maintenance, monitoring, quality control, production management, planning, training, and facility layout. Designing or art creation with AR devices does not fall into the category of manufacturing from this perspective. The following is detailed of each manufacturing operation:

- Assembly/disassembly: This is the process to mechanically connect parts or dismantle parts in a sequential manner. An AR device is commonly used to guide a human operator with instructions superimposed on a real scene. Its purpose is to improve the assembly efficiency and/or reduce errors. As shown in Fig. 4, an AR assisted function developed using Vuforia and Unity performs an automatic recognition of a part arriving at the assembly process [8]. It displays information extracted from the part-flow based manufacturing process model (PMPM) based on the recognition result, such as the assembly sequence, parts required, and production quantity. Additional yellow signs superimposed on the real scene highlight the assembly interfaces to be aligned during the process.

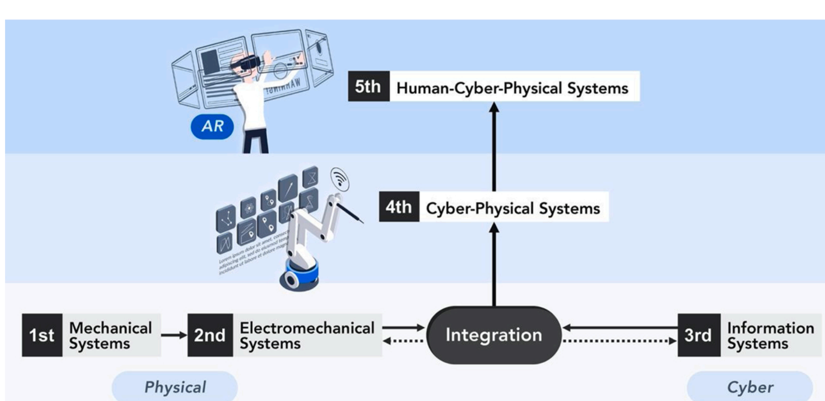


Fig. 1. A conceptual view of HCPS in Industry 4.0.

Fig. 2. SLR methodology used in this study.

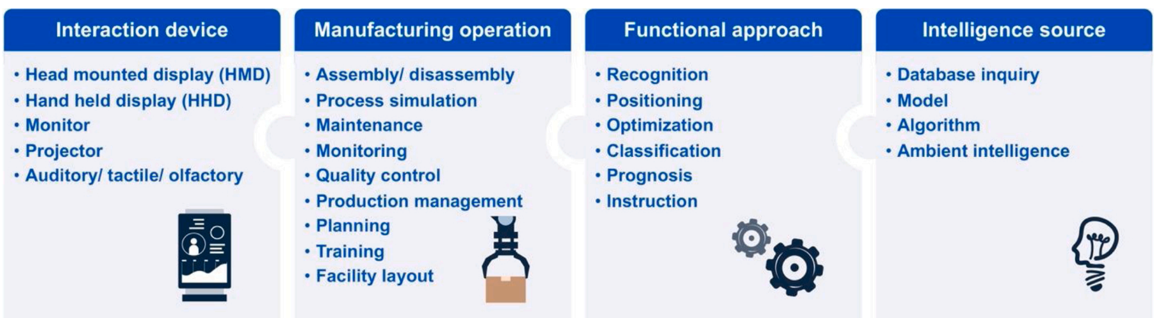


Fig. 3. Proposed classification framework.

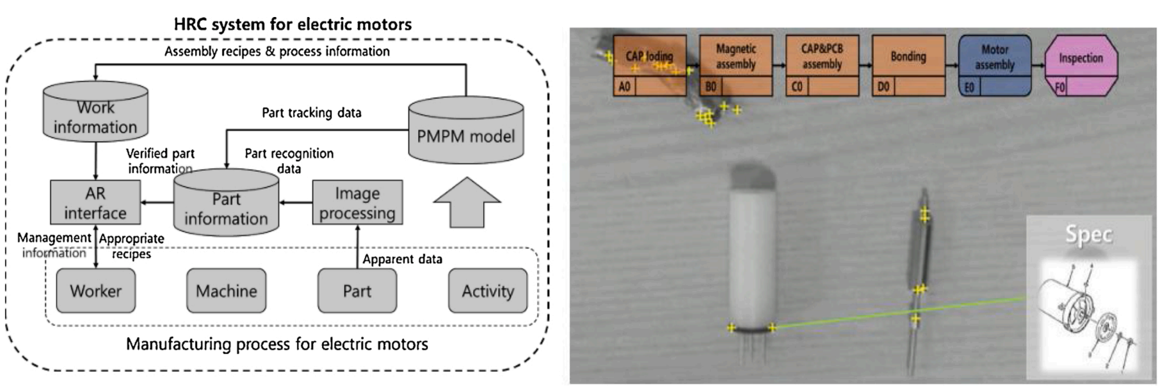


Fig. 4. Typical example of an AR assisted manual assembly involving human–robot collaboration (HRC) [8].

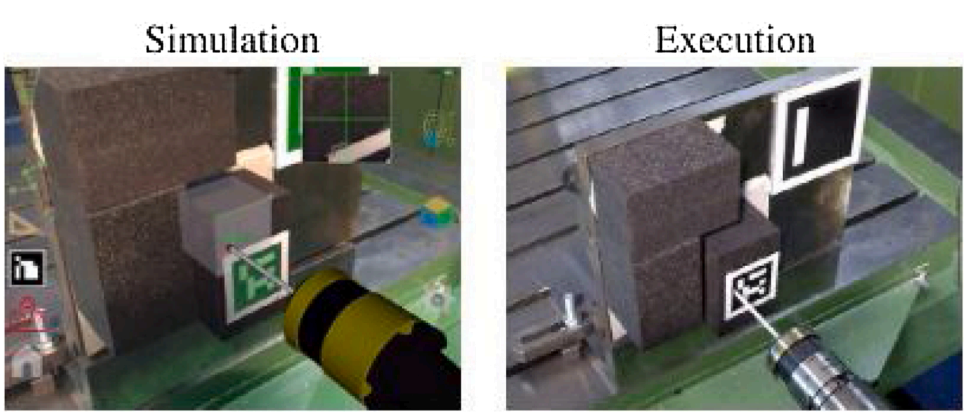


Fig. 5. Simulation of the moving trajectory of a touch probe [9].

- Process simulation: It is the process of simulating a manufacturing process in a real environment. In the CNC machining example shown in Fig. 5, a mobile device is used as the AR interface for the human operator to communicate with the machine controller. When the device detects a marker in the real scene, it projects a localization mask onto a geometric feature to serve as the machine active reference frame. The operator can translate, rotate, and scale the projected mask to precisely fit the feature through the interface. A NC part program is then executed to simulate the moving trajectory of the touch probe on the machine [9].
- Maintenance: The related tasks include functional check, servicing, repairing, or replacing parts/components for a manufacturing system. AR assisted functions automatically highlight anomalous machines, components scheduled to be replaced, and possibly the trouble-shooting procedure or safety measures [5,10]. In the example shown in Fig. 6, the AR-computerized maintenance management system (AR-CMMS) was implemented for inexperienced operators on a shop floor to quickly handle unexpected machine breakdowns [5]. The camera of a HoloLens detects the ID of a 3D printer and locates the corresponding machine information from a cloud database via PHP-based web services. An operator can report an unexpected breakdown through voice commands to retrieve the diagnostic procedure, which is displayed in the HoloLens step by step. When the breakdown is not recognized or the maintenance instructions are not found in the database, the operator can connect with a remotely located skilled technician on Skype for assistance. The diagnostic procedure continues with the aid of the technician looking at the machine through the operator's view within the HoloLens.
- Monitoring: This includes collecting, analyzing, and evaluating information to oversee the condition of a manufacturing process, operation, or system. Its purpose is to make a human operator aware of the current condition, especially to prevent abnormalities [11]. Fig. 7 shows an AR application program running on a tablet computer developed for online quality control in a production line. The program was integrated with a computer-aided quality (CAQ) software, which takes measurements by wirelessly activating the sensors installed on a work station. A human inspector can focus the tablet camera on a marker to trigger the process of measuring the dimensions and position of the part currently placed on the work station. These measurements processed by the CAQ software are then recorded and sent to the inspector for necessary precautions.
- Quality control: AR is applied to help a human control or adjust a manufacturing system to assure a pre-defined quality of the parts produced from the system. The main purpose is to reduce the human workload by automatically indicating the occurrence and characteristics of defects. For example, an AR application deployed in HoloLens supports quality control by allowing automatic defect detection for a car body (see Fig. 8) [12]. The user can select either automatic or manual inspection option in the zero-reference module. In the automatic inspection cycle, the application retrieves the identification number of the current car body from the production line controller. A query is passed to a local database server to display

Fig. 7. An AR application developed for online monitoring in a production line [11].

all the inspection results and other related information on the AR device. When the user gazes at a defect, a virtual screen appears and shows the characteristics of the defect, such as size, shape, and type. The data associated with the defect can be verified or modified in this manner.

- Production management: This involves managing the production resources (time/capacity/material) in a manufacturing system. As shown in Fig. 9, an AR application was developed and deployed in a tablet PC to optimize the production schedules using a two-way communication between a planning software system and human workers on the shop floor [13]. The optimization was performed in real time to respond to new orders and the changing status of the production resources, e.g. available machine capacity and human workers. The AR application works as a user interface for the personnel on the shop floor to receive planning instructions from experts or software tools and to update enterprise information systems with information such as estimated completion time, work progress, and machine status.
- Planning: This means planning the trajectory of a robot/machine to accomplish a manufacturing operation. For example, AR was applied to facilitate programming of a robot and its trajectory planning, considering the dynamic constraints of the robot in real time [14]. As shown in Fig. 10, the AR-assisted robot trajectory planning enables the user to evaluate the planned trajectory by visualizing the deviation between the simulation and real results in an HMD. Adjustments can be made to the planning parameters to optimize the kinematic and dynamic performance of the robot.
- Training: It is the process of acquiring the skills to complete a particular manufacturing job. An AR application program identifies the parts/tools assigned to a worker and displays related instructions or training procedures [1,15]. In an AR-assisted manual assembly training [1], the performance of a trainee is recognized from sensor data using deep learning methods. A wearable Myo armband acquires the hand gestures of the trainee during the assembly process. As shown in Fig. 11, motion analysis is also conducted on the video captured by a camera. The recognition result determines the training program that best matches the individual's technical capability. A

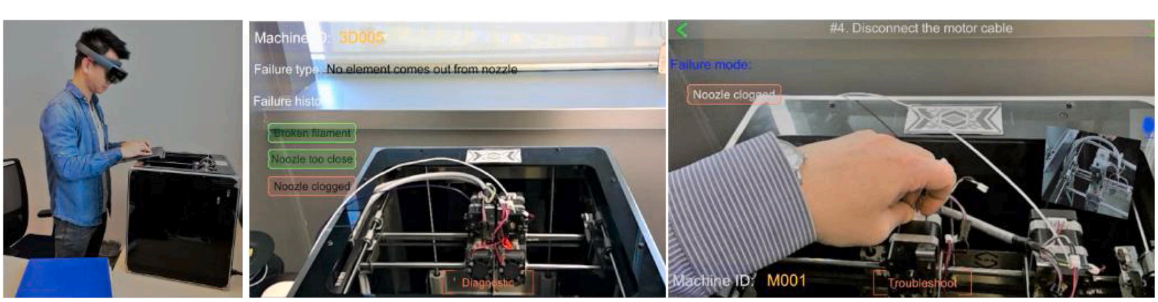


Fig. 6. AR-CMMS system assisting inexperienced operators on a shop floor in quickly handling unexpected machine breakdowns [5].

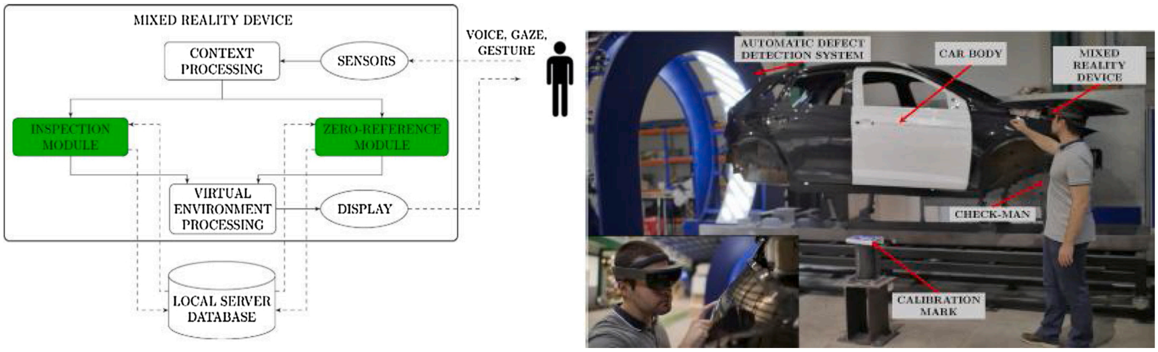
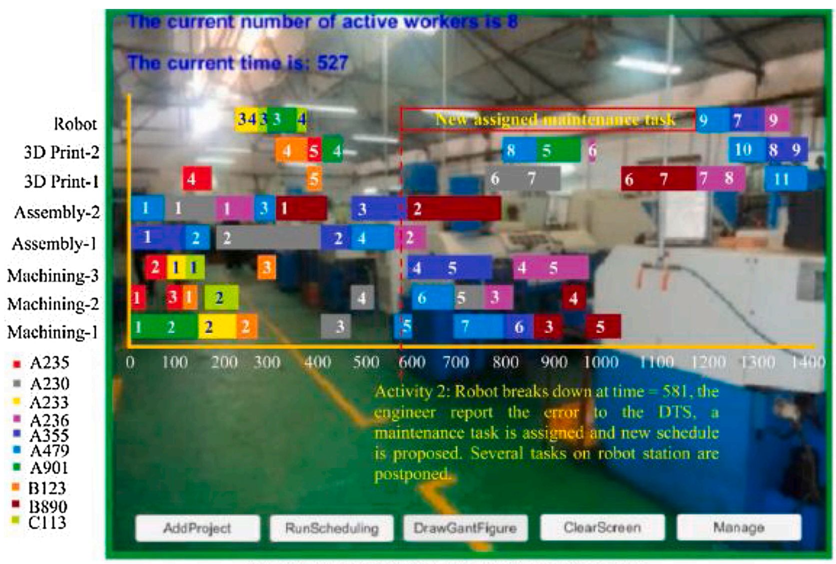


Fig. 8. An AR application supporting quality control by allowing automatic defect detection of a car body [12].



(c) Response to robot station breaks down at time = 581

Fig. 9. AR assisting in optimizing production scheduling on a shop floor [13].

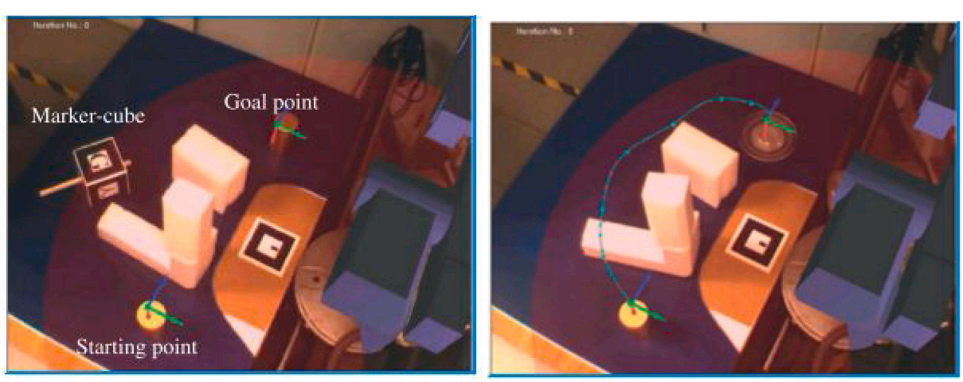


Fig. 10. A user evaluating the robot trajectory by visualizing the deviation between the simulation and real results [14].

monitor displays the corresponding assembly instructions overlaid on the real scene. The effectiveness of this AR training program was experimentally validated as well.

- Facility layout: This involves arrangement of the hardware facility of a manufacturing system. AR allows evaluating the compatibility of the virtual equipment to be installed with respect to the real facilities existing in a factory. An AR application running in a smart phone allows visualizing the on-site factory layout without using markers [16]. The layout mixes the virtual facility models and existing equipment. Static and dynamic simulations of the manufacturing environment offer an extensive analysis of the selected layout by walk-through navigation. In this case, a virtual robot was programmed to pick and place the unprocessed workpiece. This programmed movement is directly observed though a smartphone. Different robot configurations can be evaluated by re-programming the robot models in the application (see Fig. 12).

(3) **Functional approach**: This implies how AR application

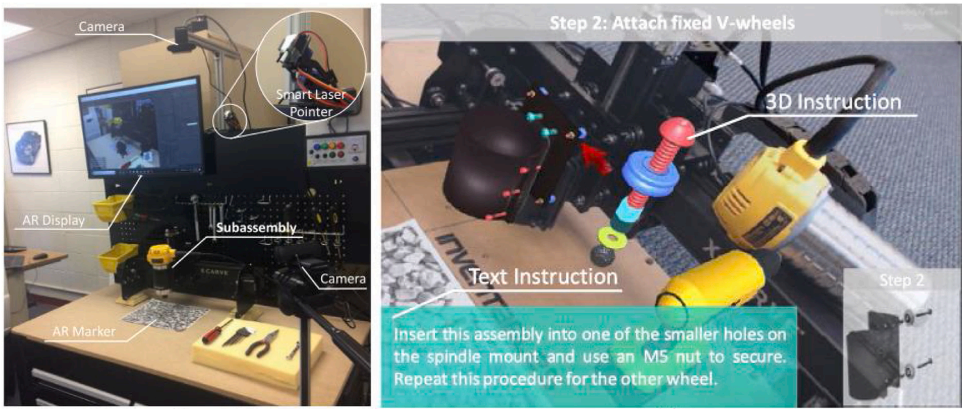


Fig. 11. AR assisted training for manual assembly [1].

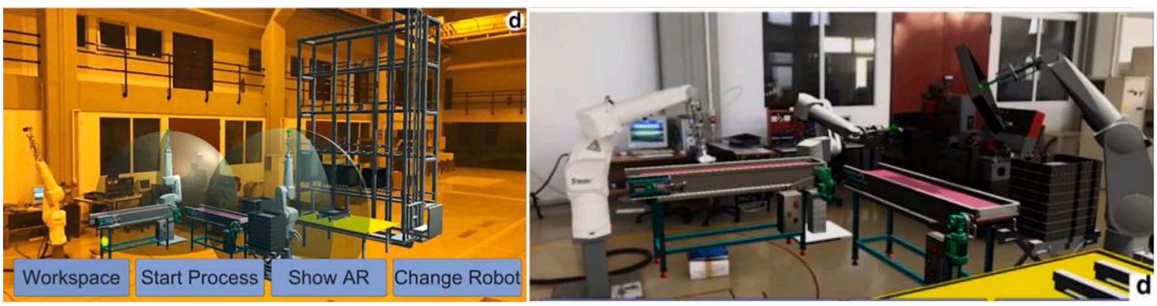


Fig. 12. Facility layout in an AR environment [16].

programs solve a specific problem or facilitate a specific operation. Some key attributes of the functional approach and their explanation are as follows:

- Recognition: to identify, detect, and understand a target object in given data, usually in an image or a video stream.
- Positioning: to track the current position or orientation of a given object.
- Optimization: to select the best option against some criterion from a set of available alternatives or a mathematical model.
- Classification: to categorize data, condition, or object.
- Prognosis: to detect abnormal conditions prior to actual occurrence.
- Instruction: to give instructive information for a manufacturing task.

(4) **Intelligence source**: It includes the means by which intelligence is generated and involves the following.

- Database inquiry: to extract existing data or information from a database system.
- Model: to estimate the parameter values from physical, engineering principles, heuristics, or simulation.
- Algorithm: a logical procedure or set of rules to be followed in a calculation by a computer program.
- Ambient intelligence: to detect or measure a physical property or status by using a hardware device.

2.3. Searching step

We searched the Scopus database using two keywords: "augmented reality" and "manufacturing" with the Boolean Operator "AND".

2.4. Assessing step

The literature collected in the previous step was assessed in three phases as shown in Fig. 13. In the first two phases, the search results were screened by various criteria, such as the year of publication, document type, language, and another keyword "intelligence". Finally, we manually processed the results by eliminating duplicates and retaining the relevant literature.

2.5. Analyzing step

The short-listed publications were analyzed, organized, and presented to derive useful findings. Table 1 presents a classification of the resultant literature according to the framework described in Section 2.2. Next, statistical analyses were conducted to derive significant findings from the results.

3. Results

3.1. Statistical summary

At the end of February 2020, there were 705 publications related to augmented reality and manufacturing available in the Scopus database. After a manual screening, only 105 articles were found relevant to this study. As shown in Fig. 14, the number of papers has gradually increased during the last five years, peaking at 27 papers in 2019. We also reviewed 11 papers published before 2015 (with four, one, four, and two papers from 2011, 2012, 2013, and 2014, respectively). Those papers were representative works in this field. About 60 % of the publications were journal papers and the rest were conference articles. The presence of a high proportion of conference proceedings may imply that the research topic is still evolving. The publications related to AR in smart manufacturing are expected to grow in the coming years because the applications have started showing practical results on the shop floor with advances being made in supportive technologies, such as IIoT, AI, 5 G, and sensors.

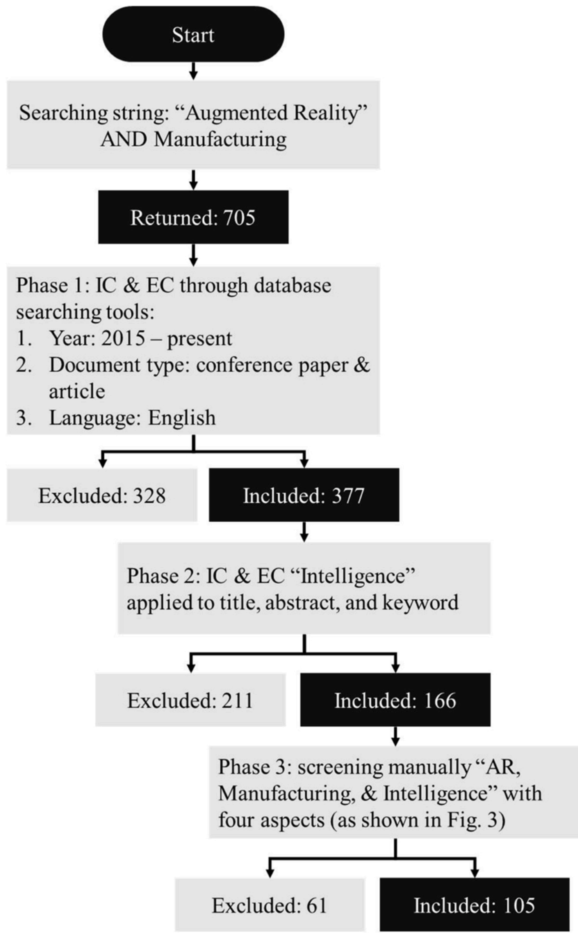


Fig. 13. Schematic diagram of the searching and assessing steps.

3.2. Interaction device

Various hardware devices have been applied for displaying information and interacting with humans in AR. Some were developed as specialized AR gadgets, for example, the HMD (or AR goggles), while the others belonged to consumer electronic products like the HHD, monitor, and projector. The monitor was predominantly an interaction device existing in manufacturing prior to 2015, while the HMDs and HHDs have been used more frequently since then, accounting for a share of 27 % and 22 % of the past studies, respectively (see Fig. 15).

The HMD is the most dominant device deployed in AR applications related to smart manufacturing. Designed as a specialized AR device, the modern HMD offers four useful design features in applications: (i) services as a turn-key system, (ii) mobility, (iii) hands-free operations, and (iv) real-time data transmission [26]. These features are important to support most manual manufacturing operations. However, HMD can cause discomfort and visual fatigue in long periods of use, limiting its practical value in industry [81]. Major usability problems yet to be solved include VAC (Vergence-Accommodation Conflict), motion sickness, limited FOV (Field of Vision), and imprecise overlay of virtual models in real scene [108–110]. The HHD works as a simple interface by allowing an intuitive view of the location-based information [13,44]. Although an earlier study [111] reported that the HHD has higher reliability, responsiveness, and agility than the HMD, projector, or haptic devices, it has several limitations. The device is certainly not optimal for manufacturing operations involving both hands of an operator such as assembly/disassembly. The user may need to spend time verifying the information through a tablet and then physically move to continue the undertaken task. The use of HHD reduces the

Table 1
Literature retrieved and organized according to the classification framework.

Ref	Interaction Device	Manufacturing Operation	Function Approach	Intelligence Source
[1]	Monitor	Training	Recognition	Multiple generations
[2]	HMD	Maintenance	Multiple functions	Database inquiry
[3]	Monitor	Production Management	Multiple functions	Multiple generations
[4]	HMD	Maintenance	Prognosis	Algorithm
[5]	HMD	Maintenance	Multiple functions	Multiple generations
[8]	HHD	Assembly	Recognition	Algorithm
[9]	HHD	Process simulation	Positioning	Ambient intelligence
[10]	Projector	Maintenance	Multiple functions	Algorithm
[11]	HHD	Monitoring	Positioning	Database inquiry
[12]	HMD	Quality control	Recognition	Multiple generations
[13]	HHD	Production management	Optimization	Multiple generations
[14]	HHD	Multiple operations	Multiple functions	Model
[15]	HHD	Training	Recognition	Algorithm
[16]	HHD	Facility layout	Multiple functions	Multiple generations
[17]	Monitor	Process simulation	Positioning	Ambient intelligence
[18]	Multiple devices	Maintenance	Multiple functions	Multiple generations
[19]	HHD	Monitoring	Multiple functions	Database inquiry
[20]	Multiple devices	Multiple operations	Multiple functions	Algorithm
[21]	Monitor	Multiple operations	Multiple functions	Multiple generations
[22]	Monitor	Multiple operations	Multiple functions	Algorithm
[23]	HHD	Multiple operations	Multiple functions	Algorithm
[24]	Multiple devices	Multiple operations	Recognition	Algorithm
[25]	HMD	Multiple operations	Prognosis	Database inquiry
[26]	HMD	Multiple operations	Prognosis	Algorithm
[27]	Multiple devices	Disassembly	Multiple functions	Algorithm
[28]	Monitor	Assembly	Multiple functions	Multiple generations
[29]	Multiple devices	Multiple operations	Multiple functions	Database inquiry
[30]	HMD	Process simulation	Positioning	Model
[31]	HMD	Disassembly	Multiple functions	Algorithm
[32]	Multiple devices	Maintenance	Multiple functions	Multiple generations
[33]	Multiple devices	Maintenance	Multiple functions	Multiple generations
[34]	Projector	Quality control	Multiple functions	Algorithm
[35]	Monitor	Assembly	Multiple functions	Multiple generations
[36]	HMD	Assembly	Multiple functions	Multiple generations
[37]	HHD	Maintenance	Multiple functions	Algorithm
[38]	Multiple devices	Assembly	Multiple functions	Database inquiry
[39]	Monitor	Planning	Positioning	Multiple generations
[40]	Multiple devices	Training	Multiple functions	Ambient intelligence

(continued on next page)

Table 1 (*continued*)

Ref	Interaction Device	Manufacturing Operation	Function Approach	Intelligence Source
[41]	HHD	Maintenance	Multiple functions	Database inquiry
[42]	Multiple devices	Assembly	Multiple functions	Multiple generations
[43]	Monitor	Maintenance	Multiple functions	Multiple generations
[44]	HHD	Maintenance	Positioning	Algorithm
[45]	Monitor	Maintenance	Multiple functions	Multiple generations
[46]	HMD	Maintenance	Multiple functions	Multiple generations
[47]	Multiple devices	Training	Recognition	Ambient intelligence
[48]	HHD	Training	Optimization	Database inquiry
[49]	Multiple devices	Planning	Recognition	Ambient intelligence
[50]	HMD	Multiple operations	Optimization	Model
[51]	Projector	Assembly	Multiple functions	Ambient intelligence
[52]	Projector	Assembly	Multiple functions	Multiple generations
[53]	Multiple devices	Maintenance	Multiple functions	Multiple generations
[54]	HMD	Assembly	Recognition	Multiple generations
[55]	Multiple devices	Multiple operations	Recognition	Ambient intelligence
[56]	HMD	Assembly	Recognition	Ambient intelligence
[57]	Multiple devices	Monitoring	Multiple functions	Algorithm
[58]	Multiple devices	Multiple operations	Multiple functions	Multiple generations
[59]	HMD	Maintenance	Recognition	Algorithm
[60]	HHD	Monitoring	Recognition	Multiple generations
[61]	Monitor	Assembly	Recognition	Multiple generations
[62]	HMD	Multiple operations	Recognition	Multiple generations
[63]	Projector	Multiple operations	Positioning	Ambient intelligence
[64]	Auditory/ Tactile/ Olfactory	Planning	Instruction	Algorithm
[65]	HHD	Planning	Positioning	Model
[66]	HMD	Monitoring	Recognition	Ambient intelligence
[67]	HMD	Monitoring	Positioning	Algorithm
[68]	Projector	Planning	Positioning	Ambient intelligence
[69]	HMD	Planning	Positioning	Ambient intelligence
[70]	HMD	Facility layout	Positioning	Database inquiry
[71]	Multiple devices	Assembly	Positioning	Ambient intelligence
[72]	Monitor	Multiple operations	Multiple functions	Multiple generations
[73]	Multiple devices	Planning	Multiple functions	Multiple generations
[74]	HMD	Planning	Multiple functions	Multiple generations
[75]	HMD	Multiple operations	Recognition	Multiple generations
[76]	Projector	Assembly	Recognition	Multiple generations
[77]	Projector	Multiple operations	Recognition	Multiple generations
[78]	Multiple devices	Assembly	Multiple functions	Multiple generations
[79]	HMD	Planning	Positioning	Multiple generations
[80]	HHD	Multiple operations	Multiple functions	Multiple generations
[81]	HHD	Multiple operations	Multiple functions	Algorithm
[82]	HMD	Planning	Multiple functions	Ambient intelligence
[83]	Multiple devices	Maintenance	Prognosis	Multiple generations
[84]	HMD	Training	Optimization	Multiple generations
[85]	HHD	Production management	Instruction	Ambient intelligence
[86]	Projector	Multiple operations	Prognosis	Multiple generations
[87]	HMD	Quality control	Prognosis	Database inquiry
[88]	HHD	Multiple operations	Multiple functions	Multiple generations
[89]	Multiple devices	Maintenance	Multiple functions	Multiple generations
[90]	HMD	Planning	Multiple functions	Algorithm
[91]	HHD	Maintenance	Multiple functions	Database inquiry
[92]	HHD	Quality control	Recognition	Algorithm
[93]	Multiple devices	Maintenance	Classification	Multiple generations
[94]	HHD	Planning	Recognition	Algorithm
[95]	Multiple devices	Training	Positioning	Algorithm
[96]	HMD	Assembly	Multiple functions	Algorithm
[97]	Multiple devices	Planning	Multiple functions	Multiple generations
[98]	HMD	Maintenance	Multiple functions	Multiple generations
[99]	Auditory/ Tactile/ Olfactory	Training	Optimization	Ambient intelligence
[100]	Auditory/ Tactile/ Olfactory	Assembly	Multiple functions	Ambient intelligence
[101]	Auditory/ Tactile/ Olfactory	Assembly	Recognition	Ambient intelligence
[102]	Multiple devices	Planning	Recognition	Ambient intelligence
[103]	Multiple devices	Training	Multiple functions	Ambient intelligence
[104]	Multiple devices	Maintenance	Multiple functions	Multiple generations
[105]	HHD	Quality control	Instruction	Database inquiry
[106]	Multiple devices	Multiple operations	Positioning	Ambient intelligence
[107]	Multiple devices	Multiple operations	Recognition	Algorithm

dexterity of users in performing operations by limiting their hands [81]. The workload and time required to complete manual assembly assisted by HHD based AR instructions were increased [38]. It is sometimes difficult for operators to hold a mobile device firmly in shop floor environment.

The percentage of shares of the projector and monitor are almost identical. Both are considered easy to implement with a low development cost/complexity. Nonetheless, the information displayed by a projector or monitor can be blocked by other objects existing in the manufacturing environment [108]. Their installation on the shop floor is not always possible due to space limitations.

The majority of the deployed AR applications interact with humans via visual communication, while other sensory stimuli (auditory, tactile, and olfactory) are less frequently used. The tactile stimulus is not as

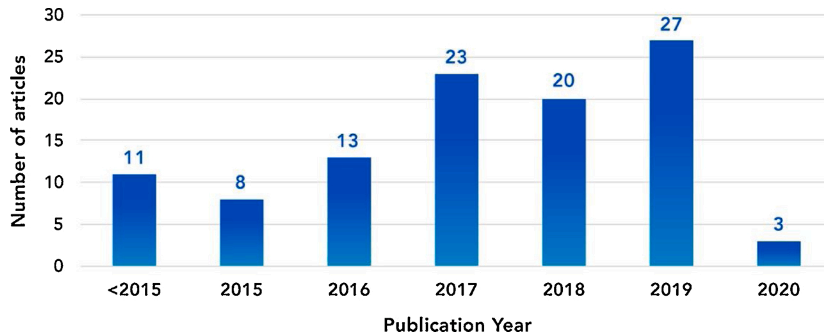


Fig. 14. Distribution of relevant papers by year of publication.

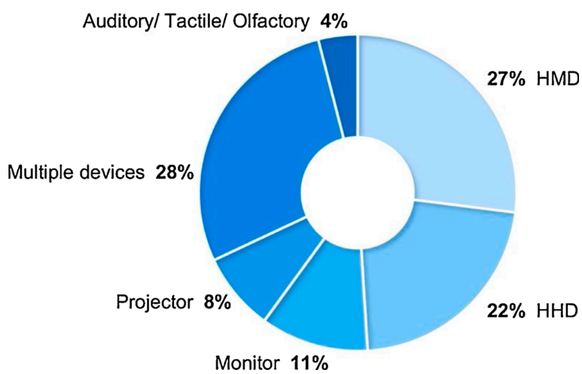


Fig. 15. Classification of interaction devices in AR with their share of the past studies.

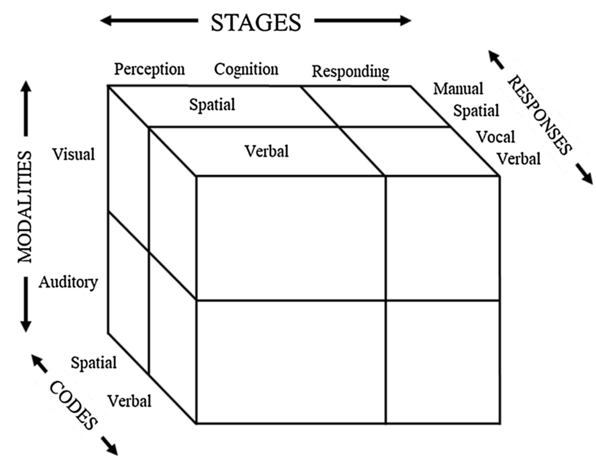


Fig. 16. Structure of multiple-resource model of attention [114].

efficient as browsing text/image on a visual interface in terms of distributing information [112]. Cost is another issue holding tactile devices back from use in smart manufacturing [113]. Auditory messages are certainly not suitable in noisy environment like factory. Olfactory devices require collection of highly reliable primary data from the real environment [33]. Applications of virtual smell may be too specialized to be useful in the current manufacturing industry. Presently, the technical complexity of incorporating tactile and olfactory stimuli in AR is higher than that of a visual interface. Nevertheless, interactions through multi-sensory stimuli closely mimic human perception of the environment using the five senses, thus improving the overall awareness of the human operator at work.

Simultaneous use of multiple devices provides flexibility to overcome limitations of the manufacturing environment and increase the comfort level of the users. A combination of an HHD and HMD occurs most often among all the options listed in Table 2. Despite this trend, combination of devices may not be a good strategy from the human information processing (HIP) perspective. The multiple-resource model of attention (see Fig. 16) states that multiple sources of information with a similar information code and similar modalities (visual clues) can interfere with each other, thus increasing the cognitive load of HIP [114].

In contrast, multi-modality is an effective strategy to increase the amount of information delivered and to reduce a receiver's cognitive load [114]. Multi-modality implies using more than one modality of human sense in information dissemination. For example, Fig. 17 shows a scenario of using an HHD and a vibrotactile device simultaneously [40]. A vibrotactile bracelet applies haptic force feedback to human arm, forearm, or wrist for enhancing the training skills of workers. Another example shown in Fig. 18 adopts a mix of visual and olfactory stimuli [33]. The AR interface simultaneously overlays both visual and odor information that allows maintenance personnel to quickly react to the condition of the machine and make decisions.

Table 2
Combination of multiple devices in AR related to smart manufacturing.

Combination of multiple devices	Count
HMD and HHD	10
HMD and monitor	4
HMD and auditory/tactile/olfactory	8
HHD and auditory/tactile/olfactory	1
Monitor and auditory/tactile/olfactory	1
More than two devices	5
Total	29

3.3. Manufacturing operation

As shown in Fig. 19, AR technologies have been deployed in multiple operations, maintenance, assembly/disassembly, and planning with proportions of 22 %, 20 %, 18 %, and 13 %, respectively. Training, monitoring, and quality control occupy approximately 5%–8% each. Process simulation, production management, and facility layout account for approximately 4%. Facing the ever-increasing manufacturing complexity, a modern manufacturing task commonly involves multiple operations and different engineering technologies. This trend is reflected by the observation that AR applications have frequently been deployed to solve multiple operations in a manufacturing environment.

Numerous studies [4,32,51,75] demonstrated the effectiveness of AR-assisted manual maintenance and assembly/disassembly operations. They tended to agree that AR-assisted functions can shorten the manual assembly process or reduce the assembly errors, although mixed results were reported by some studies [38,100]. Compared to paper-based instructions and 3D animations, AR-assisted assembly consumed the longest time during the assembly process, as automatic part recognition and verification required additional computational time [115].

Fig. 17. Multi-modal AR interface consisting of an HHD and vibrotactile device [40].

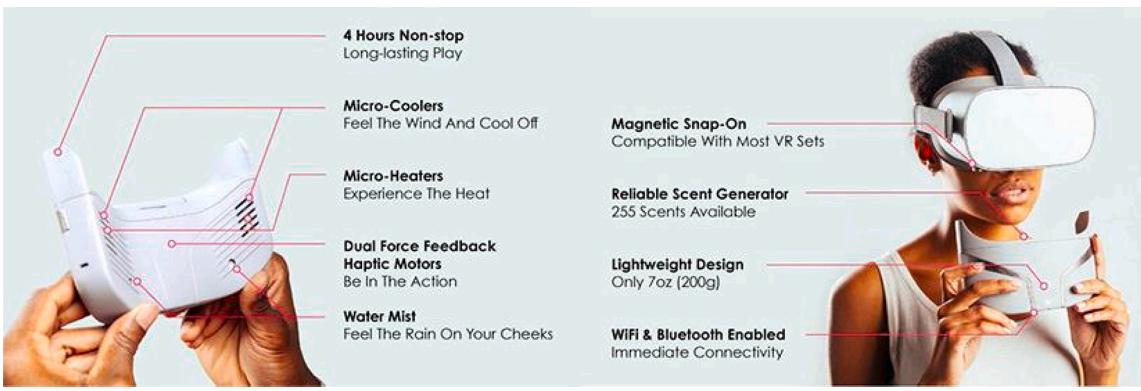


Fig. 18. FEELREAL sensory mask integrates both visual and olfactory stimuli [33].

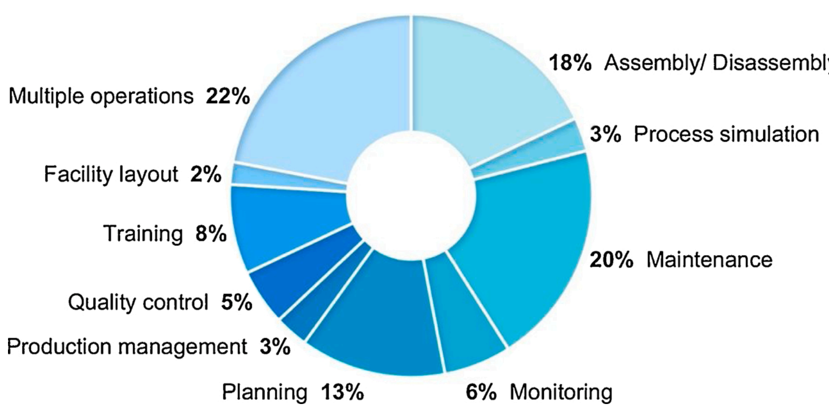


Fig. 19. Manufacturing operations, in which AR has been deployed.

Meanwhile, the AR-based system had consistently yielded the lowest number of errors when compared to the others. Based on the NASA-TLX score, the paper-based instructions showed lower workload because people are still accustomed to paper presentations.

Maintenance is an inevitable activity during a production lifecycle. It accounts for as much as 60%–70% of the total manufacturing costs [53]. Performing proper and quick maintenance on a manufacturing system helps reduce its downtime and thus increase its productivity. This usually depends on the system monitoring that detects equipment malfunctions or processes abnormal conditions before they influence the manufacturing quality. Maintenance remains predominately a manual operation on the shop floor. Inexperienced or under-trained personnel are prone to committing human errors. They may fail to detect abnormal conditions, make wrong judgments, or simply ignore standard procedures while performing a manufacturing task. AR gives the maintenance personnel an on-site context awareness and sequentially shows the operational steps to be performed with specified safety measures [91]. Intelligence functions, such as object detection and pattern recognition, help capture the equipment conditions and prevent system failures beforehand. They also reduce the mental workload or information overwhelming suffered by the human on duty [100].

A framework of an AR-based collaborative maintenance platform was proposed to provide local technicians with real-time instructions from remote experts through networks [45,46]. AR was applied for developing technical training and on-site practice programs [15,84]. They had the advantage of helping trainees learn the required skills and gain first-hand experience in a real environment. AR serves as a new method for training machine operations by providing avatars as an additional tutor representation to the existing AR instructions [116]. Different use scenarios of the avatars (non-avatar/full-body/half body) were analyzed and compared in three operating conditions (local, spatial, and body-coordinated). Experimental results showed that each condition corresponds to a different optimal use scenario. Besides, AR also was applied to assist users in performing programming by demonstration (PbD) for an industrial robot [117]. Instant feedback information was superimposed on a real scene for improving human spatial reasoning while manipulating the robot's end-effector.

A similar idea was also implemented in the planning of touch probe trajectories of a CMM in AR environment [49,73]. Guidance commands were given to move the probe tip around geometric features identified from a work part. The facility layout using the AR allows quick assessment on how virtual equipment fits into an existing manufacturing environment [16,70]. Fewer applications were found in production management [13] and quality control [12,92], as they usually do not depend on human decision making in modern production. For solving the complex issues in the planning or production management operation, collaboration requirement planning (CRP) using a hub with collaborative intelligence (HUB-CI) supporting by an augmented model is a potential solution [118]. HUB-CI is designed to manage massive information about distributed agents in real-time by receiving commands from human agents via a human-computer interface. AR is highly applicable to implement this scenario. Zhang and Kwok [119] developed a design and interaction interface for smart manufacturing using AR technologies. The motivation was that AR-based design interfaces directly communicating with a machine control unit (MCU) increases the degree of interaction and the complexity of instructions performed in manual data input (MDI) systems. Such an AR environment allows users to efficiently design customized products, and manufacture them by accessing, monitoring, and controlling the connected manufacturing systems.

3.4. Functional approach

Approximately half of the reviewed studies implemented multiple intelligent functions in their AR applications. Object recognition and positioning were the most common combination (see Table 3). As shown in Fig. 20, the recognition and positioning functions account for 22 % and 15 %, respectively. Approximately 6% of the studies deployed optimization and prognosis, while only 1%–3% involved the classification and instruction functions in smart manufacturing.

In the HIP model [114], human beings sense a change in the external environment through an initial stage of perception and cognition. They first notice signals and then detect object or condition changes using attention resources and memory (Fig. 21). This stage is critical for a human to effectively process information. Because it requires high cognitive loads, people tend to incorrectly detect or miss the signals, thus inducing human errors in subsequent decision making.

Most previous studies integrated intelligence functions into AR for improving spatial cognition, safety measures, context awareness, and remote assistance [10,32,91]. Human recognition and positioning involve acute spatial reasoning capability and require high levels of attention as well as awareness from a human operator. High mental workload, which is inevitably induced when these functions are performed, often leads to human errors or fatigue. A feasible approach to address this problem is to conduct an automatic recognition and positioning by CI. Human operators simply receive the recognition and positioning results via AR and perform the necessary reactions accordingly. Furthermore, incorporating CI lowers the performance variation of human workers resulting from differences in individual skills and experience.

The above discussion does not imply that other intelligent functions are less valuable in smart manufacturing. Some may require sophisticated intelligence that are not easy to implement using the existing technologies, for example, diagnosis and prediction (prognosis) [4,25]. Although prognosis occurs less frequently than recognition and position in AR related smart manufacturing, it is predicted to grow with the increasing interest in prognosis and health management (PHM) of industrial systems.

Table 3
Combinations of multiple intelligent functions and number of implementations in AR applications.

Combination	Number of applications
Recognition and Positioning	16
Recognition and Classification	2
Recognition and Instruction	4
Recognition and Prognosis	8
Recognition and Optimization	4
Positioning and Instruction	2
Positioning and Optimization	3
Positioning and Prognosis	3
Instruction and Classification	1
Instruction and Prognosis	2
Instruction and Optimization	1
Instruction and Monitoring	1
More than two functions	4
Total	51

3.5. Intelligence source

Intelligence required by AR applications deployed in smart manufacturing is generated using different methods. As shown in Fig. 22, the most common case involves multiple sources of intelligence, accounting for 41 % of the deployed applications. Ambient intelligence and algorithm constitute 20 % and 24 %, respectively. About 11 % of the studies used direct database inquiry and a smaller percentage (4%) acquired intelligence from model estimation. The algorithms used by AR application programs can be classified into two categories: traditional algorithms and machine learning methods. Common applications of traditional algorithms in smart manufacturing include similarity matching [20,37,61], assembly/disassembly sequence optimization [31, 78], pattern recognition [57], and 3D registration [86,96]. Various deep learning methods were implemented in AR assisted smart manufacturing, such as convolutional neural networks (CNN) [1,74], recurrent neural networks (RNN) [83], mask region-based CNN (Mask R-CNN) [62], fast R-CNN [75], and unspecified machine learning methods [64,79].

Several methods have been used in database inquiry including tri-layer assembly data structure (TADS) [36], semantic web rule language (SWRL), ontology for assembly tasks procedure (OATP) [42], expert systems [48,105], and semantic analysis [98]. Different mathematical models have been used to generate intelligence, such as convex optimization penalty [14], Poisson process [39], PMPM [8], discrete event simulation (DES), simulation-based constraint removal (SCORE) [50], and mathematical kinematic models [30]. Various sensing devices have been used to capture ambient intelligence, for example, inertial measurement unit (IMU), electrocardiography (ECG), electromyography (EMG), electroencephalography (EEG), RGB-D camera [1,5,54, 68], ambient light [95,104], length measurement, temperature, vibration, force [4,21,30,47], proximity [89], odor [33], velocity, electrical voltage [23], and infrared thermal camera [86]. Most AR applications need to process ambient intelligence captured by sensors using algorithms. Humans become more sensitive and responsive to the external conditions or changes with the intelligence thus generated. Modern manufacturing operations often face complex situations that require sophisticated decision making. This entails adopting multiple methods of intelligence generation in AR. As shown in Table 4, the most common choice is to combine algorithm and ambient intelligence.

4. Discussions

A number of interesting findings were derived from the literature analysis described in the previous section. We elaborate these findings

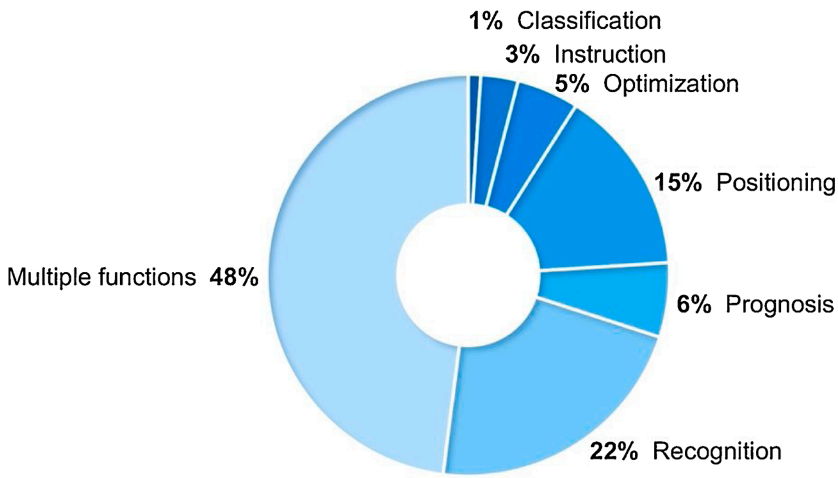


Fig. 20. Classification of functional approaches in AR applications.

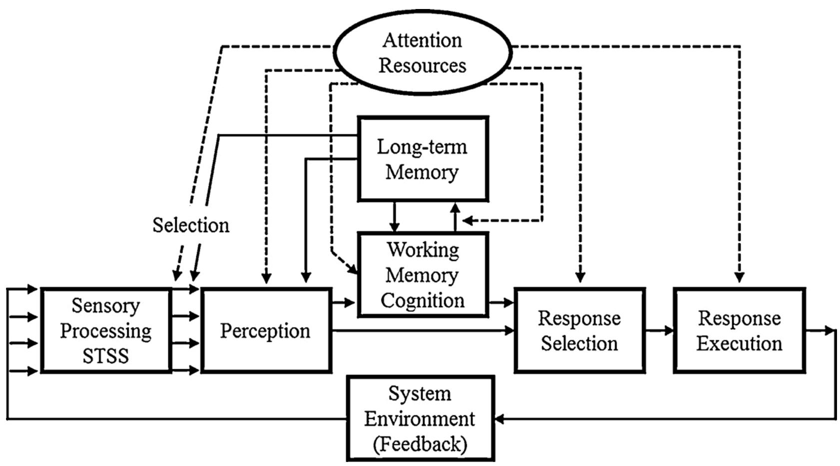


Fig. 21. Modified HIP model [114].

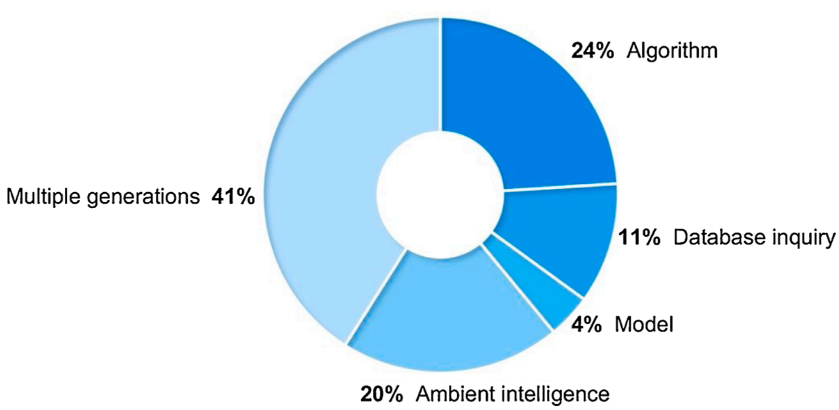


Fig. 22. Classification of intelligence generation methods.

by providing possible explanations or supplementary information, which may provide guidelines for constructing practical AR systems in smart manufacturing.

First, although AI has a tremendous potential in re-shaping the manufacturing industry, it will not be able to replace humans in all manual operations in the near future. A McKinsey's analysis [120] reported that less than 5% of manual tasks (occupations) can be entirely replaced by machines, while only 60 % of all the jobs have at least 30 % of their activities automated. They suggested that a practical approach is to facilitate manual operations using AI and other automation technologies. An example is the HRC [73,101], in which industrial robots are introduced on the shop floor and they collaborate with human workers on manufacturing tasks by complementing their strengths. AR can work as an intuitive interface for both effective communication and coordination in Human-Robot Collaboration (HRC) by offering an improved user experience. Enabled by AI, an AR interface enables in-situ

Table 4
Combination of multiple intelligence sources in AR-related smart manufacturing.

Combination of multiple sources	Number of applications
Database inquiry and algorithm	10
Database inquiry and ambient intelligence	8
Algorithm and model	2
Algorithm and ambient intelligence	13
Model and ambient intelligence	4
More than 2 sources	6
Total	43

authoring and rapid iterations of robot joint planning without conducting offline training [121].

Visual clue is a critical element to support information sharing in human-machine interaction. The reviewed literature showed that visual perception is the main channel of communication with users through AR. In psychology, the ability to visually perceive signaling is one of the most effective means for discriminating between con- and heterospecific individuals [122]. However, non-intuitive or excessive visual stimuli can distract human receivers. For example, users expressed a low usability of AR goggles owing to the poor image quality displayed in a limited field of view (FOV) [100]. Yang et al. [123] implemented an AR training program that provides improved user experience and usability. The program integrated an Intel RealSense R200 depth camera and a Leap Motion controller mounted on an HMD. The HMD thus constructed allows users to freely walk around in a room-size AR environment to operate a full-size virtual milling machine with their bare hands-free and follow their natural operation behaviors.

Incorporating multi-modality can be an effective approach to improving information dissemination or overcoming limitations in a real manufacturing environment, for example, space restrictions, noise, and poor lighting condition. A solution combining the visual and auditory clues eliminated over-dependency on visual stimuli and increased the feeling of involvement for the human operators [49,95,104]. However, multiple-resource model of attention suggests that multiple sources or modalities of similar information are likely to interfere with each other, thus increasing the cognitive load of HIP [114]. It is recommended to avoid such designs in AR applications.

Furthermore, the analysis of the reviewed literature suggested that assembly/disassembly is the most common operation in which AR has been deployed until now. A manual assembly process involves constant hand operations and decision making by humans. If properly designed, AR assisted functions can reduce an operator's mental workload by displaying procedural guidance or standardized instructions during the process [115]. They also help prevent human errors by enhancing on-site context awareness or enforcing safety measures [4,32,91]. In contrast, other operations such as production management and facility layout rarely require the physical participation of humans. They are easily represented by mathematical models and solved without human intervention. The nature of human physical participation is the key to divide the task. AI or automation can be effectively implemented in predictable physical and data collection activities [120]. The implementation is considered more difficult for other activities such as data processing, unpredictable physical work, stakeholder interactions, applying expertise, and managing. Besides, the technical complexity, costs, and reliability of automation solutions can vary significantly in different manufacturing operations. All these factors need to be considered while dividing a task between human and computational intelligence (CI). Some studies have realized the idea of facility layout in an AR environment, which offers useful functions such as instant visualization and dimensional measurements in a real scene [16,70]. Including the building information modeling (BIM) information and layout optimization may increase the practical value of lean construction [124,125].

Manually performing object recognition and positioning requires high attention and awareness from human operators. The mental workload induced from constantly focusing to identify the related clue or signal from the manufacturing environment can be excessive. Human signal detection varies with an individual's capability, sensitivity, and personality, and so does the resultant performance in a condition of high noise or less salience [114]. AR incorporating automatic recognition and positioning is a common method to solve this problem by increasing human's context-awareness in real-time with a reduced mental workload [10,97,103]. The previous work [126] developed an AR interface for both additive and subtractive manufacturing machines. The goal was to increase productivity and situational awareness of machine users with new interaction modalities during the manufacturing process. The interface provides real-time data visualization that allows the users to review sensor feedback as part of the construction process, and thus facilitate their decision making and troubleshooting. As a result, the users are no longer bound to a console in order to check machine status or issue basic commands.

"Prognosis" showed fewer implementation cases than "recognition and positioning" during the past five years; however, the trend of introducing AR into prognosis is growing compared to other functions. Another evidence is that the number of PHM patents has grown rapidly since 2010 (approximately 20 times at present). In addition, the precautions followed in detecting potential failure or abnormality usually require manual operations. AR assisted PHM has received significant attention in industry [127]. We foresee that prognostics will be commonly seen in the future AR applications developed for smart manufacturing.

Big data has started to play an important role in smart manufacturing, owing to the massive amounts of data acquired by various sensors installed on the shop floor. Traditional rule-based approaches may not be suitable to derive sophisticated intelligence from such big and heterogeneous data. Machine learning methods have shown practical value in extracting underlying patterns or implicit rules from massive data. They have been successfully applied to solve many pattern recognition and object recognition problems in the real world. The implementation of machine learning based on big data collected from manufacturing environments has an increasing presence in AR applications. The main challenge here is to assure real-time performance and interactions when machine learning models are deployed in the current AR devices, which usually do not have superior hardware specifications. Cloud computing is sometimes not feasible either, with the limited network bandwidth, which is a common situation in most manufacturing sites. One solution to overcome this problem is to implement the idea of edge computing [128]. To introduce 5 G to the shop floor is technically feasible, even though it may not be economically viable for the present.

5. Conclusion

Manufacturing industries are encountering ever-increasing task complexities on the shop floor driven by product mass customization. Recent advances in Industry 4.0 technologies empower manufacturing systems with high autonomy, adaptability, and intelligence to face such a challenge. However, a large number of operations in the current manufacturing environment continue to be manually operated. Hardware and software solutions simply cannot or economically replace human operators in those operations. The operations may involve physical jobs that require too much dexterity to be completed by machines, or decision making that cannot be logically defined. A better alternative for dealing with such circumstances is to have humans collaborate with intelligent machines. AR is considered an effective interface for humans to communicate with machine intelligence in real-time during the collaboration. This work conducted a systematic review of the recent studies related to AR applications in smart manufacturing. Over 100 publications retrieved from a research database were classified based on four different aspects: interaction device, manufacturing operation, functional approach, and intelligence source. Most studies expect AR assisted tools to find an increasing number of applications in manufacturing industries, as they have started to demonstrate practical value on the shop floor. Assembly/disassembly is the manufacturing operation that most frequently implements AR assisted tools. HMD and HHD are the interactive devices commonly used for information sharing between human and computational intelligence. A majority of the deployed AR applications involve multiple solution functions and intelligence sources to deal with the current complex manufacturing problems. Visual clue/perception is the major sensory channel to communicate with users of AR. A majority of AR applications are designed to provide automatic recognition and positioning functions, whose aim is to reduce human's mental workload. A common source of intelligence generation is to capture sensory data from the ambient and process the data using algorithms. The objective is to increase the human operator's situational awareness in the manufacturing environment.

The analysis of the related studies also reveals several important findings. AR is an interfacing technology that exchanges information with humans in real-time. It may not be an essential element in highly automated manufacturing jobs. Its technical merits become evident when AR is applied to perform tasks in which human and CI can complement each other. A critical issue is to determine how to divide the task between them. Integrating multi-modalities in an AR interface is an effective approach to overcoming limitations in a real manufacturing environment. However, the interface design should avoid presenting multiple sources or modalities of similar information, which may increase the cognitive load of human information processing.

With the progress of enabling technologies such as 5 G, IIoT, and edge computing, AR applications will further penetrate into manufacturing practices from several aspects. AR will be increasingly used to facilitate manual operations existing on the shop floor, particularly non-productive activities like inspection, calibration, set-up, and trouble-shooting. We expect a growing trend of AR assisted PHM of production equipment and their subsequent maintenance. Implementation of machine learning based on big data collected from the manufacturing environment will provide sophisticated intelligence that enhances the practical value of AR. In addition, maintaining real-time interactivity is a crucial but challenging issue in most AR applications. Advancing to 5 G infrastructure is highly advantageous to access the cloud resources. Edge computing also has a great potential for solving this open challenge. By considering AR as a collaboration interface between human and CI, this work analyzed the recent studies related to AR applications in smart manufacturing from a viewpoint different from that of the previous reviews on this subject. The findings and discussions presented here may provide guidelines for implementing practical AR-assisted functions in future smart manufacturing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was funded by Taiwan MOST grant number 108-2221-E-007-007-MY3.

References

[1] Tao W, Lai ZH, Leu MC, Yin Z, Qin R. A self-aware and active-guiding training & assistant system for worker-centered intelligent manufacturing. Manuf Lett 2019;21:45–9.
[2] Schlagowski R, Merkel L, Meitinger C. Design of an assistant system for industrial maintenance tasks and implementation of a prototype using augmented reality. IEEE Int. Conf. Ind. Eng. Eng. Manag 2017:294–8.
[3] Piardi L, Kalempa VC, Limeira M, Schneider de Oliveira A, Leitão P. ARENA—augmented reality to enhanced experimentation in smart warehouses. Sensors 2019;19:1–15.
[4] Kostolani M, Murin J, Kozak S. Intelligent predictive maintenance control using augmented reality. 22nd Int. Conf. Process Control 2019:131–5.
[5] Aransyah D, Rosa F, Colombo G. Smart maintenance: a wearable augmented reality application integrated with CMMS to minimize unscheduled downtime. Comput Aided Des Appl 2020;17:740–51.
[6] Emmanouilidis C, Pistofidis P, Bertoncelj L, Katsouros V, Fournaris A, Koulamas C, et al. Enabling the human in the loop: linked data and knowledge in industrial cyber-physical systems. Annu Rev Control 2019;47:249–65.
[7] Zhou J, Zhou Y, Wang B, Zang J. Human–Cyber–Physical Systems (HCPSs) in the context of new-generation intelligent manufacturing. Engineering 2019;5:624–36.
[8] Lee H, Liau Y, Kim S, Ryu K. A framework for process model based human-robot collaboration system using augmented reality. Adv Prod Manag Syst Smart Manuf Ind 40 2018;536:482–9.
[9] Ragni M, Perini M, Setti A, Bosetti P. ARTool Zero: programming trajectory of touching probes using augmented reality. Comput Ind Eng 2018;124:462–73.
[10] Leutert F, Schilling K. Projector-based augmented reality for telemaintenance support. Int Fed Autom Control (IFAC)-PapersOnLine 2018;51:502–7.
[11] Segovia D, Mendoza M, Mendoza E, González E. Augmented reality as a tool for production and quality monitoring. Procedia Comput Sci 2015;75:291–300.
[12] Muñoz A, Mahiques X, Solanes JE, Martí A, Gracia L, Tornero J. Mixed reality-based user interface for quality control inspection of car body surfaces. Int J Ind Manuf Syst Eng 2019;53:75–92.
[13] Wang X, Yew AWW, Ong SK, Nee AYC. Enhancing smart shop floor management with ubiquitous augmented reality. Int J Prod Res 2019;58:2352–67.
[14] Fang HC, Ong SK, Nee AYC. Interactive robot trajectory planning and simulation using augmented reality. Robot Comput Integr Manuf 2012;28:227–37.
[15] Mendoza M, Mendoza M, Mendoza E, González E. Augmented reality as a tool of training for data collection on torque auditing. Procedia Comput Sci 2015;75:5–11.
[16] Kokkas A, Vosniakos G-C. Augmented reality approach to factory layout design embedding operation simulation. Int J Interact Des Manuf 2019;13:1061–71.
[17] Kiswanto G, Ariansyah D. Development of augmented reality (AR) for machining simulation of 3-axis CNC milling. Int. Conf. Adv. Comput. Sci. Inf. Syst., IEEE 2013:143–8.
[18] Quint F, Loch F, Orfgen M, Zuehlke D. A system architecture for assistance in manual tasks. Intell Environ 2016;21:43–52.
[19] Schroeder G, Steinmetz C, Pereira CE, Muller I, Garcia N, Espindola D, et al. Visualising the digital twin using web services and augmented reality. 14th Int. Conf. Ind. Informatics, IEEE 2016:522–7.
[20] Yew AWW, Ong SK, Nee AYC. Towards a griddable distributed manufacturing system with augmented reality interfaces. Robot Comput Integr Manuf 2016;39:43–55.
[21] Liu C, Cao S, Tse W, Xu X. Augmented reality-assisted intelligent window for cyber-physical machine tools. J Manuf Syst 2017;44:280–6.
[22] Mourtzis D, Vlachou A, Zogopoulos V. Cloud-based augmented reality remote maintenance through shop-floor monitoring: a product-service system approach. J Manuf Sci Eng 2017;139:1–11.
[23] Mourtzis D, Vlachou E, Zogopoulos V, Fotini X. Integrated production and maintenance scheduling through machine monitoring and augmented reality: an industry 4.0 approach. Int Fed Inf Process 2017;513:354–62.
[24] Ivaschenko A, Khorina A, Sitnikov P. Accented visualization by augmented reality for smart manufacturing aplications. Ind. Cyber-physical syst. ICPS 2018. IEEE; 2018. p. 519–22.
[25] Liu C, Hong X, Zhu Z, Xu X. Machine tool digital twin: modelling methodology and applications. Int Conf Comput Ind Eng 2018;48:1–11.
[26] Zhu Z, Liu C, Xu X. Visualisation of the digital twin data in manufacturing by using augmented reality. Procedia CIRP 2019;81:898–903.
[27] Chang MML, Ong SK, Nee AYC. AR-guided product disassembly for maintenance and remanufacturing. Procedia CIRP 2017;61:299–304.
[28] Makris S, Pintzos G, Rentzos L, Chryssolouris G. Assembly support using AR technology based on automatic sequence generation. CIRP Ann Manuf Technol 2013;62:9–12.
[29] Makris S, Karagiannis P, Koukas S, Matthaiakis AS. Augmented reality system for operator support in human–robot collaborative assembly. CIRP Ann Manuf Technol 2016;65:61–4.
[30] Minoufekr M, Schug P, Zenker P, Plapper P. Modelling of CNC machine tools for augmented reality assistance applications using microsoft hololens. 16th Int. Conf. Inform. Control Autom. Robot 2019:627–36.
[31] Osti F, Ceruti A, Liverani A, Caligiana G. Semi-automatic design for disassembly strategy planning: an augmented reality approach. Procedia Manuf 2017;11:1481–8.
[32] Siew CY, Ong SK, Nee AYC. A practical augmented reality-assisted maintenance system framework for adaptive user support. Robot Comput Integr Manuf 2019;59:115–29.
[33] Wang J, Erkoyuncu J, Roy R. A conceptual design for smell based augmented reality: case study in maintenance diagnosis. Procedia CIRP 2018;78:109–14.
[34] Ziaei Z, Hahto A, Mattila J, Siuko M, Semeraro L. Real-time markerless augmented reality for remote handling system in bad viewing conditions. Fusion Eng Des 2011;86:2033–8.
[35] Yuan ML, Ong SK, Nee AYC. Assembly guidance in augmented reality environments using a virtual interactive tool. Int J Prod Res 2015;46:1745–67.

[36] Ong SK, Wang ZB. Augmented assembly technologies based on 3D bare-hand interaction. CIRP Ann Manuf Technol 2011;60:1–4.
[37] Di Donato L. Augmented reality and artificial intelligence to create innovative solution sisom. WIT Trans Built Environ 2018;174:181–6.
[38] Michalos G, Karagiannis P, Makris S, Tokçalar Ö, Chryssolouris G. Augmented Reality (AR) applications for supporting human-robot interactive cooperation. Procedia CIRP 2016;41:370–5.
[39] Gianni M, Ferri F, Pirri F. ARE: augmented reality environment for mobile robots. Towar Auton Robot Syst (TAROS). Part Lect Notes Comput Sci B Ser 2014;8069: 470–83.
[40] Webel S, Bockholt U, Engelke T, Gavish N, Olbrich M, Preusche C. An augmented reality training platform for assembly and maintenance skills. Rob Auton Syst 2013;61:398–403.
[41] Benbelkacem S, Belhocine M, Bellarbi A, Zenati-Henda N, Tadjine M. Augmented reality for photovoltaic pumping systems maintenance tasks. Renew Energy 2013; 55:428–37.
[42] Wang X, Ong SK, Nee AYC. Multi-modal augmented-reality assembly guidance based on bare-hand interface. Adv Eng Inf. 2016;30:406–21.
[43] Lee S, Akin Ö. Augmented reality-based computational fieldwork support for equipment operations and maintenance. Autom Constr 2011;20:338–52.
[44] Engelke T, Keil J, Rojtberg P, Wientapper F, Webel S, Bockholt U. Content first - a concept for industrial augmented reality maintenance applications using mobile devices. Int. Symp. Mix. Augment. Real. 2013 Sci. Technol. Proc., IEEE 2013: 251–2.
[45] Wang J, Feng Y, Zeng C, Li S. An augmented reality based system for remote collaborative maintenance instruction of complex products. Int. Conf. Autom. Sci. Eng., IEEE 2014:309–14.
[46] Fang D, Xu H, Yang X, Bian M. An augmented reality-based method for remote collaborative real-time assistance: from a system perspective. Mob Networks Appl 2019;25:412–25.
[47] Tzimas E, Vosniakos G-C, Matsas E. Machine tool setup instructions in the smart factory using augmented reality: a system construction perspective. Int J Interact Des Manuf 2019;13:121–36.
[48] Syberfeldt A, Danielsson O, Holm M, Wang L. Dynamic operator instructions based on augmented reality and rule-based expert systems. Procedia CIRP 2016; 41:346–51.
[49] Quintero CP, Li S, Pan MK, Chan WP, Machiel Van Der Loos HF, Croft E. Robot programming through augmented trajectories in augmented reality. Int. Conf. Intell. Robot. Syst. 2018:1838–44.
[50] Karlsson I, Bernedixen J, Ng AH, Pehrsson L. Combining augmented reality and simulation-based optimization for decision support in manufacturing. Winter Simul. Conf. 2017:3988–99.
[51] Simoes B, Alvarez H, Segura A, Barandiaran I. Unlocking augmented interactions in short-lived assembly tasks. Adv Intell Syst Comput 2019;771:270–9.
[52] Buttner S, Sand O, Rocker C. Exploring design opportunities for intelligent worker assistance: a new approach using projetion-based AR and a novel hand-tracking algorithm. Ambient Intell Part Lect Notes Comput Sci B Ser 2017;10217:33–45.
[53] Mourtzis D, Zogopoulos V, Vlachou E. Augmented reality application to support remote maintenance as a service in the robotics industry. Procedia CIRP 2017;63: 46–51.
[54] Peppoloni L, Brizzi F, Ruffaldi E, Avizzano CA. Augmented reality-aided tele-presence system for robot manipulation in industrial manufacturing. Proc ACM Symp Virtual Real Softw Technol 2015;21:237–40.
[55] Luo B, Ge S. Augmented reality for material processing within shielded radioactive environment. 8th Int. Congr. Image Signal Process., IEEE 2015:92–7.
[56] Brizzi F, Peppoloni L, Graziano A, Di Stefano E, Avizzano CA, Ruffaldi E. Effects of augmented reality on the performance of teleoperated industrial assembly tasks in a robotic embodiment. IEEE Trans Human-Machine Syst 2018;48:197–206.
[57] Ceruti A, Liverani A, Bombardi T. Augmented vision and interactive monitoring in 3D printing process. Int J Interact Des Manuf 2016;11:385–95.
[58] Mourtzis D, Zogopoulos V, Xanthi F. Augmented reality application to support the assembly of highly customized products and to adapt to production re-scheduling. Int J Adv Manuf Technol 2019;105:3899–910.
[59] Dvorak P, Josth R, Delponte E. Object state recognition for automatic AR-based maintenance guidance. Comput. Vis. Pattern Recognit., IEEE 2017:1244–50.
[60] Frank JA, Kapila V. Towards teleoperation-based interactive learning of robot kinematics using a mobile augmented reality interface on a tablet. Indian Control Conf., IEEE 2016:385–92.
[61] Liu H, Wang L. An AR-based worker support system for human-robot collaboration. Procedia Manuf 2017;11:22–30.
[62] Park KB, Kim M, Choi SH, Lee JY. Deep learning-based smart task assistance in wearable augmented reality. Robot Comput Integr Manuf 2020;63:1–18.
[63] Doshi A, Smith RT, Thomas BH, Bouras C. Use of projector based augmented reality to improve manual spot-welding precision and accuracy for automotive manufacturing. Int J Adv Manuf Technol 2017;89:1279–93.
[64] Akşit K, Chakravarthula P, Rathinavel K, Jeong Y, Albert R, Fuchs H, et al. Manufacturing application-driven foveated near-eye displays. IEEE Trans Vis Comput Graph 2019;25:1928–39.
[65] Ivanov V, Pavlenko I, Liaposhchenko O, Gusak O, Pavlenko V. Determination of contact points between workpiece and fixture elements as a tool for augmented reality in fixture design. Wirel Networks 2019;2:1–8.
[66] Malik A, Lhachemi H, Ploennigs J, Ba A, Shorten R. An application of 3D model reconstruction and augmented reality for real-time monitoring of additive manufacturing. Procedia CIRP 2019;81:346–51.
[67] Calabrò EM, Cutolo F, Carbone M, Ferrari V. Wearable augmented reality optical see through displays based on integral imaging. MobiHealth 2016, Part Lect Notes Inst Comput Sci Soc Informatics Telecommun Eng B Ser 2017;192:345–56.
[68] Andersen RS, Bøgh S, Moeslund TB, Madsen O. Intuitive task programming of stud welding robots for ship construction. Int. Conf. Ind. Technol., IEEE 2015: 3302–7.
[69] Araiza-Illan D, De San Bernabe A, Hongchao F, Shin LY. Augmented reality for quick and intuitive robotic packing re-programming. Int. Conf. Human-Robot Interact., IEEE 2019:664.
[70] Aschenbrenner D, Li M, Dukalski R, Verlinden J, Lukosch S. Collaborative production line planning with augmented fabrication. Conf. Virtual Real. 3D User Interfaces, IEEE 2018:509–10.
[71] Kocisko M, Teliskova M, Baron P, Zajac J. An integrated working environment using advanced augmented reality techniques. 4th Int. Conf. Ind. Eng. Appl., IEEE 2017:279–83.
[72] Mourtzis D, Xanthi F, Zogopoulos V. An adaptive framework for augmented reality instructions considering workforce skill. Procedia CIRP 2019;81:363–8.
[73] Ong SK, Yew AWW, Thanigaivel NK, Nee AYC. Augmented reality-assisted robot programming system for industrial applications. Robot Comput Integr Manuf 2020;61:101820.
[74] Schröder M, Ritter H. Deep learning for action recognition in augmented reality assistance systems. ACM SIGGRAPH 2017:1–2.
[75] Wang S, Guo R, Wang H, Ma Y, Zong Z. Manufacture assembly fault detection method based on deep learning and mixed reality. Int. Conf. Inf. Autom., IEEE 2018:808–13.
[76] Ahn SJ, Han SU, Al-Hussein M. 2D drawing visualization framework for applying projection-based augmented reality in a panelized construction manufacturing facility: proof of concept. J Comput Civ Eng 2019;33:1–15.
[77] Álvarez H, Lajas I, Larrañaga A, Amozarrain L, Barandiaran I. Augmented reality system to guide operators in the setup of die cutters. Int J Adv Manuf Technol 2019;103:1543–53.
[78] Bhattacharya B, Winer EH. Augmented reality via expert demonstration authoring (AREDA). Comput Ind 2019;105:61–79.
[79] Villegas-Hernandez YS, Guedea-Elizalde F. Marker's position estimation under uncontrolled environment for augmented reality. Int J Interact Des Manuf 2017; 11:727–35.
[80] Setti A, Bosetti P, Ragni M. ARTool- augmented reality platform for machining setup and maintenance. Intell Syst Conf (IntelliSys), Part Lect Notes Networks Syst, 15; 2016. p. 457–75.
[81] Zubizarreta J, Aguinaga I, Amundarain A. A framework for augmented reality guidance in industry. Int J Adv Manuf Technol 2019;102:4095–108.
[82] Neves J, Serrario D, Pires JN. Application of mixed reality in robot manipulator programming. Ind Robot An Int J 2018;45:784–93.
[83] Cachada A, Barbosa J, Leitão P, Geraldes CAS, Deusdado L, Costa J, et al. Maintenance 4.0: intelligent and predictive maintenance system architecture. Int. Conf. Emerg. Technol. Fact. Autom., IEEE 2018:139–46.
[84] Liu YK, Zhang YM. Super welder in augmented reality welder training system: a predictive control approach. Int. Symp. Ind. Electron., IEEE 2015:131–6.
[85] Mourtzis D, Zogopoulos V, Katagis I, Lagios P. Augmented reality based visualization of CAM instructions towards industry 4.0 paradigm: a CNC bending machine case study. Procedia CIRP 2018;70:368–73.
[86] Borrmann D, Leutert F, Schilling K, Nüchter A. Spatial projection of thermal data for visual inspection. 14th Int. Conf. Control. Autom. Robot. Vis. 2016:1–6.
[87] De Silva RKJ, Basnayaka BMAN. An augmented reality-based simulation guide for apparel assembly. Int J Recent Technol Eng 2019;8:3012–8.
[88] Diao PH, Shih NJ. BIM-based AR maintenance system (BARMS) as an intelligent instruction platform for complex plumbing facilities. Appl Sci 2019;9:1–12.
[89] Hao Y, Helo P. The role of wearable devices in meeting the needs of cloud manufacturing: a case study. Robot Comput Integr Manuf 2015;45:1–12.
[90] Kuts V, Otto T. Adaptive industrial robots using machine vision. Int. Mech. Eng. Congr. Expo., ASME 2018:1–8.
[91] Tatić D, Tešić B. The application of augmented reality technologies for the improvement of occupational safety in an industrial environment. Comput Ind 2017;85:1–10.
[92] Moteki A, Yamaguchi N, Karasudani A, Kobayashi Y, Yoshitake T, Kato J, et al. Manufacturing defects visualization via robust edge-based registration. Int. Symp. Mix. Augment. Real. Adjun. IEEE 2018:172–3.
[93] Nguyen V, Rupavatharam S, Liu L, Howard R, Gruteser M. HandSense: capacitive coupling-based dynamic, micro finger gesture recognition. Embed Networked Sens Syst 2019;17:285–97.
[94] Pardo-Vicente MÁ, Rodríguez-Parada L, Mayuet-Ares PF, Aguayo-González F. Haptic hybrid prototyping (HHP): an AR application for texture evaluation with semantic content in product design. Appl Sci 2019;9:1–20.
[95] Peña-Rios A, Hagras H, Gardner M, Owusu G. A fuzzy logic based system for geolocated augmented reality field service support. Int. Conf. Fuzzy Syst., IEEE 2017:1–6.
[96] Radkowski R, Kanunganti S. Augmented reality system calibration for assembly support with the microsoft hololens. 13th Int. Manuf. Sci. Eng. Conf. (MSEC), ASME 2018:1–10.
[97] Riexinger G, Kluth A, Olbrich M, Braun JD, Bauernhansl T. Mixed reality for on-site self-instruction and self-inspection with building information models. Procedia CIRP 2018;72:1124–9.
[98] Lamberti F, Manuri F, Paravati G, Piumatti G, Sanna A. Using semantics to automatically generate speech interfaces for wearable virtual and augmented reality applications. IEEE Trans Human-Machine Syst 2017;47:152–64.

[99] Ruffaldi E, Di Fava A, Loconsole C, Frisoli A, Avizzano CA. Vibrotactile feedback for aiding robot kinesthetic teaching of manipulation tasks. Int. Symp. Robot Hum. Interact. Commun., IEEE 2017:818–23.
[100] Arbeláez JC, Viganò R, Osorio-Gómez G. Haptic augmented reality (HapticAR) for assembly guidance. Int J Interact Des Manuf 2019;13:673–87.
[101] Casalino A, Messeri C, Pozzi M, Zanchettin AM, Rocco P, Prattichizzo D. Operator awareness in human-robot collaboration through wearable vibrotactile feedback. IEEE Robot Autom Lett 2018;3:4289–96.
[102] Chan WP, Quintero CP, MKXJ Pan, Sakr M, Van der Loos HFM, Croft EA. A multimodal system using augmented reality, gestures, and tactile feedback for robot trajectory programming and execution. Int. Conf. Robot. Autom., IEEE 2019:1–7.
[103] Clemente F, Dosen S, Lonini L, Markovic M, Farina D, Cipriani C. Humans can integrate augmented reality feedback in their sensorimotor control of a robotic hand. IEEE Trans Human-Machine Syst 2017;47:583–9.
[104] Dey S, Sarkar P. Augmented reality based integrated intelligent maintenance system for production line. 8th Indian Conf. Hum. Comput. Interact., ACM 2016: 126–31.
[105] Holm M, Danielsson O, Syberfeldt A, Moore P, Wang L. Adaptive instructions to novice shop-floor operators using augmented reality. J Ind Prod Eng 2017;34: 362–74.
[106] Ni D, Yew AWW, Ong SK, Nee AYC. Haptic and visual augmented reality interface for programming welding robots. Adv Manuf 2017;5:191–8.
[107] Yin X, Fan X, Wang J, Liu R, Wang Q. An automatic interaction method using part recognition based on deep network for augmented reality assembly guidance. Int. Des. Eng. Tech. Conf. Comput. Inf. Eng., ASME 2018:1–10.
[108] Büttner S, Funk M, Sand O, Röcker C. Using head-mounted displays and in-situ projection for assistive systems - a comparison. ACM Int. Conf. Proceeding Ser., vol. 29-1; 2016. p. 1–8. July.
[109] Kramida G. Resolving the vergence-accommodation conflict in head-mounted displays. IEEE Trans Vis Comput Graph 2016;22:1912–31.
[110] Huang Y-P. Visual perception and fatigue in AR/VR head-mounted displays. Inf Disp 2019;1975(35):4–5.
[111] Elia V, Gnoni MG, Lanzilotto A. Evaluating the application of augmented reality devices in manufacturing from a process point of view: an AHP based model. Expert Syst Appl 2016;63:187–97.
[112] Hsieh YT, Orso V, Andolina S, Canaveras M, Cabral D, Spagnolli A, et al. Interweaving visual and audio-haptic augmented reality for urban exploration. Des. Interact. Syst. Conf. 2018:215–26.
[113] Xia P. Haptics for product design and manufacturing simulation. IEEE Trans Haptics 2016;9:358–75.
[114] Wickens CD. Multiple resources and performance prediction. Theor Issues Ergon Sci 2002;3:159–77.
[115] Chu C-H, Liao C-J, Lin S-C. Comparing augmented reality-assisted assembly functions—a case study on dougong structure. Appl Sci 2020;10:1–16.
[116] Cao Y, Qian X, Wang T, Lee R, Huo K, Ramani K. An exploratory study of augmented reality presence for tutoring machine tasks. Conf. Hum. Factors Comput. Syst. 2020:1–13.
[117] Chu C-H, Liu Y-W, Li P-C, Huang L-C, Luh Y-P. Programming by demonstration in augmented reality for the motion planning of a three-axis CNC dispenser. Int J Precis Eng Manuf Technol 2019;4:1–9.
[118] Dusadeerungsikul PO, Sreeram M, He X, Nair A, Ramani K, Quinn AJ, et al. Collaboration requirement planning protocol for hub-Ci in factories of the future. Procedia Manuf 2019;39:218–25.
[119] Zhang Y, Kwok TH. Design and interaction interface using augmented reality for smart manufacturing. Procedia Manuf 2018;26:1278–86.
[120] McKinsey Global Institute. A future that works: automation, employment, and productivity. 2017.
[121] Cao Y, Wang T, Qian X, Rao PS, Wadhawan M, Huo K, et al. GhostAR: a time-space editor for embodied authoring of human-robot collaborative task with augmented reality. Proc. 32nd Annu. ACM Symp. User Interface Softw. Technol. 2019:521–34.
[122] Trafton A. In the blink of an eye MIT neuroscientists find the brain can identify images seen for as little as 13 milliseconds. MIT News; 2014 (accessed June 4, 2020), http://news.mit.edu/2014/in-the-blink-of-an-eye-0116.
[123] Yang C-K, Chen Y-H, Chuang T-J, Shankhwar K, Smith S. An augmented reality-based training system with a natural user interface for manual milling operations. Virtual Real 2019;24:527–39.
[124] Herr D, Reinhardt J, Reina G, Krüger R, Ferrari RV, Ertl T. Immersive modular factory layout planning using augmented reality. Procedia CIRP 2018;72:1112–7.
[125] Ratajczak J, Riedl M, Matt DT. BIM-based and AR application combined with location-based management system for the improvement of the construction performance. Buildings 2019;9:1–17.
[126] Borish M, Westfall J. Additive and subtractive manufacturing augmented reality interface (ASMARI). IEEE SoutheastCon 2020 Addit. 2020:1–6.
[127] Pecht MG, Kang M. Prognostics and health management of electronics: fundamentals, machine learning, and the internet of things. 2nd ed. New York: John Wiley and Sons Ltd; 2018.
[128] Ran X, Chen H, Zhu X, Liu Z, Chen J. DeepDecision: a mobile deep learning framework for edge video analytics. Conf. Comput. Commun., IEEE 2018:1421–9.