https://dx.doi.org/10.1016/j.jmsy.2021.07.017

Towards Proactive Human-Robot Collaboration: A Foreseeable Cognitive Manufacturing Paradigm

Shufei Li[a], Ruobing Wang[a], Pai Zheng[a,*] and Lihui Wang[b]

[a]Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong, China
[b]Department of Production Engineering, KTH Royal Institute of Technology, Sweden

ARTICLE INFO

Keywords:
Human-robot collaboration
Mass personalization
Cognitive manufacturing
Industrial Internet-of-Things
Smart manufacturing

ABSTRACT

Human-robot collaboration (HRC) has attracted strong interests from researchers and engineers for improved operational flexibility and efficiency towards mass personalization. Nevertheless, existing HRC development mainly undertakes either human-centred or robot-centred manner reactively, where operations are conducted by following the pre-defined instructions, thus far from an efficient integration of robotic automation and human cognitions. The prevailing research on human-level information processing of cognitive computing, the industrial IoT, and robot learning creates the possibility of bridging the gap of knowledge distilling and information sharing between onsite operators, robots and other manufacturing systems. Hence, a foreseeable informatics-based cognitive manufacturing paradigm, Proactive HRC, is introduced as an advanced form of Symbiotic HRC with high-level cognitive teamwork skills to be achieved stepwise, including: 1) *inter-collaboration cognition*, establishing bi-directional empathy in the execution loop based on a holistic understanding of humans and robots' situations; 2) *spatio-temporal cooperation prediction*, estimating human-robot-object interaction of hierarchical sub-tasks/activities over time for the proactive planning; and 3) *self-organizing teamwork*, converging knowledge of distributed HRC systems for self-organization learning and task allocation. Except for the description of their technical cores, the main challenges and potential opportunities are further discussed to enable the readiness towards Proactive HRC.

1. Introduction

With the prevailing implementation of advanced manufacturing technologies, artificial intelligence, industrial Internet-of-Things (IIoT) and big data analytics, towards new generation of intelligent manufacturing [1], industrial companies are striving to achieve: 1) the high efficiency and flexibility of on-demand manufacturing for mass personalization [2]; 2) the high accuracy and reliability for producing complex mechanical components [3]; and 3) the effective domain expertise support for onsite operations [4]. To tackle these challenges, human-robot collaboration (HRC) becomes a prevailing implementation strategy, which combines high accuracy, strength, and repeatability of industrial robots with high flexibility and adaptability of human operators to realize optimal overall productivity [5, 6].

The evolvement pathway of human-robot relationships is shown in Fig. 1 and further evaluated from two criteria, namely the role of human and robotic in the collaborative work (*horizontal axis*), and level of automation (*vertical axis*). In details, *horizontal axis* (i.e. the open/closed circle) depicts the role of the human's and robot's engagement in the dynamic HRC process, including inactive role, supportive role and active role. Hence, in an optimal HRC solution, human reaches an intuitive manner (mental stress-free), while the robot achieves an adaptive manner, by dynamically adjusting their respective roles. Moreover, *vertical axis* represents the automation (smartness) levels of various HRC paradigms, derived from the 5C architecture model of cyber-physical system [7, 8], namely 1) *coordination*, represents human and robot jointly working for a common goal (e.g. co-assembly of a gear); 2) *conception*, denotes the perceptual capabilities of robot (e.g. object detection by robot vision); 3) *cyber*, stands for the adaptive control of robot (e.g. collision avoidance); 4) *cognition*, represents the cognitive understanding of activities/tasks (e.g. human action recognition); and 5) *configuration*, stands for the full automation level, where human and robot co-work in a self-organized manner. Meanwhile, the shaded block in grey denotes the unreached degree of active role in each automation level. Following this manner, the key aspects of each paradigm are summarized in the box, together with its evaluation result highlighted in the three-dimensional coordinate accordingly.

Ever since 1980, early researchers have explored the co-existence of human and robots to increase welding versatility [9], where they can only perform separate tasks independently due to the lack of team consciousness, let alone active engagement for partner's execution (black dash line). Then, human-robot interaction (HRI) [10] emerged to connect human and robotic agents firstly on the basis of communication techniques, such as physical haptic [11], gestures [12] and brain-computer interface [13]. This stage is still stuck in the exploration of the supportive role of the human and robots for their coordination (green arrow). With research activities ongoing, human and robot parties can have their own autonomy (active role) at times in the execution loop. Those technologies accelerated the progress of human-robot cooperation [14] (pink arrow), of which the surge of research works are further extended to the manufacturing field from 2005 onwards [15].

From 2008 [16], HRC has been playing an ever-critical role to enable high-flexible manufacturing. In this context,

*Corresponding author:pai.zheng@polyu.edu.hk
ORCID(s): 0000-0002-2329-8634 (P. Zheng)

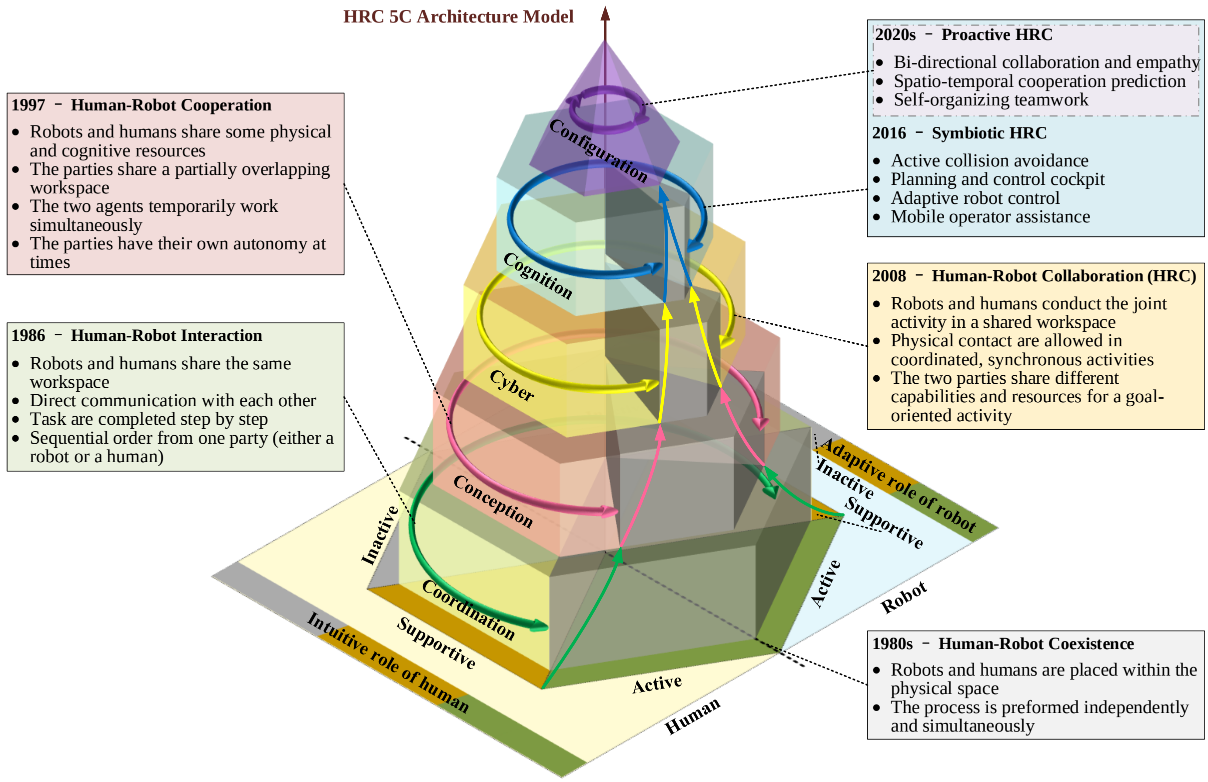

Fig. 1. An evolvement pathway towards Proactive HRC

several paradigms/concepts have been brought up to date. Reactive HRC, as the initial phase, mainly concerns two aspects: 1) safety issues [17] for human-robot coexistence without fences on the factory floor [18]; and 2) non-verbal commands for human-robot interaction [19] (yellow arrow). One typical example of reactive HRC in manufacturing is the scenario of human-centred assembly, where a robot follows the human co-worker's non-verbal instructions for performing an appointed task rather than pre-programming rigid codes. Then, Symbiotic HRC has emerged, aiming to combine the best skills of robots and humans, which "*possesses the skills and ability of perception, processing, reasoning, decision making, adaptive execution, mutual support and self-learning through real-time multimodal communication for context-aware human-robot collaboration* [20]". The prevailing development trend of Symbiotic HRC mainly addresses the following issues: 1) multimodal communication such as voice, gesture, haptic and brainwave [21], 2) context awareness of human's motion and performing tasks [22], and 3) adaptive control for robot programming without specialised expert knowledge [23] (blue arrow). Nevertheless, existing HRC development exposes two critical weaknesses, which impede efficient collaboration of robotic automation and human cognitions. The first one is that a robot in HRC normally needs to follow the human operator's commands, such as gestures or AR instructions, not attaining an optimized adaptive manner of robots or an intuitive role of the human. On the other hand, the collaboration between human and robot is unidirectional and stuck in slave/master mode, i.e., either human-centred or robot-centred manner, far from adaptability and flexibility.

To address those issues, with the prevailing research on human-level information processing of cognitive computing, the industrial IoT, and robot learning, a foreseeable cognitive manufacturing paradigm [24], Proactive HRC, is introduced and defined as "*a self-organizing, bi-directional collaboration between human operators and robots in manufacturing activities, where they can proactively work for a common goal in every execution loop over time*". Following this definition, it takes full advantage of each agent's capabilities and can be regarded as the final phase of Symbiotic HRC with high-level automation level (purple arrow), which allows a long-term bi-directional collaboration between human and robots in manufacturing activities. Despite hierarchical sub-activities along time, they can proactively work for a common goal in every progression. In this context, bi-direction cognition between humans and robots and self-organizing teamwork in manufacturing activities can be realized. Meanwhile, participants in the HRC system can understand each other's personal wellbeing or working conditions for empathy, to reach unattained collaborative efficiency and flexibility.

2. Proactive Human-Robot Collaboration

To achieve Proactive HRC, three high-level cognitive teamwork skills, including: 1) inter-collaboration cognition, 2) spatio-temporal cooperation prediction, and 3) self-organizing

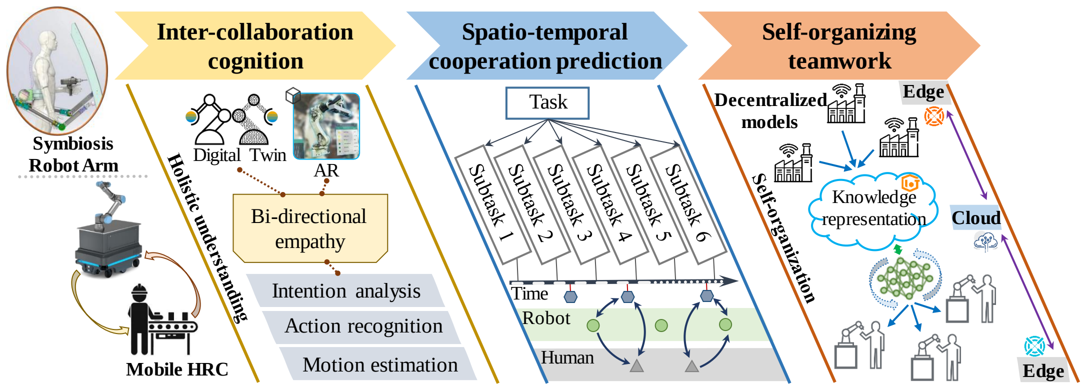

Fig. 2. Roadmap towards Proactive HRC

teamwork, as the stepwise goals are depicted in Fig. 2 and further explained below. The cognitive intelligence permeating through the total control execution loop enables proactive collaboration among robots and human operators, as shown in Fig. 3. From bottom to up, the middle cognition module achieves high-level knowledge learning from spatio-temporal human-robot relationships to semantic teamwork. While robots and human operators can collaboratively conduct exact execution of manufacturing tasks with more specific instructions from up to bottom. At the same time, various cognitive knowledge can be generated by different levels of the middle cognition module to feedback proactive cooperation between robots (left part) and human operators (right part).

2.1. Inter-collaboration cognition

Inter-collaboration cognition aims for *human-robot collaborative execution of manufacturing activities with bidirectional assistance derived from their cognitive empathy.* A holistic understanding among personal abilities of human beings and working conditions of robots is crucial to the accomplishment of the bi-directional empathy cognition, from concurrent information exchange to holistic context-awareness. For the former one, recent advances of Digital Twin [25] and AR techniques [21] can greatly upgrade concurrent information exchange in HRC, where monitoring, simulating, optimizing, and planning of the physical-digital counterparts continuously changes and updates in a virtual-real fused manner. Meanwhile, for the latter one, the holistic context awareness of the HRC scenario provides access to semantic knowledge understanding and reasoning for the bi-directional empathy. For example, from the human's motion [22], activity [26] to his intention [27], these semantic-enriched 'what-is-doing' information can be learned by the robot for knowledge reasoning of robotic execution. Instead of a traditional slave/master model in HRC, the inter-collaboration cognition encourages proactively bi-directional engagement, where the roles of human and robot are changed dynamically as required.

A holistic understanding of the HRC scenario, such as the real-time state of collaborative robots, human's current motion, and intention, can be learned by inter-collaboration cognition in an HRC system. These states and informatics are the feedback to the robot's motion controller and thus enable adaptive production execution for manufacturing tasks, as present in the bottom part of Fig. 3. Bi-directional empathy between a robot and human embeds in their co-work, from haptic interaction in close proximity to a higher degree of adaptive robot execution and intuitive human cooperation. Among the cooperation in close or even direct physical contact, physical parameters of haptic interaction and geometric interpretation of the working environment is monitored by resorting to sensor monitoring system. With robot controller sensing these force/moment signals, compliance control approaches such as impedance control [28] can be adopted for dynamically adjustment of the relating contact force and robot position. As an example, the force/moment that object being handled can be controlled to either avoid damaging the object or harming human in HRC scenarios of collision-free motion planning, safety-rated monitored stop, and power/force limiting control. As for long-range collaboration, operator assistant system and multimodal programming and control of robot can facilitate proactively bi-directional engagement among humans and robots. The operator assistant system tracks the robot's motion and planning in order to provide real-time information support for humans' intuitive task execution. Multimodal programming and control of robot [29] which combines human gestures, speeches, motion, intention, and other forms of information accessed from the sensor monitoring system, enables the robot to adapt its behaviors to make human operator work comfortably while trying to decrease the time for human and robot to finish all the tasks, increasing production efficiency.

Although the development of bi-directional HRC is still at an early stage, it presents huge potentials in manufacturing activities. The first one targets the next generation of workforce in manufacturing. With continuous information updates from AR-based digital worlds and proactive collaboration from its counterparts in the physical space, a human operator can solve problems in the manufacturing progress and conduct complex industrial tasks without specific training skills. People from various educational backgrounds, not limited to the domain of production, can ready to become the next set of manufacturing engineers with the support of inter-

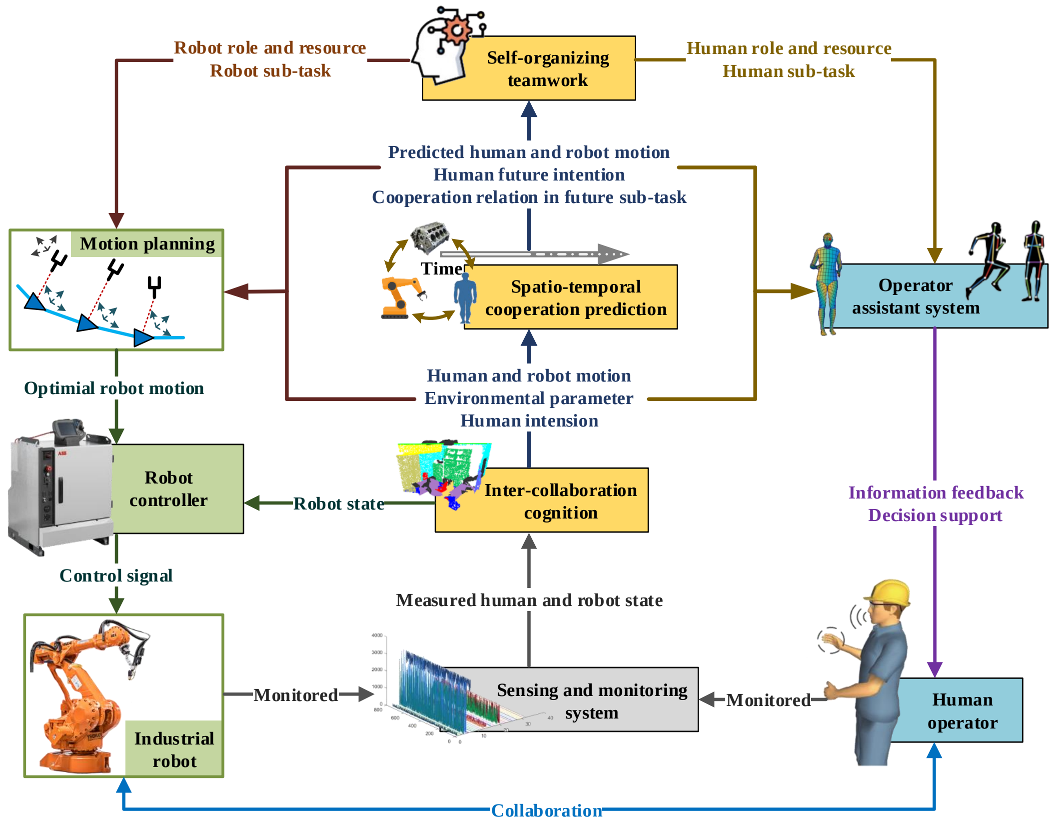

Fig. 3. Total control architecture of Proactive HRC

collaboration cognitive intelligence in HRC [30]. The second significance endows the entire HRC execution with high-level coordination and flexible allocation, both robot-to-human and human-to-robot. For example, the human may be conscious of adaptive execution updates for optimal productivity during the co-work, based on concurrent information of scheduling systems [31] and the measurement of the robot's capability [32]. In turn, the robot can present better compatibility with human in real-time operation, based on learnt knowledge of his/her intention.

2.2. Spatio-temporal cooperation prediction

In the execution loop, a manufacturing task/activity decomposes hierarchical and temporal sub-tasks/activities along the time. Spatio-temporal cooperation prediction focuses on *forecasting human-robot-object relationships in these sub-tasks/activities across time, providing foreseeable semantic knowledge for proactive planning and control in HRC.* In fact, HRC in manufacturing is a time-sensitive task, whose function modules consist of active collision avoidance [33], decision making and path planning [34], etc. Therefore, beyond existing adaptive control of robots, academia and industrial practitioners nowadays aim to forecast the human operator's future motion, trajectory and activity, eliminating the limitation of uncertainty associated with human workers [35] during the collaboration. The next level is 'how-to-cooperate' among the hierarchical sub-tasks/activities as the co-work progresses in time. Spatio-temporal cooperation of a human and a robot in HRC consists of their temporal interaction and the hierarchical relation in the progression of the sub-tasks/activities [36]. The discovery of not only current a human's intention but also future interaction events with the coexisting neighbours distils foreseeable semantic knowledge for efficient cooperation in HRC. In this context, the access of predictability of the future semantic knowledge between these entities can facilitate time-sensitive collaboration intelligence for decision-making and path planning, such as proactive assistance either from a human to a robot or from a robot to a human.

Spatio-temporal cooperation prediction consisting of human and robot's motion trajectory, human's next intention [37], and preliminary cooperation relation of the two roles in future sub-tasks, further guide robot motion planning and operator assistant system (see the middle part of Fig. 3), along with foreseeable and proactive robot control and information feedback. For motion planning, the robot controller adjusts its motion in advance for optimal performance, such as collision avoidance between human and robot and working efficiency improvement at the same time. Permeating with feedback information of human-robot interaction across spatio-temporal domains, the operator assistant system helps the human to better understand his sub-task in collaboration and prevent operating errors [38]. To some extend, spatio-temporal cooperation prediction also provides the proper cooperation relation in future sub-tasks, which can be used for further decision making and proper task allocation for each counterpart.

Spatio-temporal cooperation prediction plays an essential role in the realization of Proactive HRC, as decision-making and path planning in advance is the prerequisite for consistent teamwork in the complicated manufacturing scenario. Specifically, the current challenge is how to infer the human's next intention and predict human-robot-object interaction along the time via feeding fewer temporal data streams. Leveraging vision-text navigation [39], a human or a robot can percept what the counterpart in the collaboration really demands among the progression of sub-tasks/activities, moving towards long-range human-robot cooperation without misunderstanding. Besides, the hyperbolic embedding-based video representation learning methods [40] offer an attractive solution that learns a hierarchy of human-robot-object interaction of the future, to achieve Proactive HRC in every timespan.

2.3. Self-organizing teamwork

Self-organizing teamwork aims to *resolve divergences of leader/follower roles between a robot and a human by converging prior knowledge of co-works from decentralized HRC systems.* Robots and human participators can understand which manufacturing tasks/activities they are more qualified for in terms of their capabilities and change their roles on the fly. Similar to the manufacturing knowledge system [41], a wider applicable knowledge representation of HRC systems can be generated by bridging the information island [42] between different workshops and various factories. In case that enterprises normally struggle to share their acquisition data, federated learning trained via model aggregation rather than data aggregation can protect data privacy [43], while converging learned knowledge of different decentralized HRC systems. Especially, the 5G-based IIoT technique can greatly accelerate the knowledge convergence progression. The next stage focuses on distilling knowledge of self-organizing collaborative intelligence in HRC. The current development in industrial AI, such as knowledge graph [44], reinforce learning [45], and imitation learning [46], can offer an attractive solution for knowledge distilling, which enables the human and robot to know their preferable work during collaboration based on past experiences and learning capacities. In this context, the robot and human can make a long-range allocation of manufacturing tasks/activities and proactively vary their behaviours in response to different situations, achieving self-organization. Moreover, it may be also effective in some new situations unexpected before in a factory as convergent knowledge from other enterprises may provide a systemic guide.

The self-organizing network determines human and robot's roles in collaboration and allocates the corresponding resources and sub-tasks to each participant. Outputs of the self-organizing network are the most crucial inputs of robot motion planning and operator assistant systems, as shown in the upper part of Fig. 3. Thus self-organizing network can be considered as the central brain of Proactive HRC. Based on the measured and predicted human and robot states from inter-collaboration cognition and spatio-temporal cooperation prediction, the specific resources and sub-tasks are allocated to humans and robots by self-organizing teamwork according to certain criteria such as optimal task execution time or minimum energy consumption [47]. The robot's motion is optimized to perform the desired sub-task under required policies, such as human safety, availability of resources, and the required time of operation. The operator assistant system looks up from the database according to the allocated sub-task and provides useful supportive instructions for a human worker to carry out the assigned sub-task. Despite uncertainties arising from the presence of the human operator in the HRC loop, the self-organizing teamwork can dynamically adjust the resource and task allocation according to the human's behavior and ensures the fluent execution of the overall task.

To achieve the self-organizing teamwork for Proactive HRC, technical insights worthy of notice are given as following. The first one is the implementation of knowledge convergence via federated learning in distributed manufacturing tasks/activities. Data generated from HRC in different factories but in the same workshop, e.g., assembly workshop, share the same feature space, but differ in sample space [48], which is naturally fit for horizontal federated learning in practice. Meanwhile, data of HRC systems in different workshops but in the same factory, such as machining workshop and assembly station, coincide with vertical federated learning [49]. Secondly, the knowledge representation in this section is not used for real-time robotic decision-making and path planning, it focuses on the human-robot relationship management [50] for self-organization. In this context, the system circumvents the nature of time sensitivity of HRC execution, therefore, some knowledge modelling methods, e.g., knowledge graph, reinforce learning, and imitation learning are acceptable to optimize configuration and human-robot planning.

3. Challenges and Opportunities

As a foreseeable cognitive manufacturing paradigm, Proactive HRC stands for long-range bi-directional teamwork over the progression of manufacturing tasks/activities, based on bilateral empathy cognition and self-organization intelligence among humans and robots. Despite the three technical cores, there still lies some challenges, especially: 1) *Uncertainty of human in bi-directional collaboration cognition*. Although an AR-based Digital Twin model of the HRC system allows a human to upgrade his temporary operation planning for collaboration, some unexpected behaviours of the human worker [20] in a short timespan may lead to confusion for the bi-directional empathy development. 2) *Requirement of decision-making in advance for human-robot cooperation over time*. Existing HRC systems still lack the ability of spatio-temporal cooperation prediction [36], let alone decision-making ahead of the time, which is vital for the achievements from basic safety requirements to high-level proactive assistant planning. 3) *Information island and isolated knowledge of decentralized HRC systems*. As private data of HRC systems are normally isolated in local workshops and cannot be shared with other enterprises [46], it impedes a universal knowledge representation for self-organizing teamwork in HRC.

At the same time, empowered by cutting-edge technologies in computer vision, AR and IIoT, etc., multiple opportunities of the Proactive HRC emerge ahead, namely: 1) *Integration of holistic context-awareness of HRC execution loop and concurrent information of Digital Twin models for inter-collaboration cognition*. The continuous monitoring, perception, and cognition of an HRC scenario [51], especially the personalized behaviours, make contributions to a bi-directional empathy model for human-robot co-work, which even takes human's personal wellbeing into account during the collaboration. 2) *Time-sensitive decision-making and path planning among the spatio-temporal cooperation prediction*. Recent advances in self-driving technologies [52] offer a natural solution for decision-making and path planning over the progression of manufacturing sub-tasks/activities in time, which meets the timely requirement in the Proactive HRC execution loop. 3) *Convergence and distilling of knowledge representation of HRC systems for self-organizing teamwork*. Distributed, parallel, and cluster computing techniques, such as federated learning, show the potential to bridge the information island of various decentralized factories under data privacy protection. Based on knowledge embedding methods [53], the knowledge representation of past experience can be learnt for self-organizing teamwork between human and robots.

Except for those cutting-edge digital technologies, from the collaborative robotic design level, instead of fixed robot arms in existing HRC applications, two types of collaborative robots are emerging as a priority, capable of performing efficient and flexible collaboration in a global workspace. The first pillar lies in the prevailing implementation of mobile robots in industrial scenarios. The combination of a collaborative robot and a mobile base extends more potential applications of HRC, such as the assembly work in large-scale complex products. The other one focuses on a symbiosis wearable robotic arm. A human operator can proactively interact with the third assistant arm for collaborative conducting manufacturing activities in close proximity. This collaborative mechanism is attracting more and more attention from industry practitioners, owing to its applicability in either narrow workspace or complicated manufacturing scenarios.

4. Conclusions

With current advances in cognitive computing, IIoT, and robot learning, it is foreseeable that Proactive HRC will become dominant in the upcoming generation of cognitive manufacturing, which can largely facilitate industrial flexible production for mass personalization. Proactive Symbiotic HRC enables human operators and robots to work for a common goal in a long-term bi-directional manner, of which three unique cognitive teamwork skills should be achieved stepwise: 1) *Inter-collaboration cognition*. It enables real-time collaborative execution for shared manufacturing activities concerning bi-directional empathy among robot states and human decisions; 2) *Spatio-temporal cooperation prediction*. The prediction of human-robot-object interaction of sub-tasks/activities over time allows proactive robot motion planning and intuitive human operation, achieve ahead-of-time and foreseeable cooperation; and 3) *Self-organizing teamwork*. Various HRC models in decentralized factories, as the manufacturing "things" can be converged into a generic knowledge representation, which allocates optimal self-organizing task between humans and robots based on past experiences. Relevant technologies such as AR, IIoT, cognition computing as well as robotic mechanism design, as the key enablers towards Proactive HRC are also discussed. To this end, as a promising research topic, this comment paper welcomes more open discussions and future in-depth research on this forthcoming paradigm for ever smarter manufacturing.

5. Acknowledgments

This research is partially funded by the Laboratory for Artificial Intelligence in Design (Project Code: RP2-1), Hong Kong Special Administrative Region, and the Research Committee of the Hong Kong Polytechnic University (1-BE2X).

References

[1] Wang, L., 2019. From intelligence science to intelligent manufacturing. Engineering 5, 615–618.

[2] Zheng, P., Wang, Z., Chen, C.H., Khoo, L.P., 2019. A survey of smart product-service systems: Key aspects, challenges and future perspectives. Advanced engineering informatics 42, 100973.

[3] Li, S., Zheng, P., Zheng, L., 2020. An ar-assisted deep learning-based approach for automatic inspection of aviation connectors. IEEE Transactions on Industrial Informatics 17, 1721–1731.

[4] Liu, X., Zheng, L., Shuai, J., Zhang, R., Li, Y., 2020. Data-driven and ar assisted intelligent collaborative assembly system for large-scale complex products. Procedia CIRP 93, 1049–1054.

[5] Wang, L., Liu, S., Liu, H., Wang, X.V., 2020. Overview of human-robot collaboration in manufacturing, in: Proceedings of 5th International Conference on the Industry 4.0 Model for Advanced Manufacturing, Springer. pp. 15–58.

[6] Wang, X.V., Wang, L., 2021. A literature survey of the robotic technologies during the covid-19 pandemic. Journal of Manufacturing Systems .

[7] Lee, J., Bagheri, B., Kao, H.A., 2015. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manufacturing letters 3, 18–23.

[8] Yao, B., Zhou, Z., Wang, L., Xu, W., Yan, J., Liu, Q., 2018. A function block based cyber-physical production system for physical human–robot interaction. Journal of manufacturing systems 48, 12–23.

[9] HOLMES, J., JG, H., BJ, R., 1980. Human combines with robot to increase welding versatility .

[10] Ghosh, B.K., Helander, M.G., 1986. A systems approach to task allocation of human-robot interaction in manufacturing. Journal of Manufacturing Systems 5, 41–49.

[11] Abbink, D.A., Mulder, M., Boer, E.R., 2012. Haptic shared control: smoothly shifting control authority? Cognition, Technology & Work 14, 19–28.

[12] Nickel, K., Stiefelhagen, R., 2007. Visual recognition of pointing gestures for human–robot interaction. Image and vision computing 25, 1875–1884.

[13] Ferrez, P.W., Millán, J.d.R., 2008. Error-related eeg potentials generated during simulated brain–computer interaction. IEEE transactions on biomedical engineering 55, 923–929.

[14] Laengle, T., Hoeniger, T., Zhu, L., 1997. Cooperation in human-robot-teams, in: ISIE'97 Proceeding of the IEEE International Symposium on Industrial Electronics, IEEE. pp. 1297–1301.

[15] Stopp, A., Baldauf, T., Horstmann, S., Kristensen, S., 2005. Toward safe human-robot co-operation in manufacturing, in: Advances in Human-Robot Interaction. Springer, pp. 255–265.

[16] Bi, Z., Lang, S.Y., Wang, L., 2008. Improved control and simulation models of a tricycle collaborative robot. Journal of Intelligent Manufacturing 19, 715–722.

[17] Zanchettin, A.M., Ceriani, N.M., Rocco, P., Ding, H., Matthias, B., 2015. Safety in human-robot collaborative manufacturing environments: Metrics and control. IEEE Transactions on Automation Science and Engineering 13, 882–893.

[18] Bi, Z., Luo, M., Miao, Z., Zhang, B., Zhang, W., Wang, L., 2021. Safety assurance mechanisms of collaborative robotic systems in manufacturing. Robotics and Computer-Integrated Manufacturing 67, 102022.

[19] Cherubini, A., Passama, R., Crosnier, A., Lasnier, A., Fraisse, P., 2016. Collaborative manufacturing with physical human–robot interaction. Robotics and Computer-Integrated Manufacturing 40, 1–13.

[20] Wang, L., Gao, R., Váncza, J., Krüger, J., Wang, X.V., Makris, S., Chryssolouris, G., 2019. Symbiotic human-robot collaborative assembly. CIRP annals 68, 701–726.

[21] Wang, X.V., Wang, L., Lei, M., Zhao, Y., 2020. Closed-loop augmented reality towards accurate human-robot collaboration. CIRP Annals 69, 425–428.

[22] Liu, H., Wang, L., 2021. Collision-free human-robot collaboration based on context awareness. Robotics and Computer-Integrated Manufacturing 67, 101997.

[23] Liu, S., Wang, L., Wang, X.V., 2020. Symbiotic human-robot collaboration: multimodal control using function blocks. Procedia CIRP 93, 1188–1193.

[24] Iarovyi, S., Lastra, J.L.M., Haber, R., del Toro, R., 2015. From artificial cognitive systems and open architectures to cognitive manufacturing systems, in: 2015 IEEE 13th International Conference on Industrial Informatics (INDIN), IEEE. pp. 1225–1232.

[25] Lu, Y., Liu, C., Kevin, I., Wang, K., Huang, H., Xu, X., 2020. Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer-Integrated Manufacturing 61, 101837.

[26] Yan, S., Xiong, Y., Lin, D., 2018. Spatial temporal graph convolutional networks for skeleton-based action recognition, in: Proceedings of the AAAI conference on artificial intelligence.

[27] Liu, Z., Liu, Q., Xu, W., Liu, Z., Zhou, Z., Chen, J., 2019. Deep learning-based human motion prediction considering context awareness for human-robot collaboration in manufacturing. Procedia CIRP 83, 272–278.

[28] Yu, X., He, W., Li, Y., Xue, C., Li, J., Zou, J., Yang, C., 2019. Bayesian estimation of human impedance and motion intention for human-robot collaboration. IEEE transactions on cybernetics .

[29] Liu, S., Wang, L., Wang, X.V., 2021. Function block-based multimodal control for symbiotic human–robot collaborative assembly. Journal of Manufacturing Science and Engineering 143, 091001.

[30] Kovalenko, I., Balta, E.C., Qamsane, Y., Koman, P.D., Zhu, X., Lin, Y., Tilbury, D.M., Mao, Z.M., Barton, K., 2020. Developing the workforce for next-generation smart manufacturing systems: A multidisciplinary research team approach .

[31] Mourtzis, D., Zogopoulos, V., Xanthi, F., 2019. Augmented reality application to support the assembly of highly customized products and to adapt to production re-scheduling. The International Journal of Advanced Manufacturing Technology 105, 3899–3910.

[32] Wang, X.V., Kemény, Z., Váncza, J., Wang, L., 2017. Human–robot collaborative assembly in cyber-physical production: Classification framework and implementation. CIRP annals 66, 5–8.

[33] Realyvásquez-Vargas, A., Arredondo-Soto, K.C., García-Alcaraz, J.L., Márquez-Lobato, B.Y., Cruz-García, J., 2019. Introduction and configuration of a collaborative robot in an assembly task as a means to decrease occupational risks and increase efficiency in a manufacturing company. Robotics and Computer-Integrated Manufacturing 57, 315–328.

[34] Kanazawa, A., Kinugawa, J., Kosuge, K., 2019. Adaptive motion planning for a collaborative robot based on prediction uncertainty to enhance human safety and work efficiency. IEEE Transactions on Robotics 35, 817–832.

[35] Zhang, J., Liu, H., Chang, Q., Wang, L., Gao, R.X., 2020. Recurrent neural network for motion trajectory prediction in human-robot collaborative assembly. CIRP annals 69, 9–12.

[36] Morais, R., Le, V., Venkatesh, S., Tran, T., 2021. Learning asynchronous and sparse human-object interaction in videos. arXiv preprint arXiv:2103.02758 .

[37] Wang, P., Liu, H., Wang, L., Gao, R.X., 2018. Deep learning-based human motion recognition for predictive context-aware human-robot collaboration. CIRP annals 67, 17–20.

[38] De Pace, F., Manuri, F., Sanna, A., Fornaro, C., 2020. A systematic review of augmented reality interfaces for collaborative industrial robots. Computers & Industrial Engineering 149, 106806.

[39] Wang, H., Wang, W., Liang, W., Xiong, C., Shen, J., 2021. Structured scene memory for vision-language navigation. arXiv preprint arXiv:2103.03454 .

[40] Surís, D., Liu, R., Vondrick, C., 2021. Learning the predictability of the future. arXiv preprint arXiv:2101.01600 .

[41] Xu, X., 2012. From cloud computing to cloud manufacturing. Robotics and computer-integrated manufacturing 28, 75–86.

[42] Lou, S., Feng, Y., Li, Z., Zheng, H., Gao, Y., Tan, J., 2020. An edge-based distributed decision-making method for product design scheme evaluation. IEEE Transactions on Industrial Informatics 17, 1375–1385.

[43] Xu, Z., Yu, F., Xiong, J., Chen, X., 2019. Helios: Heterogeneity-aware federated learning with dynamically balanced collaboration. arXiv preprint arXiv:1912.01684 .

[44] Wang, Z., Chen, C.H., Zheng, P., Li, X., Khoo, L.P., 2019. A graph-based context-aware requirement elicitation approach in smart product-service systems. International Journal of Production Research , 1–17.

[45] Lathuilière, S., Mesejo, P., Alameda-Pineda, X., Horaud, R., 2019. A comprehensive analysis of deep regression. IEEE transactions on pattern analysis and machine intelligence 42, 2065–2081.

[46] Liu, B., Wang, L., Liu, M., Xu, C.Z., 2020. Federated imitation learning: A novel framework for cloud robotic systems with heterogeneous sensor data. IEEE Robotics and Automation Letters 5, 3509–3516.

[47] Mohammed, A., Schmidt, B., Wang, L., 2017. Energy-efficient robot configuration for assembly. Journal of manufacturing science and engineering 139.

[48] Liu, Y., Huang, A., Luo, Y., Huang, H., Liu, Y., Chen, Y., Feng, L., Chen, T., Yu, H., Yang, Q., 2020. Fedvision: An online visual object detection platform powered by federated learning, in: Proceedings of the AAAI Conference on Artificial Intelligence, pp. 13172–13179.

[49] Yang, Q., Liu, Y., Chen, T., Tong, Y., 2019. Federated machine learning: Concept and applications. ACM Transactions on Intelligent Systems and Technology (TIST) 10, 1–19.

[50] Du, H., Xu, W., Yao, B., Zhou, Z., Hu, Y., 2019. Collaborative optimization of service scheduling for industrial cloud robotics based on knowledge sharing. Procedia CIRP 83, 132–138.

[51] Liu, H., Wang, L., 2020. Remote human–robot collaboration: A cyber–physical system application for hazard manufacturing environment. Journal of manufacturing systems 54, 24–34.

[52] Kawasaki, A., Seki, A., 2021. Multimodal trajectory predictions for autonomous driving without a detailed prior map, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 3723–3732.

[53] Oliff, H., Liu, Y., Kumar, M., Williams, M., Ryan, M., 2020. Reinforcement learning for facilitating human-robot-interaction in manufacturing. Journal of Manufacturing Systems 56, 326–340.