Physical Human–Robot Collaboration: Robotic Systems, Learning Methods, Collaborative Strategies, Sensors, and Actuators

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***Abstract*—This article presents a state-of-the-art survey on the robotic systems, sensors, actuators, and collaborative strategies for physical human–robot collaboration (pHRC). This article starts with an overview of some robotic systems with cutting-edge technologies (sensors and actuators) suitable for pHRC operations and the intelligent assist devices employed in pHRC. Sensors being among the essential components to establish communication between a human and a robotic system are surveyed. The sensor supplies the signal needed to drive the robotic actuators. The survey reveals that the design of new generation collaborative robots and other intelligent robotic systems has paved the way for sophisticated learning techniques and control algorithms to be deployed in pHRC. Furthermore, it revealed the relevant components needed to be considered for effective pHRC to be accomplished. Finally, a discussion of the major advances is made, some research directions, and future challenges are presented.**

***Index Terms*—Actuators, collaborative robots, human–robot collaboration (HRC), human–robot interaction, physical HRC (pHRC), robotic systems, sensors.**

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I. Introduction

For decades, robots have been employed in various areas of human endeavors. A robot can operate either in autonomous or collaborative modes. In the autonomous mode, the operational process often requires little or no human support. However, this mode of operation limits the applicability of a robot to certain domains of human endeavors as it is challenging for a robot to accomplish an assigned task alone in a real-world environment, which is full of uncertainties and dynamic in nature [1]. Besides the autonomous mode of operation, a robot can collaborate with humans physically or remotely to perform a task. The collaboration perhaps includes shared knowledge, experience, and belief about the task goal to be achieved [2].

By collaborating, human dexterity and flexibility are combined with the repeatability and precision of a robot which results in reduced human workload, increased productivity, and applicability of robots in more areas of human endeavors [3], [4]. The collaboration could be seen in the human-exoskeleton skill transfer, where the exoskeleton may be required to replicate the human operator's arm impedance performance or to compensate external disturbance. Some recently conducted works to investigate the human-exoskeleton skill transfer capable of achieving desirable performance both in parametrized and unparametrized circumstances are discussed in [5] and [6], respectively. These kinds of robots are conventionally called collaborative robots and are built with unique technologies to ensure compliances with the International Organization for Standardization (ISO) specifications for designing and manufacturing collaborative robots [7]–[9].

To achieve intuitive physical human–robot collaboration (pHRC), a robot must be able to observe its surroundings in order to take cognizance and continuous update of the current state of its surroundings. With such information in place, a robot could be endowed with the ability to estimate desired actions to be performed and the best possible way to perform them. For instance, a robot collaborating with a human in a table-lifting task is expected to identify the items in the environment, including the table, predict human future intention, and coordinate its activities toward the successful completion of the task. These capabilities cannot be

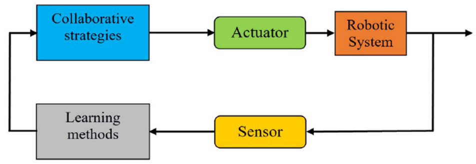
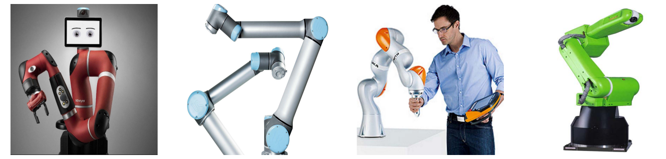


Fig. 1. Block diagram to describe how collaborative strategies relate to the learning methods, and both the sensors and actuators, and the robotic system.



(a) (b) (c) (d)

Fig. 2. Single-arm collaborative robots. (a) Sawyer [16], (b) Universal [17], (c) KUKA 7 R800 [18], and (d) Fanuc-CR35ia [19].

(a) (b) (c) (d)

Fig. 3. Dual-arm collaborative robots. (a) Baxter robot [16], (b) Yumi [20], (c) NEXTAGE Open [21], and (d) PR2 [22].

naturally endowed in the robot directly from the manufacturers but could be learned through the appropriate learning method. In recent years, robots are increasingly being taught predominantly using the machine learning techniques. This partially solves the dimensionality problem and the computational challenge of actively coding all the steps required for every collaborative action. However, after a task is learned, the issue of optimal implementation of the task follows. But with proper task planning and effective collaborative strategies, a robot can effectively collaborate with a human to accomplish a desired goal [10].

All of these functionalities could not be possible in the absence of the state-of-the-art technologies, especially the sensors and actuators. In robotics, sensors serve as channels through which a robot can acquire knowledge about their surroundings, communicate contents, and give feedback to the environment or users. On the other hand, actuators convert the control signals into motions in the relative joints and body of the robots (e.g., soft robotic systems). Hence, these technologies either embedded or physically attached the hallmarks of any robotic systems suitable for effective pHRC. More details of these two important components are further discussed in Section III of this article.

Several scholars have carried out a survey to describe the synergy that could exist between human and robot in a view to accomplish a task [11]. Chandrasekaran and Conrad [12] presented a survey on human–robot collaboration (HRC); however, little attention was paid on the collaborative strategies and sensing technologies involved. Further work has addressed the sensing and collaborative strategies [13], [14], but both works focused on the safety interaction between humans and robots in an industrial setting. Furthermore, Ajoudani *et al.* [15] reported the control strategies, interaction modalities, and collaborative interfaces for pHRC. Although these scholars made efforts to present an up-to-date overview on HRC, but to the best of our knowledge, none of them covered exhaustively the most relevant challenges due to the fast-growing trends in the pHRC technologies and the tremendous demands in the applicability of the robotic systems in our day-to-day activities.

In these regards, an updated overview of the state-of-the-art survey on pHRC is presented. This article presents a comprehensive review of the state-of-the-art robotic systems with cutting-edge technologies, such as sensors and actuators for pHRC. The collaborative strategies and the learning methods useful for pHRC are also discussed.

Fig. 1 depicts that for an effective pHRC to be implemented, relevant components, such as sensors, actuators, suitable robotic system, appropriate collaborative strategies, and learning methods need to be carefully considered and chosen.

The remainder of this article is organized as follows. Section II provides a highlight of the robotic systems and other intelligent assist devices for pHRC. In Section III, different kinds of sensors and actuators used in pHRC are discussed. Section IV concentrates on the formulation of actions, task planning, and other collaborative strategies. The robot learning methodologies in different collaborative scenarios are discussed in Section V. Safety issues, control designs, and human factors are presented and discussed in Section VI while discussion and conclusion are presented in Section VII.

II. Robotic Systems

The robotic systems discussed herein are grouped based on their application purposes, prominent mechanical structures, and adaptive features. However, we acknowledge the possibilities of overlap of the robotic system, making it possible to have a robotic assist device that is also a wearable robotic system.

A. Collaborative Robotic Arms

The collaborative robot can work safely in a shared space with humans. In addition, they are power and force limited, compact, lightweight, dexterous, and the majority could be hand guided through a path by the user in order to accomplish a task, hence allowing the users with little or no knowledge of programming to use them. Various prominent collaborative robots with cutting edge technologies suitable for pHRC operations are presented in this section. They are grouped into single-arm (see Fig. 2) and dual-arm (see Fig. 3) for clarity and better understanding, and based on their physical features and areas of application. Tables I and II present the unique features found in the single-arm and dual-arm collaborative robots, respectively. Apart from the physical and structural difference between the single-arm and the dual-arm collaborative robots, there are some salient global features which serve as strengths of each group. For instance, single-arm robots are faster and highly efficient in carrying out their tasks. They

TABLE I
SINGLE-ARM ROBOTS AND THEIR UNIQUE FEATURES

Robot	DOF	Rep(mm)	Payload(kg)
Sawyer	7	±0.1	4
UR3, UR5, UR10	6	±0.1	3, 5, 10
KUKA LBR 7R800	7	±0.1	7
Fanuc RC-35iA	4	±0.08	35
Robot	Simulator	Actuator	R/C
Sawyer	Moveit, Gazebo & V-REP	SEAs	R/C
UR3, UR5, UR10	RoboDK, V-REP Moveit & Polyscope	SEAs	R/C
KUKA LBR 7R800	KUKA Sim	SEAs	R/C
Fanuc RC-35iA	ROBOGUIDE	N/A	C

Rep = Repeatability, R/C = Research and Commercial Oriented, and C = Commercial Oriented

TABLE II
DUAL-ARM ROBOTS AND THEIR UNIQUE FEATURES

Robot	DOF	Rep(mm)	Payload(kg)
Baxter	7	±0.1	2.2
Yumi	7	±0.2	0.5
NEXTAGE	6	±0.03	1.5
PR2	4	± N/A	1.8
Robot	Simulator	Actuator	R/C
Baxter	Moveit, Gazebo & V-REP	SEAs	R/C
Yumi	RoboDK, V-REP Moveit & Polyscope	SEAs	R/C
NEXTAGE	RoboDK, V-REP Moveit & Polyscope	SEAs	R/C
PR2	RoboDK, V-REP Moveit & Polyscope	SEAs	R

Rep = Repeatability, R/C = Research and Commercial Oriented, C = Commercial Oriented and R = Research Oriented

are accurate and precise, flexible deployment, and fast set-up procedures while the dual-arm robots provide the users with human-like control over their environments, multiple simultaneous tasks, and synchronized motion which enables safe handling of larger and heavier parts.

1) Single-Arm Robots: Sawyer is a product of Rethink Robotic and was manufactured while targeting high-precision tasks. Sawyer comes with Intera Studio which is a graphical user interface (GUI) that allows the users with limited technical skills to program the robot. Other unique features include that it is faster, lighter, and more precise than Baxter (see Section II-A2). Having been designed to maneuver in a tight space or occupy a small space, Sawyer can perform more tasks and stand the chance of being a better candidate for the industries.

Universal robots (URs) came up with three sets of 6-DOF collaborative robots, namely, UR3, UR5, and UR10. The working ranges for the UR3, UR5, and UR10 are 50 mm, 850 mm, and 1300 mm, respectively. This set of UR robots is known for low noise when in production, and are easy to handle, adaptive, and easy to customize the end effector.

KUKA, a German robot manufacturer, also joined the league of collaborative robot manufacturers and came up with a lightweight collaborative robot called LBR IIWA 7-R800 [3]. Although KUKA has an excellent power to weight ratio, equipped with unique sensors that detect microimpact at the joints; it is, however, quite expensive, and that might discourage buyers.

Fanuc RC-35iA is known as the strongest collaborative robot; it weighs 990 kg and can operate at a maximum payload of 35 kg. Fanuc is good for heavy industrial applications, machine tending, and automation services. It is dexterous and compact but lacks the teaching by demonstration feature and has no research version. Some of these missing features perhaps can discourage the potential users from acquiring the robot.

2) Dual-Arm Robots: Baxter makes use of the same operating system and end-effector design interface with the Sawyer robot. It has a very nice-looking structure suitable to handle and manipulate the objects simultaneously, however, it lacks good precision when compared with Sawyer (see Section II-A1). It also occupies more space, making it less attractive to the industries.

Yumi was developed by ABB Robotic and the target is for small part assembly and for testing and packaging operations in the industries [23]. Yumi is a low-cost adaptable robot. It is also flexible, easy to program, and very sensitive to outside forces. Furthermore, its compact and small-sized appearance makes it portable and suitable for many industries and research institutions.

NEXTAGE has 6-DOF per arm. It weighs 29 kg and can support a maximum of 1.5-kg payload on each arm. It is also compatible with ROS. Other interesting features include low-power motors at its joints, making it safer if it collides with an object or a human, and the ability to perform complex tasks and fine manipulation due to the high DOFs of the rotating axes at its neck and waist. However, it is only sold in the Asian market.

The PR2, which is for research purposes, is equipped with a lot of sensors, including fingertip pressure sensors and accelerometers at the end effectors. The PR2 is also equipped with a laser-based scan rangefinder [24] and is compatible with ROS [25]. Considering the shape and size, PR2 is suitable for both small-sized and narrow-spaced research labs; it is also mobile and could easily be moved from one lab to another.

B. Wearable Robotic Systems

The wearable robotic systems are currently employed in different areas to improve a damaged body function or to enhance the physical abilities.

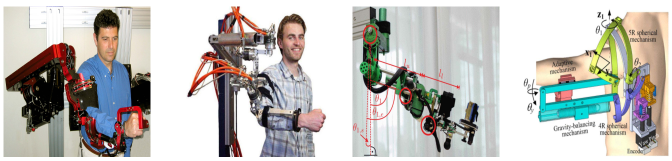
1) Upper-Limb Wearable Robotic Systems: Different types of upper-limb wearable robotic arms have been proposed and designed by various researchers. Some notable wearable upper-limb robotic arms (see Fig. 4) and their unique features are presented in Table III.

The University of California at Los Angeles (UCLA), Bionic Lab developed an exoskeleton robot (EXO-UL7) which has the same DOF as a human hand [30]. In order to support human–machine interaction, the robot is equipped with force/torque sensors on the upper arm, the lower arm, the hand, and the tips [26]. The operation of this

TABLE III
UPPER-LIMB WEARABLE ROBOTIC ARMS

Robot	DOF	Actuator	R/C
EXO-UL7	7	DC motors	R
LIMPACT	N/A	Hydraulic	R/C
ARMin-V	7	Electric motor	R
[29]	6	SEAs	R/C
HEXAR	6	Electric motor	R

R/C = Research and Commercial Oriented, and
R = Research Oriented



(a) (b) (c) (d)

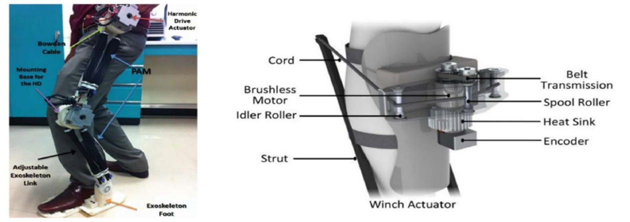
Fig. 4. Wearable robotic arms. (a) EXO-UL7 [26], (b) LIMPACT [27], (c) ARMin-V [28], and (d) CAD model of the parallel actuated exoskeleton [29].

device is based on a muscular signal generated from the human–machine interface (bioport) using electromyography (EMG). Similarly, Li *et al.* [31] proposed an asymmetric bimanual coordinate control for the dual-arm exoskeleton to perform human-cooperative manipulation. The contribution of this article focused on handling the physical constraints, such as joint limits and torque limits, via the use of human motion intention reflected during the interaction and the use of impedance parameters approximation to estimate the variable stiffness which measures the force and position of the dual-arm end effector.

The major aim of developing LIMPACT is for reflex identification on the arm of a stroke survivor. The identified reflex could be used to design an optimized program therapy for stroke survivors [27]. The LIMPACT has a torque-controlled motors with a maximum of 79-Hz bandwidth which allows for smooth zero impedance control. The actuation mechanism in LIMPACT is based on hydraulics powered by an electric motor. LIMPACT is equipped with a passive weight balancing mechanism to compensate for the heavy load, usually experienced in the exoskeleton, and to maintain a smooth trajectory.

The ARMin-V is a 7-DOF exoskeleton robot that is actuated by direct current (dc) motor [32]. The earlier version was proposed for rehabilitation of stroke patient; but does not incorporate online adaptive compensation. This feature is the major contribution of ARMin-V and it increased the performance of the robot to the level of adjusting patient's anthropometry automatically [28]. Another work in [33] presents a framework for adaptive admittance control by incorporating and considering human motion intention in order to perform more accurately in the actual physical interaction. The framework consists of double control loops with the inner loop overseeing the unknown masses and inertia of the robot dynamics while the outer loop harmonies the interaction based on the observed intention of the subject.

A parallel actuated exoskeleton was proposed in [29] to provide after stroke rehabilitation. The system is a 6-DOF exoskeleton which comes with two linear series elastic actuator



(a) (b)

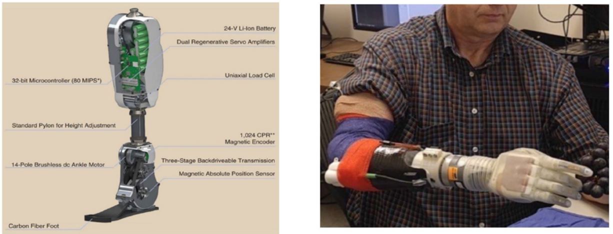
Fig. 5. (a) System uses a hybrid of pneumatic-electric system with a harmonic drive actuator to enhance its strength [35]. (b) Autonomous leg exoskeleton consists of a winch actuator and fiberglass struct that directly apply a resultant torque about the human ankle joint during walking [40].

(SEA) for interactive force control and two gravity mechanisms to increase the device compatibility and minimize the load of the motor [29]. Maciejasz *et al.* [34] claimed that using SEA reduces the impedance of the exoskeleton more than what the result of using feedback from pressure and force sensors could do.

2) Lower-Limb Wearable Robotic Systems: Several lower-limb wearable robotic systems have been developed in the past for rehabilitation and enhancement of the strength of the lower-limb to help in carrying heavy loads. Aguilar-Sierra [35] designed a hybrid actuated lower-limb wearable robot for force augmentation and cyclic rehabilitation [see Fig. 5(a)]. The lower-limb wearable robotic systems have also received great attention in the study to minimize the metabolic cost by using the powered ankle–foot orthosis [36]–[38]. Furthermore, Collins *et al.* [39] developed a recent ankle exoskeleton device which has been able to lower the metabolic cost by 7.2%. This came after the breakthrough of the one developed by the Massachusetts Institute of Technology (MIT) which led to an 8% reduction in the metabolic cost of the user [40] [see Fig. 5(b)]. As another one, Li *et al.* [41] developed a human-cooperative control exoskeleton for human locomotion assistance in climbing stairs without crutches. This is achieved by the adaptive controller designed to simultaneously incorporate the human's and robot's capabilities.

The lower-limb wearable robotic systems are often used interchangeably with the walking-assist devices (see Section II-C2), however, the former mainly aims at supporting healthy people and for lower-limb rehabilitation while the latter aims at supporting elderly people or paraplegics. Furthermore, the lower-limb wearable robotic systems are mainly employed to enhance the strength of healthy people in performing heavy tasks, like in carrying heavy loads, and as a therapy for lower-limb movement rehabilitation, like in a stroke patient while the walking-assist devices are mainly employed to reduce the load on human legs and provide motion support necessary to generate the force needed to perform the intended stride.

3) Prosthetics: The prosthesis is receiving great attention in both the upper-extremity and lower-extremity [42], (see Fig. 6). Despite the success of prosthesis, Li *et al.* [42] and Wijk and Carlsson [43] noted that the most common commercial prostheses cannot support users in performing daily living activities, such as grasping and holding onto an object



(a) (b)

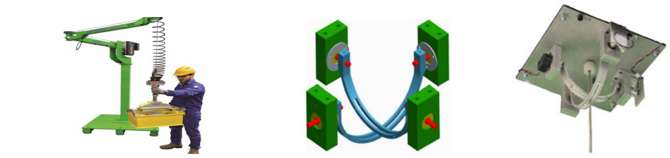
Fig. 6. Prototypes of the prostheses. (a) Powered prosthesis with a hybrid-controlled piecewise-passive impedance-based designed to provide level walking functionality for amputees [48]. (b) University of Utahs neuroprosthetic prosthetic arm which allows amputees to regain the sense of pressure, vibration, temperature, pain, and movements by creating a connection between their brain and a computer [49].

without slip, due to either the absence of perceptual tactile feedback or no tactile feedback at all. It was recorded that by measuring the characteristics of touch, tactile sensing can improve the ability of the amputee to achieve a stable grasp and prevent slip [44], [45]. To extend on that, various methods were proposed to sense slip in the prosthesis. Masuda *et al.* [46] proposed the object displacement measurement to detect when slip is obvious. However, it is hard to determine the minimum displacement required before a slip can occur. Hence, the object could be lost from the hand before appropriate actions could be taken to prevent a slip. Alternatively, sensing vibration on the hand can be an indication that a slip is about to occur and an accurate estimation of friction coefficient can help to determine the possibility of slip occurring [47].

C. Robotic Assist Devices

1) Power Assist Suits: This device is designed specially to support workers with lifting or carrying heavy objects. In 2016, Panasonic unveiled the Assist Suit AWN-03 (AWN-03) which provides a worker with lower back support [50]. The AWN-03 senses the motion of the user while lifting an object and then sends a signal to the motors to rotate the machine gears to support the weight of the object. In addition, it makes the strain on the back decrease by 15 kg as it raises the user's upper body and pushes down on his or her thighs, hence increasing the quality of work and reducing the burden of the weight on the user. The MuscleSuits (Innophys Company Ltd.), which is powered by the compressed air and hybrid-assistive limb (HAL) exoskeleton suits produced by Cyberdyne Inc., performs similar functions as AWN-03 [51].

2) Walking Assist Devices: This was developed to support bodyweight and reduce the load on human legs while walking. In 2009, Honda published a paper detailing the working principles of their WAD first product. The control mechanism of the WAD is based on finding a balancing point between the target assist desired force of the user with the generated force feedback from the force sensors attached to the foot arches of the WAD [52]. Similarly, the WalkON Suit was designed to assist paraplegics to walk and exercise [53]. The control technology is based on a hybrid actuation mechanism and a biarticular transmission system.



(a) (b) (c)

Fig. 7. (a) Handle controlled IAD for load lifting assistance, (b) and (c) depict a CAD model of the cable angle sensor and a prototype of the cable angle sensor, respectively [55].

3) Intelligent Assist Devices: Colgate *et al.* [54] described the IAD as an intelligent machine that optimizes moving and lifting operations by reducing the physical force involvement of a human partner. Compared with the traditional lifting manipulators, IAD is better because it is easier to operate, safer, and allows for easy control of the payload motion [see Fig. 7(a)]. The IADs have gained huge applications in the airport where they are used to load baggage from the chute to the open cart, in the automobile assembly plant to assembly parts, and to load and offload parcels in the parcel distribution centers, such as TNT and StarTrack.

In most IADs, the operator manipulates the system through an instrumented control handle which could be equipped with force sensors to measure the force applied on the load by the operator [54]. However, the force is affected by the dynamical effects of the payload. This must be accounted for, in order to properly estimate the force needed to effectively move the payload around. Based on that, the cable angle sensor [55] [see Fig. 7(b) and (c)] was introduced by researchers to deal with this challenge. The suspended cable [see Fig. 7(c)] is passed through the concentric groove parts in order to drive them individually as it moves along one of the concentric parts. Each concentric part is attached to a shaft and the cable angles are obtained by measuring the shaft rotation. The authors claimed that the effect of dynamics on the cable is negligible because the design makes moving the payload lighter and smoother. Despite the research progress, there is still demand for a researchable solution, as it is still challenging to find the most appropriate way to measure the inclination of the cable sensor.

III. Sensors and Actuators

A. Robotic Sensors

1) Vision-Based Sensors: Recently, camera sensors are mostly used in pHRC to observe the environment because they are convenient, relatively cheap, and easy to use. A camera sensor can provide RGB information and depth information for robot utilization. The Kinect sensor is a popular camera sensor that is designed to provide RGB-D information at the rate of 30 Hz. It can also provide human tracking API [56], which works effectively even in real time [57]. The Kinect sensor has been significantly utilized in [58]–[60] to track the human body motion that is employed for robot control. The limitation of a camera sensor is that it is prone to occlusion and suffers from light conditions, such as reflection and contrast (see Table IV for more details).

2) Robotic Skin: A lot of attention has been paid on classifying sensing technologies based on their sensing principles

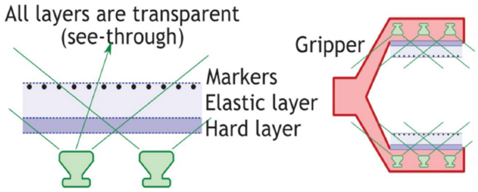


Fig. 8. Conceptual design of the optical skin-based sensor as it is installed on a robotic gripper.

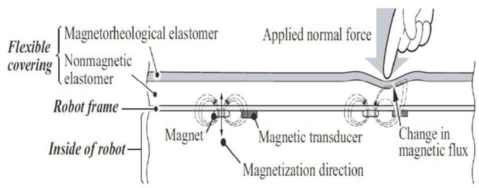


Fig. 9. Certain amount of magnetic flux generated by the magnet penetrates the elastomer as shown in the left section of the figure, however in the presence of contact force, the magnetic flux penetration increases because of a decrease in the distance between the magnet and the transducer as shown in the right section of the figure.

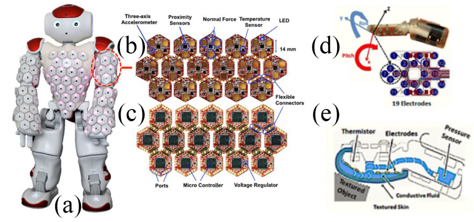


Fig. 10. (a) NAO equipped with the sensor on the chest, the fore and upper arms. (b) and (c) Front and back views of the multisensing devices, connectors, voltage regulator, ports, and micro controllers.

and designed technologies, such as resistive, capacitive, piezo-electric, acoustic, and so on. (For a more detailed review, see [42] and [61].) However, the design could be done differently by paying attention to the tactile information processing. One interesting and useful sensor that has moved toward this direction is the robotic skin. The technology provides rich and direct feedback that enables robotic systems to identify objects via multiple contact points. Details on the strengths and weaknesses of the sensors are summarized in Table IV.

1) *Optical Skin-Based Sensors:* The general idea of an optical skin-based sensor is to develop a multimodal sensor capable of providing both tactile and visual information. Inline with that some researchers proposed to cover the skin surface of the sensor with an opaque material meant to shut out external light from entering the sensor. However, the use of an opaque material limits the information provided by the visual sensor; hence, making them focus only on the tactile information. To address this, a prototype consisting of transparent skin, cameras, and colored markers was proposed in [62]. The proposed sensing skin gives a high resolution of contact force and proximity vision. The markers are used to track skin deformation which is proportional to the displacement caused by the external force. The camera lens is focused on the markers as shown in Fig. 8 to improve the markers' tracking quality. The authors discovered that the tracked skin deformed information could be used for contact force and torque estimation [63].

2) *Soft Skin-Based Sensors:* A wide variety of conventional flexible sensors faces technical issues that reduce the sensitivity of the sensor. For example, aging and mechanical stress can lead to hysteresis and reduction in the sensitivity of the sensor [64], [65]. To address this challenge, Kawasetsu *et al.* [66] proposed a magnetorheological tactile sensor consisting of a flexible upper and lower layers elastomer. A deformation on the elastomer sheet causes a change in the magnetic flux which affects the spatial response of the sensor. This is because the applied force (see Fig. 9) causes a decrease in the distance between the upper layer and the transducer which, in turn, increases the level of magnetic flux penetrating the transducer. In a similar work, Kaboli and Cheng [67] developed an in-hand object exploration tactile descriptor to extract the robust tactile information from the generated vibrotactile signal. The proposed learning transfer algorithm works by first measuring the dynamic pressure signal at a sample rate of 2 kHz and second the Shadow Hand via the impedance-sensing electrodes which explores the texture of the object at a sample rate of 50 kHz. Then, the impedance-sensing electrodes enable the deformation on the skin surface to be measured. The measured deformation amounts to the force applied on the surface of the skin. The drawback is that the vibrotactile signal is prone to noise and filtering it out is computationally expensive. In another work, a set of novel tactile descriptors for multimodal robotic skin (see Fig. 10) to discriminate among objects and material via their textural properties was proposed in [68]. Their tactile descriptors considered the statistical properties of the tactile signals both in stationary and dynamic states, hence, making it invariant with respect to exploratory movement and time.

3) Electromyography and Electroencephalography: The EMG sensor is used to record the activities of electrical signals that are generated when a muscle contracts. Information from the systems could be used to estimate human limb motion [69], [70] which is essential for the reconstruction of robotic prosthetic for amputees and also important for limb rehabilitation [71], [72]. This system has been applied to detect hand grasping actions in [73] and [74] to transfer the writing skill from a human to a robot.

The electroencephalography (EEG) signal has been used purposely for communication between the human brain and a computer system, to diagnose epilepsy [75] and other brain disorders [76]. Currently, this signal capability is extended to establish the communication between the human brain and a robotic system [77], and to send a control signal from a human to a robotic system [78]. The strengths and weaknesses of the sensors are summarized in Table IV.

4) Data Gloves: A data glove can provide information about a human hand motion, hand pose, and orientation in 3-D space [79] and even force information [80]. The application of enhanced sensors, such as inertial measurement unit,

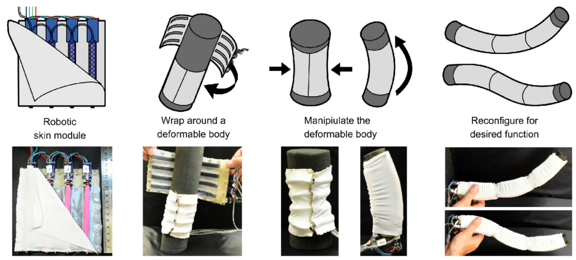


Fig. 11. (a) Robotic skins with embedded distributed actuators used to transform inanimate object into a moving object. (b) Robotic skins can be wrapped around deformable objects to produce different forms of deformetions as shown in (c). (d) Multiple robotic skins can be wrapped on a deformable object to produce complex motions [88].

has made it possible for other information of the human hand activities, such as acceleration, angular velocity, and magnetic field to be measured using the data glove [81], [82]. Fang *et al.* [83] proposed a novel data glove which can capture human arm-hand motions simultaneously. This allows the glove to be fully mapped to a robotic arm-hand system; hence, allowing the robot to perform intuitive motions when teleoperated. For convenience sake, the device is compact, portable, and uses Bluetooth for operational data transfer to the robotic system. (See Table IV for more details on the strengths and weaknesses of the data gloves.)

B. Actuators for Collaborative Robots

Generally, actuators could be categorized into pneumatic, which uses compressed air to generate motion; hydraulic, which uses compressed fluid to generate motion; electric, which uses electric current or magnet to generate motion; and a hybrid of the aforementioned categories. Table V presents the strengths and weaknesses of the discussed actuators.

1) Pneumatic Technologies: The pneumatic technology has been applied to create artificial muscle in robot hands [84], [85] and to generate motion in soft-robotics [86], [87]. This kind of actuator is desirable in safety-conscious robotic design, especially, those intended to interact with human and delicate contact surfaces [86]. One of its drawbacks is that it is difficult to control due to the nonlinearity of the actuator. Considering the unpredictable and unstructured nature of the space environment, Booth *et al.* [88] proposed a multifunctional robotic skin to enable complex motions and functions.

The device integrates both actuation and sensing into a single material to enable the multiple motions control that can turn inanimate objects into multifunctional robots. The skin is modulated [see Fig. 11(a)] and could be wrapped around deformable objects [see Fig. 11(b)] so they could be manipulated [see Fig. 11(c)] to achieve complex motions [see Fig. 11(d)]. The devices are easy to remove and apply to other objects with little or no reconfiguration.

2) Electric Motors: Electric motors often produce high speed but produce poor torque density. By using the reduced gear technique, the torque could be improved but with a trade-off to speed. Other disadvantages of using a reduced gear technique include that it introduces friction, backlash, torque

TABLE IV
STRENGTHS AND WEAKNESSES OF THE pHRC SENSORS

Sensing method	Strengths	Weaknesses
Vision-based sensors	Popular, available support from community of users, easy to use.	Affected by occlusion, suffers from light conditions such as reflection and contrast.
Optical-based tactile robotic skin sensor	Grasp stability and slip detection, contact force and torque estimation, robust to electrical interference.	Fragility and rough estimation.
Soft tactile robotic skin sensor	Suitable for object exploration, contact point manipulation, object recognition, texture & classification.	Ageing and mechanical Stress causes hysteresis & reduction in the sensitivity of the sensor.
EMG/EEG	Versatile and quick user adaptation.	Drift in sensing output, information redundancy, required advance processing technique to extract reliable control signal.
Data Glove	Complementary inputs.	calibration required, selection is technically specific, limited portability.

TABLE V
STRENGTHS AND WEAKNESSES OF THE pHRC ACTUATORS

Sensing method	Strengths	Weaknesses
Pneumatic Technologies	Desirable in safety-conscious robotic design, especially those intended to interact with human and delicate contact surfaces.	Difficult to control due to the non-linearity of the actuator.
Electric Motors	Has good shock absorbing properties, robust to electrical interference.	Often produces poor torque density.
Hydraulic Actuators	Can provide high torque, stays robust to burnout, and can maintain very strong linear motion without gears.	Susceptible to the temperature of the liquid it is made of & difficult to miniaturize.

ripple, and noise to the robotic systems [89]. Because of these challenges, the SEA could be used in their place. The SEA protects the robot from shock when it collides with an object [57]. It is even applied in exoskeletons for interactive force control between the human and the robot co-worker [90]. Despite the success of SEA, it may not be the best actuator for robots that need high degrees of stiffness. In that case, a variable stiffness actuator (VSA) is the remedy [91], [92]. The technology could also be in the form of a variable impedance actuator (VIA) which varies its stiffness as a response to change in the impedance [93]. VSA and VIA actuators have better shock-absorbing properties than SEA as they can store and release energy in passive elastic elements [94].

3) Hydraulic Actuators: The hydraulic actuator is good for carrying heavy loads and it is generally known to have fewer problems when exposed to heat. It can also provide high torque, stays robust to burnout, and maintain very strong linear motion without gears. However, the hydraulic actuators could be susceptible to the temperature of the liquid used and difficult to miniaturize. Despite its limitations, it has found favor in wearable and in mobile robotic systems as demonstrated in [95] and [96], where the authors utilized the actuator to assist human users to carry a heavier load.

IV. COLLABORATIVE STRATEGIES OF pHRC

Collaborative strategies deal with different levels of ideas: joint attention formulation, turn-taking, task planning, and knowledge representation.

A. Joint Attention Formulation

Several techniques and methods have been used in different fields to bring the attention of individuals toward activating their readiness to participate in a joint task or to establish either a common ground or bond between the minds of the collaborators [97], [98]. A successfully formulated joint attention draws the participants toward a shared focus on an object or other areas of interest [98]. These techniques have been successfully applied in HRI for children with autism spectrum disorders (ASDs) [99], [100]. Attention formulation could be achieved either by deictic words or vocal expressions, such as "look here, see me, look right, or next one," by pointing gesture, by using line of sight, by using communication cue such as eye gazing [101], [102], or by a combination of vocal and gesture commands [103], [104].

B. Turn-Taking

Turn-taking is one of the mechanisms for coordinating smooth and excellent conversation between two or more people [105]. This idea has advanced from human–human conversation to earn applications in human–robot interaction and collaboration [106]. Several approaches have been proposed to implement turn-taking. Among others are the use of signaling approach, such as gaze [107], [108]; gesture [109]; and body language [110]; and by means of verbal communications [106]. Not only does a robot needs to understand when turn-taking occurs but it is also necessary for a robot to recognize when a human is yielding to a turn and the end of a turn for a timely response to be given to the human partner.

C. Task Planning and Knowledge Representation

The most commonly used task planner is the human-aware task planner (HATP). HATP is a hierarchical task planning approach that is capable of taking into account both the state and the task preferences of a human in a collaborative task with a robot as demonstrated in [111] and [112]. Similarly, a human-aware task motion planning was presented in [113] to endow a robot with the ability to estimate human intents and produce acceptable behaviors. Furthermore, some researchers have also employed the Stanford Research Institute Problem Solver (STRIP) planner due to its simplicity and capability to solidly represent a domain of interest [114], [115]. Continuous update of symbolic knowledge about the robot belief of the world could be made available and maintained in a knowledge base like the spatial reasoning knowledge (SPARK) [116]. Sisbot *et al.* [117] proposed a situation assessment framework that focused on HRC in the object manipulation. The authors built an open robots ontology (ORO) knowledge-base to maintain a symbolic representation of the state of the world.

V. Robot Learning Methodologies

It is practically impossible to precode a robot to cope with all the actions needed to satisfactorily collaborate with humans in a complex and dynamic environment like ours. Because of this reason, the learning algorithms are employed to facilitate the ability of a robotic system to cope in such situations.

Recently, the artificial neural network (ANN) and its derivative deep learning are increasingly applied in different scenarios involving pHRC. A neural-network human emotional expression recognition model was proposed in [118]. In the paper, Vircikova *et al.* trained a humanoid robot to learn a human emotional expression and respond to it accordingly. Mayer *et al.* [119] applied the recurrent neural networks (RNNs) to learn surgical knotting for minimally invasive surgery framework. Yang *et al.* [120] proposed a neural-learning-based telerobot control at both kinematic and dynamic levels. Neural networks are generally known for having strong approximation and good at handling redundancy, noise control, and a large volume of data [121]. Pinto and Gupta [122] used the convolutional neural networks to train a robot to randomly grasp an object. The authors argued that their method eliminates the issue of bias that often come up when a human being manually annotates the grasping location of the objects. The two major drawbacks of deep learning are that it requires a long training period and has high computational cost [123].

The support vector machine (SVM) is another technique that has earned popularity in human action recognition and human motion prediction due to its good recognition accuracy and fast training time [124]. Kaplan [125] proposed a model to optimize task performance human–robot collaborative minimally invasive surgery operations using the SVM classifier. The SVM classifier was used to train the robot to predict the future human motion [126] which enables it to estimate the human's region of interest and comply accordingly.

The Gaussian mixture model (GMM) is one of the most popular methods amongst the learning techniques employed in the pHRC research work. Some of the features that made it unique are as follows.

1) The ability to tolerate an arbitrarily large number of Gaussian components and a small number of variances.
2) The fast convergence process, which makes it computationally inexpensive.

The GMM technique was systematically used in [127] to perform a human to a robot object manipulation skill transfer based on active learning. In this article, the robot observed the demonstration via the motion sensing system while GMM was used to encode sets of trajectories gathered from the sensor. Furthermore, GMM was employed in [128] to learn a trajectory tube insertion for the surgery task. Rozo *et al.* [129] proposed a framework to exploit both position and force data in HRC. The authors tested the proposed technique on two different experiments involving the robot handling both the position and force constraints in a collaborative box transportation task and collaborative assembly of a wooden IKEA table.

The hidden Markov model (HMM) has been widely used to model robot learning collaborative interaction with humans [130]–[132]. HMM is derived from a Markov process which believes that the current state of a system depends solely on the system's prior state. Several authors have suggested using HMM to encode and reproduce demonstrated action where noise in the observation is inevitable [133], [134].

Dynamic movement primitive (DMP) has been extensively used in pHRC, especially in learning the control policy of

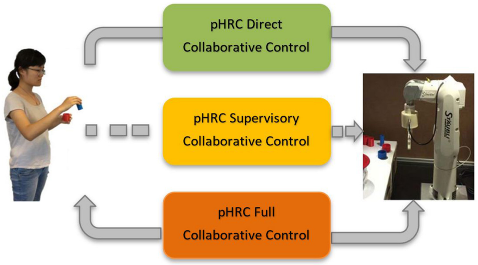


Fig. 12. Block diagram to describe the different design control concepts in pHRC.

human motion trajectories [135], [136]. Prada *et al.* [137] proposed a generic DMP framework to ensure human-friendly and fluent robot motion in object hand-over interaction between human and robot collaborator. Using a collection of sequences of captured motion configurations of two people demonstrating object hand-over task in an industrial context, the authors trained a robot to learn the control motion hand-over task.

Reinforcement learning (RL) applies a reward policy upon which an agent depends to improve its learned behavior. In RL, the error outcome of a previously performed action is used to update the action state policy of the robot, thereby serving as a way of strengthening the belief state of the robot [138]. Gu *et al.* [139] proposed an RL technique to improve the rate at which a robot learns dynamic tasks and motor primitives [140]. In this case, the tasks learned are to hold a table in a suitable position and cooperatively lift the table with human collaborator while keeping it horizontal. Dimeas and Aspragathos [141] applied the RL technique to learn variable admittance control for human–robot co-manipulation.

VI. Safety Issues, Control Designs, and Human Factors

A. Safety Issues

The coexistence of human and robot poses a safety threat both to humans and the collaborating environment. Because of that, the ISO enacted a safety standard (ISO TS 15066) for the collaborative industrial robotic systems as specified in [9]. Hence, most of the recently produced collaborative robots have the collision detection sensors embedded in them. The sensors could be in the form of an embedded accelerometer, tactile sensors, or current feedback which could be felt when an abnormal force is sensed by the robot [142]. Other approaches applied in safety include collision avoidance and collision detection. This feature could be achieved in robot applications by proper motion planning and control of some sensory systems [143], [144]. Ogren *et al.* [145] used a potential field approach to implement collision avoidance. In their work, repulsive and attractive fields were associated with the obstacle and the target objects, respectively.

B. Control Designs in pHRC

In the context of this research, the pHRC control is classified into direct, supervisory, and fully collaborative controls as presented in Fig. 12.

In direct control design, a human is totally in control of the robot manipulation and as such the control decision is wholly taken by a human while the robotic system plays a passive role only. This is not an efficient system control design as the performance of the operation depends soley on the skills and experience of the human operator. This kind of control model has found applications in motor control learning [146]–[148] and robot imitating human actions [149]. Using agonistic and antagonistic signals extracted from the human joint, Li *et al.* [150] proposed an EMG-based upper-limb robot assistant exoskeleton control system. In this article, the authors employed a linear discriminant analysis-based classifier to indicate the kind of motion in the joint which enables them to estimate the torque control signal.

In supervisory control design, human and robot establish a shared control or traded control scenario. A robot makes most of the decision while humans are required in the control loop occasionally and when necessary. This contributes so much in reducing the idle time of a robotic system in operation. A group of researchers from NASA's Johnson Space Center (JSC) has developed a graphic interface suite called predictive interactive graphical interface (PIGI) to accomplish suspensory control of a robot in the space using a communication latency of 5–10 s (see [151]).

In a fully collaborative control, the robot is made to be aware of its environment and play both adaptive and self-reliance roles, hence, making the collaboration between the human and robot intuitive. A lot of efforts have been made to address the interactive behavior between the human and robot as demonstrated in [152]. Evrard and Kheddar [153] proposed a robot adaptive control focusing on allowing the robot to play the roles of either a task leader or follower based on the intention of human collaborator. Using the game theory, Li *et al.* [154] proposed a role adaptive framework that enables the robot to adjust its role in accordance with the human intention.

C. Human Factors

Several human factors could be the issues in the usability, effectiveness, safety, and administering of a robotic system for HRC. Based on this, administering exoskeleton to a subject could be challenging due to the vast variation and compositions of various human body parts. In Cybathlon [53], the earlier evaluation revealed that the bone mineral density of the subject was within the normal limit, however, later evaluation showed that the rate of motion of his knee joints has been limited due to prolonged use of a wheelchair. Hence, how to analyze the wearable robotic devices and prosthesis to obtain the best physical form remains a challenge. Human attitude and perception toward the robotic systems are essential in the performance cooperation of human–robot teammate. The level of trust will directly affect the willingness of a human teammate to follow the robot's suggestions or instructions [155]. The need for the robotic system and a human team worker to build a mental model of each other has been suggested long ago as it would reduce the risk of human error and ensure safer interaction of them [156], [157].

VII. Discussion and Conclusion

Considering the unstructured and dynamic nature of the human environment, most of the collaborative robots are equipped with inbuilt sophisticated sensors, collaborative interfaces, and enhanced control systems to improve safety and collaborative abilities of the robotic systems. Furthermore, the enhanced physical dexterity of the robotic systems has paved the way for their potential application and relevance in various aspects of human endeavors. Similarly, wearable and assistive robotic systems have witnessed the rapid development in the last decades. This has led to the development of improved systems that could allow human upper or lower limbs movements in multiple dimensions. Despite the advancement in this research area, it is still saddled with the challenges of accomplishing a compact, lightweight, and comfortably aligned upper and lower limb exoskeletons [158]. Hence, limiting the ability of the systems to be employed in accomplishing complex interaction with human users. Furthermore, research in this area is still in a premature state as most of the proposed systems are just the prototypes and have not been evaluated across different application scenarios.

Recent trends in the EEG technology are looking at extracting the human neural response with different spatial frequencies for estimating human intention [159]. Future research direction could look at developing a high-density EEG system that can capture more neural information for better inference of the brain activities. Different kinds of sensors are currently employed in the design of the data glove to provide high accuracy and to measure the activities of human fingers. Apart from designing the low-cost data gloves, currently, researchers have focused on modular and expansible data glove design in order to improve the adaptability [81]. Future research direction includes the addition of multiple feedback in a single finger of the data glove while ensuring consistent data across a large range of the hand. Some researchers have coupled more than one sensing device together in order to produce more capable and adaptive sensors such as vision-based tactile sensors. The prospect of this system in the future is promising as it possesses the ability to enable the robotic hand to process complex dexterous manipulative tasks. Moreover, a future research direction could focus on using new flexible materials and innovative mechanisms to further achieve enhanced soft skin-based sensors suitable for practical applications in the field of medical implant services, and in other potential fields.

A lot of learning systems have been proposed to equip a robot with cognitive and cooperative capabilities that will enable it to understand its environment, and acquire desired skills that will enhance its collaborative abilities with humans but there are still some challenges that seek solutions. For instance, it is still challenging for a robot to infer the state and belief of a human collaborator with multidirectional intents. It is also very hard to model and transfer human preference because of the variation in peoples' preferences. With this little knowledge variance, research on robot predicting human preferences is still an open research question. In addition, the deep learning technique has been applied in several applications, including in robotic perception for object detection, object recognition, robotic grasps identification, environmental and place recognition, and for learning sensory-motor control. However, few previous studies have investigated applying the deep learning-based methods in pHRC; thus, further studies are needed.

In pHRC, safety collaboration is of paramount importance and there are still several unanswered research questions. To the best of our knowledge, no research work has fully answered the question "what is the best way to differentiate between accidental collision and simply touch from a robot to a human?" Improving ergonomically collision detection and avoidance in pHRC seeks further research attention.

Finally, an overview of the state-of-the-art pHRC cutting across the hardware and software concerning the implementation of effective collaboration has been reviewed. Considering the wide coverage and rigorous studies carried out in this survey, the authors have no doubt that the outcome could serve as a guide or starting point to scholars interested in pHRC.

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