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Review

Proactive human–robot collaboration: Mutual-cognitive, predictable, and self-organising perspectives

Shufei Li [a,b], Pai Zheng [a,*], Sichao Liu [b], Zuoxu Wang [c], Xi Vincent Wang [b], Lianyu Zheng [c], Lihui Wang [b,*]

[a] Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong Special Administrative Region of China
[b] Department of Production Engineering, KTH Royal Institute of Technology, Sweden
[c] School of Mechanical Engineering and Automation, Beihang University, Beijing, China

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ABSTRACT

Human–Robot Collaboration (HRC) has a pivotal role in smart manufacturing for strict requirements of human-centricity, sustainability, and resilience. However, existing HRC development mainly undertakes either a human-dominant or robot-dominant manner, where human and robotic agents reactively perform operations by following pre-defined instructions, thus far from an efficient integration of robotic automation and human cognition. The stiff human–robot relations fail to be qualified for complex manufacturing tasks and cannot ease the physical and psychological load of human operators. In response to these realistic needs, this paper presents our arguments on the obvious trend, concept, systematic architecture, and enabling technologies of Proactive HRC, serving as a prospective vision and research topic for future work in the human-centric smart manufacturing era. Human–robot symbiotic relation is evolving with a 5C intelligence — from Connection, Coordination, Cyber, Cognition to Coevolution, and finally embracing mutual-cognitive, predictable, and self-organising intelligent capabilities, i.e., the Proactive HRC. With proactive robot control, multiple human and robotic agents collaboratively operate manufacturing tasks, considering each others' operation needs, desired resources, and qualified complementary capabilities. This paper also highlights current challenges and future research directions, which deserve more research efforts for real-world applications of Proactive HRC. It is hoped that this work can attract more open discussions and provide useful insights to both academic and industrial practitioners in their exploration of human–robot flexible production.

1. Introduction

In today's transformation to human-centric, sustainable, resilient production under Industry 5.0 [1,2], industrial companies are striving to achieve: (1) transformable production without high changeover times when new products are introduced by manufacturers [3]; (2) flexible production of complicated and precise mechanical parts which relieves manual operation dependence [4]; and (3) occupational health of employees which prevents musculoskeletal disorders caused by awkward postures, excessive effort, and repetitive movements [5]. To pave the wave of this human-centric smart manufacturing paradigm [6], HRC is becoming a prominent production architecture to combine the high accuracy and strength of robots with the advanced cognition and flexibility of humans. HRC systems can shift manufacturing processes to flexible automation and maximise productivity.

HRC in a manufacturing context allows humans to work side by side with robots in close proximity [7]. In the last decade, numerous studies have explored HRC applications in various production activities. These research efforts on human safety [8], operator assistance [9], robot adaptive control [10] promote HRC applications in manufacturing, such as assembly [11], material handling, welding, picking-and-placing [12], etc. Nevertheless, nowadays HRC architecture is still stuck in a slave/master mode. The HRC systems fail to learn knowledge of on-site situations and adjust strategies to fulfil the best complementary capacity of humans and robots. Hence, by combining IT, OT, AI, and human intelligence, Proactive HRC [13] paradigm was introduced to achieve "*a bi-directional, proactive, and globally optimal collaboration for multiple human operators and robots*". Based on knowledge learning of dynamic human–robot–task relations and timely updated operation arrangements, the robot is like a part of a human body and proactively coordinates with the human, while human naturally follows flexible task decisions to enhance their close collaboration for a common goal. With the leading Proactive HRC systems changing the production structure of today's enterprises, it is

* Corresponding authors.
E-mail addresses: lihuiw@kth.se (L. Wang), pai.zheng@polyu.edu.hk (P. Zheng).

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Nomenclature

AGV	Automated Guided Vehicle
AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Augmented Reality
CCA	Canonical Components Analysis
CNN	Convolution Neural Network
CP	Constraint Programming
CPS	Cyber–Physical System
DL	Deep Learning
DoF	Degrees of Freedom
DT	Digital Twin
DTW	Dynamic Time Warping
EEG	Electroencephalogram
EMG	Electromyography
FB	Function Block
GMM	Gaussian Mixture Model
GPU	Graphics Processing Unit
HHT	Human–Human Team
HRC	Human–Robot Collaboration
HRI	Human–Robot Interaction
HRT	Human–Robot Team
ICP	Iterative Closest Point
$IIoT$	Industrial Internet of Thing
IT	Information Technology
KDL	Kinematics and Dynamics Library
KG	Knowledge Graph
LDA	Linear Discriminant Analysis
$LiDAR$	Light Detection and Ranging
$LSTM$	Long Short Term Memory
$MCTS$	Monte Carlo Tree Search
ML	Machine Learning
MR	Mixed Reality
OBB	Oriented Bounding Box
$OMPL$	Open Motion Planning Library
OT	Operational Technology
RL	Reinforcement Learning
RNN	Recurrent Neural Network
ROS	Robot Operating System
RTT	Rapidly-exploring Random Tree
SG	Scene Graph
$SLAM$	Simultaneous Localisation and Mapping
SVR	Support Vector Regression
TL	Transfer Learning
UGV	Unmanned Ground Vehicle
VQA	Visual Question Answering

necessary to figure out (1) how the paradigm evolves from human–robot relationships, (2) which architecture and attributed modules can tackle current challenges in manufacturing and present widespread practical implementations, and (3) what the future perspectives are when considering a potential combination of cutting-edge technologies, such as cognitive computing, IIoT, robot learning, etc.

In literature, some reviews have been conducted for the HRC implementation and system classification, especially on the human safety criteria [14] and specific manufacturing tasks [15]. However, for the emerging paradigm of Proactive HRC, to the best of the authors' knowledge, no comprehensive connotation has been declared in this field, let alone to point out its critical intelligent capabilities, technical challenges, and opportunities. Aiming to fill the gap, this paper attempts to systematically propose an elaborate architecture of Proactive HRC. It is hoped that this foreseeable manufacturing paradigm can inspire substantial discussions, debates, and development for real-world implementation. Firstly, the evolvement of Proactive HRC is elaborated from a 5C intelligence roadmap of human–robot relationships (Section 2). As key contributions, the mutual-cognitive, predictable, and self-organising intelligent capabilities of Proactive HRC are devised and presented in Section 3, Section 4, and Section 5, respectively. Followed by enabling control technologies of compliance controller and proactive motion planning, which are illustrated in Section 6. Then, main challenges and future perspectives are highlighted in Section 7. Lastly, major contributions and limitations of this study are given in Section 8.

2. From HRC to proactive HRC

In this section, human–robot relations in manufacturing activities and the evolution to Proactive HRC are first reviewed. Basic characteristics of Proactive HRC, i.e., enhanced operator capabilities and human-like robot skills are expounded in the following parts, to reveal the motivations and research points.

2.1. Human–robot relationship evolvement

Ever since the introduction of industrial robots to large-scale production lines, researchers and engineers have spurred a concentration on human–robot relationships.

As shown in Fig. 1, the evolvement pathway of human–robot relationships towards Proactive HRC can be divided into six phases, in terms of the two parties' complementary (*horizontal axis*) and the degree of intelligent capabilities (*vertical axis*). In this context, the horizontal axis (i.e., hexagon) depicts the engagement and responsibility that humans and robots need to take when performing a collaborative task [16]. In various phases of task execution, there are three different roles that the human and robotic agents may perform: (1) an active role which is the dominant decision-maker; (2) a supportive role which conducts aided operations desired by the teammate; and (3) an inactive role which acts as an idle spectator and trusts the teammate's manipulation. Intuitive human behaviours (physical and mental stress-free) and adaptive robot control mean humans and robots can on-demand adjust their roles for time-changing situations, respectively. Meanwhile, the vertical axis represents the smartness levels for human–robot relationships, derived from a 5C architecture of the CPS model [17], namely (1) *connection*, which represents parallelly joint work capability between humans and robots (e.g., co-assembly of a gearbox under predefined procedures); (2) *coordination*, which stands for simultaneous cooperation skills based on sensorial and perceptual results of surrounding environments (e.g., obstacle detection by robot vision); (3) *cyber*, which denotes synchronous activity from all parties in a previewable and predictable execution loop with dynamic changes (e.g., cloud robotics and sharing resources); (4) *cognition*, which stands for the cognitive understanding and high-level decision intelligence for human–robot organisations (e.g., human intention recognition and robot learning); (5) *coevolution*, which represents self-fulfilment goals and collaborative intelligence, like self-organising resource allocation and ergonomic cooperation. The higher smartness levels inherit and accumulate characteristics of underlying architectures stepwise. On the other hand, the unreached degree of active behaviours for human and robotic agents is denoted with the shaded block (grey) in each smartness level. With these considerations, the critical characteristics of each paradigm are summarised in the box, and highlighted its evaluation result in the three-dimensional coordinate accordingly.

Dating far back from 1979, a few researchers explored the possibility of modelling robots as an operator [18], which paved the way

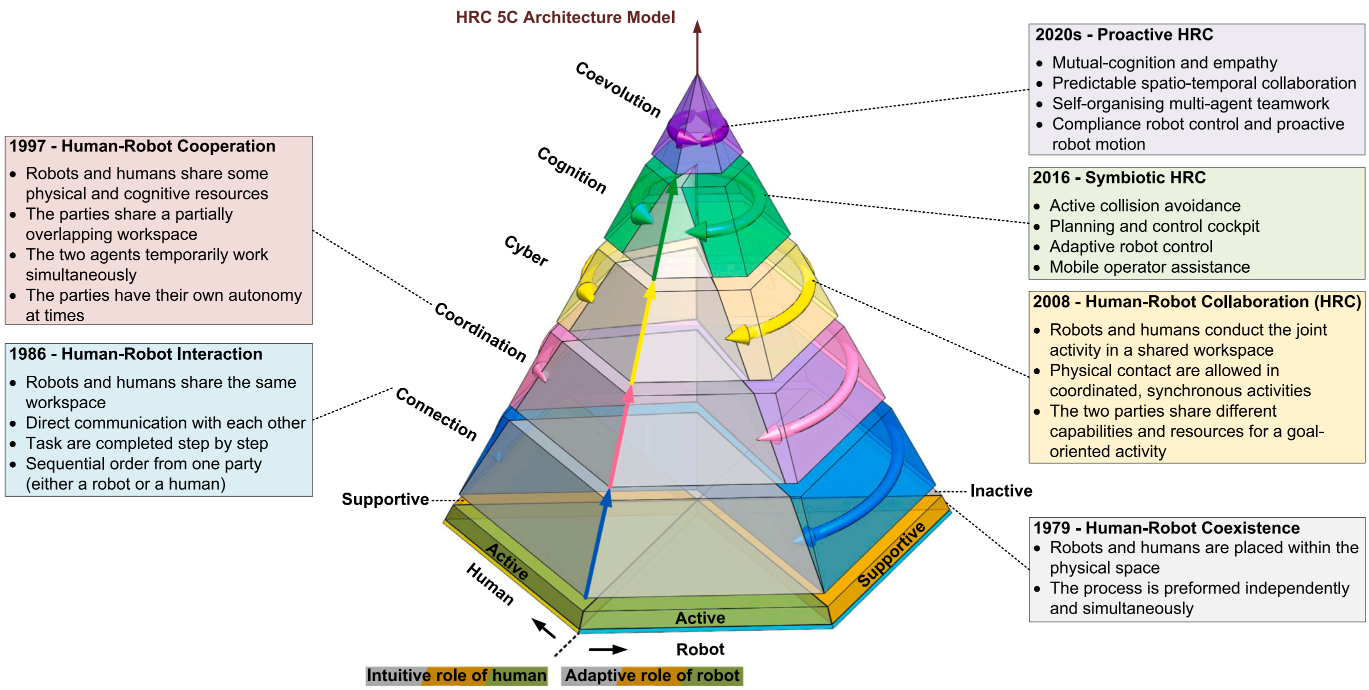

Fig. 1. An evolvement pathway towards Proactive HRC. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Source: Adapted from [13].

to human–robot coexistence in manufacturing tasks [19,20]. Despite a partially shared workspace at this stage, humans and robots merely perform respective assigned tasks (black arrows in Fig. 1) and are separated with fences (black dash line in Fig. 1), without team consciousness. Then, human–robot relationships were enhanced with smart and intelligent capabilities, and firstly stepped into interaction level [21] based on sensor and communication technology. HRI allows for seamless communication between two agents [22]. In this stage, humans and robots obey orders from teammates and sequentially complete operation sequences [23]. Even with the later appearance of advanced interactive manners, such as physical haptic [24], gestures [25], and brain–computer interface [26], the HRI allows one partner to act in supportive behaviours for the other collaborator, but scantily explores mutual active synergism (blue arrow in Fig. 1). Based on scenario perception and optimal controller [27], human–robot agents were empowered with their own autonomy (active role) and evolved into a relationship of human–robot cooperation [28], as presented by the pink arrow in Fig. 1. Then, numerous research efforts on commercial robotics applications, such as picking-and-placing [29], heavy material installing [30], and object handover [31], promote the surge of flexible manufacturing implementations from 2005 onwards [32,33].

Ever since 2008, HRC became a prevailing phenomenon for industrial participators, coinciding with the trend towards personalised production [34–36]. Using technologies of CPS [37] and robot decision-making [38], humans and robots among HRC systems could share different capabilities and on-demand resources in the execution loop. The weakness of this stage is that a high-level understanding of manufacturing tasks remains unattained, thus few active-role behaviours are promoted in the collaboration (yellow arrow in Fig. 1). For example, major explorations in this stage focused on the non-semantic perception level, like human motion estimation [39], operator stress assessment [40], and safety control strategies [41]. Then, equipped with cognitive computing and multimodal communication techniques (green arrow) [42], Symbiotic HRC was proposed to improve manufacturing performance by combining human and robotic agents' complementing competencies [16]. The paradigm is driven by four major aspects, i.e., active collision avoidance, planning and control cockpit, adaptive robot control, and mobile operator assistance. Following the smartness evolvement (purple arrow in Fig. 1), Proactive HRC [13] is rising as a key supplement and the final phase of Symbiotic HRC. The advanced Proactive HRC is characterised by four pivotal modules: (1) mutual-cognition and empathy among human–robot–workspace execution loop, (2) predictable spatio-temporal collaboration for task fulfilment, (3) self-organising multi-agent teamwork with dynamic resource allocation, and (4) compliance robot control and proactive robot motion. In this context, the Proactive HRC meets human-centric needs and reaches the best combination of human–robot intelligent skills for higher overall productivity and better product quality.

2.2. Human operator engagement

Rather than human–robot separated production, Proactive HRC focus on treating robot automation as a further enhancement of the human's physical, sensorial and cognitive capabilities [43]. The human in Proactive HRC represents the 'Operator 4.0', a smart and skilled collaborator who performs operations without physical and mental stress. The basic prerequisites of smart and skilled operator engagement in the loop relies on human safety among collaboration, intuitive perception of sharing resources and services.

Human safety gives the first priority and is a prevailing concern in HRC. Standards including ISO/TR 7250 [44], ISO 12100 [45], and ISO/TR 14121-2 [46] state human safety requirements in manufacturing tasks, which involve avoidance of physical injuries and risk reduction of occupational illnesses. For example, Schmidt et al. [47] monitored minimum human–robot distance from 3D point clouds of shop floors. Based on detected potential collision events, the system could warn an operator, stop a robot, and modify the robot path as the risk reduction measure. Besides, Peternel et al. [48] explored to improve the cooperation comfort level by monitoring the fatigue of the human muscles and providing warnings of non-ergonomic movements. The risk estimation reduces hazards to human body parts.

The human intuitive role in HRC is embodied in that the human can naturally perceive sharing information among human–robot–workspace and make cognitive decisions necessary for teamwork. Multimodal communication technologies, like AR [49], voice recognition, haptic feedback, and IIoT [50], can allow humans to seamlessly percept surrounding environments. In this context, Hietanen et al. [51] developed an interactive AR system, which allowed human operators to obtain real-time robot states and safety zone changes of the workspace. Liu et al. [52] proposed human-centred robot control with multimodal intuitive commands in the form of haptics, gesture, and voice. The enhanced perceptive ability fits in the human operators' interactive and cognitive needs, where they can observe and filter sharing resources and services throughout the collaborative execution loop.

2.3. Robot involvement and control

Other than pre-programmed control codes, collaborative robots in Proactive HRC need to timely adjust and plan new manipulation motions, especially in the production of high-mix low-volume products [53]. With human engagement in the execution loop, collaborative robot programming majorly contains supervisory control [54] and adaptive path planning [55].

Supervisory control aims to let a robot perform manufacturing tasks under human supervision and human flexible decisions [56]. Based on continuous sensory feedback (e.g., force and impedance) and human commands, a robot produces a time-varying stiffness and long-duration motion accuracy desired by the teammate. The supervisory robot control has attempted to be integrated into numerous Proactive HRC scenarios, including physical HRI [57], teleoperation [58], robot path correction [59], and multimodal control [60,61], etc. In this context, the standard ISO 10218-2 [62] regulates the power and force limitation and illustrates hazardous situations for collaborative robots in case of direct and physical contact with human operators. For example, Kana et al. [63] integrated impedance control and haptic interaction for human–robot co-manipulation. The system allowed the robot to respond to human external forces based on viscoelastic coupling. The supervisory control strategy represents the combination of robots' accuracy and strength with humans' cognitive ability to some extent.

For adaptive path planning, a robot can plan and accomplish motion trajectories, like a series of positions of the end-effector of a robot, by integrating inverse kinematics and dynamics systems and embedded smart algorithms [16]. The embedded smart algorithm constructs robot decision-making from a holistic understanding of HRC scenarios [64], including human operators' behaviours, detected mechanical components, and robot status. Then, the inverse kinematics and dynamics systems ensure robot movements to the targeted position. Adaptive robot path planning is crucial to various Proactive HRC applications, such as collision avoidance, robot path re-planning, mobile robot assistance, and so on. Meanwhile, speed and separation monitoring criteria for robot adaptive motion were defined in the standard ISO/TS 15066 [65] to eliminate potential contact hazards. For instance, Ong et al. [66] conducted experiments of robot motion planning via the KDL and the OMPL in the ROS. By inferring semantic knowledge of human intentions and task structures, the robot could generate adaptive path planning to assist human operations and perform precise motions to complete tasks.

3. Mutual cognition and empathy

Mutual-cognitive capability in Proactive HRC stands for the understanding of dynamic human–robot relations in task structures and their operational intentions. Based on this, empathetic collaboration skills are accordingly obtained to enable humans and robots to execute ergonomic operations desired by teammates. The intelligence of mutual cognition and empathy among HRC promotes human flexible decisions and improves robot manipulation skills in teamwork. A human operator shows an advantage in understanding seen situations, but fails to perceive information invisible now, like robot motion paths, updated operation procedures, and changing conditions of a manufacturing system. Thus, a mutual-cognitive HRC system firstly provides on-demand information support (like suggestion, guidance, warning, etc.) to humans. The knowledge support is inferred from task processing status and procedural operation goals in different task stages. In this way, the human becomes a super operator with enhanced cognition for holistic understanding of task execution. The human can also transfer new judgment on task process situations to a robot via multimodal communication manners, like Web interface, DT [67], VR, AR [68], haptic feedback, and brainwaves [69]. The mutual-cognition service improves human wisdom and compensates for human defects that are unable to perceive digital information. On the other hand, a robot presents empathetic skills to improve human wellbeing in HRC, beyond adaptive path planning. With knowledge learning of human intentions and ergonomic analysis of human actions, the mutual-cognitive HRC system assigns a human-needed task operational strategy to the robot. During the task execution, the robot performs manipulation comfortable for human interaction to avoid awkward posture impact and fatigue on human physical states. Meanwhile, the empathetic robot skill lifts human mental stress by responding to a worker's psychological changes with readability cues when conducting non-contacting path motions. The mutual-cognitive and empathetic capability in HRC systems is achieved by a human–robot–workspace perceptual loop, mutual-cognitive and empathetic decisions, and cognitive services, as shown in Fig. 2.

3.1. Human–robot–workspace perceptual loop

For Proactive HRC systems, the human–robot–workspace perceptual loop is a pivotal prerequisite for mutual cognition generation and on-demand collaborative behaviours. Over the past years, a wide variety of research efforts on human operator perception, readable robot status, and workspace parsing have been explored. In this context, it is important to be conscious of key elements in past efforts that promote the further perceptual loop among Proactive HRC.

3.1.1. Human operator perception

Human operator perception includes a worker's physical and psychological states during a co-work, which aims to understand humans' operation intention and wellbeing in HRC tasks. The human intention is reflected in the planning of "how to complete a collaboration task with robots", like a long-term goal for scheduled task fulfilment and short-term response to a stepwise operation and an unexpected event. In HRC systems, a worker may express operational intentions in various manifestations, such as gesture, voice, biological signals, and operation activities, as shown in Table 1. Simao et al. [70] used wearable sensors to recognise human static gestures and dynamic gestures. A robot received commands from these human gestures, such as stopping motion, rotating the robot end-effector, and opening/closing the gripper. Then, Lanini et al. [71] estimated every action change of the human upper body via signals of force sensors, as commands to the robot. For voice control in the machine hole drilling process, Birch et al. [72] developed a system that activated robot motions from voice inputs. For seamless robot control in a noisy environment, Wang et al. [73] integrated brainwaves and FB commands to drive adaptive robot actions in engine assembly, in case that the worker was occupied with other tasks on hand. For human safety, Buerkle et al. [74] measured mobile EEG signals to analyse an operator's motion intention before movement. The analysis result provided early warning to a robot and allowed the robot to re-planning paths in advance for collision avoidance. He et al. [75] estimated human lower limb motion intentions using surface EMG signals and developed a coupling dynamic model for exoskeleton robot control. As human motion sequences contain the

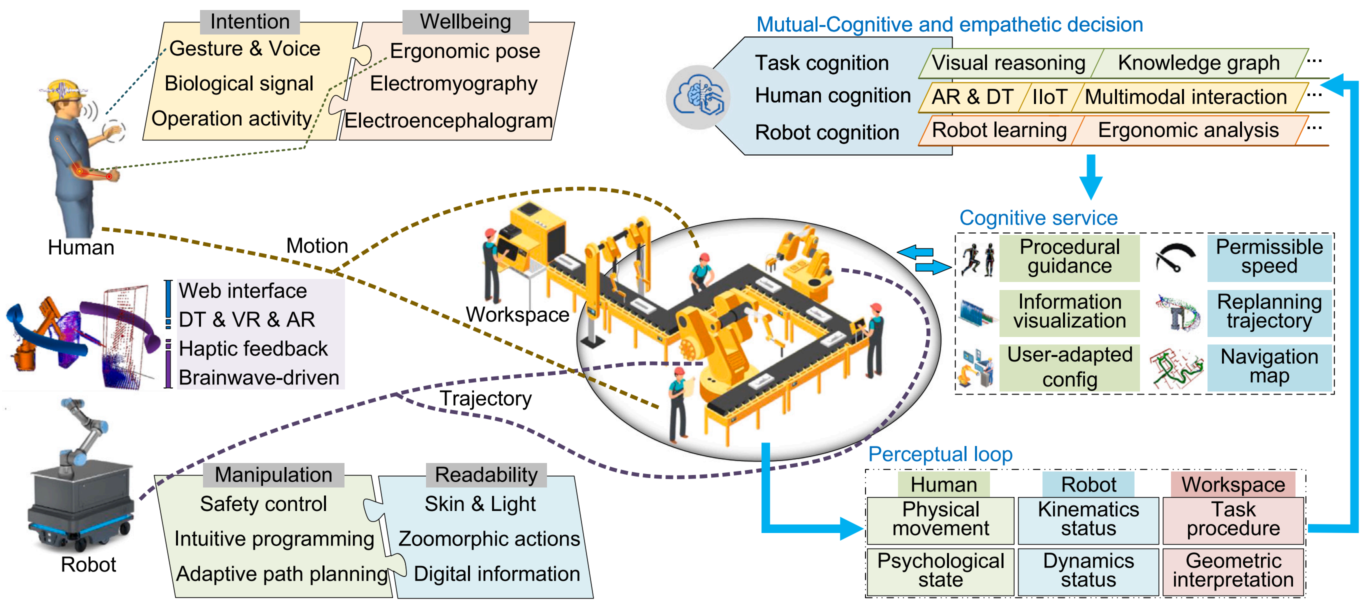

Fig. 2. Mutual-cognitive and empathetic co-work in Proactive HRC.

Table 1
Typical research efforts on the perception of human operator intentions.

Objective	Method	Superiority	Task	Ref.
Hand gesture recognition	LSTM and CNN	Online classification of dynamic gestures	Robot teleoperation (stop, move, rotate)	[70]
Limb pose recognition	LDA-based classifier	Low computation consuming	Human commands (start, stop, accelerate, and decelerate)	[71]
Voice recognition	DTW and user-dependent dictionary	Analysis of machine noise effects	Commands for machine hole drilling	[72]
Brainwave control	Wavelet transform and TL algorithms	Seamless communication without disturbing human hand operations	Adaptive robot control in engine assembly	[73]
EEG-based arm movement recognition	LSTM and CNN	Early warning of human upcoming movement	Re-planning robot operation for safety	[74]
EMG-based human lower limb motion estimation	LSTM and adaptive robust iterative learning control	Human torque estimation with impedance force	Exoskeleton robot	[75]
Human activity recognition	Relation history image extraction	Different activities of multiple persons	Robot assistant	[76]
Human activity recognition	Spatio-temporal joint based CNN	Combination of human activities with ambient events	Robot assistant	[77]
Human group activity recognition	Multisensory data and Laplacian embedding	Pairwise relation between teammates	Search and rescue with mobile robot	[78]

operation intention, Gori et al. [76] explored an activity recognition approach in which humans perform different action types concurrently and sequentially, beyond short-term operator motions. On this basis, the semantic context between human activities and ambient events was explored by Abdelkawy et al. [77], and followed by group activity recognition from multisensory input data completed by Lu et al. [78]. Based on these detected human activities, robots can make a suitable decision to conduct assisted operations for human operators.

Human wellbeing denotes "*which level of expectation reaches for resource allocation and task completion in teamwork*", which is reflected in physical experience (e.g., fatigue) and mental satisfaction (e.g., stress) among collaborative operations. Extensive overload and improper body posture may lead to potential health risks and occupational injuries, such as musculoskeletal disorders. As shown in Table 2, numerous research efforts have explored the estimation of human wellbeing from body poses, EMG signals, and EEG states. For instance, Kim et al. [79] proposed a statically equivalent serial chain model to calculate the load in human joints and adjusted the robot trajectories for ergonomic body poses throughout the HRC task. For muscle fatigue management, Peternel et al. [48] separated the external force into individual muscle groups and then altered the direction and position of the robot endpoint to selectively offload the force of tired muscles. The muscle fatigue management system maximised the fatigue-related endurance time and facilitated ergonomic co-manipulation setups for human workers. In an HRC polishing task, Makrini et al. [80] introduced a postural optimisation method to improve human poses and decrease workload. The method used a graphical interface to inform non-ergonomic postures and control the robot to adjust the pose of a co-manipulated part. Besides, Peternel et al. [81] used EMG sensors to measure human muscle activities and fatigue for analysis of human physical endurance. With the information of human behaviours, the robot adjusted reciprocal execution speed and frequency to let the human continuously recover strength in different phases of wood sawing tasks. For a sustainable HRC system, Lin et al. [82] used EMG for detection of muscle signals and then designed ergonomic HRC cells to reduce loads and ineffective human motions during assembly tasks of GPU products. To evaluate cumulative fatigue over time induced by light payloads, Lorenzini et al. [83] measured whole-body overloading torques by the EMG signals. The robot in the system continuously adjusted co-manipulated postures to allow the human to perform a repetitive task in an ergonomic way. To improve human wellbeing when facing unexpected situations, Buerkle et al. [84] used a mobile EEG sensor to detect

Table 2
Typical research efforts on the analysis of human wellbeing.

Objective	Method	Superiority	Task	Ref.
Joint overload estimation of human body	Statically equivalent serial chain	Center of pressure estimation	Co-carrying heavy loads	[79]
Selective muscle fatigue management	Force prediction, muscle fatigue model and impedance controller	Offline calibration and online muscle force prediction	Co-manipulation tasks of polishing and drilling	[48]
Postural optimisation of neck, trunk and leg	Feedback interface and ergonomic robot controller	Human body model using virtual kinematics chains (springs and dampers)	Collaborative polishing tasks	[80]
Human muscle fatigue estimation with EMG	Two-order system for fatigue estimation and robot control	Humans desired robot task execution speed and frequency control	Human–robot wood sawing and robot-assisted surface polishing	[81]
Sustainable HRC practices	Motion analysis, communication and ergonomic design	Wavelet transform and CNN	Assembly line of GPU products	[82]
Cumulative effect of the overloading fatigue	Whole-body fatigue estimation used RC circuit model	Cumulative human fatigue model over time	HRC painting task	[83]
Awareness of potential emergencies	Decision tree model and continuous wavelet transform peak counting	Visualisation of the classification logic	Assembly task of 3D printed boxes	[84]
Cognitive conflict between human–robot exchanged forces	Independent component analysis and admittance control	Online estimation of prediction error negativity for mechanical resistance	Physical HRI	[85]
Objective, subjective, and physiological assessment	ML and RL	Plug-and-play HRC architecture	Manual assembly and collaborative assembly	[86]

potential emergencies in HRC tasks, such as dropping a workpiece, crushing the piece on the worktable, and performing a malfunction. The awareness of potential emergencies allows a robot to execute fast actions and avoid harmful results to humans. Aldini et al. [85] evaluated the cognitive conflict when users experienced mechanical resistance opposing their motions during physical HRI. The result could help the robot to adjust the impedance control, so the operator can comfortably and safely interact with the robot. To allow HRC systems to adapt to the uniqueness and dynamic nature of human behaviours, Buerkle et al. [86] tested objective, subjective, and physiological metrics of a manual and a collaborative assembly task based on workload from EEG signals, NASA task load index, task completion time and a number of errors/assistance requests.

The human operator model among the perceptual loop allows the robot teammates to reach the full degree of an adaptive role and perform high-level adjustable behaviours, especially in the following aspects for the Proactive HRC implementation: (1) adaptive robot control aware of human intentions, which generates robot re-planning motions appropriated for humans' ongoing actions; (2) supervisory robot control with human cognition, which allows human operators to guide robot execution via natural action commands; (3) empathetic robot skills in terms of human wellbeing, where a robot acts assist-as-needed movements and ergonomic path motions desired by the human.

3.1.2. Readable robot status

A robot mainly performs supportive operations to assist humans or assumes active manipulations to complete tasks in HRC. Robotic kinematics and dynamics parameters control these motions such as safety control, intuitive programming, adaptive path planning, etc. As shown in Table 3, Pupa et al. [87] developed a dynamic system for HRC, to avoided drastic drops of the robot velocity by continuously checking infeasible robot trajectory in terms of safety-aware constraints. Besides, Nascimento et al. [88] proposed a collision-avoidance approach for physical HRI via combining visual depth data and proprioceptive robot status. The data fusion method tackled problems of occluded robots in the camera view and dynamically predicted robot–obstacle distance for the generation of repulsive forces that control the robot. For intuitive robot programming, Macchini et al. [89] mapped body pose to robot control parameters, which realised the natural teleoperation of mobile robots with high accuracy. Then, Wang et al. [90] proposed a teaching–learning-collaboration model to allow the robot to learn from human demonstrations. The robot could learn suitable motion trajectories from human languages and operation sequences to perform a new task. For adaptive robot control, Cheng et al. [91] proposed an online path planning algorithm, which modified only the part of the path that collided with obstacles, and the rest of the path remained close to the original task trajectory. Dalmasso et al. [92] developed a multi-agent shared plan model, which allowed a robot to replan path motions under human goals. Human operators have easy access to these robot statuses for further correction and modification.

Beyond dexterous robot manipulation, the intention of robot motions should be easily readable to human operators. The research effort on robot operation readability is shown in Table 4. In [93], a robot current position was indicated by lighting skins which could attract humans' attention for safety during a manufacturing operation. Then, Hetherington et al. [94] designed projected arrows and flashing lights on a mobile robot, which could communicate its path and goal information. To allow humans to discern robot intent sooner, facial gestures and human-like motions were added to interaction manners for social robots [95]. For a higher complicated robot states (e.g., progress of task completion) expression, Sauer et al. [96] proposed zoomorphic gesture-based methods and evaluated the user preference (e.g., attractive, joyful, and intuitive) for the communication manner. With VR and DT techniques developing, Oyekan et al. [97] utilised the digital space to represent trajectory information of a physical robot. These visual indications provide intuitive robot status in HRC systems, and resist to high noisy environment in factories. Then, an AR-based HRC system was developed to present robot states in a virtual-reality fusion environment, which combined accurate robot control and intuitive information support to humans [55].

Readable robot status aims to intuitively communicate robots' actions and planning (predictable and unpredictable) to human operators, as feedback for humans' enhanced cognitive decision-making. Past efforts on robot status understanding cover non-verbal legibility indications from tower lights, zoomorphic actions (e.g., eye gaze, head orientation, and arm movement) [98] to digital manners such as DT, VR, and AR. In addition, these shared robot state variables can be corrected and adapted to be feasible, with human-decision intervention or continuous self-reaction. Hence, instead of storing invisible robot status in controllers, Proactive HRC systems encourage robot motion with legibility cues, for humans' "intention reading" capability. The readable robot status promotes humans play the best supportive role and optimal active decisions in a co-work, with benefits reflected in the following aspects: (1) humans' prompt decision and reaction to robot legibility signals during a manufacturing operation; (2) easy and

Table 3
Typical research efforts of robot manipulation in HRC.

Objective	Method	Task	Example	Ref.
Safety control	Dynamic system	Adaptive trajectory planning and scaling	Hindering incidents in HRC	[87]
Collision avoidance	Depth space representation and Kalman filtering	Human safety in occluded zones	Physical HRI	[88]
Robot teleoperation	CCA and SVR	Body-robot operation mapping	Simulated drone to real quadrotor control	[89]
Robot learning from demonstration	Speech recognition and operation learning	Robot learning of task-based knowledge	Hybrid block assembly task	[90]
Online adaptive path planning	A GMM-based algorithm	Path replanning closer to the task trajectory	Picking, placing and assembly	[91]
Robot replanning	Monte Carlo tree search	Human semi-autonomous teleoperation	Collaborative search testbed	[92]

Table 4
Typical research efforts on readable robot status.

Objective	Method	Task	Example	Ref.
Robot position	Robot light skin	Human safety	Assembly of nut, bolt, and washer	[93]
Robot motion	Projected arrows and flashing lights	Motion legibility cues	Mobile robot services for pedestrians	[94]
Robot motion	Facial gestures and motions	Robot anticipatory motion	Social robot interaction	[95]
Robot state	Zoomorphic gestures	Status preview	Robot-to-human communication	[96]
Robot trajectory	VR & DT	Digital information	Transportation of boxes	[97]
Robot state	AR system	Accurate robot control	Picking and placing	[55]

intuitive teamwork in industrial settings with one or more robots that require different levels of priorities; (3) on-time correction for robot infeasible status to avoid drastic drops of the robot velocity and led poorly efficient robot behaviours.

3.1.3. Workspace parsing

Workspace parsing aims for geometric and semantic knowledge interpretation of the working environment, which includes detection of static and dynamic objects, their spatial pose estimation, holistic scene construction and task interpretation [99]. As shown in Table 5, Rosenberger et al. [100] utilised a deep CNN series model (YOLOv3) to detect industrial components from a heavily cluttered background. For higher localisation accuracy, Lee et al. [101] introduced object segmentation methods (Canny edge detector) to obtain fine shape information of working-in-progress parts during the electric motor assembly process. Then, Tsarouchetal et al. [102] estimated the pose information of shaver handles based on predefined CAD models, for robotic picking and placing in production lines. Followed by precise 6D pose estimation of mechanical components in manufacturing tasks, Franceschi et al. [103] adopted OBB to obtain rough results and further leveraged the ICP algorithm for refinements. For surrounding environment construction, Moon et al. [104] utilised a GCN-based 3D semantic graph map to generate the scene description. Besides, Dias et al. [105] explored the occupancy grid to represent the positions of a robot team, which also served as an interactive interface for robot controlling sequences. Liu et al. [106] constructed the 3D occupancy status of the HRC workspace via OctMap, for robot active collision avoidance. To design an HRC workspace, Mateus et al. [107] proposed a work decomposition structure, which generated multiple options for each task considering collaborative modes and spatial allocation of both parts and resources. Then, Bruno et al. [108] defined a strategy for task assignment, which allocated workload and detailed activity planning to human and robotic agents by considering their different skills and assets. For assembly sequence generation, Mateus et al. [109] split production precedence into sub-assemblies by identifying comprising parts, parallel task execution, and collision matrices. The generated assembly sequences optimised elements of resource sharing capability, collaborative workplace design, and safety requirements.

With the manufacturing task proceeding, workspace parsing provides real-time information support for adaptive robot control and intuitive human operation. Preliminary exploration on this area adapts portable and flexible visual sensor systems such as binocular camera, depth camera, and LiDAR. Combined with advanced computer vision and DL techniques, the workspace parsing system achieves high recognition accuracy and satisfies strict time constraints, even for heavily cluttered environments. Supported by the workspace parsing knowledge, humans and robots can reach their largest active roles among the co-work, which represents in the following aspects: (1) on-demand task arrangements in response to state changes of HRC settings, such as time-varying subtask operation and predictable collision avoidance; (2) high-precision and dexterous robot operations with pose estimation providing refined spatial and location information of targeted parts; and (3) active human decision and robot planning based on holistic scene construction and task process understanding.

3.2. Mutual cognitive and empathetic decision

The mutual-cognitive and empathetic decision intelligence in Proactive HRC is embodied in three parts: (1) task cognition among operational sequences, (2) enhanced human cognition for super operation skills, and (3) robot cognition for human desired manipulations. Based on mutual cognition, Proactive HRC systems make empathetic task-planning decisions for bidirectional-needed and ergonomic teamwork.

3.2.1. Task cognition

Task cognition among HRC devotes to learning interpretations of human–robot–task structures and their intentions from perceptual results in task processes and embedding decision intelligence to plan bidirectional-needed ongoing operations. Current visual reasoning and KG methods advance context-awareness capabilities in HRC from perception to cognition levels, as shown in Table 6. For example, Ahn et al. [110] proposed Text2Pickup networks, which allowed the HRC system to generate questions and ask for further communication when facing ambiguous task instructions. The cognition generated by mutual communication enables robots to understand the task intention and pick the user needed objects from the workspace. Then, VQA-based approaches were leveraged to obtain HRC task understanding by encoding associated cues of speech, gesture, and visual detection [111]. To capture contextual information of the current scenario, Riaz et al. [112] utilised a multi-level scene description neural network to predict the SG in the warehouse environment. The SG was useful for the risk

Table 5
Typical research efforts on workspace parsing.

Objective	Method	Key elements	Task	Ref.
Object detection	YOLOv3	Industrial components in a heavily cluttered environment	Handover	[100]
Object segmentation	Canny edge detector	Shape information of working-in-progress part	Electric motor assembly	[101]
2D pose estimation	Shaver handles	Mapping 3D CAD model to observed images	Robot picking and placing	[102]
6D pose estimation	OBB & ICP	Point cloud construction and post refinement	Bulky component assembly	[103]
SG	GCN & RNN	Graph map of perception results	Scene description	[104]
2D map	3D CNN and Robot control sequence	Occupancy grids-based robot team position	Robot control interface	[105]
3D representation	OctMap & PoseNet	3D occupancy status of workspaces	Collision avoidance	[106]
Hierarchical task analysis	Part dependent task complexity and task functional structure	Work decomposition, creation of task options, quantitative evaluation	Collaborative workspace design	[107]
Task assignment	Classification tree	Task indicators, task classification, task assignment	Assembly of a snowplow mill	[108]
Assembly sequence generation	Liaison and collision matrices	Matrix creation, sub-assembly and precedence determination	Gearbox assembly	[109]

Table 6
Typical research efforts on task cognition and HRC applications.

Co-work cognition	Method	Application	Ref.
Understanding of ambiguous task instructions	Text2Pickup Network for object detection and language command understanding, question generation network for human commands feedback	Robot pick-up tasks following ambiguous commands	[110]
VQA for task instructions	Object, detection, and gesture recognition, symbolic reasoning for answer and instruction	Task-oriented HRC	[111]
Scene understanding for safety analysis	Mask R-CNN for object detection, multi-level SG	HRI in warehouse environment	[112]
Dynamic SG for co-work strategy generation	Object detection, link prediction, graph embedding	Disassembly of ageing electronic vehicle batteries	[113]
Inferring semantic properties of the world	Probabilistic representation for semantic knowledge, Bayesian formulation for incremental estimation	Picking and placing Pelican cases	[114]
HRC KG for cognitive decisions	Holistic scene perception, HRC KG construction, EvolveGCN for graph embedding	Quality checking of electronic vehicle batteries	[115]

management process to predict and avoid unsafe situations. Then, to dynamically infer human–robot operation intentions, Li et al. [113] leveraged SG to learn scenario interpretation of on-site co-works. The SG assigns task planning strategies as human information support and robot commands in the system. With prior factual knowledge, Arkin et al. [114] inferred task-relevant instructions from both human linguistic descriptions and measurements derived from the robot's physical interaction with the environment. The inferred semantic properties of the world allowed the robot to correct errors in task instructions. Then, Zheng et al. [115] introduced KG to describe HRC processes, which contained accumulated expertise in task allocation and planning. Based on temporal sub-graph construction for real-time perceptual results, HRC task planning strategies are triggered by the KG and assigned to human and robotic agents.

With task cognition in Proactive HRC, both humans and robots are supported with time-changing operation planners for on-demand task fulfilment strategies. These cognitive co-work planners in Proactive HRC systems enable the best complementation between human intuitive activities and robot adaptive behaviours, and are derived from the following aspects. Firstly, cognitive planners are immersed in the execution loop and provide mutual support and intuitionistic guidance of suitable operations for human–robotic agents, based on advanced AR, DT, and IIoT techniques. Then, by understanding human–robot–task relations, task cognition assigns operations to humans and robots under a consistent co-work goal. Lastly, these task planners are the cognitive rethinking of the current task progressing for optimal resource sharing and assignment.

3.2.2. Enhanced human cognition

For enhanced human cognition in HRC systems, it is essential to improve workers' perception capability of procedural information, skills in manual operations, and communication with robots. To date, research efforts on AR, DT, IIoT, and multimodal interaction illustrate applications for enhanced human cognition, as shown in Table 7. For example, Liu et al. [116] utilised AR devices to present intuitive instructions of assembly guidance to humans during the HRC assembly of large-scale complex products. Multiple operators among the system could obtain and share assembly procedure information with the help of an AR helmet. Besides, Wang et al. [117] introduced an AR-based bare-hand interface to provide various modalities of guidance to assembly operators in different phases of assembly tasks. With a qualitative evaluation, the HRC system was intuitive, easy to use and satisfied human domain knowledge support in assembly. In [118], the decision-making and optimisation of production scheduling from real-time updating of the shop floor DT are delivered to human operators via the AR tools, to relieve the worker's physical and cognitive stress. Tuli et al. [119] developed a knowledge-based DT, which divided human activities into actions and predicted interaction regions and objects. The DT-based HRC system could give human suggestions of parts potentially to be assembled in the next step. In parallel, Liu et al. [120] proposed an advance-execution DT system based on function blocks to performs assembly planning and adaptive robot control. For a user-friendly communication, Macchini et al. [89] proposed a user-adapted body–machine interface via personalised body–machine mapping, which realised the natural teleoperation of mobile robots with high accuracy. Then, Losey et al. [121] utilised Bayesian inference to learn interaction strategies between robots and end-users, allowing

Table 7
Typical research efforts on enhanced human cognition and HRC applications.

Human cognition	Method	Application	Ref.
AR-based assembly guidance	3D reconstruction of environments, multi-operator interaction, human to machine interoperation	Assembly of large-scale complex products	[116]
Multi-modality assembly guidance	Bare-hand interface, AR guidance manager, user request interface	Assembly of a Mitsubishi MEO77789 motorbike alternator	[117]
Decision and optimisation from DT	AR and wearable devices, IIoT system, DT-based process design and optimisation	Assembly of a bus	[118]
Procedural suggestion from DT	Knowledge-based DT, human motion modelling and simulation, action and attention recognition	Assembly and maintenance	[119]
Personalised body-machine interface	CCA and SVR for personalised motion synergy identification	Teleoperation of a simulated drone and a real quadrotor	[89]
Personalised HRI	Bayesian inference for human interaction strategy, inverse RL simulation for robot motion	Robot learning and teaching	[121]
Kinesthetic teaching of robot arm tasks	Human motion recognition and segmentation, a hybrid sensing interface for motion feature recording	Human-guided tasks in a KUKA robot	[122]

for personalised robot teaching. The approach aimed for personalised HRI which resisted human uncertainty during the interaction process and reduced confusing results of fixed, predefined interactive strategies. To ensure high-precise robot motion in kinesthetic teaching, Chen et al. [122] recognised human action and extracted action features from the velocity profile, force torque, and gripper information sequentially. These primitives were then reconstructed to robot trajectories which could maintain robot motion accuracy in 2.37 millimetres. The personalised configuration was capable of achieving humans' intuitive control for complex robotic systems.

The enhanced human cognition equips human operators with super operational skills in Proactive HRC, especially for three aspects, i.e., self-learning capability, enhanced decision-making, and friendly co-work experience. Firstly, a human operator can constantly learn new knowledge for personal growth and self-actualisation with on-demand domain knowledge support in the execution loop. Then, with requisite procedural information, humans are able to see what is invisible now and incoming events, like suggestions and warnings from a holistic understanding of HRC tasks, for further decisions. Lastly, human individual wellbeing is improved with more flexible robot control based on self-adapted interaction. A worker can correct or re-plan robot motions to respond to humans' further task understanding and decisions.

3.2.3. Robot cognition

Robot cognition aims to let a robot understand human partners' behaviours and intentions, and correspond with task common goals, then plan adaptive manipulation desired by humans. The rising robot learning and ergonomic analysis, such as RL and ergonomic control, pave the way to cognitive robot operations, as presented in Table 8. For example, Sasagawa et al. [123] proposed bilateral control-based imitation learning, where the robot could adjust force and motion speed when imitating complex human motions. Sun et al. [124] proposed a human teaching and robot-learning framework, which allows a robot to assist humans by learning from demonstrations. Zhang et al. [125] utilised RL models to generate optimal robot sequences in HRC systems. The inferred operational sequences ensured successful task fulfilment, no longer needing human decision-making and reducing human workload. For suitable robot action selection, Nikolaidis et al. [126] proposed a probabilistic decision process that balanced the tradeoff between gathering information on human uncertain behaviours and moving towards the task goal. The robot acted adaptive motions for a better way of completing the task. For adaptive robot navigation, Aggravi et al. [127] presented a decentralised haptic-enabled connectivity-maintenance control framework for human–robot teams. A mobile rescue robot adaptively planned easy-to-follow navigation movements for humans based on the current connectivity level. To achieve robot path re-planning at any time, Tonola et al. [128] combined online path re-planning and speed optimisation modulation. The re-planning algorithm could make the robot able to complete its task despite unexpected situations, such as the presence of humans or obstacles. For human desired robot manipulation, Granados et al. [129] utilised physical feedback from long-term interaction processes to allow the robot to understand human's needs and adjust its behaviour. Then, the ergonomic risk prediction was applied to picking-and-placing tasks to let a mobile robot actively assume high-risk actions or repetitive medium-risk actions over extended time periods [130]. Ansari et al. [131] explored a task execution and control scheme which could generate optimal robot forces to reduce human effort in cooperative object manipulation. The force desired by the human was computed using the trajectory of the identified task and defined as the input to the robot, while the robot directly tuned parameters to perform corresponding tasks with the calculated force. Besides, Khatib et al. [132] exploited robot kinematics to allow the robot to present a workpiece to humans following time-changing positions and orientations which were easy for human coordination.

More than basic characteristics (such as collision avoidance), a collaborative robot with cognition evolves into an intelligent agent and embraces empathic teamwork skills for Proactive HRC systems. Towards the intelligent agent, the first one is human-like cognition, which is achieved by knowledge representation learning of human intentions and task planning strategies for adaptive, human-needed manipulations. Followed by robot learning, a robot can actively assist human operators or quickly plan appropriate motions by imitating and learning from human operations and commands. For the empathic teamwork skills, a robot needs to analyse ergonomic satisfaction of human postures in co-work, and dynamically changes end-efforts' positions and orientations for easy and comfortable human following. In this way, a robot performs operations with human desired forces, poses, and speeds by adapting control parameters with human movement models, relieving human physical and mental stress.

3.3. Cognitive service

The cognitive service focuses on transmitting mutual-cognitive HRC task planning to human and robotic agents with natural and non-misleading communication. The cognitive services are provided along co-work progress in HRC systems, such as necessary information sharing, or on-demand guidance and control commands. In this context, typical studies are listed in the Table 9. Even in 2005, Marin et al. [60] developed a remote robot teleoperation system, which transformed human voice commands into six-DoF motions of robots, such as moving to a position with permissible speed or grasping an object with a specific angle. Then, Rey et al. [133] introduced a web interface to manage manufacturing processes of the production line in a paint factory. Human operators created and updated orders via the interface, whereas AGV-based robots performed motions following these orders, like picking and transporting raw materials to mixing tanks. For

Table 8
Typical research efforts on robot cognition and HRC applications.

Robot cognition	Method	Application	Ref.
Human skills imitation	4ch bilateral control for human–robot cooperative execution in terms of force information and fast motion	Scooping and transportation tasks	[123]
Robot learning from human demonstration	A dual-input DL algorithm, online automated data labelling	A realistic car assembly task	[124]
Optimal robot sequence allocation	RL algorithms for task allocation, human fatigue model with adding noise	HRC assembly task for alternator	[125]
Two-way robot adaptation to a human	Bounded-memory adaptation model for human changing behaviours, mixed observability Markov decision process for robot actions	Co-carrying a table through a door and hallway-crossing tasks	[126]
Coordinated mobile robot movements	Connectivity-maintenance robot control, grid covering and path planning, wearable haptic feedback for humans	Urban search and rescue robot	[127]
Anytime robot path re-planning	PathSwitch algorithm, speed and separation monitoring, RTT	HRC cases with robot mounted upside down a work-table	[128]
Ergonomic robot control	Ergonomic risk prediction and pattern extraction of human actions	Picking and placing objects of different weights and heights	[130]
Robot actions with humans required force	Velocity identification of the human-performed task, robots' contribution to each degree of freedom of the task, a task-based role allocation control scheme	Cooperative manipulation of a rigid-body object held jointly by a human and a robot	[131]
Time-varying poses desired by humans	Coordinated motion-based collision avoidance, saturation in the null space algorithm	Surface finishing task	[132]

bidirectional information exchange, Casalino et al. [134] used wearable vibrotactile rings in HRC tasks. Robots understood the operator's forthcoming actions while the human received vibrotactile feedback. To transfer human experience to a robotic system for delicate sanding of complex surfaces, Marullo et al. [135] proposed a decentralised control strategy based on contact and impedance forces. The human utilised force feedback to fit the robot's path trajectory to the slightly deformed surfaces. For human welders' operation skill transfer, Wang et al. [136] utilised VR hardware to teleoperate a 6-DoF robot. The VR platform enabled human welders to intuitively transfer new operation trajectories to robot manipulations. For natural and seamless communication, Hietanen et al. [51] utilised an interactive AR system to allow human operators to monitor real-time robot states and safety zone changes in the workspace, while the robot could receive users' instructions on the fly to execute the corresponding task. Then, Malik et al. [137] used DT to construct collaborative production systems with high complexity, which achieved resource sharing along the system's life cycle by modelling physical–digital space connection of assembly tasks in each phase and corresponding environment, components, and task allocation. To exchange information between human physiological response and robot optimal planning, Liu et al. [138] leveraged wearable EEG and EMG biosensors to develop a physiological communication interface. The human physiological awareness was obtained and provided as a precondition to produce logical decisions for robotic control and manipulations. Besides, Liu et al. [61] fused multimodal commands from brainwaves, gestures, and voice for an accurate translation of robot commands. These cognitive services clarify operation schedules and minimise operation confusion when humans and robots operate coordinated tasks.

The cognitive services can be achieved via multimodal and bidirectional information exchange between humans and robots, such as web interfaces on displays and tablets, gesture and motion command recognised from camera devices, speech information from microphones and speakers, haptic sensors, DT, VR, AR, brainwaves and so on. Some typical examples including tasks of welding, assembly, co-grasping, and robot route planning were explored for the successful implementation of cognitive services in HRC systems. For natural and intuitive characteristics of cognitive services in Proactive HRC, MR-based execution loop encapsulated DT and AR technologies require further exploration. The MR-based cognitive services enhance human context awareness by providing procedural guidance, information visualisation and user-adapted configuration in a virtual-reality fusion manner. Then, the MR environment online simulates and predicts robot motions with reasonable permissible speed, replanning trajectories, and navigation maps, avoiding robotic runtime errors. Lastly, the MR-based cognitive services allow for natural communication between multiple humans and mobile robots in a large spatial space, where one or more agents exchange information and communicate with other multiple parties who require different levels of priority.

4. Predictable spatio-temporal collaboration

The predictable spatio-temporal collaboration aims to reason optimal task fulfilment plannings and forecast co-work execution processes across time, by predicting human–robot motions and system resource allocation from a holistic vision. A production process consists of various manufacturing knowledge (e.g., resource management and operation goals) and can be decomposed into different hierarchical sub-tasks/stages with tasks progressing. Within one stage, a human operator cannot understand the complicated procedural knowledge of an entire manufacturing task and make reasonable co-work strategies for the next operation goal, especially when facing unexpected task proceeding situations. The predictable spatio-temporal collaboration learns prior knowledge from predefined task schedules and infers the current task process status. By fusing the in-time operational status and manufacturing prior knowledge, task planning decisions for the next co-work are triggered and assigned to human and robotic agents for optimal task completion, especially when facing some industrial uncertainties. For specific decision execution in a task stage, a human operator may suffer psychological stress if one is uncertain how about robot motions and what may happen in the near future. By modelling and predicting human movements in the execution loop, the predictable spatio-temporal collaboration also provides previewable robot trajectories to humans and allows robots to plan proactive motions in advance. The predictable intelligence in Proactive HRC relieves human psychological workload and towards foreseeable HRC task accomplishment with human natural participation and robot proactive behaviour. As presented in Fig. 3, the predictable spatio-temporal collaboration in Proactive HRC is realised with analysis of human uncertainty and error operations, task precedence constraint planner, spatio-temporal task fulfilment, and foreseeable execution loop.

Table 9
Typical research efforts on HRC cognitive services.

Key element	Interface	Method	Example	Ref.
Voice commands (grasp, position, rotation)	Web interface	Remote programming based on networking protocols	Robotics teleoperation tasks	[60]
Manufacturing process management	Web interface and manufacturing system database	Autonomous robot navigation, human position detection and tracking	Dispersion process of a paint factory	[133]
Bidirectional information exchange	A wearable vibrotactile ring	Human behaviour estimation and wearable vibrotactile feedback	Box assembly task	[134]
Path trajectory for delicate sanding of complex surfaces	Contact force feedback	A decentralised control strategy based on impedance force	Picking and placing large and heavy objects	[135]
Welders' operation skill transfer	VR head-mounted display	Motion-tracked handle controller, welder operation prediction	Welding robot teleoperation	[136]
Display of robot status, operator instructions, workspace changes	Projector and a wearable AR gear	Interactive AR user interface, depth-based workspace modelling, safety monitoring	Engine assembly tasks	[51]
Resource sharing along systems' life cycle	DT and user interface	Physical–digital space connection for each phase of HRC	An industrial assembly case	[137]
Human physiological response and robot optimal planning	Wearable EEG and EMG biosensors	ANN-based classifier, robotic control system	Collaborative masonry tasks with UGV	[138]
Translation of brainwave command phrases into robot commands	Brainwaves, gestures and voice commands	A DL algorithm for command classification, function block for robot control	A partial car engine assembly	[61]

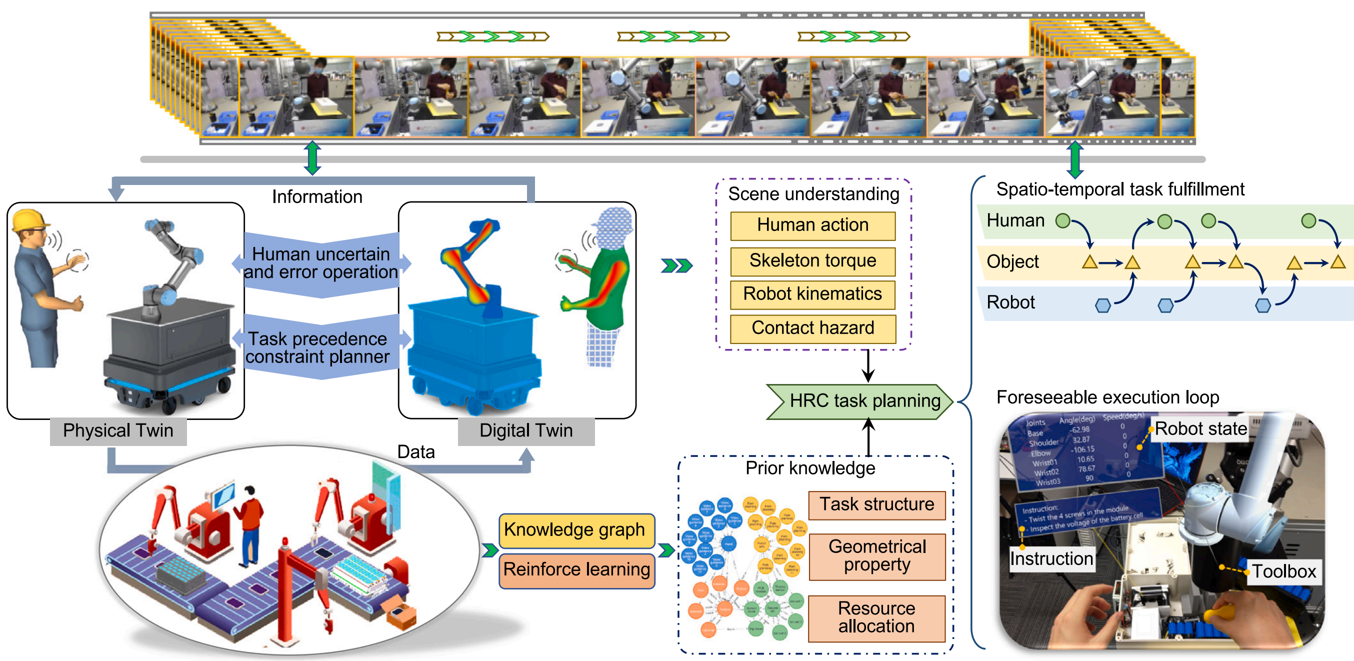

Fig. 3. Predictable spatio-temporal co-work in Proactive HRC.

4.1. Human uncertainty and error operation

In HRC tasks, human operations are characterised by uncertain movements and incorrect operation risks, which may disturb robot corresponding manipulations or even lead to safety issues. To maintain fluent task progress and balance the unexpected disturbance, analysis of human uncertainty and error operations is a critical precondition of predictable spatio-temporal co-work in Proactive HRC. As shown in Table 10, Talebpour et al. [139] utilised a constant velocity dynamic model to predict human motion uncertainty for adaptive risk-based replanning for multi-robot task allocation. The mobile robot can actively modify its plans with updated motions about humans. Kim et al. [140] leveraged radio wave sensors to predict operators' misuse of permissible speed control of the robot. By integrating with consideration of robot runaway motions, the HRC system ensured potential contact force and energy transformation do not cause injury to humans. To allow a robot to provide the right assistance at the right time, Hawkins et al. [141] developed a probabilistic model for human action prediction. The robot could infer the current state of a task and make appropriate decisions for human potential actions. Maderna et al. [142] proposed a DTW algorithm to monitor movement trends of the current human activity in real-time, in case the human performed a task in uncertain ways, such as at different speeds, occasional errors, and short pauses. Thus, a robot could handle the variability of human behaviours. Then, Tuli et al. [119] developed knowledge-based DT to model human motions and predict human action intentions. Also, Yi et al. [143] developed a DT-based HRC assembly for accurate prediction of the key points of the human skeleton model and high-precision human body localisation. The robot could assist human workers in terms of possible human motion sequences and ontologically defined task descriptions. To model and simulate human motion, behaviour, and physical load, Maruyama et al. [144] developed digital humans in HRC systems by real-time monitoring, predicting the full-body dynamics of workers. The system fused digital human, virtual robot modules, and

Table 10
Typical research efforts on prediction of human uncertainty and error operations.

Predicted output	Method	Specification	Application	Ref.
Human motion uncertainty	A hoplites-based multi-robot task allocation, risk bid estimation of human uncertainty	Risk-based robot replanning	Multi-robot multi-human systems	[139]
Human errors and contact risk	Radio wave sensors for distance monitoring, simulation of transfer energy of contact	Permissible speeds for robots	Battery assembly task	[140]
Human action prediction	Bayes network for task structure representation, probabilistic model for action prediction	Robot wait-sensitive planning	Toy assembly task	[141]
Monitoring of human task advancement	DTW-based algorithm, template tree for task description	Robot adaptive manipulations	Assembly of a wheeled base	[142]
Human action prediction	Knowledge-based DT, human motion capture system	Time reduction for assembly tasks	Hybrid assembly system	[119]
Human modelling and simulation	Digital human analysis of motion, behaviour and physical load	Real-time prediction and ergonomic evaluation	A part-picking scenario	[144]

production management modules to promote dynamic task scheduling and improve production efficiency and ergonomic performance.

In HRC systems, the human uncertainty and error operations can be monitored and predicted in various manners, such as torque sensors, laser scanners, visual cameras, and DT modelling. The analysis of human uncertainty is vital for smooth and efficient HRC work, especially in eliminating contact hazards, detecting geometric occlusions, optimising robot kinematics status, estimating human joint torque, and evaluating ergonomics. In this context, the robot completes tasks with human permissible speeds, risk-based replanning, and less waiting and idle times. In Proactive HRC, the digital human is a key element for simulation and prediction of a worker's physical actions and psychological states, as shown in the left part of Fig. 3. By real-time updating and connection with a physical human, a worker's future attention, behaviours, and physical and mental load can be predicted in digital environments. For example, a digital system can simulate the frequency of individual human gaze at a robot in different operations, and then proactively provide previewable robot trajectories to humans at the right time. Besides, a digital human model with production management knowledge deserves more attention, which can identify human uncertainty and correct error operations in advance. The prediction of human uncertainty and incorrect operations enables HRC systems to recover irregular and risky situations to the expected co-work strategy, which facilitates compassion and coevolution of human–robot agents.

4.2. Task precedence constraint planner

The operation precedence constraints exist in hybrid HRC task proceedings. For example, some manufacturing stages need to be completed by human manual operations first, followed by robot manipulations or handovers. The task precedence constraint planner is crucial prior production knowledge which should be learned in HRC systems, thus achieving a predictable spatio-temporal collaboration. As presented in Table 11, Pulikottil et al. [145] inferred knowledge of task temporal constraints based on human and robot operational goals. The HRC system could plan the best robot motion for fluent collaboration with knowledge of task constraints. For example, humans were not allowed to pick robot-handled objects before the robot ends on its manipulation. Besides, Cheng et al. [146] decomposed a task into hierarchical and temporal subtasks and plans, and explored the hierarchical relationship of action sequences to finish the task. Based on task decomposition and human trajectory prediction, a task planner was developed for efficient subtask cooperation in advance. To model resources and workload for shared tasks, Nikolakis et al. [147] utilised a task allocation search tree to online schedule and timely adjust manufacturing operations when facing unexpected events during task execution. Then, Ferreira et al. [148] formulated a scheduling problem for multimode and multiprocessor tasks by considering different production settings and eligibility. Based on a CP model and a genetic algorithm, the generated optimal solutions for collaborative tasks reduced the total work time, especially when facing numerous precedence constraints and low robot eligibility. To learn knowledge representation and constraint ranking in disassembly tasks, Ding et al. [149] established a task KG, which could query and search stepwise operations for human and robot agents. Then, Yu et al. [150] conceived HRC working processes as a chessboard game with specific rules determined by the constraints in assembly tasks. With decomposing a product into tasks with step procedures, a multi-agent RL method was utilised to generate task schedules for HRC disassembly processes. The task schedule remained feasible even for a broader product family with similar task structures.

The knowledge representation of task precedence constraints can be inferred and learned with numerous methods, like the probabilistic model, tree structure, KG, RL, etc. The understanding of task constraints is essential to both online scheduling for long-term task fulfilment and timely strategy generation for close-proximity execution, as presented in the left-bottom part of Fig. 3. For example, physical structure constraints of the product can be regarded as prior knowledge for dynamic task strategy adjustment when HRC systems assemble or disassemble it. While the understanding of machining process constraints ensures high surface quality and precision in HRC grinding systems [151]. To infer knowledge of various task precedence constraints for product variants, the cutting-edge technologies including KG and RL provide feasible solutions. The holistic task structure for the manufacturing of a product can be learned and linked in a KG. Manufacturing constraints of partial components of the product are sub-graphs of the entire task structure. Different HRC task stages are represented by these sub-graphs, whereas operation sequences in a specific subtask are depicted by edges in the KG. Besides, the KG can transfer existing knowledge to learn task precedence constraints for product families with similar structures by inferring general rules of various node attributes. For HRC production of a new product in large variants, RL methods can be utilised to learn the task structure via iterative simulation and optimisation of working processes in DT environments.

4.3. Spatio-temporal task fulfilment

The spatio-temporal task fulfilment pays attention to preparing holistic co-work planning for hierarchical HRC subtasks in the future stage based on current scene understanding and prior manufacturing knowledge. There are two kinds of situations for the spatio-temporal task fulfilment (see the right-upper part of Fig. 3). The first one is for the long-term expected HRC working processes, which are achieved by learning the task precedence constraints as key prior knowledge for co-work planning. Meanwhile, the current scene understanding is monitored and reasoned as real-time feedback to ensure fluent and smooth HRC task completion. The other one targets situations of human uncertainty and error operations in the current scene. The HRC system needs

Table 11
Typical research efforts on knowledge learning of task precedence constraints.

Key element	Method	Specification	Application	Ref.
Explicit temporal constraints of task sequences	Maximum entropy inverse optimal control for human goals, partially observable Markov decision process for robot goals	Next robot action	Quality check of workpieces	[145]
Hierarchical subtask plan	Bayesian inference for trajectory prediction, DTW distances based plan recognition, a planner for robot motions	Hierarchical and temporal decomposition of a task	A desktop assembly task	[146]
Task online scheduling	Task allocation search tree for decision-making, FB for connection of execution status	Shared task scheduling	Assembly of a turbocharger	[147]
Task scheduling under different settings	A CP-based model for various constraints limiting the search space, a genetic algorithm for near optimal solutions	Shorten cycle time in co-work	An hybrid working cell	[148]
Task KG	A domain knowledge representation model for collaborative disassembly, KG establishment	Domain knowledge support	Roller chain disassembly task	[149]
Task scheduling with specific rules	Product decomposition, a Deep-Q-Network based multi-agent RL algorithms	Task structure for a product family	Desk assembly task	[150]

Table 12
Typical research efforts on spatio-temporal task fulfilment.

Predicted output	Objective	Method	Example	Ref.
Next operations to perform	Three agents scheduling	DT of HRC cell, AND-OR tree and Petri Nets-based scheduling algorithm, visual and tactile interface	Assembly tasks of emergency buttons	[152]
Task scheduling with temporal constraints	Task performance prediction of each agent	Simple temporal networks, mixed-integer linear program	LEGO kit assembly	[153]
Online task scheduling with specific rules	Two agents scheduling	An MCTS and CNN-based RL algorithm	Desk assembly tasks	[154]
Re-scheduling of task operations	System response to resource breakdown	A hybrid hierarchical model for both resources and workload, intelligent search for task allocation and re-rescheduling	Assembly of vehicle supercharger	[155]
Disassembly sequence planning	Task planning with rules and constraints	A graph model for disassembly rules, sequence planning optimisation	Disassembly of a wooden toy box	[156]
Dynamic task assignment	Task allocation with changing attributes	Intuitionistic fuzzy number definition, three-way decision theory	A numerical example	[157]

to re-plan and dynamically adjust the next task operation arrangements by integrating the prior manufacturing knowledge for successful co-work execution. To date, some research efforts have explored efficient solutions for the achievement of spatio-temporal task fulfilment in HRC systems, as shown in Table 12. Maderna et al. [152] developed an HRC system with flexible scheduling and tactile communication. The scheduling algorithm accounted for the variability in the duration of human tasks and the occurrence of robot faults to online generate task allocation and sequences, which were delivered to a human and two robotic agents for their next operations. With considerations of temporal constraints and human task duration, Liu et al. [153] explored real-time scheduling and optimisation of future team activity allocation for human and robot agents. Besides, Yu et al. [154] utilised an RL algorithm based on MCTS and CNN to generate the working sequences in the HRC system by considering some specific rules. The RL algorithm could be trained to perform task scheduling without any supervision or domain knowledge guidance. In case of unexpected events in HRC systems, such as resource breakdown, Nikolakis et al. [155] used a hierarchical model for resources and workload representation, then leveraged intelligent search to online adjust and schedule new task allocation. Then, Lee et al. [156] introduced a graph model to address disassembly sequence planning problems by complying with disassembly rules, such as disassembly cost by robot and human, the various starting points, the safety consideration for human operators, and the feasible operations for a robot. Lastly, Zhang et al. [157] utilised attribute weights in intuitionistic fuzzy environments, which generated task assignments in HRC systems with human uncertainty considerations.

The spatio-temporal task fulfilment can be achieved with advanced techniques, like KG, RL, and DT. The current focus of HRC task fulfilment mainly lie on task scheduling problems, rather than arranging reasonable operation sequences for humans and robots in future stages, which impedes their truly collaborative execution with task proceeding. For the widespread implementation of spatio-temporal task fulfilment in Proactive HRC, the first feasible solution is to construct KG of working processes containing various levels, such as components, operations, and task decomposition. The HRC KG links different prior knowledge including task structure, geometrical property, and resource allocation together for task planning in each stage with detailed operating instructions. The second one embeds prior knowledge into RL algorithms for HRC task planning. In this case, when generating task planning instructions for a new and ever unseen task, the RL algorithm can be speeded up to search efficient schemes by avoiding redundant trials and errors. The last one is to build knowledge-based DT environments for HRC task re-planning. The knowledge-based DT can distill current scene representation, such as human action, skeleton torque, robot kinematics, and contact hazards. By inserting the scene understanding into holistic prior knowledge of a task, the knowledge-based DT can dynamically simulate, predict and re-plan the specific next operations for human and robotic agents.

4.4. Foreseeable execution loop

The foreseeable execution loop aims to promote robot proactive actions to coordinate with human intention in advance and avoid potential error operations, as shown in the right-bottom part of Fig. 3.

Table 13
Typical research efforts on foreseeable execution loop.

Predicted output	Type	Method	Example	Ref.
Human's reaching motion	Robot manipulation without interference	GMM algorithms and unsupervised learning	Picking and placing	[158]
Human on-going action	Robot turn-taking event and motion starting	LSTM for action prediction with multimodal signals	A robotic scrub nurse system	[159]
Human motion trajectory	Proactive robot movements based on human future locations	A RNN model for motion prediction	Assembly of a car engine	[160]
Human trajectory and obstacle	Robot action selection	Hybrid motion prediction, game theoretical action selection strategy	LEGO bricks assembly	[161]
Human near future intention	Proactive robot path planning	Multimodal human action prediction, decision tree	Brackets assembly in aircraft cabins	[162]
Human assembly rate and risk perception	In-time robot response to human requests	A hidden semi-Markov model	GPU assembly line	[163]

On one side, a robot can reason, re-plan and reach interactive points ahead of time, based on the prediction of future human movements. On the other side, the HRC system is capable of making decisions and assigning a robot's next manipulations with early detection of human motions and operational intentions. As presented in Table 13, Luo et al. [158] leveraged a GMM-based algorithm to predict human reaching motion in a shared workspace. Thus, the robot could move and perform operations without interfering with human actions. To allow a robot to comprehend a human's on-going actions, Zhou et al. [159] introduced an LSTM model to predict a surgeon's early actions. Meanwhile, a robot nurse could foresee the precise time of a turn-taking event and execute its action to reduce human waiting time. Besides, Zhang et al. [160] utilised an RNN model to predict human motion trajectories in HRC settings, based on which a robot could proactively plan actions to assist human operations, like picking up tools and reaching predicted handover positions in advance. For suitable robot actions in HRC, Oguz et al. [161] predicted the motion of a human teammate and utilised a game theory strategy to plan and select robot operations. Then, Li et al. [162] proposed multimodal action prediction methods with a partial observation of visual and skeleton data of human operations. Among the HRC system, a decision tree is leveraged to generate proactive robot path planning based on the predicted human intentions in near future. Lastly, Lin et al. [163] predicted human assembly rate in task and used a hidden semi-Markov model to link predicted human behaviours and robot responses. The robot could respond in time to human requests in HRC systems, which reduced the assembly cycle time and operators' waiting time.

For a foreseeable execution loop, the leading AI models including DL, TL, and multimodal learning pave the way to robust and accurate human action prediction. In Proactive HRC, the foreseeable execution loop can be further enhanced by embedding a knowledge model, which learns and indicates the priority of different prediction elements. For example, human actions with turn-taking events and risk properties desire more attention, like handover, interaction, and contact hazards. While smooth and long-playing human operations are relatively not sensitive to time limitations, such as the unscrewing process standing in one location. Besides, the DT environment should be immersed in the foreseeable execution loop, which can simulate and predict human fatigue, working ergonomic conditions and runaway motions in real time. With the DT and knowledge model, a robot can infer, reason, and plan suitable path planning in advance to reduce human waiting time, increase efficiency and enhance naturalness in a collaborative task.

5. Self-organising multi-agent teamwork

The self-organising multi-agent teamwork focuses on coordinated and synchronous activities between multiple human and robotic agents in a large and unstructured space based on their qualified capabilities and operational roles, to satisfy stringent requirements of required execution time, resource availability, minimum energy consumption, etc. The multiple agents in a Proactive HRC system consist of human operators, fixed robot arms, and mobile robots. The self-organising intelligence is the central brain of Proactive HRC, which bridges the information island between multiple agents and reasons for global optimal co-work processes by learning knowledge of human–robot preferable operations and task policies. In this way, the self-organising knowledge is learned from four aspects, (1) task structures and decomposition, (2) dynamic environment and event relations, (3) resource occupation constraints and ergonomics, and (4) capable agent execution rules in unstructured space. The demonstration of self-organising multi-agent teamwork in Proactive HRC is shown in Fig. 4. From the organisation level, a working cell design for multiple agents in HRC is a vital precondition, which should distill the knowledge of general rules of human–robot qualified operations. Therefore, the HRC system can transfer learned knowledge to quickly generate task arrangements even facing product variants. From the task level, the self-organising multi-agent teamwork relies on three key aspects: (1) information communication between multiple humans for various scenarios in different places, (2) resource allocation and management between collective robots for optimal task planning, and (3) interaction and role-playing between hybrid human–robot agents for global task assignment. For the interplay of human–human, robot–robot, and human–robot organisations, the participators can share their different capabilities for various specific tasks with these essential techniques of information exchange, task planning, and task assignment.

5.1. Working cell design and configuration

The working cell design and configuration focus on adaptable working station design for human–robot layout in tasks and functional structure configuration for robot participators. As presented in Table 14, Gopinath et al. [164] designed a layout of a collaborative assembly cell that contained a large industrial robot and a human worker, by taking risk assessment and productivity concerns into account. In the station cell, the robot could flexibly lift tools to aid the human operator. For robotic cells with one or more robots and accessory equipment, Zhang et al. [165] proposed a systematic layout planning method with an objective of time and cost efficiency. The approach tackled problems of the proper configuration for a given HRC task by involving considerations of the robot programming system, collaborative tool chain, scheduling optimisation of robot motions, and gripper design. Then, Arkouli et al. [118] designed an HRC work cell that included multi-typer and multi-purpose robots. With decision-making in the DT-based HRC, high payload robots and mobile manipulators were used to handle heavy operations. Meanwhile, humans' physical and cognitive stress was relieved by exoskeletons and AR tools. For robot configuration, Salvietti et al. [166] designed a soft gripper and a wireless ring-shaped interface in HRC. The design both guarantees a safe interaction and enables bidirectional communication through the haptic feedback information. Besides, Pang et al. [167] designed a soft robot skin with the features of softness, variable stiffness, and sensitivity. By inflating the internal air pressure and loading external force, the stiffness of the skin

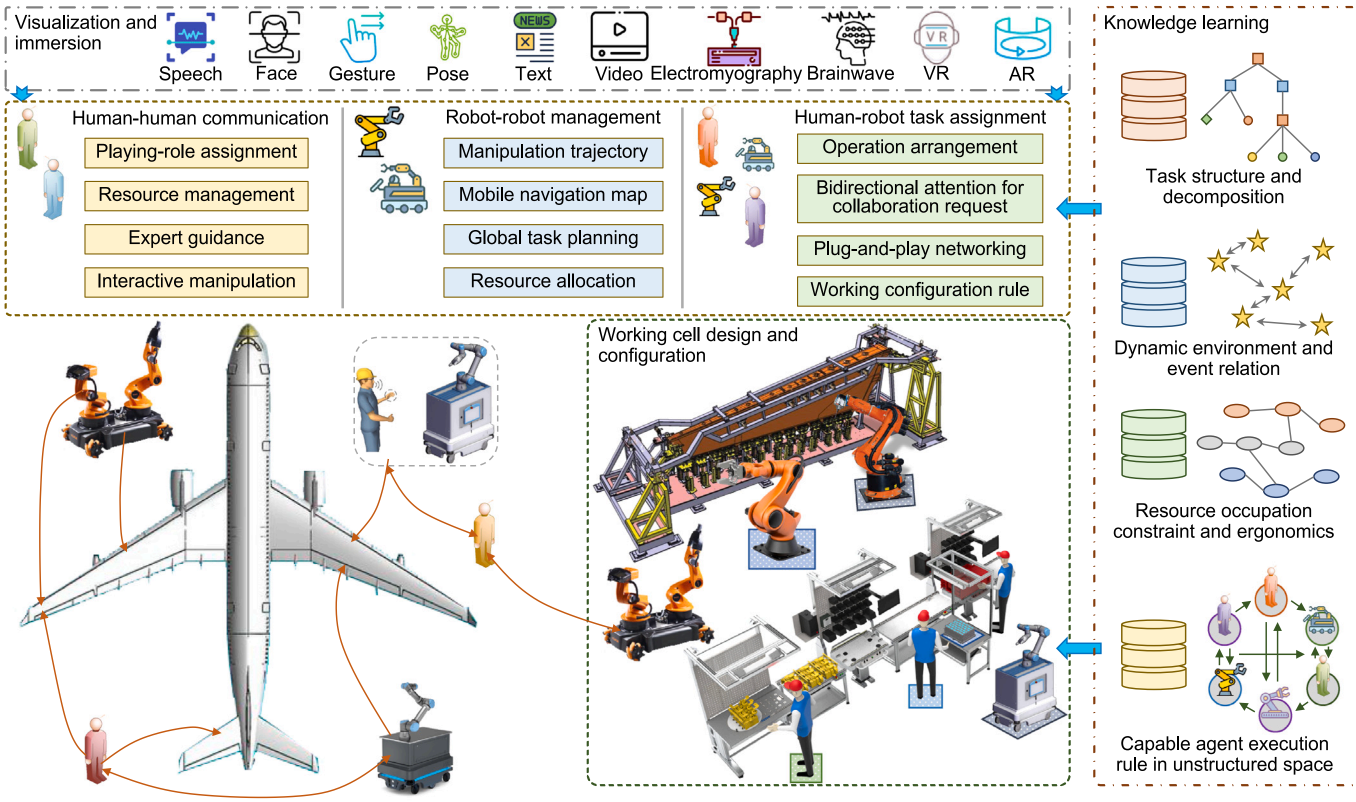

Fig. 4. Self-organising multi-agent teamwork in Proactive HRC.

Table 14
Typical research efforts on HRC working cell design and configuration.

Structure	Method	Example	Ref.
Layout design of a collaborative assembly cell with a worker and a robot	Risk assessment, system safety, feedback interface	Assembly of a flywheel housing cover	[164]
Optimal design of a robotic cell layout with one or more robots	Configuration selection for tasks, cell layout scheduling, tooling optimal design	3C (Communication, computer and consumer electronics) manufactory	[165]
Working cell design for multi-typer and multi-purpose robots	AR tools for operator support, VR tools for ergonomic optimisation, DT-based simulation	Assembly of large-scale parts	[118]
Soft gripper, wearable ring-shaped interface embedded with a vibrotactile motor	Bluetooth communication protocol, perceptual thresholds for the vibrating ring	Pipe grasping test	[166]
Robot skin composed of an array of inflatable units and sensing units	Adjusting the internal air pressure supplied to inflatable units	Physical HRI	[167]
Mechanical and control design of industrial exoskeleton with high payload ratio	Compliant actuator modelling, trajectory tracking controller, safety-based fuzzy logic controller	Manipulation tasks for heavy parts	[168]

could be adjusted to reduce the peak impact force. To assist humans in onerous work, Mauri et al. [168] proposed mechanical and control design solutions for a low-cost hardware industrial exoskeleton. The industrial exoskeleton with a high payload ratio could help a human operator to lift and transport heavy parts, such as a car bumper.

The working cell design and configuration are the first procedure to achieve self-organising multi-agent teamwork in Proactive HRC. For the design of a configurable working station layout with task-oriented robots and human operators, two potential research directions still require more exploration. The first one is AI-based HRC cell generation, such as RL methods. The AI-based HRC cell generation can learn from the historical experience of working station design and create a reasonable human–robot layout by iterative optimisation from constraint rules, such as human's limited physical strength in doing repetitive labour tasks. The HRC cell avoids assigning humans with durable tasks over time beyond one's physical limit. The other one is wearable and augmented robots, like a light exoskeleton with active or passive actuation. The wearable exoskeleton robot can enhance human payload abilities and their symbiotic relations with safe hardware design and user-friendly software interfaces. With the working cell design and robot configuration, the next step is to achieve self-organising resource allocation in multi-agent HRC systems, including human–human communication, robot–robot management, and human–robot task assignment.

5.2. Multiple human communication and collaboration

Information communication and collaboration between multiple humans are common in a lot of working scenarios. The two sides in communication may be in close proximity or remotely staying in different places. Intuitive and natural multiple human communication and collaboration should adapt to different user-playing roles, operation habits, and tendencies of interactive actions. As presented in Table 15, Shang et al. [169] used Unity3D tools to develop an AR-based multiplayer collaboration system for disassembly tasks of ship power

Table 15
Typical research efforts on multiple human communication and collaboration.

Key element	Method	Example	Ref.
Multiplayer collaboration without conflicts of synchronisation and access	Unity3D development and data transformation in Server/Client mode	Disassembly of ship power equipment	[169]
User decision for quality assessment with AR headset	3D model of components, surface discretisation, AR alignment	Surface polishing tasks	[170]
Knowledge transmission between remote experts and local workers	A projector-based MR system, calibration of a projector and cameras	Water pump assembly	[171]
Information communication between operators of different roles	AR assembly guidance, TCP/IP server for message communication	Assembly of large-scale complex products	[116]
Differences and similarities between HHT and HRT	Nine considerations based on dimensions of teamwork	HRT design	[172]
Trust violations in HHT and HRT interactions	A mixed factorial design in a social context	Anthropomorphic robots	[173]

equipment. The system tackled problems of scenario synchronisation and access conflicts in multiple human communication. Then, Ferraguti et al. [170] developed an online quality assessment system for polished surfaces in AR devices. Multiple users could see metrology data projected on the mould to learn about the automatic robot polish process and make faster decisions about where are required polish again for refinements. To transmit domain knowledge between remote experts and local workers, Wang et al. [171] developed a projector-based MR system. The system allowed a remote expert to project gestures into the real worksite to guide a local worker, thus improving the co-work performance, co-presence awareness, and user collaboration experience. Liu et al. [116] developed an AR-assisted assembly system that supported collaboration between multi-operators and machines. The system contained operators in four roles, e.g., group leader, main operator, auxiliary operator, and apprentice. Through the AR helmet, multiple humans exchanged real-time information and completed the teamwork with different duties. Then, Tokadli et al. [172] investigated differences and similarities between HHT and HRT for interaction adaptation between different kinds of teams. The results provided potential interaction paradigms for HAT design with considerations of communication, coordination, and cooperation. Lastly, Alarcon et al. [173] investigated the effects of trust violations in HHT and HRT interactions. For anthropomorphised robots, the result demonstrated that there was no significant difference in trustworthiness perceptions between human partners or robot partners in a social context.

In complex industrial settings, human–human communication and collaboration are characterised by social wellness and esteem needs. The multiple human collaboration in HRC mainly contains different playing-role assignments, human resource management, expert guidance, and interactive co-manipulation. In Proactive HRC, the fusion of AR and DT provides communication tools to achieve self-organising multiple human co-work, with three critical aspects requiring more attention. The first one is the time consistency between multiple human communication. When different interaction events happen, it is necessary to assure synchronous access without conflicts in network communication mechanisms. Thus, various working scenarios can synchronously switch and deliver to multiple humans via display devices at the same time, for information communication and further co-work. The second part is the space consistency for scenario visualisation between multiple humans in remote spaces. With tracing and positioning technologies, such as SLAM, human operators in different locations can share a holographic display of the same view of a manipulated product and conduct operations for a common task goal. Lastly, visible fidelity and immersion during information communication are key to improving naturalness and fluency between multiple human teammates. For example, when an onsite worker receives domain knowledge from a remote expert, the AR and DT tools can enhance their coexistence relationships and user experience by adapting to their action habits, personalised interactive gestures, and working roles.

5.3. Multiple robot management and task planning

Multiple robot management aims for optimal task planning and resource allocation between collective robots, such as fixed robot arms, AGV, and mobile robots. Nowadays, numerous research efforts on multiple robot collaboration have affirmed its broad applications in manufacturing tasks of complicated products, as shown in Table 16. For example, Hassan et al. [174] developed a multi-robot collaboration system for optimal robot positions and orientations when conducting surface coverage tasks. Robots in the system were able to share information on the environment mapping, operation status, and their capabilities for team objectives. For task trajectory planning of multiple underwater robots, An et al. [175] introduced an integral sliding mode controller to guide a large group of robots to destinations along desired paths. The system also built an acoustic communication system under low noise ratio conditions for information transmitted between multiple robots. For multi-agent path planning, Chang et al. introduced deep RL models to learn optimal control policies for UAV [176]. Besides, Liu et al. [177] proposed a multi-agent visual semantic navigation system, which allowed multiple mobile robots to collaboratively find multiple target objects in unseen scenes. The system was developed by semantic mapping of perceived scenarios, prior knowledge learning of relationships between surrounding objects, and a real-time communication module. Then, Liau et al. [178] developed a task allocation model for one human with two robots by considering the task characteristics and resources, i.e., each agent's capability to perform a task. In the task allocation model, the work process was decomposed into a series of functional actions based on the component's geometrics, tolerance, and required force exertion in motions. For dynamic task allocation between a human operator, a mobile manipulator, and a dual-arm manipulator, Karami et al. [179] utilised an AND-OR graph to represent concurrent and sequential operations in the team.

The multiple robot collaboration in industrial settings can achieve optimal manipulation trajectories, mobile navigation maps, and global task allocation. Multiple robot management and task planning advance HRC systems from a traditional leader-follower manner to an intelligent multi-agent system, which improves fault tolerance. The self-organising multiple robot teamwork in Proactive HRC plays a key role to minimise task completion time, less occupation of capable agents, and ergonomic risk of humans, which can be achieved by following aspects. The first one is to use cutting-edge techniques, such as KG to decompose a complex manufacturing task into a sequence of executable subtasks. These subtasks are constructed into nodes in a graph across different task levels with attributes of constraints of resources, execution time, relation rules, and costs. Then, with the knowledge distilling from task decomposition, the characteristics and capabilities of different robot agents are analysed to find the agent assignment preference for each manipulation trajectory, navigation path, and subtask. Lastly, each robot in Proactive HRC systems can autonomously explore the dynamic environment, determine relations of surrounding objects, and communicate with others for feedback on task execution goals.

Table 16
Typical research efforts on multiple robot management and task planning.

Key element	Method	Example	Ref.
Optimal robot positions and orientations considering team objectives	Discretisation of the search space, multiobjective optimisation	Surface coverage tasks in unstructured environments	[174]
A multi-robot control strategy based on a leader–follower scheme	Acoustic communication system, Lyapunov analysis-based control law	Spherical underwater robot	[175]
Path planning for multiple robots under human supervision	A deep RL model with consideration of dynamic environments	UAV	[176]
Visual semantic navigation for multiple agents and objects	A hierarchical decision based on semantic mapping, scene prior knowledge, and communication mechanism	Multi-agent collaborative searching in indoor scenes	[177]
Task allocation between a human worker and two robots	Assembly operation decomposition, analytic network process, genetic algorithm	Small-volume mould assembly	[178]
Dynamic task allocation based on sequential task representation	An AND-OR graph for multiple human–robots cooperation flow	Inspection of product defects	[179]

5.4. Hybrid multi-agent interaction and task assignment

Hybrid multi-agent interaction and task assignment aim to achieve seamless communication between human operators and different kinds of robots, determine their dynamic working roles and make global optimal operation arrangements for their teamwork. As shown in Table 17, Antakli et al. [180] developed an agent-based web-supported simulation environment for hybrid teams in production scenarios, which included resources of digital human models, robots, and a visualisation interface. The configurable simulation could be used to evaluate the feasibility of planned production schedules and task assignments to team members. Then, Patnayak et al. [181] built a wearable supercomputing platform as a multi-agent CPS for distributed humans and robots. The system could be utilised to create maps, segment tasks, and generate paths for hybrid multi-agent collaboration with available power and networking capabilities. The virtual simulation and physical networking platforms provide a precondition for real multi-agent interaction and task assignment in manufacturing scenarios. For multi-agent interaction in distributing tasks, Galin et al. [182] first classified their interaction types based on working time, area, and shared workspace. Then, a particle swarm algorithm was leveraged to generate a structure to indicate which agents were allowed for information exchange and interaction in separated tasks. To enable bidirectional and empathic interaction, Costantini et al. [183] fused speeches, verbal exchanges, face muscles, body postures, voice modulation, and skin responses as communication manners in multi-agent HRC systems. With logic multi-agent system configuration, human and robotic agents could communicate with each other and pass real-time messages according to hierarchical and asynchronous events in systems. To tackle human attention occupation when collaborating with multiple robots, Yao et al. [184] utilised an analytical timing model to schedule which robot the human should collaborate with first. Robots could maximise their performance and start the co-work with a human worker with the scheduled collaboration requests. Mokhtarzadeh et al. [185] leveraged a CP-based approach to solve the task allocation problem in hybrid multi-agent HRC systems. The method could achieve acceptable results for large-scale task assignments, which included up to 200 tasks in different groups and no-wait scheduling tasks.

The hybrid multi-agent HRC is an efficient solution for configurable and flexible production of small-medium volume products characterised by large variants in unstructured spaces, such as aircraft manufacturing. With multi-agent participants, ultra-precise operations can be completed by industrial robot arms, such as welding and machining processes, while heavy manipulation required a large workload can be performed by mobile high-payload robots, such as material handling. Meanwhile, dexterous production of exact components can be assigned to human operators, whose workload can be reduced with the assistance of light collaborative robots. To achieve the self-organising, hybrid multi-agent teamwork in Proactive HRC, there still needs more research explorations, especially in the following aspects. Firstly, bidirectional attention to collaboration requests from human to robot and from robot to human should be developed to avoid disordered resource occupation. KG methods can model various human and robotic operations and link their relations in a task, such as robot manipulations for product state monitoring, picking and placing, human remote control, screw inserting and mounting, etc. With the constructed knowledge base, a multi-agent interaction structure based on collaboration requests between human and robotic agents can be reasoned and determined to minimise idle time and makespan of HRC tasks. The second one is plug-and-play networking and connection between hybrid multiple agents in HRC systems. The IIoT techniques based on cloud–edge computing should provide multi-agent communication and extensible network access for the configuration of different human–robot teams. In this way, agent-based services can be quickly created and provided to end-users, for optimal task planning when the HRC system adds or removes some agent resources. Lastly, the general rules of hybrid human–robot collaborative work processes should be learned and used as prior knowledge for new types of teammates with heterogeneous robots. For a new human–robot configuration, the learned knowledge representation can guide human operators on what to do and also train robots on how collaborative decisions are taken.

6. Compliance robot control and proactive robot motion

Proactive HRC is expected to have close collaboration between robots and humans in close proximity. According to the classification of interactions and definition of HRC [16], collaborative actions can be categorised into direct and indirect contact between humans and robots from the perspective of the robots. The former allows physical interactions where compliance takes a critical role in the success and performance of safe cooperative actions. The latter covers multiple subjects and here the scope of the indirect contact cases is limited to the investigation of path planning.

6.1. Robot compliant control

6.1.1. Compliance behaviours

Robotic applications to manufacturing and/or assembly tasks require mechanical interaction with the environment or objects to be handled, especially in a dynamic yet constrained environment. The success of such tasks relies on the compliant behaviours of manipulators/robots. HRC envisioned for future factories will require close physical collaboration between humans and robots in shared working environments. Within the context, compliance takes the main role in easing interaction between robots and humans, and it is often required to facilitate safe and efficient human–robot cooperative actions. This section starts with the revisit of compliance control in robotics, especially in HRC/HRI, and then provides detailed treatments on relevant issues with a focus on the compliant control of robotic applications.

Table 17
Typical research efforts on hybrid multi-agent interaction and task assignment.

Key element	Method	Example	Ref.
3D configurable simulation of hybrid teams in production scenarios	Resource oriented architecture, motion synthesis, Unity3D simulation	Aircraft wing assembly	[180]
A wearable super-computing platform for distributed human–robot agents	On-board Ethernet network, multi-modal data aggregation and sharing	UAV system	[181]
Multi-agent interaction in distributing tasks	Interaction type classification, particle swarm algorithm	A multi-agent robotic system	[182]
Multi-modal bidirectional communication including speech, verbal and emotional exchange	Multimodal communication recognition, multi-agent system organisation algorithm	Daily robotic interaction with humans	[183]
Scheduling of human attention to collaborate with multiple robots	Condition of immediate access model, analytical timing model	Human attention occupation with three robots	[184]
Allocation of different groups and sequences of multi-agent task	A CP-based approach, a sequence of boards problem	Assembly of printed circuit boards	[185]

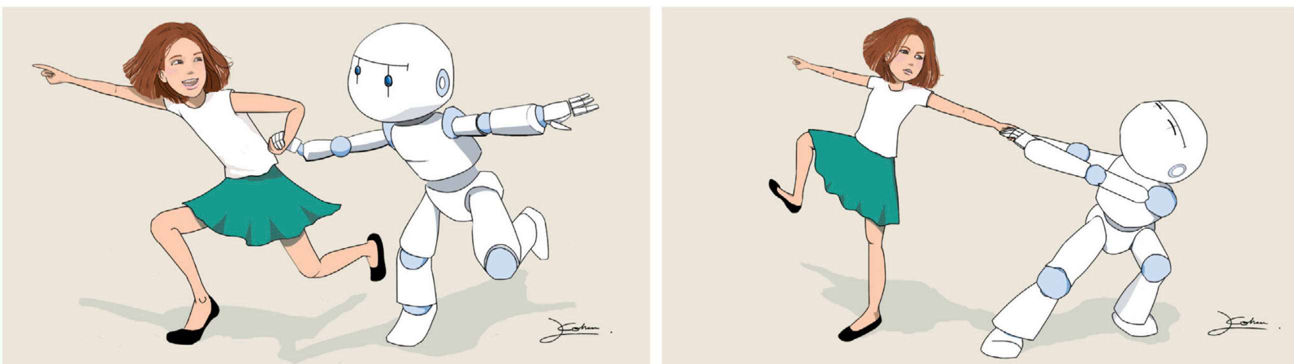

Fig. 5. Illustrations of the compliance behaviours between humans and robots.
Source: Adapted from [186].

In robotics, the term "compliance" refers to the flexibility of a robotic manipulator, and compliance relates to impedance control to some extent, which refers to the robot motion absorbing or resisting the interaction force. The term compliant control can be originally inspired by natural mechanical compliance of the human body [186]. Back to the initial proposal of the compliant control, the theory and experiment of compliant robot control were performed by Waibel and Kazeooni in the 1950s [187], where a compliant controller was defined and developed to modulate the contact force for compliant motion. In the last decade, research efforts on compliance behaviours of manipulators have been numerous. Various approaches to facilitate the performance of the robot compliance control and compliant motion have been reported in the literature. The compliant control approach mainly focuses on the relationship of the robot position, the commanded quantity, the interaction force, and a specified function of the command signals. Aude presented the etymology of compliance and gave a vivid interpretation of compliance as shown in Fig. 5 [186]. As shown in the left-side subfigure, the robot complies with the requests of the human to start running, while the robot resists the human's request and forces the human to execute the compliant behaviours as shown in the right-side figure. The compliance is directly interpreted from the haptic signal, and the compliant behaviour during interactions is regulated through dominance and role distribution and results in the change of motion in the cooperative actions. Compliant motion is produced by two primary methods, and they are passive mechanical compliance built into the manipulators and active compliance realised in the control servo system. Various interaction scenarios define a varying degree of proximity for humans and robots, and the relationship of humans and robots can be categorised as '*coexistence*', '*cooperation*', and '*collaboration*' [16]. '*Coexistence*' represents working independently on different tasks in adjacent workspaces without safety fencing, but not in a shared workspace. '*Cooperation*' defines the same workspace where humans and robots work alternately on different tasks within a process, but no direct interaction. '*Collaboration*' means that humans and robots simultaneously work on the same tasks in a shared workspace with direct contact if necessary.

Table 18
Classification of force control approaches.

Name	Explicit specification	Implicit specification	Difference
Direct force control	Hybrid force/motion control; Parallel force/motion control	–	Maintaining a desired force by the closure of a force control loop.
Indirect force control	Impedance control; admittance control	Impedance control	Force control via position/motion control, without explicit closure of a force feedback loop

6.1.2. *Robot force control for compliance*

Within the context of HRC, the compliance behaviours of the robots are regulated by force and position control. Robot force control is of paramount importance when the robot is interacting with the environment or humans [188], accordingly, the classification of the force control schemes can be summarised as follows, and it provides fundamental support to compliance behaviours of the robotic control system listed in Table 18.

- *Direct force control* schemes are developed which achieve force regulation when the end effector is in contact with a compliant environment, thanks to the adoption of an integral action on the force error generated by an outer force loop [189]. In the case of direct force control, the abstraction that aims is able to directly "*control*" the contact force.
- *Indirect force control* schemes achieve force control via motion control, without explicit closure of a force feedback loop. Indirect

force control regulates the dynamic relationship between the position and the interaction force of the robot with its environment without direct measurement of the interaction forces.

In direct force control, an explicit model of the interaction task is necessary, in which the desired motion, contact force and moment need to be specified in a constrained way with respect to the constraint imposed by the environment. Hybrid force/motion control, as a typical approach widely adopted in direct force control, is to regulate the motion along with the unconstrained task directions and force/moment along the constrained direction [190]. Parallel force/position control is adopted by superimposing force and motion control actions if an accurate description of the environment is not available. In this case, the force control dominates motion control, resulting in accurate force regulation and tolerated position errors.

Indirect force control does not need measurement of contact forces and moment. Two main approaches which are composed of admittance control and impedance control are adopted to achieve the indirect control of the interaction force. Within the context, the position deviation between the end-effector motion and the desired motion due to the interaction with the environment is related to the contact force through parameter adjustment of mechanical impedance/admittance. Mechanical impedance can be defined as the resistance to motion of a structure forced by the applied contact force. On the contrary, mechanical admittance formulates a function of the velocity and input contact force and is to transform the contact force into the reference velocity, in which the reference position and acceleration can be calculated by the zero-hold method. Impedance control and admittance control can be used to implement the same control goal but their stability and performance during the control process are mutually complementary. The former better performs dynamic interaction with a stiff environment but suffers from poor accuracy in free space because of friction and unmodelled effects, and the latter is better suitable for interaction with a soft environment in a high-accuracy means, but with the issue of instability during the interactions. When only consideration of the static relationship of the end-effector position and orientation deviation and contact force/moment is defined, stiffness control and compliant control are special cases of impedance and admittance control. Hybrid position/force control provides the potential and fundamental control methodology for the compliance behaviours of manipulators, and the task space that hybrid position/force control works is composed of position-controlled and force-controlled subspaces. However, both position and force cannot be accurately controlled along any given direction in the hybrid position/force control because it ignores dynamic coupling between the manipulator and the environment. For this purpose, impedance control bridges the relationship between the end-effector's position and force. In the subject of the compliant motion, compliant control is the subset of the impedance control and it is defined as 'any robot motion during which the end-effector trajectory is modified, or even generated, based on online sensor information'.

6.1.3. From passive compliance to active compliance

In any HRC system, human safety is of paramount importance. Compliant control is highly relevant to human safety in physical HRI. Various approaches to facilitate the stability and performance of compliant control have been developed and applied to industrial practices. Here, we briefly give a summary of the methods used to implement compliance behaviours. It summarises a brief investigation of the development and progress of compliant control and its variants. Passive compliance control and active compliance control are two main methods to achieve compliance behaviours of a robot manipulator and offer the fundamental basis of variants of compliance control such as adaptive compliance control, variable compliance control, RL-based compliant control, and cognitive compliant control.

Passive compliance control is an approach to control the force–displacement interaction between a manipulator and a stiff environment [191]. Passive compliance is the intrinsic flexibility in a robot manipulator inherited by its mechanical structure or by compliant actuators such as belt and pulley mechanism or an artificial muscle [192]. It can improve actuator characteristics such as back drivability, motor link decoupling, peak torque, power requirements and energy storage capabilities, but also increases the system complexity and control effort, e.g., to suppress undesired oscillations, and decreases the position or force control bandwidth [193]. The study of passive compliance control to manipulators is widely investigated in the literature. Rice and Schimmels studied passive compliance control using redundant serial manipulators with real-time adjustable joint stiffness to achieve effective interaction for performing constrained manipulation tasks. Through extending the redundant inverse kinematics problem to include compliance, the challenge of finding suitable joint commands for producing the desired time-varying end-effector position and compliance in the passive compliance control was addressed [194]. Followed by previous work, they investigated globally optimal passive compliance control for tasks having multiple-homotopy classes and found a globally optimal joint manipulation path (sequence of joint positions and compliances) that yields a desired task manipulation path (sequence of end-effector positions and compliances) when there is one degree of redundancy [191]. Kim et al. [195] developed a passive compliance controller for aerial manipulators to ensure stable interaction with passive environments, and it can guarantee the passivity of the manipulator through a proper choice of end-effector coordinates. Schiavi et al. [196] discuss the integration of active and passive approaches to robotic safety in an overall scheme for real-time manipulator control. The active control approach detects the presence and position of humans in the vicinity of the robot arm, and generates motion references by the use of a supervisory visual system, while the use of variable joint impedance combination with velocity control guarantees safety in worst-case conditions in the passive control. Calanca et al. [197] considered that compliant control can be defined as the control technology to produce compliant motion. Some of the studies on passive compliant motion in the assembly have been explored. For this purpose, Park et al. [198] used kinematical information without force feedback to design robot motions and implemented compliant robotic behaviours by combining conventional controllers, and Su et al. [199] investigated robotic precision assembly by using the combination of passive and active compliant control, where the passive compliant motion in the constraint region is adopted to eliminate the uncertainty of the manipulator's orientation. In addition, Pettinger and Pryor [200] studied the implementation of complex contact tasks using combined active and passive compliant control approaches, and Liu et al. [201] developed a robust insertion control method for precision peg-in-hole assembly by visually supervising the deformation of the passive compliance based on microscopic vision and force information.

Compared with passive compliance, active compliance has advantages in terms of increasing the force transmission ability and improving safety with monitored force output [202]. In active compliance systems, compliant motion is often realised by the combination of a speed control system and a sensor-based control system. The former in the robotic system is composed of motors or motors with geared transmission systems, and the latter uses sensors for the detection of the joint torque or speed. Active compliance has been increasingly used in many robotic industrial processes due to its advantages in flexibility. This is why use active compliance. For example, robotic applications such as grinding, polishing, and deburring require active compliance since the differences from one part to another. A good example of such applications of compliant joints is the Selective Compliance Articulated Robot Arm, with the acronym of SCARA, and SCARA robots provide flexibility for vertical assembly. Inspired by benefits of the active compliance, industrial robot companies investigate the incorporation of active compliance in the robotic system or software design. ABB's SoftMove provides the robot with compliance in one direction, which can enhance high accuracy and reliability. A compliant robot is one that can perform tasks with respect to an external force by modifying its motions in a way of minimising forces. The induced motion is implemented through lateral, axial or rotational compliance. In addition, a compliance control function is developed in DENSO robots for the protection of workpieces and hands from the excessive load by regulating the pressing force. It enhances the efficiency of the work that has direct contact with other objects such as the accurate insertion of a part into another part. In parallel, robotic force compliance devices can be used to automate processes and make an industrial robot have the capacity of "human" touch, and the active compliant devices can accurately apply the desired force to the parts by the use of closed-loop feedback control along with position and force sensors. Active compliant control enables to quickly and freely adjust properties and dynamic behaviour of interactions of mechanisms within certain limits, and an introductory review of active compliant control was investigated by Schumacher et al. [193]. Liu et al. [203] proposed a sensorless haptic approach for compliant control of the robot manipulators through the demonstration in HRC assembly tasks. Queißer et al. [204] extended a hybrid approach combining classical and learning elements into an active compliant control mode, and it implements a kind of gravitation compensation to allow for kinesthetic teaching of the robot based on the implicit knowledge of gravitational and mechanical forces. Lefebvre et al. [205] presented a literature survey of the state-of-the-art active compliant motion. In addition, to investigating the applications of the compliant control in robotic grasping manipulation, Sadun et al. [206] presented an overview of active compliance control for a robotic hand, where active compliance is classified into force control and impedance control. Humanoid robots are often designed to have physical interactions in human environments. For this purpose, Dean-Leon et al. [207] investigated the whole-body active compliance control for humanoid robots with robot skin, and the experimental results show that multimodal tactile information can be fused hierarchically with multiple control strategies, producing active compliance in a position-controlled stiff humanoid robot. Through the use of active compliance via an admittance control scheme, a locomotion controller for lower limb exoskeletons is developed to enable the combined robot and user system to exhibit compliant walking characteristics when interacting with the environment [208]. Compliance control for heavy-duty manipulators is a typical challenge because of high loads and modelling problems. To address such a challenge, Li et al. [209] studied active compliance control of fine manipulation for heavy-duty manipulators where a genetic neural network-based position/force same loop control algorithm is developed for the compliant control of hydraulic heavy duty manipulators, and Onogi et al. [210] proposed a new compliance control to achieve stable coordinated motion of robotic ultrasound probes in any operational velocities through the use of using a velocity-depended viscosity coefficient corresponding to applied force magnitude. In parallel, Zhu et al. [211] studied active compliance control of a hydraulic quadruped robot aiming for a reduction of the impact of the feet, and the active compliance strategy is composed of an inner-loop position servo control and an outer-loop impedance control. To have stable locomotion of legged robots, a nonlinear active compliance control is developed and applied to the steel wire transmission-based legged robots, with the achievement of better interaction capability [212]. The study on continuum robots with compliance in the minimally invasive surgery facilitates safe operations with the robots and the surrounding tissues, and Jake et al. [202] proposed a RNN-based active compliant motion control approach for continuum robots, which is based on a complex derivation of their mechanics models. For Rotary-Spherical–Spherical parallel manipulators, a sensor-less full-body active compliance approach is developed for the detection of an external disturbance applied at any movable part of the parallel manipulator and then achieving active compliant behaviours to such disturbance, without using any force/torque sensors [213].

6.1.4. Adaptive and learning-based compliance control

To overcome uncertainties in the dynamic parameters of the robot manipulator, adaptive control approaches for compliance behaviours have been developed. Colbaugh et al. [214] presented an adaptive compliant control approach for dexterous manipulators, in which an adaptive impedance control approach was developed for torque-controlled manipulators, and an adaptive admittance control approach was developed for position-controlled manipulators. Zhou et al. [215] developed a RNN-based adaptive compliance control of manipulator. Also, Seraji [216] presented new position-based force and compliance control schemes for robot manipulators using nonlinear and adaptive controllers, and it offered a stable and uniform performance in contact with surfaces having unknown or varying stiffnesses. Adaptive compliant control schemes have been developed to achieve safety during physical interactions between humans and robots. Khan et al. [217] designed a safe adaptive compliance model reference controller for a 4-DoF humanoid robotic arm in Cartesian space, and the robot controller follows the compliant passive behaviour of a mass–spring–damper system model with an externally applied force. Then, the developed adaptive compliance control approach was extended to have better multi-variable control performances [218]. Eich et al. [219] presented an adaptive compliance control architecture for hybrid multi-legged robots, which can deal with various stairs and allow robots to move with high velocity on flat ground without adjusting control parameters. To control the exoskeleton, Akgun et al. [220] implemented an adaptive compliance control strategy for all active and passive rehabilitation tasks. The performance of compliance control heavily relies on environment dynamics and the choice of the target impedance. Therefore, the target impedance was adaptively adjusted to maintain the performance of various environments, and Matinfar and Hashtrudi-Zaad [221] designed a 'static-optimised' compliance controller with the minimal values of a combined generalised position and force trajectory error metric, in which the control parameters of an adaptive compliance control scheme are adjusted based upon environment stiffness and damping. Also, Samy et al. [222] utilised an adaptive compliance predictive control scheme to allow a humanoid robot to actively control its compliance. Through augmenting optimisation variables of Hierarchical Quadratic Programming formulation, maintaining an impedance-like behaviour under external disturbances, while switching to an admittance-like behaviour when collaborating with a human can be achieved by incorporating Cartesian reference and an adaptive compliance controller [223]. In addition, adaptive compliance control schemes have also been applied to perform compliance behaviours of hydraulic and aerial manipulators [223,224]. Motoi et al. [225] used a force-based variable compliance controller for flexible motion control systems to achieve "approach task" and "pushing task". The former task is the motion for a robot to approach an environment without direct contact, and the latter task is the motion for the robot to contact and push the environment for achieving several tasks.

In recent years, the success of learning algorithms such as RL and DL in parameter learning and optimisation has made them effective at tuning control parameters of compliance behaviours of manipulators. Ren et al. [226] designed and developed a learning-based variable compliance controller to govern the insertion processes during robotic assembly, and the controller can switch the operation strategy between passive compliance and active regulation in continuous spaces. A deep RL approach was proposed to implement compliance control of robotic peg-in-hole assembly with hole-position uncertainty [227]. Khan et al. [228] proposed an optimal compliance control scheme based on bio-inspired RL to facilitate the safety of robotic walk assist devices, and this dynamic-model-free scheme uses joint position and velocity feedback as well as sensed joint torque (applied by the user during the walk) for compliance control. Peng et al. [229] utilised the RL method to achieve compliant physical HRI by allowing the robot to have an optimal compliant motion to adapt to interaction forces.

Table 19
Feature of different terminologies for robot motion control.

Name	Representations	Explicit distinction
Path planning	Generating a geometric path from an initial to a final point in the joint or Cartesian space of the robot [232]	Without time information
Trajectory planning	Generating a geometric path from an initial to a final point with time information [232]	With time information
Motion planning	Frequently refer to motions of a robot in a 2D or 3D world that contains obstacles [233]	Process of defining the set of actions the robot needs to execute to follow the path planned

Compliance is considered an essential element to facilitate safe and efficient human–robot cooperative actions. In humans, compliance is considered from mechanical, cognitive, and social perspectives [186], and the author gave a brief review of mechanical, cognitive, and social dimensions of that compliance takes in HHT and HRT interactions. In addition, the author refers to the design of algorithms for determining compliance parameters as cognitive compliance approaches. From the perspective of neurorobotics, Chame and Tani [230] investigated the distinctions between motor and cognitive compliance, and then use predictive coding and active inference-inspired variational model to describe the cognitive compliance with the capability that can be driven by sensory information. Leidner [231] combined-based cognitive reasoning methods and compliant robot control to achieve human-like performances in the manipulation tasks, and the robots allow for cognitive abilities to interact as sophisticated with the world as humans do through representing, planning, executing, and interpreting compliant manipulation tasks.

6.2. Proactive robot motion

In robotic applications, a generic task is implemented by a robot by performing a specific motion to the end-effector. When the robot does not have a physical interaction with the environment or the object to be handled, it is a free motion. The robot motion control is controlled through the execution of a generated trajectory either in the joint space or in Cartesian space.

6.2.1. Terminology for robot motion

Numerous research efforts on robot motion control have been reported in the literature. Different terminologies with respect to robot motion are optionally used in studies. Nevertheless, confusions exist in the definitions and relationships of the terminologies: path planning, trajectory planning, and motion planning. For the purpose of clarification, the summary of the three terminologies is listed in Table 19.

The motivational problem of robot motion planning is how to transform high-level task specifications (provided by humans) into a low-level description suitable for controlling the actuators [233]. The planning needs to address the implicit representation of the state space that is defined as the configuration space in the literature on motion planning [234]. In this case, the motion planning can be considered a path search in a high-dimensional configuration space that contains implicitly represented obstacles, and a motion plan is viewed as a continuous path in the configuration space [234]. Therefore, the core of motion planning is the transformation of a continuous model into a discrete model [235]. Motion planning in robotics is a process of dividing the desired movement task into discrete motions with the satisfaction of constraints. For example, consider a mobile robot moving at an assembly line to a specific target point, the robot performs this task while avoiding obstacles. The description of these tasks is defined as the input to the motion planning algorithm, and the motion with the velocity, and turning commands are produced to let the robot execute. For robot motion control, research efforts on path planning and trajectory planning have been widely studied. As shown in Table 19, path planning is to generate a geometric path from an initial to a final point in the joint or Cartesian space of the robot with no mention of any specified time law, and it is merely geometric matter [232]. Trajectory planning characterises a time law as a geometric path [236]. In a special case of point-to-point trajectories, there are no obvious distinctions, and the two problems can be solved at the same time. The complexity of robot path planning can vary from application cases. For example, a generic task requires the generation of the path according to the geometry of the task.

6.2.2. Path planning and algorithm classification

In the case of robots performing the task in a dynamic yet constrained environment, more constraints such as obstacles avoidance are considered. For this purpose, the studies of planning algorithms have been widely explored for path planning and trajectory planning for robot motion. Different interpretations of classifications of planning algorithms are discussed and used in literature, and different classification criteria for path planning and trajectory planning algorithms are summarised in Table 20.

Here, the main algorithms of path planning are briefly presented as follows. The roadmap techniques perform a graph-based search from a set of one-dimensional paths that are transformed from high-dimensional configuration space [240]. It means that this approach converts the connectivity of the free space into a one-dimensional curve-based system in the C-free space or its closure. The cell decomposition approaches firstly divides the free space of the robot into a set of convex, non-overlapping regions, and each region is defined as a cell [232]. The path between any two configurations in a cell can be generated and represents the adjacency relations of a connectivity graph. Within the graph, the nodes and an edge between two nodes represent the cells extracted from the free space and a path with adjacent cells. The use of graph-searching techniques can solve path planning problems.

The artificial potential field algorithms view the robot in the configuration space as a moving point subject to a potential field, and the sum of attractive and repulsive potential fields that are produced by the target configuration and the obstacles in the C-space is considered an artificial force [241]. In this case, the robot is controlled to reach the goal point and avoid obstacles in an unknown environment by attractive force to reach the goal point and repulsive force, respectively. In addition, many variants of the artificial potential algorithm have been developed to widen its applications to different problems. Some of the examples are summarised as follows: improved artificial potential field methods, modified artificial potential field methods, balance-artificial potential field methods, evolutionary artificial potential field methods, and adaptive artificial potential field.

The probabilistic roadmap planner employs a probabilistic algorithm to solve the problem of determining a path between an initial configuration of the robot and a target configuration while avoiding collisions, and a probabilistic roadmap is a network graph of possible paths in a given map based on free and occupied spaces [242]. It is composed of a roadmap construction and planner phases. The former builds a graph by connecting a set of random configurations in the C-free by means of a path, and the latter is to find the shortest path using algorithms like Dijkstra's algorithm or the A* search algorithm. The complexity of the probabilistic roadmap planners does not reply to the dimension of the configuration space and the environment's complexity, which makes them efficient in the path planning of the robots with high-dimensional configuration space.

In addition, AI knowledge facilitates the development and improvements of path planning methods in robotic applications, and a comprehensive review of learning-based path planning algorithms is investigated and summarised, and they are categorised into learning-based algorithms; DL-based algorithms; RL-based algorithms; variants of RL-based algorithms; combined algorithms of RL and other learning

Table 20
Classification of algorithms for path planning and trajectory planning.

Category	Algorithm	Classification criteria	Ref.
Path planning	Roadmap techniques; cell decomposition algorithms; artificial potential methods; probabilistic roadmap planners; learning-based methods driven by AI	Model-based; model-free; classical methods; learning-based methods (DL, RL, and ML); methods with stationary obstacles; methods with dynamic obstacles; with predictable environment/with unpredictable environments.	[232,237,238]
Trajectory planning	Minimum execution time methods; energy-efficient methods; optimal jerk methods; learning methods driven by AI (such as DL and RL)		[232,239]

Table 21
Typical research efforts on learning-based path planning algorithms.

Task	Method	Specification	Ref.
DL-based algorithms	DL, ray tracing algorithm, waiting rule, and RTT;	The use of DL algorithms to identify the type of obstacles and distinguish between static obstacles and dynamic obstacles; the improved ray tracing and the waiting rule for static and the dynamic obstacle avoidance, respectively, the RTT for the path planning	[243]
RL-based algorithm	Deep q learning and CNN algorithm	CNN analyses the exact situation using image information on its environment and the use of deep q learning to path planning for the robots based on the status	[244]
Deep RL-based algorithm	Deep Q-network	Deep Q-network approximates the mobile robot state–action value function, and the original RGB image captured from the environment without any hand-crafted features and features matching as the input; robot reaches the goal point while avoiding obstacles ultimately by executing the current optimal mobile robot action	[245]

methods (such as probabilistic roadmap and neural networks); and learning-based end-to-end algorithms. Some of the typical research efforts on learning-based path planning algorithms are listed in Table 21. In addition, the applications of RL-based path planning algorithms have been numerous. Variants of RL-based path planning algorithms are widely designed and developed including deep RL, inverse RL, iterative RL, and hierarchical RL-based algorithms, and the detailed introduction and discussions of the variants of RL algorithms can be found in [238].

6.2.3. Trajectory planning and algorithm classification

Compared with a robot path, a trajectory is a geometric path with a specified time law. In principle, the inputs of trajectory planning algorithms are the path description such as initial and final points, geometrical constraints on the path, constraints on the mechanical dynamics, and constraints due to the actuation system, and the output is a trajectory, given a time sequence of values specified by position, velocity, and acceleration. The planning modality of the trajectory varies with the cases of point-to-point motion and motion with a predefined path, and also the trajectory can be either in the joint space or in the Cartesian space. To plan a desired trajectory, the geometric path and motion law need to be specified. The former is obtained by assigning initial and final values for the configuration variables, with the desired motion laws that specify functions up to a given order of derivations (such as velocity and acceleration). For the joint trajectory, the planning algorithm formulates a function interpolating the given vectors of joint variables at each point, with respect of the imposed constraints. The nonlinear effects of direct kinematics make the end-effector motion resulting from the joint space trajectory motion unpredictable, and the trajectory planning in the operative space is generating a sequence of position and orientation values of the end-effector of the robot that is transformed from the joint values through a kinematics inversion. Therefore, trajectory planning is often performed in the joint space where the control actions on the robot are employed.

In robotic applications, the tasks often have specific requirements for the execution objectives such as good productivity. Therefore, the optimisation criteria for the trajectory planning algorithms can be mainly categorised into four types that are composed of minimal execution time, minimal energy (or actuator effort), optimal jerk, and a combination of some of them, and the classification criteria of the trajectory planning algorithms are summarised in Table 22 [232]. The hybrid criteria of trajectory planning are defined as the combination of the two or three criteria such as the optimal time-jerk trajectory or the optimal time-energy-jerk trajectory. These trajectory planning algorithms generate the optimal trajectory given a planned path with the satisfaction of constraints and requirements.

6.2.4. Motion re-planning in a dynamic environment

Within the context of HRC, the dynamic environment poses a difficulty for the motion planner of robots due to the unpredictability of the interaction with humans or objects to be handled. For example, the execution of a robotic assembly task can be interrupted by one or many of these unknown and unpredictable moving obstacles such as humans and mobile devices, and four types of safety policies are often employed to ensure safe interactions within the monitored areas [249], and they are (1) firing an audio warning and reducing the speed of the robot to prepare for a full stop when the obstacles moving into the monitored areas; (2) a retrievable stop interruption to the robotic system if the human or the obstacle steps into a defined hazard zone; (3) the robot arm will move away automatically to keep a safe distance from the obstacles (humans) for collision avoidance when the obstacle moves towards the robot; and (4) dynamic modification of current robot trajectories to prevent any collision with the obstacles. The last safety policy involves dynamic planning of robot trajectory or path for collision avoidance. Studies on dynamic trajectory/path planning for collision avoidance have been reported in the literature. Kamil et al. [250] gave a comprehensive review of motion planning algorithms for mobile robots with moving obstacles from the perspectives of the smooth path, safety, path length, run time, accuracy, stability, less computation cost, control, efficiency, and future prediction (uncertainties). Wei and Ren [251] proposed an autonomous obstacle avoidance dynamic path-planning method for a robotic manipulator based on an improved RRT algorithm, in which a path optimisation strategy based on the maximum curvature constraint is presented to generate a smooth and curved continuous executable path for a robotic manipulator. In

Table 22
Classification criteria of the trajectory planning algorithms.

Name	Optimality criteria	Methods	Ref.
Trajectory planning	Minimal execution time	Maximum admissible value for the pseudo-velocity of the end-effector derived from the constraints; dynamic programming for the minimum time trajectory; model-based approach to maximise the speed of the robot; the phase plane method with variant constraints	The detailed introduction to these methods can be found in [232]
	Minimal energy consumption	Energy considered as constraints on the motion of the end-effector, and the objective is often formulated as the integral of squared torques	The detail algorithms are summarised in [246]
	Optimal jerk which is defined as the time derivative of the acceleration	The optimal jerk is to smooth the profile of the actuator torque and obtain smooth trajectories	The detailed algorithms are summarised in [247]
	Hybrid criteria	It combines some of the optimisation criteria as optimised objectives, such as minimum time–energy, time–jerk, and energy–jerk optimisation objective	The detail algorithms are summarised in [248]

the presence of obstacles, no matter of static or dynamic, the robot has to decide how to proceed when one of these obstacles is obstructing its path. For this purpose, Connell et al. [252] proposed a dynamic path replanning approach using RRT* algorithms in a dynamic environment with random, unpredictable moving obstacles. In addition, Berg et al. [253] presented an efficient approach for anytime path planning and replanning in partially-known, dynamic environments, which considers all prior information about both the static and dynamic elements of the environment, and efficiently updates the solution when changes to either are observed. Yoshida et al. [254] developed a reactive method for online robot motion replanning in dynamically changing environments by combining path replanning and deformation, and this approach allows the planner to deal with more dynamic environments including continuously moving obstacles, by smoothly deforming the path during execution. Within the context of not adding additional control burden, Li et al. [255] proposed a hierarchical replanning framework that assists 7-DoF redundant manipulators to avoid dynamic obstacles during HRI through rapid modulation of the ongoing trajectory. This framework is composed of three steps. Step 1 is to initialise the path in the joint space by the use of an improved RTT planner; Step 2 is using a hybrid scheme combining local path rewiring and redundancy-based node self-motion to replan the part of the pre-planned path affected by dynamic obstacles, and step 3 is a real-time adjustment of the trajectory and generating smooth motion primitives for actuators by employing an adaptive online trajectory generator. Yu and Zhang [256] pointed out the drawbacks of optimal path planning of the robot manipulator in low computational speed and tedious training induced by the changes in assembly lines, and accordingly proposed a novel path planning approach of a slice-based heuristic fast marching tree, which is based on joint space to achieve real-time path planning speed without modelling or training the workspace in advance. There is no need for learning obstacle models in advance in that the proposed approach can examine collisions online.

7. Challenges and future perspectives

Proactive HRC is a foreseeable paradigm towards mutual-trustworthy, preferable, and high-configurable collaboration production. From the aforementioned literature, technical, practical, and ethical issues and theories need further exploration for the real-world implementation of Proactive HRC. This section outlines a couple of challenges that deserve attention to realise the mutual-cognitive, predictable, and self-organising perspectives of Proactive HRC. Future directions are also highlighted to give a great vision for the Proactive HRC evolution.

7.1. Online recognition of both short-term and long-range human intention

Human intention recognition in manufacturing activities is a critical cognitive capability for Proactive HRC. A human operator has both long-term and short-term operation goals when performing tasks with robots. Past research efforts focus on recognising human physical and psychological behaviours within a fixed time series. Nevertheless, these approaches fail to learn dynamic human operation intentions in uncertain time lengths. In this context, social and technical problems stay unresolved to advance the sequential online recognition of human intentions. For example, which kinds of human intentions across an entire task process deserve consideration? That is a real-world question without a socially trustworthy consensus. It is noted that there is no significant alteration between human current operations and next-stage actions. For the technical methodologies, the online human intention recognition algorithms need to tackle the problem of how to decompose continuous human actions into different sub-stage intentions and determine when to recognise the human next operation goal. The last problem is continuous classification and even prediction of these consecutive sub-stage human intentions in various time lengths.

To deploy successful human intention recognition in Proactive HRC, two potential research directions are also highlighted here. Firstly, more explicit and implicit human intention patterns can be distilled by fusion of multimodal data, such as actions in visual patterns, commands in voice records, workload changes in EMG signals, and mental states in brainwaves. With ample information in multiply modalities, attention and fusion mechanism can be introduced into the recognition model to determine the turning span time between different human operation goals and continuously predict human intentions in various time spans among a task. The second one is to link human intention data and prior knowledge of HRC tasks by a KG. The connection between human behaviours and manufacturing knowledge provides a guideline and alteration cue for sequential human intention recognition across time.

7.2. Handy human wellbeing estimation

Human wellbeing estimation nowadays attracts particular attention for improvement of co-work satisfaction in Proactive HRC. A human operator may suffer physical fatigue and mental stress in manufacturing activities with robots in close proximity. Previous explorations leveraged EMG and EEG devices to measure human muscle workload and monitor human psychological activities, respectively. Nevertheless, human agility and flexibility are damaged when a worker wears bulky equipment and onerous sensor systems. The situation in turn interferes with human wellbeing. The ethical challenge in human wellbeing estimation is whether it is reliable and acceptable when modelling human emotional fluctuation with human physical and mental states. The technical aspect is to estimate human wellbeing among HRC tasks in a handy manner, without disturbing human agile operations.

To enable handy human wellbeing estimation, two ways show large application potentiality. Firstly, a DT-based human physical fatigue modelling method can be achieved by fusing human body mechanics and real-time visual perceptual results of human poses, motions, and point clouds. A digital replica of a human worker provides load-carrying simulation for human manipulation in HRC systems. Furthermore, ergonomic analysis methodologies can be integrated into human DT. Human mental stress can be analysed and reasoned by observation of a worker's continuous feedback to surrounding environments, such as the number of gazing at nearby robots.

7.3. Human–robot–environment parsing and cognition

Human–robot–environment parsing and cognition infer their dynamic relations and make explainable resource allocation decisions to support their co-work processes. Past studies have provided feasible solutions for HRC scene parsing with monomodal consideration, such as human action recognition, robot motion monitoring, object pose estimation, and navigation map generation. However, the practical challenges stay strong in how to define contextual and interpretative relationships between human operations, robot manipulations, and surrounding environments. It is critical to determine which kind of fusion between these elements is more important for the generation of suitable HRC task arrangements. For example, the simultaneous occurrence of human handover and quick robot reaching actions may lead to contact hazards, which is a priority concern for safe cognition in HRC systems.

To solve the problems of human–robot–environment parsing and cognition, the current visual reasoning and KG methods deserve more exploration. Especially, visual reasoning modules across the object, semantic, and knowledge spaces can align with the knowledge expression of HRC tasks in perceptual results, their relations, and implicit cognition, respectively. The visual reasoning process fusing these spaces explains the mechanism of knowledge fusion and cognition generation based on human–robot–environment parsing results. Besides, the KG provides a natural interpretation of their contextual relations by linking human–robot–environment elements into different structural schemas. The KG approach bridges the gap of explainable knowledge learning for the decision-making mechanism in HRC.

7.4. Mutual-cognitive and empathetic teamwork

Mutual-cognitive and empathetic teamwork in Proactive HRC maximises the intuitive, friendly, and preferable experience for humans and robots. Previous works made reasonable decisions for planning robot motions and human operations by learning a task structure and production goals. Nevertheless, few studies involve specific elements and evaluation criterias for the empathetic HRC working process. It is necessary to train agents in an HRC system on what to do for teammates' emotional needs and explain how the decisions are taken.

For the future development of Proactive HRC, the first step can consider creating standards to evaluate the performance of mutual-cognitive and empathetic teamwork by introducing ergonomics criteria, psychological factor assessment, and productivity measurements. Then, when human operators are equipped with information display devices for domain knowledge support and enhanced skills, the time and space consistency of the visualisation devices should be ensured to improve human participation and immersion degree. Lastly, robot learning modules can advance robots owning human-like cognition and pay more attention to robot path re-planning for adaptation of human-changing manipulation needs.

7.5. Fusion of current scene understanding and prior knowledge

By fusion of current scene understanding and prior knowledge of HRC tasks, decisions for human and robotic operations in the next stage can be inferred and generated. Previous studies explored knowledge learning of current scenarios and overall task structure in HRC settings. However, there are technical challenges on how to integrate the knowledge of what is happening in recent scenes and holistic prior arrangement of an HRC task. For example, the problem includes how current scene understanding influences subsequent human and robot operations in the prior knowledge base.

To guarantee smooth and predictable HRC task fulfilment, the fusion of current scene understanding and manufacturing prior knowledge can consider KG methods. Firstly, a holistic HRC KG can be constructed by denoting production elements of 'Human, Robot, Material, Method, Environment' as nodes with different attributes. Then, the elements appearing in the current scene are activated in the HRC KG, followed by searching and determining suitable graph configurations for next-stage human and robot operations. On the other hand, the production elements from onsite scenarios can be constructed as an SG firstly, then align to the holistic HRC KG to adjust the graph retrieval strategies for linking suitable next-stage task planning.

7.6. Task re-planning and knowledge transfer for unexpected or unseen situations

The task re-planning mechanism suspends incorrect robot operations and recovers to normal procedural sequences when facing unexpected situations caused by human motion uncertainty. Besides, the mechanism can transfer knowledge of previous co-work strategies to update appropriate task planning for new but similar HRC task variants. To date, numerous efforts on HRC task planning majorly focus on scheduling exact and specific operations for predefined tasks. Nevertheless, the conventional task planning algorithm may be invalid when facing human uncertainty and product variants which are unavoidable situations in a realistic world. For instance, what re-planning decisions can be made to restore correct HRC task fulfilment if a human operation fails to obey task precedence constraints or there are additional manufacturing process requirements for new products?

In this context, three potential directions are highlighted to offer feasible solutions of task re-planning and skill transfer in Proactive HRC. Firstly, a DT-based HRC system can model, simulate, and predict each agent's attention, behaviours and workload in the near future, thus discovering human potential error operations or robot runaway motions in advance. Even with unexpected task proceeding situations, RL models can be utilised to find global optimal task re-planning for subsequent operations by integrating simulation processes in the DT environment. Lastly, a TL-based KG can be built to transfer HRC skills to general operations rules which are applicable to new but similar HRC tasks.

7.7. Configurable and cognitive ergonomics-based HRC cell design

Configurable and cognitive ergonomics-based HRC cell design is a prerequisite for a comfortable and user-friendly experience among hybrid human–robot teamwork. The past studies on the direction mainly focus on working cell design for human operators with fixed robot arms. This kind of HRC cell only considers basic ergonomic requirements and task goals to arrange robots, humans, and manipulated objects, far away from reaching self-configuration and cognitive ergonomics-based design. In this context, social and technical challenges remain untackled. For example, when resource overlapping and occupation problems exist in shared workspaces, the HRC cell design theory should consider usage precedence management while satisfying the personal esteem needs of different human operators in social aspects. From technical parts, task structure knowledge, dynamic environment changing, and each agent's qualified capabilities should be considered and learned for configurable HRC cell generation.

To achieve widespread applications of HRC cell design, two future directions are highlighted here. Firstly, cognitive ergonomics metrics should be developed to assess both human physical states (e.g., fatigue and overload) and human psychological experience (e.g., esteem and emotional satisfaction) based on one's role-playing behaviours in HRC tasks. Based on the ergonomics need, task resources, and operation roles between humans and robots, KG methods can be leveraged to configure HRC cells by mapping these considerations to graph nodes with various attributes and learning design requirements from these nodes. RL-based generative design approaches can be utilised to directly generate a layout of HRC cells by learning from huge historical design experiences with cognitive ergonomics constraints.

7.8. Plug-and-play network connection for extendable human and robotic agents

The involvement of additional human and robotic agents in HRC systems may improve overall productivity for complex tasks. The past works normally focus on computing consumption and latency issues caused by increased agents in HRC. Few studies are conscious of the development of a plug-and-play network connection for extendable human and robotic agents. Technical and practical issues need to be solved for the achievement of Proactive HRC with hybrid multi-agents. For instance, it is difficult to seamlessly add a new human–robot group and let them conduct tasks with existing members for maximum usage of their capabilities.

An efficient solution is to build extendable and multi-agent Proactive HRC from cellular human–robot groups, followed by the plug-and-play network connection in hardware, information and knowledge aspects. For the hardware connection, various cellular groups of human and robotic agents can join a uniform IIoT environment through a standard communication interface. For the information connection, the data flow transmission among the IIoT can use infrastructures such as 5G and Wi-Fi 6 to reduce communication latency. Then, different KGs are constructed for each human–robot group, which contain preferable capabilities and qualified operations of each agent in the cellular group. For the knowledge connection, federated learning can be utilised to aggregate, converge, and align knowledge across these distributed human–robot groups. Despite the additional connection of a new cellular group of human and robot agents, they can perform task operations qualified for their capabilities.

7.9. Evaluation index for proactive HRC performance

Despite the blossom of HRC applications in manufacturing, there is no generally accepted evaluation index for the system performance. It is unfair to directly introduce indicators from automatic systems, since HRC systems contain manual human work that may cost a lot of time. Thus, both quantitative evaluation and qualitative analysis need further development to assess HRC performance for flexible automation. Open discussions are given to construct widely acceptable standards based on our understanding of HRC studies.

For evaluating robot performance, previous quantitative experiments remain effective, such as robot execution time [257], trajectory length [258], and movement precision [259]. Nevertheless, for the human-centric needs and the whole HRC system evaluation, there are different considerations. Within a mutual-cognitive perspective in Proactive HRC, cognitive ergonomics metrics can be defined and leveraged to measure human physical load [260] and mental effort [261]. The entire system can be assessed by safety mechanisms (e.g., human–robot distance [257]) and task execution fluency [153] when facing dynamic scene changes and uncertain human motions. For the predictable capability in Proactive HRC, comparative experiments can be conducted to test the accuracy of human trajectory prediction [160] and how much time can be ahead in the human action prediction [162]. The performance of a predictable HRC process can be verified by task plan complexity [262] and waiting time [141]. For the self-organising intelligence in Proactive HRC, human subject ratings [146] for the teamwork with other human operators and robots from questionnaire scores can be used for quantitative assessment. Meanwhile, the successful task planning probability [115] and the knowledge transferability [15] for new co-work configurations can be introduced to analyse the self-organising system performance. Except for these metrics, we admit many other assessment approaches exist, such as robot end-effector position errors and orientation errors [132], which may be suitable to test HRC system performance and deserve exploration.

8. Conclusions

In the age towards human-centric smart manufacturing, both industry and academia are striving for an actual human–robot collaborative production, where the foreseeable Proactive HRC paradigm plays a vital role. This study elaborately extends our position paper [162] that HRC systems should and can embrace mutual-cognitive, predictable, and self-organising intelligence for flexible, natural, and efficient production. We systematically illustrated the rising evolution trend to Proactive HRC with increasing needs and motivations, then declared our findings on the concept, referenced architectures of this foreseeable manufacturing paradigm, and discussed its challenges and enabling technologies.

For the most irreplaceable contribution, we established the Proactive HRC architecture with a definition and elaborate depiction from four aspects, (1) mutual-cognition and empathy, (2) predictable spatio-temporal collaboration, (3) self-organising multi-agent teamwork, and (4) compliance robot control and proactive robot motion. The former three modules are ever-evolved intelligent capabilities in Proactive HRC, whereas the last one is the enabled control technologies for realistic implementation. Based on this theoretical foundation, participants are devoted to exploring theories and techniques for mutual-cognitive capabilities in Proactive HRC, such as visual reasoning [115] and KG [113] methods. Meanwhile, there are a few studies starting to show interest in the predictable intelligence in Proactive HRC, like works on motion trajectory prediction [160]. Then, it is foreseeable that more researchers will find and locate a new hotspot in the self-organising capabilities for multi-agent teamwork in Proactive HRC. Lastly, along with the appearance of more algorithms of compliance robot control and proactive path planning, the grand challenges in making Proactive HRC applications in modern factories deserve many years of effort.

There are also limitations in the paper when interpreting the thoughts represented. Most of our discussions of the research connotations of Proactive HRC come from literature analysis, research experience, and enterprise investigation. Despite the authors' great efforts which make our hypothesis with convincing materials and evidence results, it is inevitable some thoughts may be bold in future development. Therefore, we encourage readers to elicit meaningful content of our paper carefully and comprehend that with independent judgment.

However, we deeply believe that the rising Proactive HRC trend will be widely deployed in modern enterprises to achieve large-scale, flexible, and automatic production for personalised and ultra-complicated products. Especially with the explosive growth of technologies appearing in cognitive computing, knowledge learning, and automation theories, the transformation to the Proactive HRC paradigm is accelerating and changing production structure in industries. We hope our early thoughts on Proactive HRC could spark more insightful discussions, proofs, and rebuttals on this topic.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.rcim.2022.102510.

Data availability

No data was used for the research described in the article.

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