A Comprehensive Review of Artificial Potential Field Techniques in Human–Robot Collaboration from 2019 to 2024

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ABSTRACT

With the increasing application of collaborative robots (cobots) in manufacturing and service sectors, ensuring smooth motion planning and collision-free interaction is a major concern in Human–Robot Collaboration (HRC). Among different local path planning schemes, the Artificial Potential Field (APF) approach has become one of the most popular strategies due to its simplicity and effective computation. However, traditional APF models still have some challenges, such as local minima, limited adaptability in dynamic environments, and no integration with human-aware perception. This study delivers a systematic review of the related developments of APF approaches in HRC for the period of 2019-2024. Totally, 169 papers were first collected from major scientific databases, and then 32 peer-reviewed articles with strict selection criteria were chosen for in-depth analysis. This work is divided into three broad research avenues: (i) algorithmic improvement of APF towards better stability and adaptability, (ii) integration of sensors and Machine Learning (ML) to provide smart perception, and (iii) HRC for improvement of interaction quality and security. The results of the review suggest an intense trend towards hybrid structures integrating APF with Reinforcement Learning (RL), biosensing, and Digital Twin (DT) technologies. These integrations significantly enhance real-time responsiveness, safety, and robustness in dynamic conditions. Finally, this review highlights several limitations and outlines further research directions for improving APF-based methods for more perceptive and human-centered robot systems.

Keywords-APF; cobot; obstacle avoidance; motion planning; reinforcement learning; human-robot interaction

I. INTRODUCTION

With the development of intelligent manufacturing, it is popular for robots to be integrated into cooperative working areas with humans. Unlike traditional robot systems, which have to be supported by safety cages in order to ensure operational security, cobots are designed to be utilized in working environments involving direct human contact. This has established the HRC strategy, which demands higher degrees of safety [1], flexibility [2], and efficiency [3]. State-of-the-art HRC solutions in [4] often deploy ML in behavior modules of the robot to enhance performance and safety, particularly in flexible and changing production environments.

One of the most significant technical challenges of HRC is motion planning and collision avoidance in shared workspaces. The robots must be able to travel smoothly and securely and also adapt to human routines and respond in real-time to physical and environmental surroundings changes. The APF algorithm is a popular and well-accepted technique in industrial robotics applications (i.e., factory automation, autonomous ground vehicles, multi-robot task allocation) due to its superior performance and various advantages: simple and intuitive architecture, ease of implementation, fast computation, and robust real-time capability. These properties enable robots to move autonomously in complex and dynamic environments while still performing tasks and maintaining safety in public environments. Furthermore, APF can be easily integrated with sensory systems to enhance the navigation of mobile robots in unknown or dynamic environments [5, 6] or with ML approaches, namely Deep Reinforcement Learning (DRL) for enhancing autonomous navigation and decision-making in complex environments [7].

Among different local trajectory planning techniques, APF is one of the most intuitive and widely applied, modeling the motion of the robot as a reaction to virtual attractive and repulsive forces within the robotic workspace. The APF technique, first introduced in [8] and later extended to related studies, estimates the robotic motion as a challenge of minimizing an artificial potential energy function:

$$U(q) = U_{att}(q) + U_{rep}(q) \quad (1)$$

where U_{att} is the attractive potential that pulls the robot toward the target, and U_{rep} is the repulsive potential that pushes the robot away from humans and obstacles. The control law is correspondingly derived from the negative gradient of the total potential, described as:

$$F(q) = -\nabla U(q) \quad (2)$$

This mechanism allows a robot with a continuous, real-time, and reactive controller that guarantees collision-free motion for both industrial manipulators and grounded robots operating in complicated environments. Although it is simple and effective, the classical APF model still suffers from typical challenges such as being trapped in local minima and fluctuations in narrow passages. These disadvantages have motivated the further development of different hybrid, adaptive, or ML-based variants aimed at enhancing the capability of global planning schemes and safety performance in collaborative robotic systems [9].

In modern HRC systems, the APF algorithm is not only used for geometric collision avoidance but also as an active motion generation model for physical Human–Robot Interaction (pHRI). Authors in [10] combined an admittance controller and APF-based trajectory planner with a robot so that it can take the lead in moving a shared object during cooperative interaction and human-instructed guidance when conflict was predicted by a random-forest classifier trained using haptic feedback. This hybrid approach reduced human force and effort by up to 42.7% without sacrificing smooth coordination, and thereby demonstrated the potential of APF as an intention recognition and conflict resolution mechanism for co-manipulation tasks.

However, traditional APF approaches still entail a series of drawbacks, such as local minima traps, oscillation in narrow regions, unsuitability for real-time dynamic environments, and lack of effectiveness in optimizing path efficiency for dense collaborative environments with mobile obstacles [8-9, 11]. To counter these drawbacks, some studies have proposed combining APF with other technologies, and others have proposed enhancing the traditional APF algorithm:

- DRL has been used to solve the safe control problems in HRC systems to reduce human intervention in deployment and enhance the autonomy of robots [12]. This enhances both the safety and intelligence of cobots to aid in decreasing the risks of robot behaviors [13].
- DT, a smart virtual replica of physical systems supported by virtualization, sensing, and computing developments, enables individuals to simulate and assess risks within real production conditions, thus minimizing economic loss and potential human injury [14]. According to [15], DT, combined with deep learning, can detect and classify human and robot motion, thus enhancing safety in collaborative systems.
- Augmented Reality (AR) that imposes computer-generated information on the actual world, increases user awareness and context perception in HRC conditions, and improves safety and interaction performance [16].

Moreover, some advanced and adaptive APF models have been developed, e.g., Modified APF, Adaptive APF, Dynamic APF (D-APF), and Hybrid APF, which improve the real-time performance of the algorithm and enable robots to perform even with isolated configurations. These developments also overcome local minima and oscillation issues by incorporating virtual obstacles, so that robots can free themselves from local traps without additional input [17]. Robots can, therefore, navigate effectively across a vast array of obstacles in crowded and dynamic environments. A key variant is D-APF, which is used for UAVs [18] and facilitates online 3D path planning, effective obstacle avoidance, and mobile target tracking within dynamic environments.

Despite various individual studies on these techniques, there is a lack of systematic review of the application of APF variants specifically in today's human–robot collaborative spaces. Particularly, no systematic investigation has yet been conducted on: the versions of the APF algorithm used in HRC; the level of incorporation with ML; the robots, collaboration environments, and performance metrics employed; and current gaps in research and directions for future research. Addressing this need, the present work conducts a systematic review of 169 articles published during 2019-2024, noting the application of APF algorithms in motion planning and collision avoidance for robots in HRC settings. The present work aims to:

- Classify main APF-based methods
- Assess the integration of APF and emerging technologies.

- Synthesize evaluation metrics, fields of application, and academic trends.
- Outline potential research avenues towards the development of intelligent, safe, and context-aware collaborative robot systems.

Authors in [9] conducted an overview categorizing various APF variants, such as modified, adaptive, and dynamic, as well as their primary applications in the robotic field, including mobile robots, UAVs, autonomous vehicles, and Human–Robot Interaction (HRI). However, they failed to present a systematic analysis of how precisely APF algorithms are employed in HRC environments, notably lacking a synthesis of behavioral models, robot perception, integration of ML, and sensor systems in the context of state-of-the-art HRC.

The current study extends and strengthens earlier works by providing a systematic review dedicated to the application of APF in HRC systems. Aside from algorithmic variant analysis and classification, the study delves further into behavior-oriented perception, sensing, ML integration, and evaluation metrics, and offers a clearer understanding of how APF ensures safety and efficiency in HRC.

II. RESEARCH METHODOLOGY

This study was conducted in March 2025 to construct a systematic review of prominent scientific documents using the APF method for motion planning and collision evasion in cobots under the HRC. Information was taken from trusted scientific databases, including: ISI Web of Knowledge, IEEE Xplore, Scopus, Springer, Elsevier (ScienceDirect), and JMLR.org.

An extensive set of search queries was constructed, with full coverage of relevant subjects, i.e.: ("artificial potential field" OR "APF" OR "modified potential field") AND ("human–robot collaboration" OR "collaborative robot" OR "cobot" OR "HRC" OR "shared workspace" OR "interaction" OR "collision avoidance" OR "motion planning"). These keywords were applied to the title, abstract, and keyword fields of English-language scientific documents from 2019 to 2024. The number of articles found at each source was:

- ISI Web of Knowledge: 61 articles
- IEEE Xplore: 19 articles
- Scopus: 65 articles
- Springer: 6 articles
- Elsevier (ScienceDirect): 16 articles
- JMLR.org: 2 articles

After removing duplicates and merging the datasets, the initial list of 169 articles was reduced to 72.

A. *First Screening Round*

The first screening (Identification) was done by scanning the presence of motion planning and collision avoidance with the use of APF in HRC environments, such as in the title or abstract. Articles that mentioned the topic but had no practical or experimental studies were also excluded. This narrowed down the dataset to 62 articles.

B. *Second Screening Round*

The second screening (Screening) applied a stricter set of inclusion criteria to ensure that the studies included effectively dealt with APF applications in HRC settings. The criteria were:

- Use of APF or its variants in the robot's navigation or collision avoidance module.
- Presence of humans and robots in the same working space during experiments.
- Presence of actual HRI, either physical (e.g., haptic contact with objects) or cognitive (e.g., common goals, action coordination).
- Clearly defined common goal to be achieved jointly by the human and the robot.
- Implication of adaptive or reactive behavior in the robot based on environmental or human feedback.

Regarding criterion 3, joint assembly or shared-space coordination experiments were included, although physical interaction was quite minimal. This is because the majority of such studies examine cognitive interaction or action coordination through indirect means such as object transfer or shared knowledge. Hence, if the other criteria were met, these experiments were included in the final analysis set.

C. *Final Dataset*

Following the application of all screening criteria, the final dataset included 32 eligible studies, grouped according to year: 5 studies in 2019, 5 in 2020, 15 in 2021, 2 in 2022, 2 in 2023, and 3 in 2024.

Following this rigorous selection process, articles fulfilled all the criteria and underwent in-depth qualitative and thematic analysis. The inclusion and exclusion were noted on a three-step flowchart, as shown in Figure 1, which provides a concise visual overview of the filtering process. Despite the fact that the excluded studies are not listed separately, this quantitative value highlights the magnitude, representativeness, and methodological rigor of the review process so that the final dataset can actually truly reflect contemporary trends of research and scientific progress in APF-based HRC. Those representative examples of the selected studies are summarized in Table I, which stresses their main characteristics such as task type, robot platform, interaction mode, and APF variant. To enhance clarity and readability, Table II summarizes the reviewed studies categorized under the three main themes of this review: (i) algorithmic enhancements, (ii) sensor and ML integration, and (iii) levels of HRC. Each article is reported with publication year, key method or concept tags, the type of HRC tasks covered, and concise notes describing the core contribution trends.

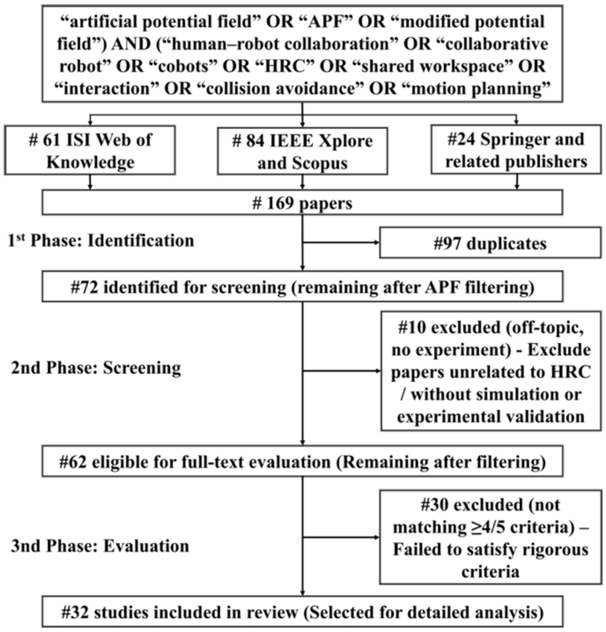

Fig. 1. Three-stage screening flowchart for the systematic review of APF applications in motion planning and collision avoidance for cobots in HRC.

III. ANALYSIS OF APF APPLICATION TASKS AND EVALUATION METRICS IN HRC

The objective of this analysis is to provide in-depth insights into how the APF algorithm is applied in HRC research. Specifically, the types of interaction tasks explored in the selected studies, along with the primary evaluation methods used in each study, were synthesized and analyzed. Most studies employ manipulator-type robots as cobots and generally assume only one human participant during the trials.

In cases involving more complex robot architectures, only the arm control functions are utilized for HRC tasks. Based on common characteristics of interaction functionality and the degree of cognitive versus physical engagement, as shown in Figure 2, the studies are grouped into different categories of collaborative tasks. Figure 3 shows the directory-based tree diagram, which explains how the content is divided into two branches: (i) types of collaborative tasks with the APF algorithm and (ii) types of performance evaluation measures in HRC. This diagram helps generalize the organization of the content and visually track the subsequent system of analyses.

A. Types of APF Applications in HRC

The classification of the HRI types based on task-sharing levels and shared workspace engagement has been clarified in various studies. According to [19], HRC can be categorized into four levels: coexistence, synchronization, cooperation, and collaboration. Among these, true collaboration is the highest form, requiring simultaneous interaction in a shared task, where the actions of humans and robots directly influence each other through force feedback, computer vision, or strategic coordination.

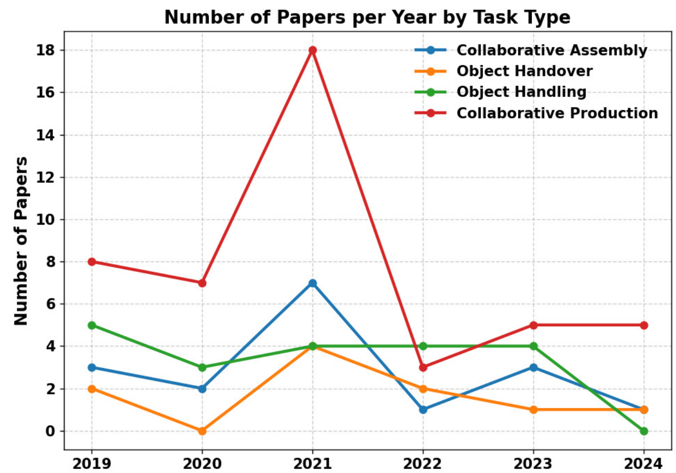

Fig. 2. Temporal distribution trends of collaborative tasks in HRC research using the APF algorithm.

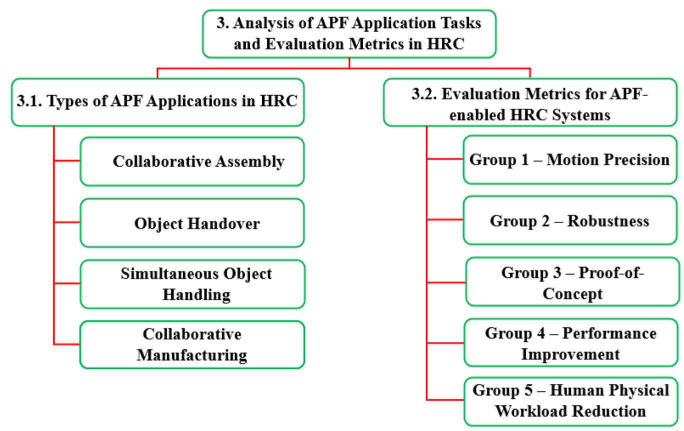

Fig. 3. Diagram of the structural classification of group work task types and measurement metric groups in HRC using the APF algorithm.

Beyond functional classification, authors in [27] also emphasized that successful HRC task execution relies on satisfying physical safety modes, such as Power and Force Limiting (PFL) and Speed and Speed and Separation Monitoring (SSM), as defined by ISO/TS 15066. These safety modes significantly influence how planning algorithms such as APF must be tuned for safe operation in shared human environments.

In the field of HRC, studies using the APF algorithm mainly focus on four characteristic collaborative task types: collaborative assembly, object handover, simultaneous object handling, and collaborative manufacturing. This classification is based on two key criteria: the level of cognitive and physical interaction between human and robot, and the specific functional role of the robot in each task.

TABLE I. SUMMARY OF STATE-OF-THE-ART RESEARCH IN SELECTED FIELDS ON THE APPLICATIONS OF APF IN HRC

Study	Robot type	Interaction type	Integrated technologies	General objective	Adaptive behavior	Setup (simulation / experiment)	Evaluation metrics	Note(s)
[70]	UR10e	Perception (behavior monitoring, collision prediction)	YOLOv8 Tiny, Convolutional Neural Network (CNN), NMS, K-means, SORT	Collision detection to ensure HRC safety	Human behavior analysis to predict risks	Experiment	90% recognition accuracy, 96.4% collision prediction	Multilayer deep learning system for HRC behavior recognition and prediction
[15]	UR10	Perception (behavior classification, decision making)	DT, Faster R-CNN, ROS, Unreal Engine	Detect and classify behaviors to support safe HRC	Decision-making based on human behavior	Simulation + experiment	Accuracy comparison between supervised and semi-supervised models	Enhanced DT with deep learning, labeling tools, and real UR10 test
[19]	UR5, LBR iiwa	Physical (industry-based interaction analysis)	Not focused on specific tech – standards and applications	Analyze HRC trends and applications in the industry	No detailed adaptive behavior analysis	Literature review (35 case studies)	No quantitative metrics – focused on classification	Classified 4 HRC types, presented ISO/TS 15066, reviewed 41 studies
[2]	Industrial and social robots	Perception (communication, behavior prediction, adaptive learning)	ML, simulation learning, computer vision	Review ML in industrial HRC	Focused on adaptive capability via data learning	Literature review (no experiments)	No quantitative evaluation – focused on safety and performance criteria	Proposed new HRC interaction level classification, cross-disciplinary ML strategies
[71]	Industrial cobot (battery disassembly)	Physical + perception (collaborative assembly, human behavior prediction)	Dual APF, DLS comparison, real-time trajectory planning	Collision and singularity avoidance during collaborative assembly	Real-time trajectory adjustment based on human state and robot configuration	Experiment (real industry case)	Compared with APF + DLS in terms of time and performance	N/A
[72]	Fixed manipulators, collaborative robots, mobile robots, mobile manipulators	Human perception, collision avoidance, proactive collaboration	RGB-D camera, LIDAR, Human-Robot Perception (HRP), Cyber-Physical Human Systems (CPHS), multimodal sensor integration	Enhances HRP, ensures safety and performance in HRC	Yes – adaptation based on human and environment recognition, CPHS-oriented design	Comprehensive analysis + two experimental prototypes	Perception capability, safety level, and robot collaboration potential	A comprehensive survey on HRP in industry emphasizes the role of sensors and unified data in HRC; introduces 2 CPHS prototypes
[45]	Collaborative robot in packaging tasks	Behavioral collaboration, human action prediction	Deep RL, Graph Convolutional Network (GCN), Recurrent Q-learning, Behavior Trees	DRL, GCN, Recurrent Q-learning, Behavior trees	Optimizes human–robot coordination, balances timely actions and risk of errors	Yes – actively learns from raw sensor data without manual labeling	Simulation (using motion capture suit data)	Improved coordination timing and eliminated unnecessary delays, unsupervised end-to-end learning, timely collaboration, uncertainty handling, and no need for manual labeling
[46]	Mobile Robot	Physical interaction (continuous dual-arm collaboration)	Motion capture data, anthropometric modeling, and a graph search algorithm	Optimizes posture and reduces musculoskeletal risks for human operators	Customizes plans based on individual anthropometry and specific tasks	Simulation + Experiment (small-scale user study)	REBA scores significantly reduced	Proposes a human posture model + collaborative planning optimized according to anthropometrics; evaluated with a dual-arm robot and real users
[14]	Cobots	Perception + real-time space–time sharing	DT, virtual modeling, design–operation simulation	Design, validation, and control of HRC systems throughout the entire lifecycle	Does not address real-time behavioral adaptation	Simulation (demonstration model and industrial case)	Not specified	Applies DT as a 'forerunner' to design and optimize HRC systems, especially in highly collaborative assembly tasks

[16]	Not specified	Perception (adaptive human–machine interaction)	AR, wrist motion tracking, haptic module, image detection module, adaptive interface	Maintenance support through adaptive feedback	Content adaptation based on user behavior	Experiment (case study)	Preliminary usability evaluation – positive	The ARMS framework includes 3 modules; it supports maintenance with context- and behavior-adaptive content, improving the effectiveness of receiving instructional information compared to traditional systems

TABLE II. SUMMARY OF REVIEWED STUDIES CATEGORIZED UNDER THE THREE MAIN THEMES IN APF-BASED HRC

Theme	Reference no.	Method / concept tags	HRC level / task type	Main
Improvements to the APF algorithm	[3], [5], [6], [8], [11], [18], [19], [23], [24], [25], [26], [33], [34], [36], [37], [38], [39], [42], [43]; [45], [58], [68], [69], [71]	Improved/Hybrid APF, Local-minima avoidance, dynamic/real-time planning	Path planning and collision avoidance, manipulators/mobile robots (HRC, USV, UAV)	Improved Artificial Potential Field (IAPF), avoids minima, and safe dynamic navigation
Sensor and ML integration	[2], [7], [2], [12], [13], [14], [21], [22], [31], [41], [44], [51], [53], [54], [55], [56], [57], [61], [62], [64], [65], [66], [67], [70], [72]	Sensor fusion and perception, learning-based policy such as DRL/ Inverse Reinforcement Learning (IRL) /IL), Safety/impedance/CBF	Industrial HRC (manipulators), mobile robots, autonomous driving, co-manipulation, action prediction, collision avoidance	Fuse sensors with ML to learn safe policies
HRC levels	[1], [4], [9], [15], [16], [17], [20], [28], [29], [30], [32], [35], [40], [50],[52], [59], [60], [63].	Taxonomy and safety standards, DT/AR and HMI, reactive/context-aware HRC	Industrial HRC with manipulators/cobots and mobile manipulators, co-assembly, handover, human-following, safety monitoring/UI	Defines HRC levels, standards, DT/AR, reactive, context-aware collaboration

1) *Collaborative Assembly*

Collaborative assembly is one of the most prevalent and ubiquitous activities in HRC, especially in high-level manufacturing and smart factory scenarios. Collaborative assembly involves coordination between humans and cobots in the same space and time to conduct assembly tasks with each side leveraging the other's strengths. Humans focus on work that requires dexterity, flexibility, and complex decision-making (e.g., alignment, screwing, or problem-solving), while robots supply components, carry parts, or execute repetitive, high-precision tasks.

Here, the APF algorithm plays a key role in ensuring safe motion and collision avoidance, particularly in thin, unstructured, or dynamic environments. The most common APF-based methods are:

- Creating repulsive forces from the operator's movement to push the robot away from danger zones.
- Interleaving APF with data from 3D cameras, proprioceptors, or vision sensors to determine real-time safe operating areas.
- APF interfacing with DT models of task sequencing and human-robot workload allocation.

The application of APF from 2019 to 2024 has been expanded through the integration of APF with modern techniques such as ML, DL, and Perception-Based Control. For example, DL models based on RGB image data have been utilized to recognize human behavior and infer human intent to support improved motion planning. Authors in [20] proposed a Symbiotic Graph Neural Network (Sym-GNN) that is designed to co-determine human actions and guess future human motion from 3D skeletal information. Although the network structure is not of interest here, the relevance of this work to APF-based HRC consists of its capacity for making precise, short-term motion predictions. These predicted motion trajectories could be utilized to adaptively redefine the repulsive and attractive potential fields in real time so that robots can anticipate human motion and pre-emptively alter their trajectories in shared workspaces. By integrating Sym-GNN output with APF-based control, the potential field around a human operator can be dynamically updated according to the predicted positions and task scenario, leading to smoother and safer collaborative motion. This merger dataset demonstrates how data-driven human motion insight can be used as the dynamic input layer of an adaptive APF algorithm to enhance the responsiveness of the robot and reduce the likelihood of collisions in cooperative assembly environments.

The general architecture of the model is presented in Figure 4, consisting of three components:

- Backbone Network: A multi-branch and multi-scale feature learning network for skeleton sequence input data processing.
- Recognition Head: Human action classification at the current observation time.
- Prediction Head: Predicts future joint states in the future time sequence.

To attain the capability of accurate and responsive prediction of human behavior in collaborative assembly settings, the fundamental framework of Sym-GNN is designed as a multi-branch, multi-scale deep GCN, as displayed in Figure 5. This integration process allows the network to effectively mimic both micro-movements (e.g., wrist or finger joints) and macro-behaviors (e.g., arm waves or torso bends), both of which are crucial in assembly situations wherein people make precise movements within a confined space, but convey their meaning through larger body actions.

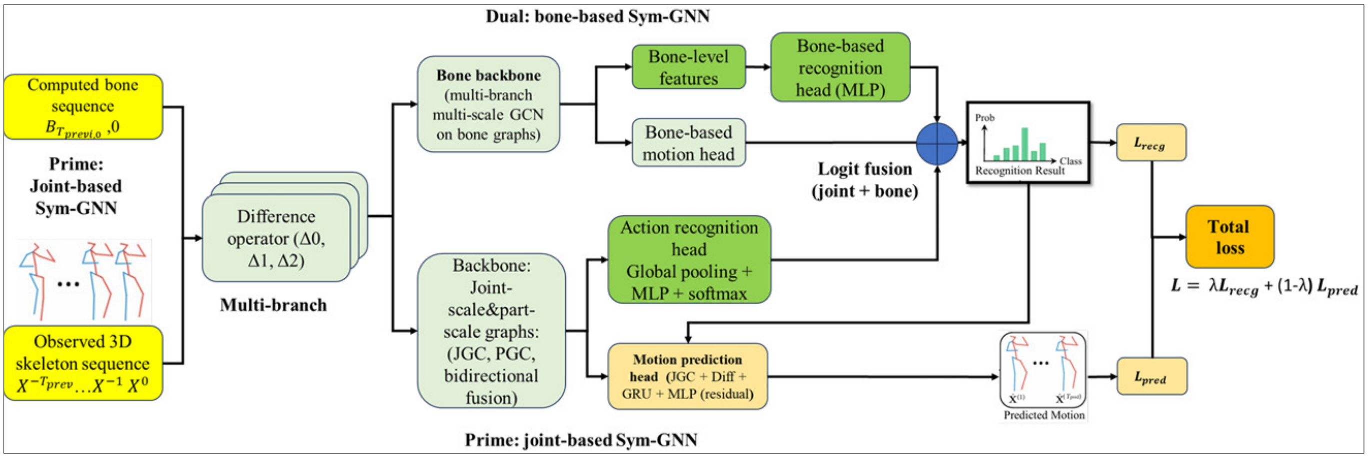

Fig. 4. Overall architecture of the Sym-GNN, consisting of a feature learning backbone, a behavior recognition head, and a motion prediction head.

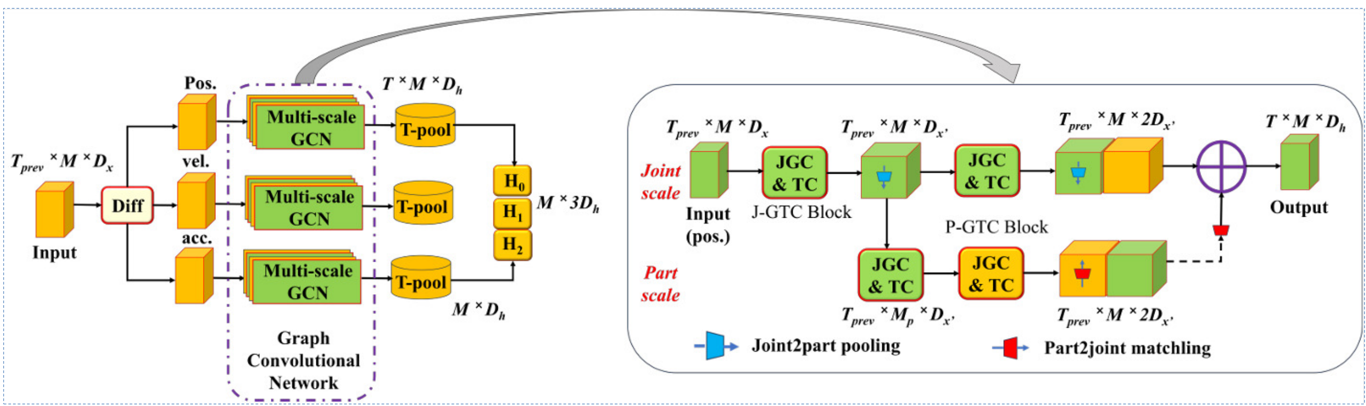

Fig. 5. The backbone structure of Sym-GNN consists of three GCN branches that process three types of data (position, velocity, acceleration), learning features at both the joint and body part levels, incorporating a bidirectional fusion mechanism to enhance the understanding of human behavior in collaborative assembly environments.

Following individual processing in each branch, the outputs are merged to form a feature-rich space, utilized by both output heads: action recognition and motion prediction. In cooperative robotic environments, this output may be integrated with motion planning modules such as the APF algorithm, where the robot can respond dynamically to human gestures by scaling repulsive and attractive force areas proportionally to offer protection and support.

Other advances involve placing force vector fields into constraint-based control systems to enhance the safety and responsiveness of robot arms [21]. Integration of APF with geometric processing of sensor data within constraint control systems also enhances real-time collision avoidance in human-sharing workspaces [22]. One of the interesting approaches is to optimize APF algorithms through motion prediction and local minima evading methods [23].

Another approach combines APF with meta-heuristic optimization algorithms to improve motion planning in cluttered spaces. In [24], APF-IMOSO, integrates APF with multi-objective snake optimization to optimize path length, safety, energy, and travel time concurrently. In collaborative assembly, APF-IMOSO enables the robot to calculate energy-efficient and safe paths in proximity to human workers.

Multimodal transfer learning for human action prediction is another promising direction. The system uses image and skeleton data to predict short-term action and transfers knowledge between daily activities and factory settings. This enables robots to support operators more proactively, especially in complicated tasks such as bolt tightening or component mounting.

Another promising hybrid approach combines ACO and APF. Authors in [25] applied this optimized ACO-APF to Unmanned Surface Vehicles (USVs), with the goal of reducing path length and iteration count in dynamic environments. In an interesting approach, authors in [72] designed a double-APF model with distinct repulsive forces to avoid both collisions and singularities. Applied to the Fanuc CRX-20iA robot, it reduced pick-and-place execution time by 43% in high-obstacle scenarios.

Overall, APF-based methods have shown tremendous potential in improving performance and flexibility and minimizing the utilization of physical barriers with safe HRC. Nevertheless, some of the significant challenges remain, including high sensor accuracy demands, real-time response and perception capabilities, and algorithm robustness to cope with constantly changing collaborative environments.

2) Object Handover

Object handover is a core function in HRC, where robots and humans collaborate to transfer objects securely, efficiently, and naturally. The operation generally occurs in sectors such as retail, industrial production, healthcare, and creative work. The primary aim is for the robot to aid human action by handing over or grasping objects [26].

In such operations, the APF algorithm is typically utilized to maneuver the robot's motion. APF simulates attractive forces towards the target point (e.g., position of human hand or object) and repulsive forces to avoid the human body or obstacles. This enables the robot to move smoothly and safely without sudden or uncomfortable motion.

APF-based handover systems generally use computer vision in order to locate the object position and orientation within the hand of the user. APF is then merged with haptic feedback and admittance control to provide flexibility and naturalness. Studies show that the use of force and tactile feedback allows the robot to adjust its grasp force in real time so that it can conduct a safe and stable handover even amidst sudden movement of the user [27]. Advantages of APF application in object handover are:

- Enhanced safety from collision avoidance with humans and the environment.
- Enhanced naturalness and intuitiveness by using optimized robot paths.

Real-time responsiveness to dynamically reconfigure paths whenever the human position or movement changes.

Apart from APF, studies in this direction emphasize that more than one sensor modality, such as vision, force, or tactile sensing, is required to sense human states and intentions. Model-based, event-triggered, and ML control techniques are also employed to enhance coordination between the human and robot during handover.

This approach is basically analogous to the ML approach APF model, where the feedback force has been utilized as a form of attractive or repulsive force in motion control. But in contrast to the utilization of virtual forces from the machine models in APF, this system responds according to physically sensed forces. This is an experimental demonstration of the requirement of real-time adaptive control and multi-modal sensing for object handover tasks.

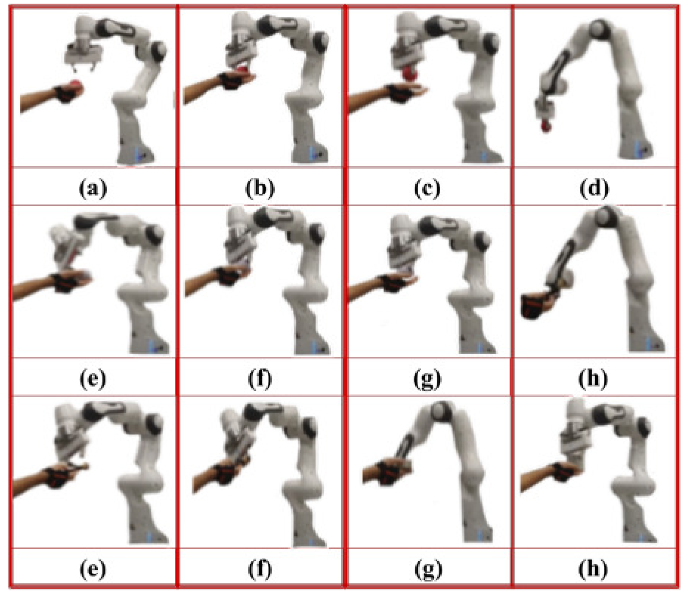

Fig. 6. Sequential illustration of object handover between human and robot (H2R and R2H), demonstrating real-time responsiveness and safe, smooth tactile control.

3) Simultaneous Object Handling

This type of task exhibits the most apparent physical interaction in HRC, where the human and robot both grip and move an object together to a destination shared in assembly, mold fitting, or balance assistance during transport. In [28], a human partner was combined with a mobile manipulator to push a soft object by fusing wrench sensor feedback and skeleton tracking. A reactive control system allowed the robot to respond to humans in a flexible manner without path planning, without sacrificing stability and safety in the process. In [29], a predictive motion planning system was proposed, where the robot is used to anticipate human action with a view to offering components or tools at optimum positions during assembly. By using proper distances and real-time path adjustments, coordination is improved.

In [30], it was highlighted that physical interaction is not just a mechanical response but a way of deliberate communication. In this study, the physical interactions are used as learning signals for behavioral adaptation and acceptance in collaboration with the robot. Among the significant contributions is the mathematical formalization of pHRI as implicit communication, where the human not only exerts force but also conveys underlying goals via the force. By presenting the problem as a Partially Observable Markov Decision Process (POMDP), physical interactions are being treated as observations, helping the robot to estimate the user's intended objective function θ for optimization.

Figure 7 illustrates the contrast between two designs: (a) the robot perceives interaction as noise and attempts to maintain its original trajectory, which renders its behavior stiff and unnatural; (b) the robot learns via physical interaction, adapts its objective function and path to align with the human intention. This model can be easily integrated into control techniques such as APF or IAPF, where the human-imposed forces are no longer simple avoidance signals but can be re-coded as smart repulsive or attractive components that adapt to the collaborative state as well as the shared goal.

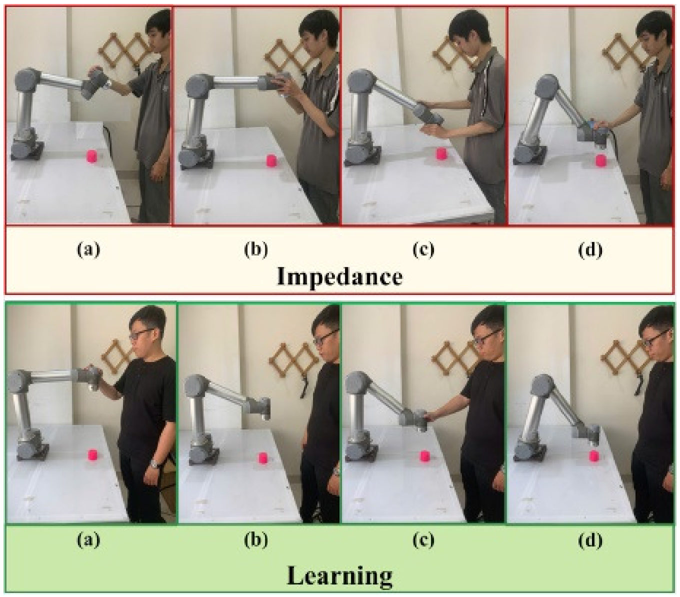

Fig. 7. Demonstration of the learning goal-oriented behavior of the robot from physical interaction rather than merely resisting it.

Similar technical capabilities have been indicated even without human presence. Authors in [32] developed a multi-layered controller based on Proactive AI-Controlled Interaction (PACI), enabling the robot to select the best control modules for each segment of a task through cost-based switching logic, enhancing safety and productivity in smart manufacturing HRC applications. Most of these contributions are so far in simulation or semi-realistic environments, but are urging more real-world testing.

4) Collaborative Manufacturing

This less common task group of HRC involves complex physical contact and intimate coordination between humans and robots. During manufacturing processes, such as bending, drilling, cutting, or metal machining, robots not only pick objects but also apply significant forces to the workspace. Such types of operations demand tight control of dynamic parameters, such as cutting force, torque, and impact point, while ensuring stability and safety in dynamic, confined workspaces.

In [33], an IAPF-based collision avoidance strategy was applied to dual-arm robots, casting attractive and repulsive forces from joint space to workspace via Jacobian matrices. This enabled precise joint-level velocity control in proximity operations. In [34], IAPF was blended with Rapidly-Exploring Random Tree (RRT) algorithms to drive a 5- Degrees of Freedom (DOF) bending robot, solving local minima issues and smoothing trajectory planning.

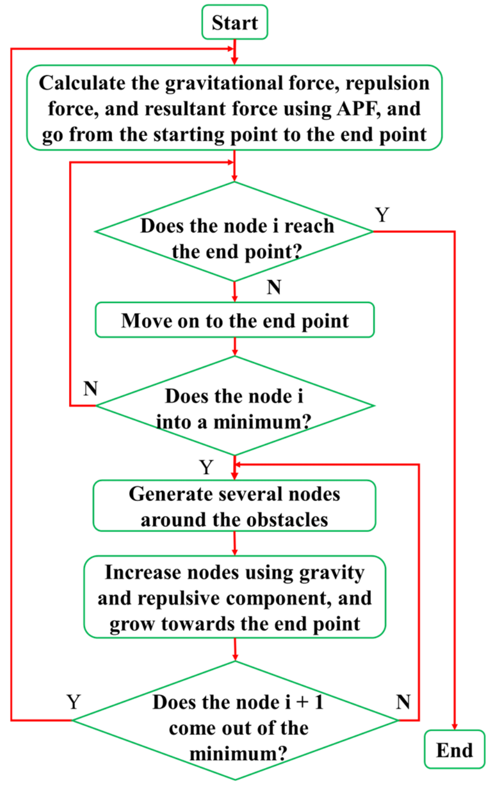

Fig. 8. Motion planning process of a 5-DOF bending robot using the IAPF algorithm combined with RRT.

This less common set of tasks in HRC involves complexity in physical touch and close coordination among robots and humans. In manufacturing processes, such as bending, drilling, cutting, or metal machining, not only does the robot handle objects, but it also exerts high force on the work area. Such types of tasks require strict control of dynamic parameters such as cutting force, torque, contact points, stability, and safety in constrained and dynamic settings.

A commonly applied solution is the integration of the IAPF algorithm with path planning methods at the global level, such as RRT, to avoid local minima and optimize motion paths. IAPF is used to control the robot in the workspace, but when the robot is caught in a local minimum, the system automatically transfers to RRT to search for alternative paths over and around obstacles and then switches back to the APF-based algorithm. The capability enables the robot to move accurately and smoothly with the integration of safety features in high-density manufacturing environments with obstacles.

Figure 8 displays the entire process of this path planning algorithm. The robot is initially pulled towards the target using attractive, repulsive, and gravitational forces calculated in the first step. Once a local minimum is achieved, the system also generates more nodes in the space through RRT, and keeps on monitoring for escape directions at every point. Upon exploration of a possible path, the process once again commences with the conventional APF strategy to reach the target. This design ensures smooth motion, reduces oscillation, and increases reliability in production applications.

For flexibility improvement, authors in [34] introduced a context-aware planning method that adjusts robot trajectories dynamically based on real-time operator activity and posture. It improved coordination, reduced collision hazard, and enhanced task performance. A DT framework utilizing Unreal Engine 4, coupled with physical systems using ROS, was proposed in [15] to enable real-time control. Figure 9 illustrates this DT framework for monitoring and controlling the cobot. Pose and behavior detection utilized supervised and semi-supervised DL models trained with DT data and validated using physical tests.

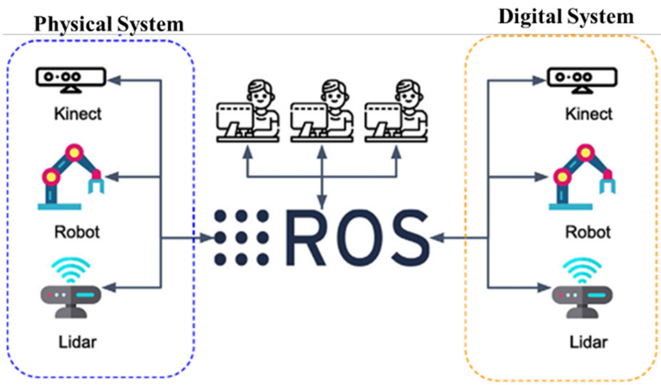

Fig. 9. DT framework using Unreal Engine 4 integrated with the physical system via ROS, enabling real-time monitoring and control of the cobot.

Authors in [35] applied an IAPF to dual-arm palletizing robots. Their collision detection model had a safe distance between arms and eliminated difficulties such as target overshoot and oscillation. Compared with traditional APF and RRT, their method improved convergence time by 14.2% and planning speed. Similarly, authors in [36] noted that traditional APF was still effective in station transfer tasks and ensured accurate collision avoidance and smooth motion in dense obstacles. The growth in the amount of co-assembly and object manipulation studies, as portrayed in Figure 2, reflects a trend in HRC towards tasks with high levels of cognitive, force-based, and parallel coordination levels of control.

B. *Evaluation Metrics for APF-Enabled HRC Systems*

In HRC research with APF, system effectiveness must be measured to validate feasibility, reliability, and usability. The measurements are performed through simulation or real experiments according to criteria that are commensurate with the scope and purposes of research. Significant indicators, such as accuracy, conformity, and physical safety, usually come from ISO/TS 15066.

The four widely accepted modes of safety in HRC, following [19], are: Safety-rated Monitored Stop (SMS), Hand-Guiding (HG), SSM, and PFL, as illustrated in Figure 10. These are employed to design APF-based collision avoidance algorithms for real-time force-constrained interaction scenarios.

1) *Group 1: Motion Precision*

Motion precision is a key metric in evaluating collaborative robot systems based on the APF algorithm, particularly for physical interaction tasks with accurate and secure motion trajectories. Authors in [32] implemented an IAPF model combined with a velocity field to work with dual-arm robots. Attractive and repulsive forces in this case were converted to velocities and then to joint space through a Jacobian matrix. This approach permitted an accurate and high-resolution control of joint speeds with enhanced joint distance security in limited spaces. Simulations confirmed significantly better trajectory precision, especially in self-collision avoidance.

Similarly, authors in [36] developed a path planning system for a 6-DOF robot arm in a real industrial application, converting from Cartesian space to configuration space. By combining attractive and repulsive forces and including trajectory smoothing, the system achieved precise obstacle response and smooth, safe robot motion. Authors in [37] presented an IAPF for 6-DOF robotic arms that could compute attractive torques directly in joint space without the need for Jacobian mapping. The method reduced joint error by 45.41% and planning time by 54.89% against traditional APF. IAPF addressed two critical APF limitations: local minimum trap and unreachable targets.

Authors in [38] employed an APF only in the joint space, with the potential function being considered only once within a control cycle. This reduced computational time and avoided Cartesian-to-joint space mapping errors. The system also included a virtual obstacle mechanism to escape local minima. Real-world experimentations showed that it produced short, smooth, and accurate collision-avoidance paths with very little computation time and hence was suitable for real-time HRC.

In addition, authors in [35] also proposed an IAPF variant that operated solely in joint space with repulsive forces calculated as functions of the shortest distance of each joint to obstacles. The gradient was also determined analytically and needed to be computed once per control cycle. A virtual obstacle was added to escape local minima without more input. Their experiments demonstrated stable, smooth, and short trajectories with dynamic obstacles.

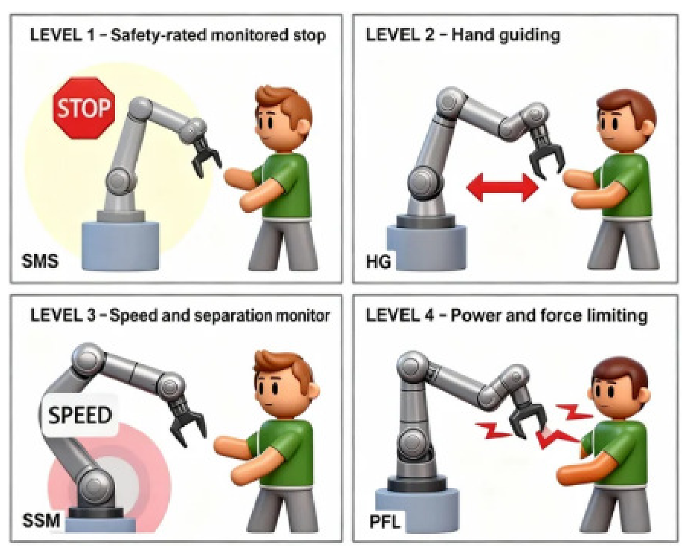

Fig. 10. Four collaborative operation modes in HRC (SMS, HG, SSM, and PFL), serving as safety foundations for evaluating and designing APF-based

collision avoidance strategies (adapted from ISO 10218-1/2:2011 and ISO/TS 15066).

Authors in [3] combined numerical inverse kinematics (Jacobians-based) with a novel APF for real-time motion planning of a 7-DOF manipulator. The robot automatically avoided obstacles, and its movement direction was modified without the intervention of a human being. The simulation and experiments proved position error below 0.006 mm, orientation error around 0.5 degrees, and computation time of only 0.08 s, having high accuracy and real-time capability.

2) Group 2: Robustness

Robustness is the flexibility and adaptability of robot control systems with APF when encountering uncertainties such as abrupt human behavior change, environmental variation, or sensor data shortage. Robustness is a critical standard in HRC to ensure task continuity, stability, and safety, especially in highly uncertain real-world environments. Authors in [29] built an algorithm for human motion prediction so that real-time trajectory adaptation becomes possible in an effort to maintain safety margins as well as avoid collisions, most effective in responding to unexpected operator movements. Structural enhancements of APF achieve robustness using low-obstacle-density region preference and adaptively step-size varying methods according to environment states. This allows for timely responses to unexpected changes without pre-defined routes.

In [13], APF-DRL integration maintained stable performance even with noisy or incomplete sensor information, improving HRC system reliability and safety under suboptimal environments. Additionally, in [39], a wearable haptic feedback system was coupled with an HRC system based on APF-based collision avoidance. When visual information was blocked, the robot was able to modify its trajectory from real-time tactile feedback. Tests resulted in a 4.1 cm increase in average safety distance and an 81% reduction in robot path length in collision avoidance, demonstrating the merit of integrating APF with other senses in dynamic manufacturing environments.

Authors in [40] investigated a method combining 3D depth information from Microsoft Kinect with robot proprioceptive information for estimating the posture, even when the robot was out of sight of the camera. Utilizing a safety envelope concept, the system calculated the robot-obstacle distances and generated repulsive forces at the wrench level. In experiments, the system maintained a minimum of 240 mm safety distance and generated smoother and more stable trajectories than traditional depth-only methods. Overall, these studies highlight the role of robustness as a main measurement criterion, indicating the suitability of APF systems for variable and hazardous real-world HRC settings.

3) Group 3: Proof-of-Concept

Proof-of-concept is a common set of conditions in pilot experiments that are intended to validate the potential of APF algorithms in simulated environments before actual implementation. Though lacking in extensive experimental evidence and statistical analysis, experiments of this type serve as a foundation for further APF-based HRC system construction. Authors in [42], which proposed an IAPF variant for a 6-DOF UR5 robot arm. Robot geometry was modeled using multi-joint cylindrical segments, and repulsive and attractive forces were optimized to handle spherical and hollow cylindrical obstacles. Simulations using MATLAB and Robotics Toolbox showed collision avoidance with an average planning time of 1–1.3 ms, which was real-time ready. However, the study was simulation-level without physical validation.

Authors in [32] introduced a collision avoidance method for dual-arm robots through a Velocity-Field APF (VP-APF). The technique converted attractive–repulsive velocities into joint space using the Jacobian and its inverse to enable joint-wise differential velocity control against self-collision. Simulation verification was conducted through MATLAB and Adams, with no experimental results available.

Authors in [37] introduced IAPF for the control of a 6-DOF EC63M robot for harvesting citrus in a system. The algorithm computationally determined attractive torques in joint space, reducing error by 45.41% and planning time by 54.89% over traditional APF. While the results were positive both in simulation and actual trials, the implication was in a particular case and did not have generalization data.

Finally, authors in [42] proposed a multi-objective optimized IAPF for mobile robots that addressed the three primary APF limitations: local minima, unreachability to the target, and smoothness of the path. Adaptive step control, steering corridor optimization, and quadratic programming were implemented to generate 97.3% smoother trajectories than APF and 45.1% quicker trajectories than DWA. However, the results were limited to MATLAB simulations only. In summary, studies in this category show the potential of sophisticated APF in HRC operations. Even in the absence of a huge body of empirical evidence, they establish algorithmic bases for future high-level uses.

4) Group 4: Performance Improvement

Performance improvement is used to assess how effective APF algorithms are in terms of planning time, control accuracy, response time, and performance in unstructured environments. The benchmark follows the proof-of-concept phase, as a switch to quantitative evaluation and practical feasibility. Authors in [37] presented an improved version of APF for 6-DOF arms by the straightforward computation of torques in joint space. This reduced the motion planning time by 54.89% and the joint angle error by 45.41%, demonstrating the effectiveness of the algorithm in attaining maximum robotic control in the uncertain context.

Authors in [13] combined APF and DRL with Hindsight Reward Architecture (HRA) and Hindsight Experience Replay (HER). The system was 85% effective in dynamic obstacle avoidance with rapid learning and predictable response. Authors in [43] developed a dynamic environment mobile robot navigation system via the integration of Soft Actor-Critic (SAC) DRL, expert trajectory imitation, and Recurrent Neural Networks (RNNs). The method improved collision avoidance and training efficiency with weighted HER and surpassed state-of-the-art DRL baselines. In an application, the APF-based transfer station system was implemented in an MA1440 welding robot in [36]. The system allowed planning directly in configuration space, eliminating geometry and performance without human guidance.

Authors in [44] integrated IAPF with a cosine-adaptive genetic algorithm to navigate a 5-DOF gripper path in environments full of obstructions. The solution improved task execution time and the quality of grasping. Authors in [25] proposed a joint space APF strategy pre-computing the gradients and evaluating the potential function only once per cycle. Coupled with a virtual obstacle escape mechanism, it generated short, smooth paths with quick computation and singularity stability, enhancing real-time performance and robustness for industrial cooperation. Furthermore, authors in [3] implemented real-time trajectory planning by combining an improved potential field and Jacobian-based numerical algorithms. The system computed trajectories in 0.08 s per cycle while enabling smooth navigation in unlearned space without any user intervention.

Authors in [71] developed a double-APF model on a Fanuc CRX-20iA robot to perform pick-and-place actions in dynamic environments. Two domains simultaneously addressed collision avoidance and singularity correction, reducing task time by 43% compared with the reference method. These efforts, thus, reveal an increasing trend towards incorporating APF with smart control and ML. These approaches not only improve real-time effectiveness but also improve accuracy, flexibility, and usability in practical implementation in complicated production environments, facilitating the realization of secure, adaptive, and highly automated HRC systems. In parallel, sophisticated APF versions, such as D-APF [18], have made remarkable progress, with 0.65% position error at target speeds of 1 m/s and providing 3D collision avoidance without oscillations inherent in traditional APF.

5) *Group 5: Human Physical Workload Reduction*

In HRC, the reduction of the physical load on human operators is a requirement to achieve sustainable and secure shared working environments. APF algorithm-based control systems, especially combined with advanced sensing techniques and RL, have shown potential in supporting operators in maintaining ergonomic postures, reducing interaction forces, and preventing unnecessary motions. Through synchronizing flexible and optimized motion, the system significantly reduces negative postures, thereby alleviating muscle fatigue and static load during assembly.

RL has been used as well to minimize spurious interactions and maintain seamless cooperation. Authors in [12] introduced the IRDDPG algorithm, which tunes intrinsic rewards to enable the robot to learn motion policies that are safe and minimize latency and emergency stop issues contributing to physiological load on human operators. Authors in [45] proposed an RL system that simultaneously trains decision-making and perception and enables the robot to learn human behavior adaptability from unsupervised data, thereby circumventing repeated posture fine-tuning in collaboration packaging processes.

Ergonomics-focused approaches have also shown encouraging results. Authors in [46] integrated a posture assessment model based on the REBA index into the action planning module, such that mutual motion patterns between human and robot at the same time could be planned while considering biomechanical load factors. Authors in [47] used an HRC system equipped with wearable devices to monitor human motion and regulate the posture of the robot, resulting in an 80% reduction in unwanted postures for assembly tasks. However, authors in [48] employed a variable impedance control and MPC–CEM optimization-based model for RL that reduced interaction forces significantly and maximized single-adaptability.

Overall, these studies affirm that the application of APF algorithms, especially when combined with biosensors, contextual awareness, and RL, can be an important contributor to counterbalancing the physical load on human operators. Not only does this enhance comfort and safety in HRC workplaces, but it also optimizes operational efficiency and extends uninterrupted working durations without compromising human health.

IV. ROBOT PERCEPTION AND BEHAVIOR IN HRC USING APF

The application of APF algorithms in HRC architectures has evolved from being a geometrically founded conventional collision avoidance system to a perception- and behavior-oriented control paradigm. Depending upon the type of interaction being studied, each application of APF revolves around developing one or several robot perception and behavioral adaptation capabilities. These capabilities include responding to external stimuli, action planning in context, decision-making under conditions of uncertainty, and online adaptation to environmental or human state change.

Figure 11 illustrates four main research directions in robotic cognition and behavior using the APF algorithm, including: behavior-oriented perception and policy learning, modeling of human behavior and intention, context-aware and environment-specific perception, and classification of cognitive-behavioral levels. Current developments suggest that the fusion of APF with ML techniques, such as RL, DL, or adaptive control, significantly contributes to the contextual sensitivity and flexibility of the robot's behavior. This enables robots to transform from reactive tools to proactive partners, not only responding to human actions but also predicting interactions, allocating roles, and adjusting actions based on the physical or cognitive states of humans.

A. Behavior-Oriented Perception and Policy Learning

The majority of the research indicates hybrid control models combining APF with RL, particularly deep RL, to enhance robot behavior in complex environments. With Industry 5.0, cobots need to cross the safe passage to the symbiotic integration with humans. Such vision conforms to the "Age of Augmentation," where "humans and machines live and work together harmoniously" [49]. Such methods make use of state data and sensor measurements to construct reward functions that dynamically adapt attractive and repulsive forces of the potential field in real-time.

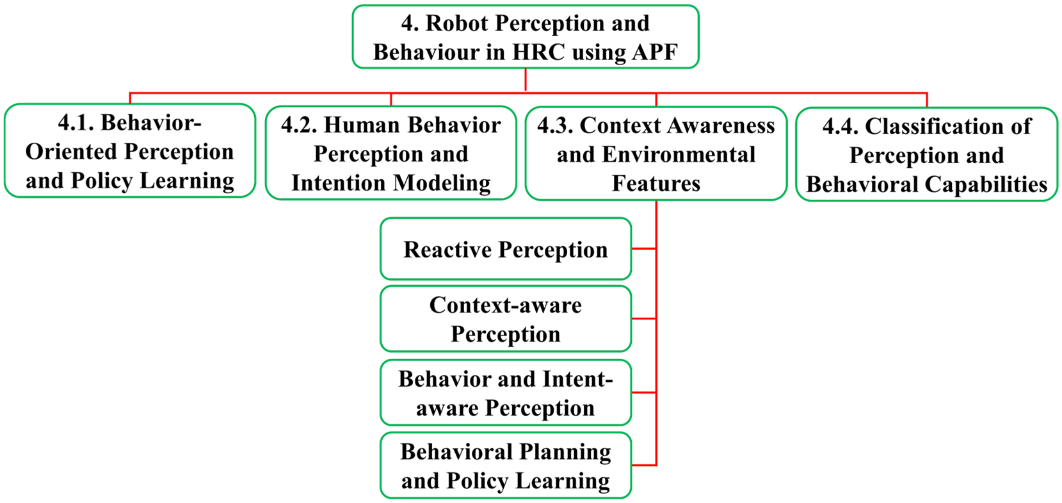

Fig. 11. Structure of robotic cognition and behavior in HRC using the APF algorithm.

Authors in [50] introduced GNN-RL-APF-Lagrangian as an algorithm for distributed navigation in multi-robot systems, where APF repulsive forces are directly integrated into deep RL-generated trajectory optimization. This greatly improves collision avoidance and provides scalability in large teams of robots while maintaining safety and decentralized control.

Authors in [12] proposed an SAC-based architecture integrated with an RNN to enhance transfer inference and navigation skills in dynamic settings. Hybrid data between both agents and experts and imitation learning methods allow for policies to converge faster, safer, and with higher chances of real-world deployment.

Authors in [45] proposed a human-centric HRC framework in which perception policy and action policy are simultaneously learned end-to-end using deep RL. This allows robots to collaborate with humans without manual labeling or separate behavior recognition modules. The system is highly robust with respect to novel collaborators and tasks and shows the promise of user state-based policy adaptation in real-world applications.

This advancement is harmonious with the Proactive HRC model [51], where robots and humans are able to share states with each other, predict spatio-temporal interactions, and self-organize task delegation in cognitive manufacturing environments. The three basic capabilities in Proactive HRC - inter-collaboration cognition, spatio-temporal cooperation prediction, and self-organizing teamwork serve as pillars of support for integrating APF into proactive systems, facilitating real-time adaptive coordination in flexible environments.

In addition to APF combined with RL, research also uses multi-channel sensing, specifically vision and proprioception, to complement state representation for policy learning in occluded or dynamic environments. Authors in [52] used a variational autoencoder to derive a vision proprioception model to learn latent features from images and integrate these with the robot end-effector state. This facilitates goal-directed RL of planar object-pushing tasks with good generalization to novel objects. Authors in [53] introduced LocoTransformer, an end-to-end RL approach that integrates depth and proprioception within cross-modal transformers. This enables quadruped robots to learn adaptively navigating on challenging and dynamic environments. While they do not directly estimate reaction forces, the two works show the strength of multi-sensor integration for adaptive motion control.

B. Human Behavior Perception and Intention Modeling

Roughly half of the covered works deal with modeling human behavior, including intention prediction, motion recognition, and reliability estimation. Among them, human intention recognition is a hot topic, particularly in close-contact or physical interaction environments. Accurately and in real time, sensing human intent enhances not only robot responsiveness but also safety and coordination in HRC systems.

This solution involves an online risk–benefit estimation mechanism for user intention inference so that robots can make context-aware decisions proactively. Integration of intention modeling and decision-making makes it possible for robots to better anticipate human actions and react dynamically, improving collaboration efficiency.

Considering physical co-manipulation, authors in [54] demonstrated that human intent can be effectively recognized from force–kinematic signals. They presented novel signal features recognizing user intent in real time that serve as symbolic inputs to high-level robot controllers. This enables robots to read and adapt to human behavior while actively guiding the interaction toward consensus.

Authors in [55] argued that RNNs can effectively be used for human motion trajectory prediction in human-robot collaborative assembly. The RNN in their study exploits kinematic correlations between parts of the body and integrates probabilistic reasoning via Monte Carlo dropout to handle uncertainty in prediction. Results have shown that there is a 40% reduction in prediction error compared to baseline RNNs, with improved safety and reliability in human–robot coordination. Future research can extend trajectory prediction to tasks with varying assembly sequences, enhancing the flexibility of robots in flexible assembly lines. Overall, these approaches show a growing tendency to utilize multimodal hints and ML techniques to equip robots with robust human behavior perception. These capabilities are necessary for achieving harmonious, safe, and efficient cooperation in dynamic and uncertain workspaces, and for advancing intention-aware robotic systems.

On this basis, Proactive HRC enlarges the robot's role from reactive to predictive, enabling it not only to read current human activity but also to anticipate future intention and plan proactively in space and time. According to [51], this represents a transition from reactive HRC to bidirectional collaboration, allowing robots to actively participate in the production process without continuous instruction, towards cognitive automation.

Complementing these approaches, computer vision and robot vision, specifically in integrated applications of DL techniques, such as object detection, semantic segmentation, and human action recognition, have become imperative in advancing the situational awareness of robots. These techniques allow robots to accurately sense their surroundings and interpret human actions, which supports robust collaboration [56]. Replicating biological visual functions using deep neural networks is one way toward the realization of context-aware, proactively interactive, and naturally adaptive cobots for flexible manufacturing.

C. Context Awareness and Environmental Features

A second, even smaller collection of research adopts a spatial cognition and environment modeling perspective and focuses on spatial feature detection, object location, or best path planning for the purpose of facilitating collision avoidance and cooperative behaviors. One such instance is in [40], where 3D depth data gained from Kinect sensors are integrated with the proprioception data of the robot in order to provide spatial perception even when the robot moves out of the camera's field of view. The system utilizes a principle of constrained safety boundary to calculate repulsive forces that avoid collisions in human-occupied space.

The repulsive force is operational vertically with a horizontal component, allowing the UAV to move around objects and maintain target-aligned distances. Authors in [57] developed the eAPF-CPP algorithm for UAV navigation through dynamic 3D environments with obstacles. With redescription of attraction and repulsion fields, the algorithm avoids local minima and maintains smooth paths in complex spaces. Although designed for UAVs, the method also holds promise for mobile robot use in shared human spaces, especially if integrated with spatial perception aids such as SLAM or machine vision.

Beyond that, authors in [58] presented AR interfaces for enhancing situational perception. AR is an interactive bridge between human beings and Computational Intelligence (CI), providing natural real-time feedback on spatial data, object position, and collaborative activity in manufacturing environments. Authors in [59] used an interactive AR system in a real manufacturing environment for observing robot-to-human safety distances. Their workspace structure facilitates dynamic robot, human, and hazard zone segregation, and visually communicates safety information to users. This AR paradigm enables environment awareness and coordination efficiency in HRC.

Authors in [23] presented the Predictive Artificial Potential Field (PAPF) algorithm, which integrates temporary goal determination processes based on predicted movement and virtual barriers (top quarks). The algorithm provides smoother, shorter, and more energy-efficient path planning without being stuck in local minima, a limitation inherent with typical APF systems. Although applied to AGVs, the PAPF algorithm can be extended to human-populated cooperative spaces due to the flexibility of motion guidance and spatial flexibility.

Finally, authors in [60] highlighted that machine vision represents the most prevalent sensor mode in ML-based APF-capable HRC research. IMUs and EMGs are also utilized to complement human state awareness. Most of the existing work remains at the proof-of-concept stage, but the trend of uniting ML with spatial cognition modeling has very optimistic potential to increase robot navigation and collaborative abilities in HRC settings.

Building on this trend, authors in [15] designed a perception system for HRC through the use of a DT model combined with a UR10 robot via ROS. The system trains Faster R-CNN detectors and semi-supervised models with hybrid data from Unreal Engine 4 and physical sensors to classify HRI behavior in various scenarios. The results show that the approach overcomes the disadvantage of real-world datasets and achieves better perception reliability in collaborative manufacturing tasks.

D. Classification of Perception and Behavioral Capabilities

Research within the field of HRC with the APF algorithm has been shown to demonstrate a significant step in robotic models of cognition, from simple reactive behavior to complex behavioral control techniques. In a review of 72 exemplary academic papers, cognitive and behavioral capabilities can be classified into four main levels: Reactive Perception, Context-aware Perception, Behavior and Intent-aware Perception, and Behavioral Planning and Policy Learning.

Figure 12 illustrates a quantitative summary of studies on different levels of cognitive perception in APF-based HRC systems. Rather than giving individual citations, this analysis reports the aggregate research, which emphasizes reactive, context-aware, behavior-aware, and policy-learning perception. Such a numeric summary illustrates a better understanding of which cognitive competencies have been more prioritized and where gaps in research are still evident. In fact, context-aware perception occurs most often, in approximately 70 studies, and then reactive perception in 68 studies, which hints at the importance of real-time sensing and awareness of the workplace environment. Behavioral policy learning and planning are discussed in 62 studies, reflecting the trend of adaptive and autonomous control policy developments in HRC.

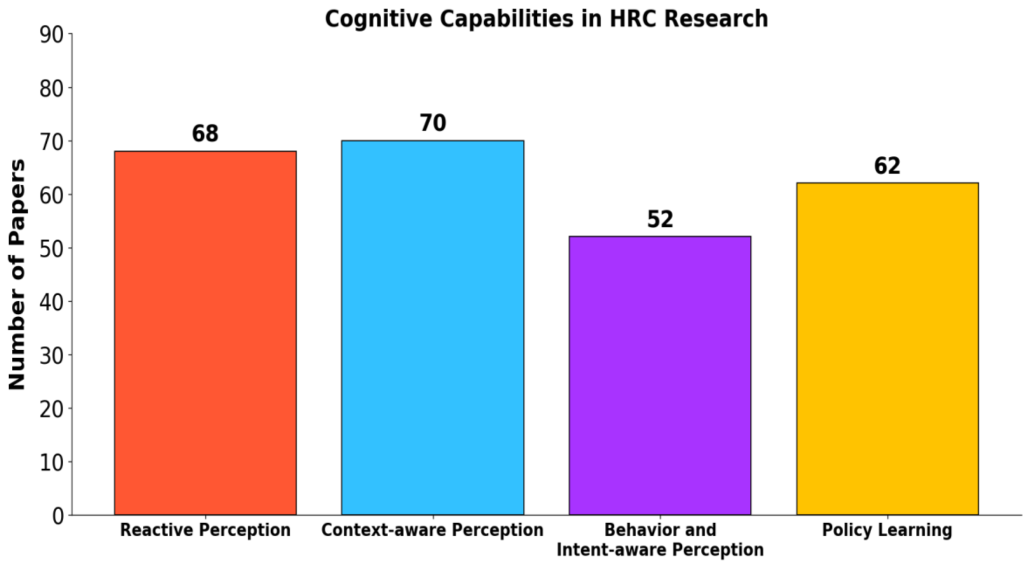

Fig. 12. Number of studies referencing each level of perception in HRC systems using the APF algorithm (each study may belong to multiple levels simultaneously).

Finally, behavior and intent-aware perception are addressed in 52 studies and are accountable for inferring goals, predicting actions, and smooth coordination with humans. The fact that many studies address multiple levels of cognition is an expression of a continuing research direction towards developing multi-layered cognitive HRC systems engaging anything from immediate reflexes to long-range behavioral planning to equip robots with greater flexibility, security, and cooperation abilities in dynamic production environments.

1) Reactive Perception

This is the most basic level, where the robot reacts directly to environmental sensor cues, e.g., collision forces, depth, or obstacle distances. Conventional APF-based systems typically belong to this class, where repulsive forces are generated as soon as an obstacle comes into range. In spite of being direct, this method is effective in semi-static as well as low latencies environment. Authors in [61] employed laser and IMU sensors to calculate the minimum real-time distance between a human and a robot to enable the robot to adjust its path according to a personalized potential field to avoid immediate collisions while operating in a shared workspace. Additionally, authors in [53] presented a modified version of the APF algorithm using static environment information to construct priority regions and tune the step size based on distance and direction to obstacles, which reduces local minima and improves trajectory smoothness. The algorithm operates in a reflexive mode using familiar sensors and is suitable for non-dynamic environments. Authors in [36] also utilized a path planning system on the 6-DOF MA1440 industrial robot deploying the APF method to produce repulsive forces from real obstacles. The system reacts in real-time to sensor input to find collision-avoidance paths for the entire robotic arm by explicitly illustrating the reflexive perception mechanism typical of APF-based systems. Authors in [41] proposed an algorithm of motion planning in terms of environment-attractive-repulsive forces for collision avoidance to ensure real-time responses to hollow cylindrical or spherical obstacles. Real-time calculation of the collision-free path was performed utilizing a virtual torque model in order to drive the joints of a UR5 robot arm with high compatibility with reflexive perception features. Authors in [57] proposed the eAPF-CPP algorithm that reconfigures attractive and repulsive fields from squared distance so that UAVs can react efficiently to obstacles and avoid local minima. The system reacts immediately to real-time environmental barriers, significantly demonstrating the nature of reflexive perception.

2) Context-Aware Perception

These systems not only react to current sensor feedback but also rely on context information such as motion history, environmental maps, or human being state. APF in this case is most commonly conditioned to context using dynamic parameters or blended with reinforcement controllers to shift the potential function depending on specific situations. This is the foundation for adaptive behavior and smooth coordination in actual-world HRC environments. Authors in [25] developed an algorithm with integrated superior APF and an adaptive early warning system to achieve path planning in complicated sea environments. Environment complexity adaptive dynamic adjustment of the collision avoidance space and step size provides context-aware perception for the system and the capability to avoid unmapped objects in field environments. Authors in [60] reviewed the use of ML in HRC, highlighting how techniques such as RL and Unsupervised Learning (UL) are applied to model perceptual variables and acquire behavior adaptation from context in tasks ranging from object handover to collaborative manufacturing. They aimed at addressing the necessity of integrating real-time sensory information with adaptive cognitive architectures to enhance interaction performance. Authors in [62] developed a Cyber-Physical System that integrates visual sensing and closed-loop control and enables the robot to adjust its behavior depending on its actual distance from a human. This is context-aware perception in collaborative scenarios with no physical barriers. Furthermore, authors in [24] proposed an improved multi-objective snake optimization algorithm (APF-IMOSO), where the APF is used to evaluate in real-time safety and is integrated with other objective functions such as path length, energy, and travel time. The system supports the generation of multiple optimal solution paths scalable for dynamic situations, and therefore conveys unequivocal context-aware perception and behavior optimization in diverse environments.

3) Behavior and Intent-Aware Perception

At this level, robots can perceive and conclude human behavior, intentions, or goals from kinematic data, force sensors, vision, or physiological signals. ML techniques, particularly DL and RL, play a critical role in discovering and interpreting human behavioral features. They enable this fusion to provide the ability of robots to predict behavior rather than react solely, allowing proactive coordination and safer interaction. Authors in [63] point toward the importance of making inferences about human behavior and intent in HRC. While the former applied multimodal transfer learning to predict operator action in industrial assembly tasks, authors in [26] were concerned with bidirectional object handover and included cognitive learning to enhance coordination capability. In addition, authors in [30] treated physical contact as an end goal communication modality, enabling robots to learn and adapt behavior in real time according to purposeful human-imposed forces.

Authors in [54] explored force-based communication mechanisms for cooperative manipulation and proposed a real-time human intent classifier based on dynamic force features. This enables robots to sense and deduce intent through unstructured physical interactions, enabling guided interaction and flexible coordination improvement. Furthermore, authors in [27] developed a handover manipulation control strategy with tactile sensing alone, allowing robots to perceive human purpose through force feedback and load sharing in real time. The system supports smooth and safe adjustment of grasping force and release time, demonstrating the ability to infer behavior and purpose in HRC.

4) Behavioral Planning and Policy Learning

This is the highest level, wherein robots not only perceive but also learn control policies to achieve goals in uncertain and dynamic situations. APF is formulated as an RL system or integrated into end-to-end control networks. Robots here can make real-time adjustments of interaction strategies, optimal collaborative performance, and learning from experience or new tasks without reprogramming. Overall, the build-up of perception and behavior skills in HRC using APF reveals a migration from rule-based control towards learning and predictive mechanisms that are adaptive.

Authors in [45] developed an end-to-end, unsupervised DRL framework that enables robots to make effective decisions under uncertain perception and achieve smooth coordination in packing tasks. Authors in [13] proposed a deep RL framework that encodes task requirements and safety constraints for industrial robots, aiming for real-world deployment. Authors in [64] developed an RL policy with a customized reward function that enables robotic arms to avoid dynamic obstacles during HRC. Authors in [52] built an end-to-end perception–action model using vision and proprioception, allowing the robot to learn a transferable object-pushing policy from simulation to reality. Authors in [53] integrated cross-channel Transformers into RL policies for flexible behavior planning of quadruped robots in complex terrains.

Authors in [65] employed unsupervised RL to explore transferable manipulation skills, learning task-independent control policies. Authors in [66] developed NavRep, an unsupervised representation framework that enhances navigation learning efficiency in dynamic HRC environments. Finally, authors in [67] combined an IAPF with BHDQN to overcome local minima and adapt to multi-objective dynamic scenarios.

Authors in [48] applied Model-Based Reinforcement Learning (MBRL) and Model Predictive Control (MPC) to control variable impedance, optimizing interaction forces based on human behavior in HRC, demonstrating the ability to learn safe and adaptive control policies. Table III presents a general comparison of the four levels of cognition; such a comparison not only structures the application of APF in modern HRC but also guides the development of more intelligent, safer, and more autonomous cobots in the future.

TABLE III. GENERAL COMPARISON OF THE FOUR LEVELS OF COGNITION

Level	Distinguishing characteristics	Advantage	Limitation
Perceptual cognition	Perceives current state and sensory information	Simple, fast, reactive	Not adaptable, low-level decision making
Executive cognition	Slightly uses experience; has short-term memory	Makes better decisions based on feedback	Not proactive, lacks deep planning
Behavioral cognition	Uses experience to adjust behavior; has certain prediction ability	Autonomous behavior, flexible interaction	May lack reasoning ability and generalization
Social cognition	Understands human behavior; adapts through long-term interaction	Learns habits, intentions, and emotions; highly adaptive	Difficult to model, requires large amounts of data and training

V. ML TECHNIQUES IN HRC USING APF

ML is a key factor in enhancing the adaptability, perception, and decision-making capacity of robots within HRC systems based on the APF algorithm. Among the 72 studies considered, over 24 studies (approximately more than 33%) integrated at least one ML approach to address issues such as motion planning, collision-free motion, behavior recognition, or policy control learning within cooperative environments.

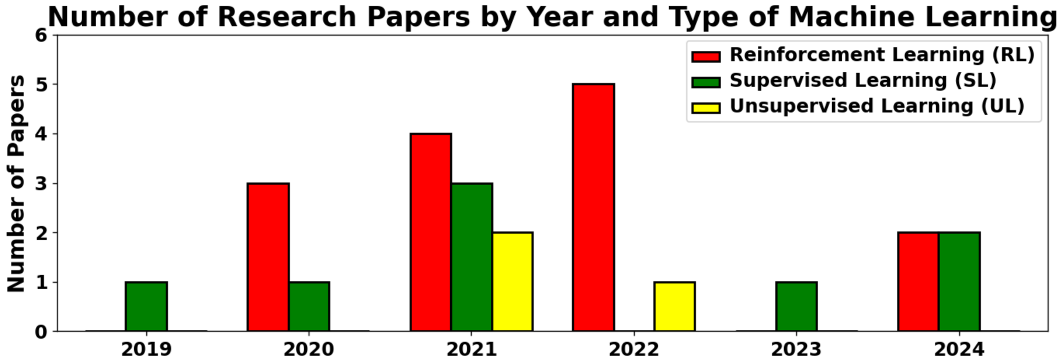

Fig. 13. Distribution of studies applying different groups of ML techniques in HRC using APF from 2019 to 2024.

As proposed in [60], ML methods are classified into three main classes: UL, RL, and Supervised Learning (SL). Each of these classes has unique characteristics with respect to problem-solving approaches, data types required, and levels of integration with APF algorithms. The distribution of the quantity of publications of each ML group is presented in Figure 13, with an increasing trend in the application of ML techniques, especially RL, in complicated collaborative systems. This aggregate presentation shows the direction of research momentum.

A. Unsupervised Learning

UL is commonly used in HRC studies with APF to build statistical models or discover latent features from unlabeled sensor observations. The common algorithms are Gaussian Mixture Model (GMM), Task-Parameterized GMM (TP-GMM), Hidden Markov Model (HMM), and Variational Autoencoder (VAE). Both GMM and TP-GMM are used to model user movements or behaviors as probability distributions. For example, authors in [69] proposed a TP-GMM/R variant by adding a ring-shaped Gaussian model (rGaussian) to account for orientation-independent coordinate systems. Such a methodology enhances robot adaptability within adaptive manufacturing environments and improves robustness in Learning from Demonstration (LfD) scenarios in HRC.

Advances in UL for HRC systems have moved beyond traditional statistical models to Unsupervised Reinforcement Learning (URL). Unlike supervised methods, URL can facilitate self-exploration of environments by robot agents and learning interaction skills without task-specified rewards. Authors in [65] utilized intrinsic rewards from mutual information to learn reusable and task-agnostic manipulation behaviors, diverse in nature. The experimental results show that such training protocols improve sample efficiency by 2 to 5 times in multi-task and goal-conditioned RL settings, even when observations are noisy. These findings show URL's potential for constructing flexible skill-learning systems that can be used on difficult real-world HRC problems.

UL techniques have also been utilized in robot navigation to mitigate the limitations of end-to-end RL, which suffers from poor sample efficiency and generalization. Authors in [66] introduced predictive unsupervised representations learned from raw sensor inputs to enable policy learning in human-populated dynamic environments. Comparing 20 model architectures, two end-to-end and eighteen unsupervised models, the research showed unsupervised features capable of matching or even exceeding in known and novel environments. The representations possess features such as modularity, generalizability, and potential integration into simulation-based training loops. In HRC scenarios requiring adaptive and interpretable spatial reasoning, the latent features are a promising foundation for scalable and transferable navigation policies.

B. Reinforcement Learning (RL)

RL is a very common method in HRC research based on APF, especially when there is a necessity for robot decision-making in dynamically changing conditions. Out of the 72 studies that employ ML, at least 13 employ RL, with some common types such as Q-learning, Deep Q-learning, Model-based RL, IRL, and Interactive RL. Authors in [45] employed Deep RL to learn robot response based on context perception to enable the system to learn optimal control policies without precise dynamics models.

Authors in [48] used model-based RL combined with dynamic neural networks to simulate adaptation evolution with time, with smoother and more accurate outcomes in unstable cooperative situations. Authors in [67] proposed the Black-hole Potential Field Deep Q-Network (BHDQN), a combination of IAPF and Deep Q-learning to facilitate robots' adaptation learning in multi-obstacle and local-stable-points environments. This method enables agents to leave stable traps with no pre-specified knowledge and to optimize efficient paths in static and dynamic environments.

Authors in [68] combined APF with Deep Q-Learning for COLREGS rule-based path planning and collision avoidance in dynamic maritime environments. APF is employed to expand the action space and reward function, demonstrating the flexibility and effectiveness of the APF–DRL combination in autonomous systems. Interactive RL, where humans give real-time feedback during training. This system was also used in [12], further improving responsiveness in close-contact maneuvers.

Similarly, authors in [43] combined SAC with expert imitation learning, weighted experience replay, and RNNs to improve policy stability and generalization in dense obstacle scenarios. This is particularly fitting for continuous inference and real-time response applications, such as in HRC environments.

C. Supervised Learning

SL is applied in the majority of HRC research studies with APF for action state classification, human intention recognition, or feature extraction from input sensor data. This approach requires a labeled dataset to learn the correspondence between sensor inputs and desired behavioral outputs. A few of the well-known algorithms include Artificial Neural Networks (ANN), RNN, Long Short-Term Memory (LSTM), CNNs, and Gaussian Process Regression (GPR).

In [15], SL was used to train a detection model to locate humans and robots in collaborative workspaces. Specifically, a Faster R-CNN network was trained on a synthetic labeled dataset of a DT model and the COCO human datasets. The model maps input images onto behavioral labels, which enables accurate classification of human and robot actions in production environments. The method enhances safety and reliability without complex physical calibration.

Authors in [70] trained a YOLOv8 Tiny model using annotated images of robot parts and human body parts in collaborative workplaces. The model maps input images to object classes for human–robot detection and uses a CNN to predict collision risk. The approach is highly accurate, demonstrating the effectiveness of SL for real-time HRC safety monitoring. In [32], a non-collision HRC system utilized supervised transfer learning for contextual classification of operator assembly postures. The model learned the labeled posture data so that the robot system may respond flexibly and safely in real-world collaboration environments. This module is essential in embedding contextual information in the robot's decision-making.

VI. RESEARCH CHALLENGES AND FUTURE PERSPECTIVES

Although the APF algorithm has demonstrated its potential in HRC systems, numerous technical challenges remain to be addressed to achieve higher levels of intelligence, safety, and flexibility. Figure 14 illustrates the research challenges and future directions for APF-based HRC systems.

First, it is essential to develop hierarchical perception–action architectures that integrate the four levels of cognition: reactive perception, context-aware perception, intention understanding, and policy learning. Such multi-layered control systems allow robots to flexibly alternate between rapid responses to the environment and long-term behavioral planning in collaborative tasks. Second, lifelong learning capabilities and real-time responsiveness must be enhanced. Current RL architectures are limited in their ability to generalize and to retrain for new tasks. Future research should focus on continuous learning models, enabling robots to adapt to changing collaborative environments without forgetting previously acquired behaviors.

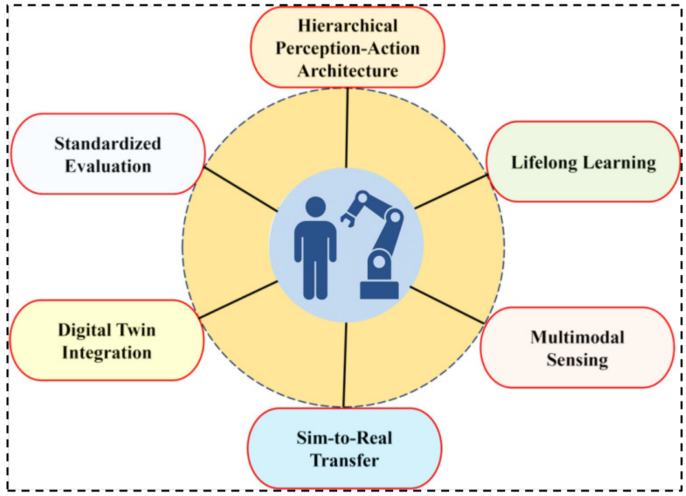

Fig. 14. Key research challenges and future directions for APF-based HRC systems.

Third, integrating multi-modal sensing (vision, force, tactile sensors, EMG/EEG) is key to improving the robot's understanding of human state and intention. These data streams can be used to dynamically adjust the potential field according to context, thereby improving mutual adaptability in HRI. Fourth, the challenge of transferring learned control policies from simulation to the real world must be addressed. This includes domain adaptation techniques and safe deployment procedures to ensure that policies trained in simulation can be reliably applied in industrial environments with minimal manual tuning.

Fifth, integrating DT models with APF-based motion planning presents great potential for real-time system monitoring, predictive control, and virtual experimentation. DT allows robots to proactively adapt their behavior based on predicted operator states or environmental conditions, thus enhancing system safety and flexibility. Sixth, linking APF with next-generation human modeling, such as biomechanical simulations or cognitive load estimation, can help generate physiologically optimized motion plans and support effective physical assistance in complex tasks.

Finally, it is crucial to establish standardized assessment frameworks for APF-based HRC systems. A unified set of evaluation criteria for safety, performance, flexibility, and user acceptance will provide a basis for fair comparison between methods and foster practical adoption in industrial applications.

VII. CONCLUSION

This system-level review analyzes the evolving role of Artificial Potential Field (APF) algorithms in Human–Robot Collaboration (HRC) systems from 2019 to 2024 based on 32 out of 169 scientific studies. In a systematic analysis, the present study sorts out collaborative tasks into four broad categories: collaborative assembly, object handover, simultaneous manipulation of objects, and collaborative manufacturing. The study also evaluates how APF is tailored to adapt to the unique requirements of each category of tasks.

The article presents a four-tier APF-based HRC system taxonomy of behavior and perception: reflexive perception, context-conscious perception, intent-conscious and behavior-conscious perception, and policy learning. The taxonomy reflects the transition from traditional geometric collision avoidance algorithms to adaptive, intelligent, and context-conscious robot behaviors. In parallel, integration of Machine Learning (ML) techniques such as Reinforcement Learning (RL), Supervised Learning (SL), and Unsupervised Learning (UL) has enhanced the capabilities of APF-based systems, particularly in behavior prediction, path adaptation, and safe decision-making under uncertainty.

Despite significant progress, most of the applications remain at the proof-of-concept level, highlighting the need for continued development and testing in realistic industrial environments. Potentially fruitful research directions in the future include extending continuous learning frameworks, multimodal sensor fusion, policy transfer from simulation to reality, and standardizing performance metric evaluation.

Overall, the study affirms that while APF remains a basic method for motion planning and collision avoidance, only through combinations with modern artificial intelligence software, cutting-edge sensor systems, and cognitive models of human thinking it realizes its complete potential. Such integration is a requirement for the creation of the next generation of cobots that are safer, smarter, and more responsive to the Industry 5.0 vision, which is human-oriented

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