Embodied Communication: How Robots and People Communicate Through Physical Interaction

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Abstract

Research on physical human robot interaction (pHRI) has necessarily focused on device design—the creation of compliant and sensorized hardware, such as exoskeletons, prostheses, and robot arms, that enables people to safely come in contact with robotic systems and to communicate about their collaborative intent. As hardware capabilities, including sensing, have become sufficient for many applications, and as computing capabilities have become more powerful, algorithms that support fluent and expressive use of pHRI systems now play a prominent role in determining their usefulness. In this review, we describe a selection of representative algorithmic approaches that regulate and interpret pHRI, describing the progression from algorithms based on physical analogies, such as admittance/impedance, to computational methods based on higher-level reasoning that take advantage of multi-modal communication channels. Existing algorithmic approaches largely enable task-specific pHRI, but they do not generalize to versatile human-robot collaboration. Throughout the review and in our discussion of next steps, we therefore argue that emergent embodied dialogue—bi-directional multi-modal communication that can be learned through continuous interaction—is one of the next frontiers of pHRI.

Contents

1. Introduction

As robots have become more capable over recent decades, physical human–robot interaction (pHRI) is no longer a nuisance but instead an opportunity for improved human-machine communication and closer collaboration (1). A major milestone in pHRI has been the introduction of specialized hardware approaches for pHRI, including series-elastic actuators, co-bots, and distributed sensing. Progress in perception has made robots more situationally aware of people during operation. Improved sensing, both novel (e.g., haptic skins) and traditional (e.g., improved force sensing at the joints) has made pHRI practical, particularly in terms of safety. Progress in interfaces for capturing intent (dry EEG, high density EMG, context-sensitive joysticks, etc.) have made devices easier to use. In parallel, progress in computing power has enabled real-time execution of sophisticated algorithms. Although there is still plenty of room for hardware innovations, these developments have made algorithm design an important next stage in pHRI. With novel algorithmic approaches, available information channels have new potential utility as affordances for embodied communication—multi-modal communication through actions, explicit interfaces, and physical contact. Thanks to these advances, we can start to design for facets of pHRI that were previously impractical, e.g., the subtle ways in which physical interaction creates an opportunity for dialogue between a robot and a person during use.

Historically, pHRI methods have focused on one-directional communication, typically a robot inferring something about a person through observation and providing assistance in response. Sometimes robots provide feedback about the environment or their internal state. This type of mostly uni-directional communication can be effective, but it does not take advantage of the collaborative potential of the human-robot pair—the ability to negotiate approaches, mutually adapt to each other and the environment, or coordinate a response

Physical human-robot interaction (pHRI)

The term pHRI, as used in this review, spans multiple forms of physical interaction, ranging from haptics and forceful touch to less traditional interfaces, such as vibrotactile sleeves, on-body sensors, or haptic joysticks. As a consequence, facilitating pHRI plays a key role in the design of any robot that works in close proximity with its human partners, including tightly coupled exoskeletons that move synchronously with the wearer as well as stand-alone robot arms that experience intermittent contact with their human collaborators.

to novelty. As a result, this approach tends to be best suited to narrow pre-specified applications without generalizing well to novel unstructured interaction. If we want robots to be versatile collaborative partners, we need better communicative capacity.

Notably, effective human-human communication relies on a bi-directional dialogue. In his book "Speaking Our Minds" (2), Thom Scott-Phillips distinguishes two ways of describing human communication: code model or ostensive-inferential communication, and builds a case for why code model communication cannot explain people's incredibly flexible communication capabilities. Code model communication is achieved through pairs of association: one between a state of the world and a signal, and the other between the signal and a response. Morse code is an example of this type of communication—it is defined by unambiguous symbols that can be broadcast into the ether and interpreted reliably with a decoder. The code enables an efficient exchange of information, but it does not allow fluent collaboration. Current human-machine communication at best aspires to code signal communication.

Ostensive-inferential communication is different—it relies on people's ability to express and recognise intentions (2). Ostensive communication strictly depends on one agent influencing the mental state of another agent, and so any behavior can, in principle, be used communicatively, so long as it influences the mental state of the other agent in the intended manner. In this viewpoint, natural languages function to make ostensive communication more precise and more expressive than it otherwise would be, but they are only one tool in the communicative toolbox. In addition to communicating verbally, people largely rely on non-verbal cuing during joint action, wherein they model each other's activity and contributions to a shared goal and enact voluntary non-verbal signalling in service of the shared goal (3, 4, 5, 6, 7, 8, 9). Human-machine collaboration, specifically involving pHRI, stands to benefit from an ostensive-inferential communication approach.

Secondly, much research and development effort is spent on making human-machine communication as intuitive as possible. This includes designing the robot to interpret either anthropomorphic signalling (e.g., hand gestures and natural language) or intuitive intent signalling through biological signals (e.g., EMG and EEG) to influence robot behavior. These forms of communicative conventions are often insufficient for fluent/expressive device use and may not even be optimal for human-machine communication—anthropomorphic signalling evolved and works well for human-human communication while measurable biological signals are noisy and only somewhat informative. Importantly, people are good at adapting and developing communication protocols. How can we put more emphasis on the emergence of embodied communication *through* pHRI rather than replicating familiar

communication conventions *for* pHRI?

In this review, we explore how embodied communication can create a path for more natural collaborative workflows and how it can facilitate safer, more effective interaction. In Section 2, we describe existing algorithmic approaches to facilitating human-machine communication, from algorithms based on physical analogies, such as admittance/impedance, to computational methods capable of task-level reasoning and adaptation. In Section 3, we discuss the state-of-the-art communication paradigms for different applications of pHRI and comment on how embodied human-machine dialogue could improve performance. In Section 4, we conclude with an outline of future directions for developing embodied communication in pHRI systems. We discuss the need to algorithmically facilitate bi-directional human-robot communication, where both the human and robot can both play a role in shaping the communication protocol. As a key position statement established by this review, we argue that to achieve versatile human-machine collaboration, we need algorithmic methods that enable ostensive-inferential communication.

EMBODIED COMMUNICATION

From uni-directional human-machine communication... Human-robot teams rely on embodied communication—a multi-modal exchange of information through actions, touch, forceful interaction, biometric signals, verbal cues, and more. In its current form, communication is often uni-directional and static over time: the robot is a passive observer of human intent, providing limited feedback back to its human partner; and the communicative conventions do not evolve over time.

...towards emergent embodied dialogue. Effective human-robot collaboration can benefit from flexible bi-directional dialogue that relies on an ostensive-inferential model of communication and emerges through interaction. In this viewpoint, the human-robot pair are collaborative agents, refining their communicative capacity over time and using communication to negotiate approaches to physical tasks.

2. Algorithmic approaches to embodied communication

Effective robotic assistance depends on successful communication of collaborative intent from both the human and the machine. In pHRI, the simplest form of embodied communication is through movement and physical contact, which can be regulated on an action-by-action basis (10). With additional sensing, the robot can reason about the person's intent and assess their performance (1); depending on the goal of the interaction, it can adjust assistance, often putting its control strategy into the context of a task. The interaction benefits if the robot can adapt its communication protocol and assistive strategy to its collaborative partner (11, 12). In this section, we describe the current approaches to embodied communication in pHRI, ranging from task-agnostic communication through compliant physical contact to adaptive task-based communication strategies.

2.1. Admittance/impedance

Admittance and impedance control are arguably the first algorithmic approaches for regulating pHRI that have enabled reasonably safe human-machine interaction. Admittance control dates back to the late 1970s (13), where it was used to respond to hard contact in industrial applications. Impedance control gained academic interest in the 1980s (10) and was one of the first algorithms used more broadly to control physical interaction with a robot.

Fundamentally, both impedance and admittance control imitate mechanical properties of contact between non-rigid systems, modulating elasticity in the collision. In impedance control, motion is detected and converted into interaction forces through an internal model. Impedance control is good at rendering low inertia but has difficulty with stiff virtual surfaces. In robot-assisted rehabilitation, it can be used to implement active assistance or active resistance proportional to participant movement (14) without the hardware requirement of a force sensor. Admittance control (15), on the other hand, converts measured forces into motion, requiring sensors to measure applied forces. It enables rendering stiff virtual surfaces but struggles with constrained motion, e.g., interacting with real surfaces (16). In human-robot collaboration, it can be used to account for unintended collisions (17) or to jointly manipulate an object (18). It is commonly used to reduce inertia of bulky devices with a payload (19) or to ease movement during rehabilitation (14). The HapticMaster (20) is an example of a commercially available admittance-controlled end-effector robot.

Impedance/admittance control assumes a static model that maps human actions to robot actions based on mechanical analogies. The model's parameters can be tuned, using intuition about the mechanical analogies as a guide, but, given that the robot is not responsible for any high-level reasoning about the task goal, the complexity of the interaction is limited. Communication is constrained to negotiating real-time actions without the possibility of task-level coordination of movement. Algorithmically, this is a conservative attitude to facilitating pHRI, restricting the physical interactions to those that have mechanical properties (even if not always mechanically plausible, such as in (21)). With richer sensory inputs and on-board computation, the robot can begin to reason about the task, in terms of both its goal and a plausible solution. As a result, admittance/impedance control is often combined with online algorithms that reason about human intent and enable more effective task-oriented assistance, as described in the sections below.

2.2. Predicting intent

In human-robot collaboration, the human-robot pair often have complementary roles: the person has a high-level understanding of the task while the robot has physical capabilities that can help the person accomplish the task. One way of framing the communication that occurs between a person and the robot is to view the robot as an observer, tasked with inferring the person's intent. Once the autonomy has an understanding of high-level intent, it can provide assistance that is not simply proportional to a person's motion or forces (as is the case in impedance/admittance control). Below, we describe different ways of inferring intent based on available sensory information. Example sensors for pHRI have been visualized in Fig. 1.

2.2.1. From body motion and eye gaze. Motion data can be captured passively (without requiring explicit human input) through a range of sensors on the body, including inertial

Figure 1

Example devices for capturing human intent. From left to right: Shadow motion capture, high-density EMG from OT Bioelettronica, wet EEG cap from TMSi, MERU joystick, sip-n-puff from Therafin Corporation.

measurement units (IMUs), motion-capture markers, cameras, or encoders on back-drivable electric motors. With recent advances in computer vision, it is possible to reliably estimate pose from RGB images (22), as well as to track eye gaze during real-time interactions (23). For stand-alone robots, camera-based monitoring of motion offers a significant advantage over most alternatives, because it does not require sensors to be placed on the human body.

However, even with information about motion history, it is challenging to *anticipate* intended human motion. Many methods have been proposed for recognizing motion (24), often by classifying motion into primitives or modes, where mode sequences can be predicted based on the task objective. This type of reasoning enables a high-level prediction of mode sequences (25, 26) and an anticipation of motion trajectories within modes based on an approximation of motion dynamics (27). Other studies have proposed velocity-based position projection (28), general value functions and temporal-difference learning (29), or a combination of multiple approaches (28). Inferring intent from motion assumes that the kinematics of motion are sufficiently rich to capture a person's goals. In most scenarios, motion trajectories are dependent on contextual information, and so inferring the situational context and/or additional sensory inputs are required to improve predictions. As an example, some studies augment kinematics data with electromyography (EMG) signals to improve predictions of motor intent (29, 12).

Motion can also be used to purposefully communicate intent, e.g., through gestures (30), motion cues (31), facial movements (32), or gaze (33, 34). Substantial progress has been made in sign language recognition that could be used in human-robot collaboration (35). However, explicitly prescribing a set of communicative conventions for each motion type is difficult and impractical because of the scope of possible communicative symbols. In Section 4, we describe the need for algorithmic solutions that would enable communicative conventions to emerge from interaction.

2.2.2. From electromyography (EMG). Electrical activity from skeletal muscles is an appealing source of intent prediction, particularly for prosthetics and exoskeletons—assistive devices that are directly coupled with the human body. There are many approaches to EMG-based control (29, 12, 36, 37). Despite a rapid increase in the use of advanced machine learning methods (36), two of the most commonly studied control methods continue to be: (i) proportional control, where the EMG signals are used to generate low-level trajectories (38, 39), and (ii) mode-based control, where the EMG signals are classified into modes based on pattern recognition techniques and used in combination with an autonomous low-level controller (40, 41). Proportional control gives the user direct control over robot

motion but requires precise decoding of EMG signals. As a result, multi-joint motions are typically difficult to achieve. Mode-based control expects sparser high-level commands from the human operator and has been shown to achieve better performance (42). However, studies highlight the need for more research on the benefits of pattern recognition for mode-based control (43, 44). Combining EMG signals with other control inputs is noted by the community as a promising path forward (12). One example is EMG combined with electroencephalography (EEG) (45, 46), which has shown promising initial potential.

While the person has some control over the EMG signal by voluntarily generating muscle contractions, they are limited by their physiology in the variety and expressivity of patterns that they can generate. As a result, even though a significant appeal of EMG signal is its intuitiveness, some work explores EMG control using non-biological mappings, where the person generates maximally differentiated muscle contractions (e.g., internal/external rotation of the forearm) and these contractions are mapped onto useful configurations of a robot (e.g. different grips of a hand prosthesis). These approaches show promising performance, but can be difficult for a person to learn. Emergent interfaces, discussed in Section 4, might offer a solution.

EMG-based methods are in many ways similar to motion-based approaches, in that they infer intent based on a planned execution of motion. EMG methods have the advantage of being able to anticipate motion before it happens or, as in the case of amputees, detect motion intent. However, neither motion-based nor EMG-based methods attempt to infer the cognitive intent of a person. EEG-based techniques, discussed next, try to use high-level signalling in the brain to infer cognitive aspects of intent.

2.2.3. From electroencephalography (EEG). Reliably capturing and interpreting electrical activity of the brain would enable 'thought-controlled' devices, or at least devices that are explicitly dependent on what a person is thinking. If successful, EEG paves the path for intuitive interfaces to control multi-dimensional robots. However, thus far surface EEG (sEEG) has proven difficult to use as a control interface for robots (47) because of the noisiness and low spatial resolution of sEEG signal. EEG signal is much stronger when measured inside the brain through an implant, rather than noninvasively on the surface of the skin. This is a promising avenue of research but has received limited attention because of the risks associated with its invasiveness (48, 49).

Algorithmic approaches for interpreting EEG signal range from using combinations of pre-specified features (e.g., amplitudes of signal within frequency bands in the motor cortices) (50) to training deep neural networks on the raw signal (51). State-of-the-art algorithms enable reaching a target in a 2D plane by interpreting sEEG signal as one of a handful of mental states, corresponding to possible target locations of the robot's end-effector (47). As an example, EEG-predicted mental states in combination with a context-aware controller enabled navigating a mobile robot through a network of connected rooms (52). Given the low spatial resolution of sEEG signal, researchers have had difficulty identifying more than three classes of distinct mental activities (47). In more recent studies, the error potential (errP) has been shown to successfully correct the 3D motion of a robot arm (53, 46). This is an interesting approach that takes advantage of a biological interpretation of EEG signal—the errP is detectable when a person perceives error.

The key outcome of these studies is that sEEG provides a way to record an array of signals from the brain and, for now, to interpret them in a small number of ways. One of the points we will make later is that this small number of interpretations are pre-specified—e.g.,

they are trained to mean *right*, *left*, *straight*—when they could be an unlabeled range of mental states that the robot learns to interpret over time.

2.2.4. From controller signals. There is a range of designated interfaces that can provide human-generated input for an assistive robot. The most common are control devices that can be operated by the hand, such as a joystick or remote controller with a range of buttons. Hand-operated control devices are currently in commercial use and, although they require effort (compared to passively measured biological signals), their control signal is more informative and less noisy—they already achieve adequate performance for the control of powered wheelchairs to warrant wide adoption.

In addition to hand-operated devices, there exist a range of control interfaces that are designed to be used by individuals who are paralyzed below the neck. These include a head array (that enables button presses with the head) or a sip-n-puff (that records a 1D continuous signal from exhaling and inhaling air into a sensorized straw) (54). Signals from these interfaces are lower dimensional than from a hand-operated controller, posing a challenge even when controlling a 2D powered wheelchair.

In commercially available devices, the physical interfaces mentioned above (i.e., joysticks, head arrays, or sip-n-puff devices) are treated like many control interfaces used in non-robotic applications (e.g., video games)—the interface and its mapping of control inputs onto the action space are designed ahead of time, and it is up to the person to learn and adjust to the pre-specified mapping. However, research shows that the physical interaction with the control interface is non-negligible and should be taken into account when designing the mapping from interface inputs to control outputs, particularly for impaired individuals (55). Although intentionally generated, the signal is often imperfect—recent work highlights the effects of impairment and interface type on the acquired control signal, including the timing, transient noise, and accuracy of a signal (56). When designing control interfaces, particularly for impaired individuals, there is a need to enable adaptation to the person's unique physical and cognitive capabilities—effective communication can give the person increased agency over their interaction with the robot.

2.2.5. Through natural language. With recent progress in natural language processing (NLP) (57, 58), there are also many studies that incorporate voice commands into human-robot interaction (59). This can be a useful tool for high-level task alignment and will likely remain an important research direction. However, natural language control has three main limitations: (i) it is non-pragmatic for many applications (e.g., a robot assisting with eating), (ii) socially inconvenient (e.g., walking in a prosthesis and talking), and (iii) requires high levels of effort for continuous control (i.e., guiding low-level movement). In the context of pHRI, the most NLP can do is align the robot with the person's high-level intent, but actual robot actions need to be planned in the context of the body, environment, and continuous-time continuous-space decision-making. Natural language will likely be used in combination with other interfaces to provide high-level directions or corrective feedback.

2.3. Metrics of motion for adjusting assistance

Given a prediction of high-level intent, a robot requires a mathematical specification of performance that enables continuous evaluation of human actions. In combination with decision-making techniques (e.g., linear control, optimal control, reinforcement learning),

this enables computational synthesis of real-time assistance.

2.3.1. Motion quality. One way to assess performance is by quantifying motion quality. As an example, energy minimization has been shown to explain the dynamics of human motion and so energy is a universally used assessments of motion quality (60). Motion has also been assessed in a task-independent manner using the norm of mechanical jerk—the third time derivative of state (61). Jerk is a way to quantify motion smoothness with the underlying assumption that smooth motion is desirable.

2.3.2. Task performance. Another intuitive way to assess human actions is with respect to a reference solution to a task goal. If one defines a task solution as a trajectory in time, one can use error with respect to a pre-defined trajectory to provide real-time assistance (61). This approach works well if there exists an optimal solution to a given task but over-specifies the task solution when many trajectories can, for practical purposes, be considered equally correct. For most tasks, there exist many correct ways to execute an action sequence and achieve a high-level goal (62).

As an alternative, new metrics of solution quality have been proposed based on decomposing trajectories in ways that ignore the solution's time evolution in the state space. Solution quality can be assessed based on the relative positioning of joints with respect to one another (63). Task performance can also be measured using distribution-based metrics that evaluate the statistics of a motion trajectory relative to the statistics of a task (64, 62), or using frequency-domain assessments that quantify motion bandwidth (65, 66). Time-independent ways of specifying the task allow one to include multiple approaches to solving a task and do not constrain the solution as a function of time.

2.3.3. Motion predictability. Learned forecasts of movement and movement anomalies can also be used as a metric to modulate pHRI. As one key example, researchers showed that general value functions (GVFs) can be used to build predictions of anticipated motion and to make control decisions based on the motion's deviation from the learned prediction (67, 68). Similarly, researchers have introduced and made use of metrics that quantify surprise, e.g., the Unexpected Demon Error (69). As an example, a study illustrated that unexpected perturbations can be characterized through the process of continual temporal-difference learning and that the resulting metrics can be used to effectively modulate assistance (69).

2.3.4. Effort. Lastly, in physical assistance, there is often interest in assessing physical effort exerted by the individual (70). Effort can be measured directly using EMG (71), heart rate (HR) variability (72), or respiratory data of the flow rates of oxygen and carbon dioxide (73, 74). As an example, one can adjust the parameters of an admittance or impedance controller based on EMG readings to maintain a desired level of physical effort (75). Task effort can also be approximated via cognitive load. Researchers are attempting to measure cognitive load directly through EEG signal (76); other studies quantify cognitive effort via proxy metrics, such as gaze trajectory and pupil size (77), or a combination of physiological data, such as HR, breathing frequency, skin conductance, and skin temperature (78). As with metrics of physical effort, metrics of cognitive load can be used in closed-loop to provide real-time adjustments to the provided assistance (78) and maintain patient engagement.

While it is challenging to quantitatively assess task performance in real-time and to math-

ematically specify motion quality or effort with enough generality, flexible specifications of motion can both improve the adjustability of robotic assistance, as well as enable verifying safety and developing provable safety guarantees for pHRI systems.

2.4. Task-based shared control paradigms

Once a task goal and performance metric are established, a consideration for the autonomy is when and how much assistance to provide. Shared control paradigms distribute control between the human and robot to improve overall performance and/or safety.

Performance-based shared control schemes rely on an estimate of the user's intent, as described in Section 2.2. Intent could be a high-level goal, such as a navigation landmark to drive a wheelchair towards or an object to grasp using an assistive robotic arm (79). Avoiding obstacles could be a high-level intent, in which case distance to obstacles could be a metric for allocating control between the human and robot (80).

Once a task goal is identified, user control inputs can be directly modified by the autonomy in a variety of ways. User input can be blended with the assumed optimal action, obtaining an average action at every timestep (81). User input can be filtered using a task-based criterion and, if sufficiently suboptimal, either ignored or replaced with an assumed optimal action (82). Intervention could be conditioned on the certainty of the autonomy in its prediction of the task goal (83, 84). If the robot is operated through mode-switching (explained in more detail in Section 3.5), a shared control paradigm may be designed to assist with autonomous mode switching based on a prediction of the most likely mode (67, 85).

While many approaches vary assistance to optimize performance, others provide assistance solely based on safety. This strategy has two significant advantages: (i) it limits interference, relinquishing control to the human operator, and (ii) it is often easier to specify—safety constraints of a human-machine system are usually easier to define than the full task space. Even so, the optimal shared control paradigm is often specific to the person and the application (86), highlighting the need for solutions that enable adaptation. Bi-directional communication can help a person and a robot most flexibly agree on an optimal shared control strategy and to renegotiate that agreement throughout the course of use. We discuss this idea in more detail in Section 4 on future directions.

2.5. Adaptation

Adaptable control interfaces show promise in their ability to improve performance and safety, as well as to increase user satisfaction. The robot can adapt (i) its predictions or model of its human partner, (ii) the mapping (or interpretation) of human inputs onto predicted intent and (iii) the shared control paradigm, adjusting its intervention strategy based on user capabilities and individual preferences. Unlike the majority of work described above, adaptation assumes that how people start using a device will not necessarily be the same across individuals as well as that how they use the device will change over the course of use.

Many researchers have investigated options to personalize algorithms for pHRI to accommodate biomechanical and physiological differences between individuals. A common example is the customization of gait in an exoskeleton (87, 88), usually through an initial calibration period of walking without assistance. Another example is the calibration of EMG (42, 89, 37, 36, 12) or EEG (90, 91) mappings to an individual's signal pattern or to the specific placement of the electrodes on the body. A personalized remapping has also

been shown to be beneficial for more established input devices, such as a joystick, when the human operator suffers from physical limitations due to a neuromotor impairment (92).

In addition to personalization based on physiology, biomechanics, and physical capabilities, users value the ability to customize an interface based on preferences. As an example, individuals might exhibit preference for different shared control paradigms irrespective of the objective performance benefits (e.g., time to task completion) (93). As a result, some work utilizes the user's control behavior to automatically vary parameters of the shared control paradigm (94, 12). While preferences vary between participants, there is a general trend favoring paradigms that retain stronger autonomy for the human operator (93). People prefer interfaces that are intuitive to use and transparent in how they work (95).

Adaptation to the individual is important, but it is also important to recognize that individuals' performance and capabilities change over time, due to factors such as learning, fatigue or disease progression. In particular, in a study with a smart wheelchair, people's performance was shown to improve significantly between just two experimental sessions (93)—the trend was observed across different control interfaces and shared autonomy paradigms. Another study showed that novices and experts prefer different shared control paradigms (56). These results suggest that the shared control approach should not be static over time and that continual adaptation of the communication paradigm can benefit the human-machine system. While to date few research studies evaluate the adaptation of pHRI interfaces over time, we discuss in Section 4 that continual adaptation in an important research direction for pHRI.

ALGORITHMIC APPROACHES: SUMMARY POINTS

1. Over the past decades, algorithmic approaches that facilitate pHRI have progressed from algorithms based on physical analogies, such as admittance/impedance, to computational methods based on higher-level reasoning.
2. Intent inference is often multi-sensory, taking advantage of a variety of technologies that measure biomechanical and bioelectrical activity to inform control.
3. The algorithmic paradigms (incl. signal processing, optimal control, machine learning, and more) can be customized to the robotic systems and personalized to the individual, but they do not adapt beyond an initial calibration, limiting the human-robot collaborative potential.
4. Existing algorithms successfully enable task-specific interactions; future progress can expand robotic applications from, e.g., semi-automated manufacturing and precision surgery to versatile at-home assistance.

3. Applications of pHRI

Physical HRI plays an important role in a number of applications, ranging from robot-assisted rehabilitation to collaborative assembly during manufacturing. Here, we describe how physical robotic assistance is being used in different settings. We comment on state-of-the-art performance and discuss the current challenges associated with human-machine communication in each application area. Example robotic platforms that have been developed for these applications are visualized in Fig. 2.

3.1. Robot-assisted rehabilitation

One of the major applications of pHRI focuses on robot-assisted physical therapy (96, 97). Robot-assisted rehabilitation offers promise of therapeutic regimens that are more effective, more accessible, and more engaging than traditional therapy. To date, results are mixed on the impact of robot-assisted training on clinical outcome measures. While some studies show benefits of adaptive robot-assisted training compared to conventional therapy (98, 99), other studies show no statistically significant differences in clinical outcomes (100). However, the evidence is strong that there are benefits from patients' active participation in therapy (101). These positive findings encourage research that promotes patient engagement through reliable detection of intent and real-time metrics of performance and effort.

Research solutions attempt to maximize patient engagement using two approaches: (i) assist-as-needed paradigms and (ii) measures of patient intent that guide robotic assistance (97). Assist-as-needed strategies use adaptive controllers that estimate patient effort and assess performance in real time, enabling adjustments to the level of assistance even during a single movement (102). These strategies can rely on task-specific performance metrics or measures of motion quality and effort, as discussed in Section 2.3. As an example, in 2017, the HAL rehabilitation exoskeleton, which uses EMG signal to adjust assistance, was officially approved by the US Food and Drug Administration (FDA) to enter the US medical rehabilitation market. In parallel, intent detection—e.g., using biometrics from EMG or EEG—can further involve the patient by providing them agency over generating movement trajectories (103). Intent prediction methods are particularly important for engaging more severely impaired patients in robotic training, because these patients have difficulty with independently generating voluntary movement (104).

More recently, work is being done on developing impairment-specific assessments of motor abilities (105, 106, 107), with some metrics showing promise of real-time use (65). With new algorithmic solutions, it should be possible to design patient-specific training protocols, dependent upon each patient's type of injury, level of impairment, and phase of recovery. Embodied communication could play a role in designing interactive paradigms for assessment of physical deficits. Specifically, interactive methods could enable more accurate diagnosis of motor capabilities and lead to improved therapeutic efficacy through adaptive, impairment-specific rehabilitation protocols.

For individuals with physical limitations, the ultimate goal is for robotic devices to provide both therapy and assistance (108). Some devices are already attempting to show efficacy for combined assistance and at-home rehabilitation (109). With robot-based continuous metrics of impairment, person-specific rehabilitation protocols can be more effectively incorporated into activities of daily living.

3.2. Physical assistance with exoskeletons

Exoskeletons—portable devices that are physically coupled with an individual—are the most commonly considered type of robot for providing physical assistance. Many exoskeletons have been developed to augment people's physical capabilities for both impaired and able-bodied individuals (110, 73, 111). Most rigid exoskeletons are controlled in admittance mode using force amplification and for some applications, such as level-ground walking, this control mode works reasonably well (110). In fact, for level-ground walking, it is challenging to do better than admittance control in terms of movement freedom and flexibility. However, while task-agnostic assistance performs well for walking, it does not provide help-

Figure 2

Example robotic platforms. From left to right: Kinova MICO arm, Quickie Q500 M powered wheelchair, Ekso Bionics lower-limb exoskeleton, ShirleyRyan Ability Lab upper-limb prosthesis, Open-Source Leg, ACT3D (a modified HapticMaster end-effector robot).

ful support during unexpected events, e.g., tripping, or changing activities, e.g., climbing stairs or transitioning to sitting (110). Alternatively, exoskeletons rely on a state-machine controller, where an initiation event—e.g., a button press or a specific motion—are used to communicate movement intent (112). Other controllers provide assistance through a learned movement trajectory, giving the person little control over motion execution (112).

While exoskeletons have received substantial academic and commercial attention, their practical adoption has been limited. Traditional rigid exoskeletons (113, 73) are bulky and expensive. While they offer assistance with generation of gait, even for individuals with full paralysis (112), they do not guarantee assistance with balance and hence require crutches or therapist-assistance during use. More recently, lightweight designs have shown promising results, reducing physical effort required to walk long distances (114) or increasing ability of carrying heavy load (115).

When the human and machine are physically coupled, there is both a unique opportunity for continuous communication (as in partner dancing (116)) as well as the challenge of arbitration between human intent and robotic assistance—communication takes places through subtle haptic cues and concurrent negotiation of movement. Interestingly, human-human physical coupling can reliably lead to improved performance even if one of the partners is less adept at the task (117). Studies on human-robot coupling show that forceful interaction can lead to improved task performance even after the robot coupling is removed and the person performs the task independently (118). These pieces of evidence illustrate the potential of communication through physically coupled motion. However, while physical interaction is a natural part of joint activity between people, how humans control motor interaction with peers is still largely unknown (119). Human-robot interaction (e.g., via exoskeletons) can help us discover the potential of physical communication and in turn help improve algorithms for human-machine collaboration.

3.3. Physical augmentation through prosthetics

Powered prostheses offer promise of restoring lost functionality to individuals with a missing limb. With recent progress in reducing the weight of the physical devices, the prostheses' usability largely depends on the effectiveness of the algorithmic solutions. Commercially available lower-limb powered prostheses (e.g., EmPower, Ottobock, Germany) use onboard sensing (e.g., a load cell or motion sensor) to drive autonomous controllers for pre-programmed activities (31). Transitions between gait phases can be triggered by sensor measurements, while transitions between locomotion modes (e.g., over-ground walking or stair climbing)

often require input from the human user (e.g., specific body motions measured by sensors) (31). Some research solutions consider incorporating contextual information (e.g., a laser distance meter) (120) to improve decision-making by detecting terrain, and some explore incorporating EMG signal to improve prediction of user intent (31). Existing control techniques can already achieve decent performance—most lower-limb amputees feel confident in forward walking on level ground (121), while maintaining balance and walking on uneven ground or on slopes remains a concern (121).

For the upper limb, the task space is more varied and open-ended, increasing the difficulty of control. The main challenge is obtaining rich enough control signal from the human partner to infer their movement intent without interrupting the person's workflow. Intent prediction using EMG has received the most attention (122, 12, 37) with EEG being a close second. While EMG signals are usually stronger and more discernable than EEG, amputees might have limited muscle fibers in their residual limb, depending on their level of amputation. To increase the strength and clarity of the EMG signals in the residual limb, two clinical procedures have shown promising results. (i) Targeted motor and sensory reinnervation (TMR/TSR) can increase the number of information channels available to an amputee for communicating with a prosthetic limb (123, 124). During the TMR/TSR clinical procedures, a surgeon reroutes nerves from the residual limb to a large muscle group, such as pectoral muscles, restoring the number of intuitive EMG channels and sensory inputs available to the individual. (ii) More recently, osseointegrated prosthetics controlled via intramuscular EMG from implanted electrodes (125) have been shown to provide stronger control signals and a robust mechanical coupling. These surgical advancements significantly increase the capacity of the human-prosthesis communication channels, improving usability. Even so, control of the prosthesis is for now limited to single degrees of freedom, and the prosthetic arm is usually used passively as a support arm in bi-manual tasks (e.g., holding a bowl while stirring with the other hand) (126).

A relatively new research effort focuses on restoring sensing capabilities to the individual. Thus far, there are almost no clinical prosthetic systems for upper or lower limbs that transfer sensations to the user (121). Interestingly, some prosthesis users find mechanical prostheses more intuitive to use because the more rigid devices mechanically transmit haptic feedback from the prosthesis tip to the residual limb. Osseointegrated prostheses share this benefit (125). In socket-based powered prostheses, researchers are considering alternatives for providing sensory feedback (12, 127). As an example, pressure stimulation in a prosthetic socket is being used to communicate forces perceived by the hand (128). Systems leveraging TSR (124) can increase the amputee's capacity for sensory feedback as well as make the sensory feedback more intuitive.

The human-prosthesis interaction can also benefit from communication to the user about the prosthesis' current state or movement intent (68). As an example, haptic feedback about the opening or closing of a prosthetic hand has been shown to lead to a lesser need for visual attention and improved task performance (129). Rich sensing and reciprocal communication of both the device's perception and its intent is expected to improve the effectiveness of the human-prosthesis interaction. While powered prostheses are meant to be natural extensions of the human body, there is a desire to seamlessly integrate the artificial limb into the person's workflow without the need for explicit, cognitively-taxing communication of intent. In this viewpoint, powered prostheses remain a challenging domain for inferring intent, especially in contextually rich settings during activities of daily living. Bi-directional communication for pHRI is an important area of research that could improve performance,

as we discuss in Section 4.

3.4. Collaboration in close proximity with an autonomous robot

Some assistive robots are stand-alone devices that operate autonomously in close proximity of a human partner. Physical interaction during this type of collaboration is arguably one of the more difficult pHRI scenarios, because the human-robot pair has to work together with the ability to (i) mostly avoid each other and (ii) intermittently seek out safe physical contact. In the first scenario, physical interaction is an unintended byproduct of working in close proximity. A large body of research focuses on intent prediction for avoiding accidental interaction while working in close proximity with a human partner (130, 131) or for avoiding collisions when navigating in crowded environments (132, 133). A common focus area is interacting with a robot by jointly manipulating objects in the workspace. This can involve collaboratively moving a table (134, 135) or handing over objects between the human and the robot (136). These studies makes progress on relevant pHRI challenges, yet they often explicitly separate the periods of physical interaction and autonomous operation. Incorporating intermittent pHRI as a natural component of collaborative interaction will be key to the emergence of complex, rich, and flexible collaboration.

A commonly studied form of prescribed pHRI involves kinesthetic demonstrations, where the human moves the robot to demonstrate desired movements. Kinesthetic demonstrations provide an intuitive avenue for people to teach robots new skills or customize assistance without having to program reward functions or low-level behaviors (137). As an example, learning from demonstration (LfD) paradigms have been successfully used for manipulation tasks with a robot arm (138). One of the current challenges is that LfD approaches have difficulty learning salient aspects of a task. As a consequence, learned robot policies do not generalize well to future unstructured human-robot interactions. Many studies show that a learned policy can generalize to new environmental conditions (139, 140), such as new locations of objects, similar objects, and clutter. However, there are fewer works that demonstrate motor skills that generalize between different tasks. Without the ability to reuse motor skills for novel goal-oriented activities, the learning solutions are less applicable to a versatile assistive robot. The question remains of how to algorithmically structure the interaction with the person to enable the robot to extract task-relevant information from demonstrations (137).

New research directions explore interactive learning—the goal is to improve learning of salient task elements by actively soliciting clarifying input from the human teacher. Some approaches ask users to rank demonstrations (141, 142) or provide corrective input on the learned task executions (143, 144). Additional feedback often increases task performance, but it does so at the cost of an individual's time and effort. Even though in their current implementation the interactive paradigms might be inefficient, they are a step towards bi-directional communication which will enable more versatile human-robot collaboration.

3.5. Teleoperation of a semi-autonomous robot

Robotic teleoperation has enabled robotic surgery, space exploration, assistance for physically impaired individuals, and more. Here, we focus on teleoperation as a way to control a co-located collaborative device (e.g., a powered wheelchair or wheelchair-mounted robot arm) rather than a remote robot (e.g., Mars rover or the Da Vinci Surgical System).

A semi-autonomous assistive device, like a smart powered wheelchair, can be successfully

controlled by a hand-held joystick (54). Here, control is near-trivial because a 2D joystick intuitively maps to a 2D control space. Direct control of the robot is more difficult when the controller is lower-dimensional (e.g., a sip-n-puff as described in Section 2.2.4) or the robot is more complex (e.g, a multi-degree-of-freedom robot arm), because low-dimensional input has to be used to control high-dimensional motion. Mode-switching—toggling between independent and typically orthogonal control directions, which usually span translation and rotation in the xy- or xyz-coordinate space—has been proposed as a possible solution (145). Autonomous switching of modes can speed up task performance (85). However, control via single degrees of freedom in a Cartesian coordinate space is an unintuitive approach to specifying robot movement, because people do not think about motion in terms of one-dimensional adjustments. Instead, we tend to plan trajectories in terms of functional movements or motion primitives (146).

In recent work, researchers have proposed using latent variables to map control inputs onto task-specific movement trajectories (147, 84). These approaches offer a way to map control inputs onto more natural and functionally relevant movements of the robot. In their current implementation, these approaches require a task library and a high-level controller to determine the applicable latent space for the task, but this is a promising research direction as it enables learning a communication manifold from human-robot interaction. Algorithmically structuring the interaction, in a way that will effectively enable these mappings to emerge, is an important future research direction.

4. Future directions for embodied communication in pHRI

Future work on pHRI will benefit from greater incorporation of embodied communication to exploit the richness of the available communication channels both for human-robot communication and increasingly robot-human communication. Aspirations for future pHRI systems include safe operation enforced by the autonomy while allowing continual adaptation, bi-directional communication, and support for emergent, unanticipated behavior and communication during collaboration (as visualized in Fig. 3. Each of these goals anticipate that the person and the environment change over time and that the human-robot pair will need to co-adapt to each other. Each of these goals also have something in common technically—they lack standardized algorithmic tools, which are currently in development in terms of theory and implementation, as we discuss below. As a result, datasets are needed for developing pHRI-relevant algorithmic tools, for benchmarking algorithms prior to use with people, and for comparing and evaluating current pHRI capabilities.

4.1. Continual adaptation with safety guarantees

Physical HRI involves potential safety hazards because of the direct mechanical contact and energy exchange. As a result, safety has been a core focus of facilitating pHRI (148). Even so, it is not clear how to guarantee safety without limiting parameters of robot motion (e.g., torque or velocity) and bounding the robot's performance (149, 148). Due to the lack of reliable alternatives, ISO guidelines released in 2016 suggest just that—they recommend quantitative biomechanical limits, such as allowable peak forces or pressures for various parts of the body, as a requirement for collaborative robots (150).

As an alternative, recent work takes advantage of predictive modelling to impose data-driven safety guarantees (151). Other approaches involve modelling and closely monitoring

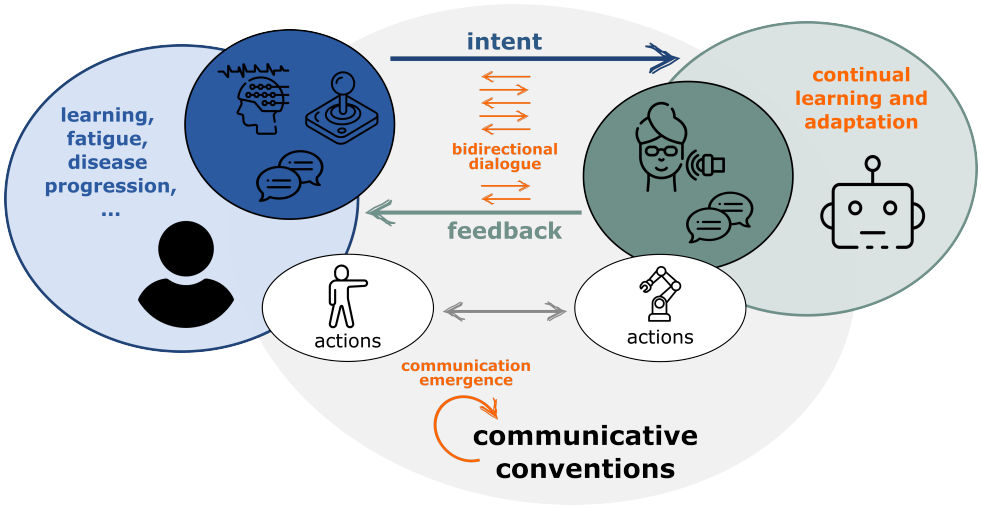

Figure 3

Embodied communication enables effective human-robot collaboration. Developing new algorithmic tools to facilitate human-machine dialogue and enable emergence of communicative conventions without compromising safety is one of the next frontiers for pHRI.

people's behavior in anticipation of unsafe robot motion. As an example, researchers show the utility of hidden Markov models for estimating, in real time, human affective state during pHRI (152), and propose using it as a feedback mechanism to prevent unsafe interactions. Separately, safety can be formalized and theoretically analyzed in the context of efficient value alignment (153). For Brown et al., the goal is to construct a kind of "driver's test" that a human can give to a robot for assessment prior to use. These efforts are a step towards providing standardized safety guarantees (under reasonable assumptions) for data-driven robotic systems.

In Section 2.5, we discussed the value of adaptation and data-driven methods for algorithmic regulation of human-robot interaction. Notably, few studies consider continual or long-term adaptation—most work focuses on learning within a confined period of initial interaction. One reason for this is that while it is challenging to assess the safety and performance for data-driven methods, it is even more challenging for systems that are continually adapting. Developing methods for data-driven verification of safety while enabling long-term learning is an important direction for future work. As discussed by Kress et al. (154), we should aim to provide safety guarantees that at minimum maintain states within safe sets and satisfy temporal logic guarantees while also providing specifications that are appropriate for non-stationary models and reason about human variability and adaptation.

4.2. Multi-modal bi-directional communication

Just like we seek to infer informative measurement signals from the human for the robot, the robot should seek out to provide informative signals to the person. Many human-robot systems rely on the robot movement as implicit feedback for the human partner. Some work augments the interaction with exaggerated robot movements (155, 156, 9) or

anthropomorphic signalling (157). Purposefully communicative motion can be beneficial for the interaction, because it makes robot behavior more predictable, allowing the person to anticipate robot movements and adapt their own behavior accordingly (158). If robot motion is predictable and allows humans to adapt—e.g., how humans swiftly adapt to robot motion in crowd navigation (132)—safety constraints on the robot might be relaxed to enable effective collaboration.

Other work takes advantage of communication through modes other than motion to provide explicit feedback about robot intent. For instance, recent studies use vibrotactile feedback in the form of a vibrating sleeve (129), pressure spots in a prosthetic socket (128), or friction modulation on the surface of a touch screen (159). Other studies explore using vibrotactile feedback to communicate emotion, imitating social touch with patterns of haptic sensations on the arm (160, 161), or to communicate learned predictions of upcoming hazards (162, 163). Without disturbing the task flow, vibrotactile stimulation and haptic cues can significantly increase the information communicated to the person by the machine. This can significantly increase collaborative potential.

As discussed throughout the review, one-way signalling about intent—from the person to the robot—has enabled task-specific robotic assistance. We described how most work on communication in pHRI treats the robot as a passive observer of human behavior. In parallel, evidence shows that reciprocal signalling from the robot to the person can improve the interaction (164, 66, 129, 68). Though bi-directional, thus far this type of communication does not rely on improving understanding and alignment over time. Bi-directional dialogue—where communication is dependent on both the mental state of the communication partner as well as the communication history—could enable more versatile collaboration.

4.3. Emergent interfaces

The model of signalling described above assumes that the communicating agent (human or robot) has a correct mental model of the communicative conventions, and this assumed mental model is typically static. If we are to move towards active non-verbal dialogue between the human and the machine, novel non-verbal languages will form a foundation for communication. As described in (165), we can capitalize on our kinematic, muscular, and neural null space—excess degrees of freedom—to enable communication with assistive devices without causing excessive increases in cognitive load. The question remains how to facilitate efficient 'neural resource allocation' for a novel human-robot system (165).

As a baseline approach, the languages can be pre-defined and encoded in the robot—the programmer determines a set of vectors in the neural null space and the human operator is instructed in their interpretation and trained to generate them. However, how can functionally optimal or near-optimal symbols be specified? And how can the cognitive burden on the human partner—who is expected to learn the newly introduced vocabulary of non-intuitive symbols—be reduced? If we are mapping joystick commands to the action space of a powered wheelchair, there is an intuitive way to specify the mapping of the continuous 2D control space onto the analogous 2D action space of the robot, making the language easy to learn. However, if we are using shoulder shrugs to control movements of a robot arm (166) or sips and puffs to maneuver a wheelchair (56), the mapping is no longer as intuitive, either to specify or to learn, and may not even be within the motor control capacity of a given individual.

Interestingly, experiments show that humans are good at adapting and developing novel communication protocols (167). For instance, in an experimental setup with an unfamiliar task (168), people learned how to interpret vibrotactile stimulation without being given a description of what the stimulation is intended to evoke. In the experiment, the vibrotactile stimulation was synthesized by an optimal controller (rather than embodying a state measurement) and context was sufficient for participants to infer the meaning of the vibrotactile signals—subjects successfully learned to use the stimulation as a cue for motor response to improve performance. Such anecdotal evidence illustrates potential for fluent co-adaptation of the human-robot pair, on fast time scales and in an individualized manner.

There is a body of work that studies how to enable and facilitate communication emergence in artificial agents (169), with recent studies exploring the role of deep reinforcement learning (170, 171). These algorithmic approaches to facilitating collaborative development of non-verbal languages have the potential to form the foundation for humans and robots to cooperate flexibly (172) and to continuously negotiate their partnership. Enabling the human-robot pair to jointly develop a communication protocol could reduce the cognitive burden on the human partner and enable more effective communication protocols that are uniquely relevant to the human-machine system and to the corresponding task space. However, unlike the anecdote mentioned above, the deep learning algorithms are data-intensive, requiring thousands or millions of interactions in order to achieve a non-verbal language. The opportunity is that these approaches assume naive agents that know little about their environment or about each other. Incorporating these approaches into collaborative language creation between a human and robot is the next step in bringing these theoretical studies closer to the fast, individualized physical communication needed in human-machine interaction.

4.4. Datasets & benchmarking

Acquiring human data is costly in terms of time and effort of both the researchers and study participants, particularly when running experiments with vulnerable populations. As a result, research studies focus on evaluating novel algorithmic solutions and few carry out direct comparisons with existing approaches. To accelerate progress, sharing datasets of benchmark tasks would be beneficial. Although statements of 'data availability upon request' are common, they have been shown to be inefficient (173). This suggests that the pHRI community needs open datasets and standards that define them, both in terms of standardized sharing practices and standardized data formats.

Some researchers have already initiated this practice. A recent paper featured a dataset of kinematic and EMG signals collected during reach-to-grasp movements with online adjustments in response to visual perturbations (174). Datasets like this one, which record human kinematics in response to environmental stimuli, can be used for training robotic controllers that aim to mimic human behaviors. Similarly, a multi-modal dataset of assistive human-robot collaboration was released, including eye tracking, EEG, EMG, camera images, joystick signals, and more (175). Although this data cannot substitute for an experimental evaluation of a novel algorithm because of the interactive aspect of online control, it can enable a baseline comparison of task performance. Sharing data is of particular importance in fields, like pHRI, where active participation of human volunteers is required to collect data.

While the benefits of sharing data are clear, we will need to create data standards that

enable wide adoption and reliable benefits. Such standards may require a standarization of task—this could be similar to clinical assessments of impairment (176) that are well-defined and typically based on sets of standardized mini tasks that get scored independently and summed to provide an estimate of motor deficit. The standards will also need to focus on ease of use—e.g., sharing raw anonymized data along with Jupyter Notebooks for server-side visualization, or making available code for reproducing statistics used in the original study. Sharing data can improve benchmarking, facilitate collaborations, and accelerate progress in designing machines that can effectively interact and communicate with people.

5. Conclusions

In current applications of human-robot collaboration, pHRI is largely avoided or completely prescribed. The robot is often treated as a passive observer of human intent; in some scenarios, it can provide reciprocal feedback. While this type of embodied communication has enabled successful collaboration within the constraints of a specific task, taking the interaction a step further towards embodied dialogue—comprised of a multi-modal exchange of information based on a mental model of the collaborative partner and including intermittent physical interaction—will enable effective human-robot collaboration in unanticipated settings. Developing new algorithmic tools to facilitate human-machine dialogue and to enable emergence of communicative conventions is one of the next frontiers for pHRI. If we achieve flexible dialogue between the human-robot pair, human-robot collaboration will be more effective and will become possible in currently impractical applications, such as flexible co-existence in the home or continuous rehabilitation during robot-assisted execution of daily activities.

FUTURE DIRECTIONS

1. **Continual adaptation with safety guarantees:** With growing use of data-driven methods that learn over time, there is an increased need for provable safety bounds that do not unnecessarily constrain the human-robot interaction or limit overall performance.
2. **Multi-modal dialogue:** While many existing solutions rely on the robot to infer intent from communicative signalling generated by its human partner and some enable reciprocal signalling from the robot, continual bi-directional communication could enable more versatile collaboration.
3. **Emergent interfaces:** While it is difficult to pre-specify a comprehensive multi-modal vocabulary of symbols, a human-robot pair could gradually expand their communicative capacity by establishing relevant conventions through interaction.
4. **Datasets and benchmarking:** With a growing number of algorithmic approaches and the costliness of comparison-based evaluations, robust benchmarks and reliable data-sharing could speed up innovation while reducing experimental overhead and barriers to entry.

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