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Co-robots: The synergy of humans and robots operating as partners

The confluence of engineering-based robotics and human-centered application domains

Brian Scassellati · Katherine M. Tsui

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Abstract A new era of robotics research is being driven by pressing societal problems and creating a transformation in the way that we envision human-robot interactions. In this chapter, we discuss three application domains that best capture both the promise and the challenges that this transformation has generated: the effort to build robots that support cognitive and social growth, robots that work in the home doing domestic tasks for users that have no training in robotics, and collaborative robots that work side-by-side to solve manufacturing and assembly tasks with human workers.

Keywords Human-Robot Interaction (HRI) · Socially Assistive Robotics (SAR) · Domestic Service Robots · Cooperative Manufacturing

1 Introduction

Robotics is undergoing a transformation that is reshaping research priorities, opening new application domains, and creating possibilities that were unheard of only a decade ago. With its roots in industrial automation, most of robotics had been focused on creating machines that performed repetitious tasks with high precision at superhuman speeds and with minimal downtime. The most salient advances were the result of intersections between mechanical engineering, electrical engineering, and computer science.

Just as personal computers ushered in a new era of computing by shifting attention from highly precise numerical calculations to computation that supported day-to-day activities, the availability (and the promise) of consumer

B. Scassellati and K.M. Tsui
Department of Computer Science
Yale University
New Haven, CT, USA
E-mail: {brian.scassellati, katherine.tsui}@yale.edu

robots has triggered a new convergence of applications, research, and collaborations. Research today centers around human-centered applications, most frequently in which robots are seen not as fulfilling a role independently but rather in cooperation with human partners (Fig. 1). These “co-robots” eschew some of the traditional engineering metrics that were the hallmarks of successful factory automation; instead of pursuing accuracy, reliability, speed, and complete autonomy, they instead are designed to be intuitive to use, to be safe operating in close proximity to people, and to operate semi-autonomously in collaboration with a human partner. Advances continue to be driven by engineering-based confluences, but new intersections between robotics and the social sciences, healthcare, psychology, and neuroscience have begun to shape research priorities and application foci.

In this chapter, rather than attempt to provide a comprehensive description of the wide range of new research directions in robotics, we focus on three representative domains that show how the changing confluence of research around robotics is being oriented toward collaborative, user-driven applications. These domains are: (1) *socially assistive robotics*, in which robots act as mentors or coaches to encourage long-term behavior change or maintenance, (2) *domestic service robots* that fulfill useful activities within the challenging uncontrolled home environment, and (3) *cooperative manufacturing* which abandons the closed assembly-line of traditional factory automation in favor of shared workspaces with collaborative human partners.

2 Socially Assistive Robotics (SAR)

Perhaps the most unusual development in robotics is the rapid growth of an application area that involves no physical contact with the user or direct manipulation of the environment. Socially assistive robotics (SAR) puts robots in the role of a therapist, mentor, coach, or guide and provides the user with social or cognitive, but not physical, support [Rabbitt et al., 2015; Scassellati et al., 2012; Tapus et al., 2007]. SAR refers to a unique area of robotics that exists at the intersection of assistive robotics, which is focused on aiding human users through interactions with robots (e.g., mobility assistants, educational robots), and socially interactive or intelligent robotics, which is focused on socially engaging human users through interactions with robots (e.g., robotic toys, robotic games) [Feil-Seifer and Matarić, 2005]. Combining aspects of engineering, health sciences, psychology, social science, and cognitive science, SAR systems are being developed that help to reduce isolation in seniors [Hutson et al., 2011], support the learning of social behaviors for children with autism spectrum disorder [Kim et al., 2013], and provide first graders with additional one-on-one educational opportunities at school [Leyzberg, 2014]. Much of the drive to construct SAR systems comes from the growing needs of special needs populations, including those with physical, social, and/or cognitive impairments. These impairments can occur at any stage of life, be it developmental, early onset, or age-related. A rapidly aging population, the explosive growth

(a) USC's Bandit

(b) iRobot's Roomba vacuum

(c) KIVA Systems' inventory station and drive robot

(d) Intuitive Automata's Autom weight loss coach

(e) Willow Garage's PR2 mobile manipulation robot

(f) Rethink Robotics' Baxter

Fig. 1 (Left to right) Examples of co-robots from the domains of socially assistive robotics, domestic service, and cooperative manufacturing [JBLM PAO, 2015; Lütkebohle, 2010; Newth, 2006; Rethink Robotics, Inc., 2014; Trowbridge, 2011]; not shown to scale. Photos of Bandit and Baxter are courtesy of the University of Southern California and Rethink Robotics, respectively.

in diagnostic rates of developmental disorders, and growing economic inequalities have made personalized care unavailable to many people. The prospect of providing individualized support on-demand and at scale to support long-term behavior change has driven these investigations.

While SAR systems do not physically interact with the world, they cannot be replaced with virtual agents; the robot's physical embodiment is at the heart of SAR's effectiveness, as it leverages the inherently human tendency to engage with lifelike (but not necessarily human-like or animal-like) social behavior. Foundational studies in this domain show that compared to virtual agents, physically present robots keep users enrolled in treatment programs for longer periods of time [Kidd and Breazeal, 2008], generate more compliance and cause users to engage in activities the robot suggests [Bainbridge et al., 2011], and even to learn more rapidly [Leyzberg et al., 2014].

An effective socially assistive robot must understand and interact with its environment, exhibit social behavior, focus its attention and communication on the user, sustain engagement with the user, and achieve specific assistive goals [Okamura et al., 2010]. The robot must do all of this through social rather than physical interaction, and in a way that is safe, ethical, and effective for the potentially vulnerable user. While many of these capabilities have been the focus of robotics research for decades, four topic areas are generally seen as critical to the future development of viable SAR deployments: (1) personalization and adaptation to individual social and cognitive differences, (2) managing autonomy over periods of months to years, (3) constructing models of the dynamics of social interaction, and (4) addressing the ethical issues that arise from automated socially supportive agents. We address each of these in turn.

One of the promises of SAR systems is to deliver enhanced learning and therapy outcomes as a result of personalized interactions tailored to each individual's unique social, cognitive, and physical abilities. Personalized lesson plans from both human tutors and automated tutoring systems has been shown to have a substantial impact on learning gains [Bloom, 1984], and this same effect has been demonstrated with personalized robotic systems [Leyzberg et al., 2014]. While existing studies in social robotics often focus on a single matching process by which the behavior of the robot is changed to optimize the properties of the interaction at a single moment in time, adaptation and personalization in assistive tasks should ideally treat the goal as an ever-changing target. Computationally, the challenge in constructing such a system stems from the individual differences among users and that adaptation must occur at multiple levels of abstraction and time scales. At a given moment, robot responses that one user might find frustrating might be optimally engaging to another, or even to the same user under different conditions or at different times. Their responses should also change over time as the user becomes tired, frustrated, or bored. Responses must also vary from session to session or day to day so that interactions remain engaging and interesting. Research in this area focuses on questions such as: How can we design a robot that adapts to each user's individual social, physical, and cognitive differences? How can a robot utilize patterns of interactions observed with other users (and possibly other robots) to bootstrap its own attempts at interaction?

Certainly, creating robots that can participate in the often complex and subtle aspects of human social interactions is a challenging task. Because of this complexity, many (but not all) SAR systems operate either partially or fully under human control, giving the human and robot roles similar to puppeteer and puppet, respectively [Lu and Smart, 2011]. Of course, the long-term goal is to create SAR systems that operate autonomously and can be used without any type of human operator controlling the interaction. Furthermore, the level of autonomy required for SAR systems to succeed, allowing for autonomous operation over months or longer, is more a more demanding requirement than those faced by other robotics applications that can rely upon occasional human intervention. The challenge is further complicated by the need for these systems to operate under the complex and unconstrained environments that humans occupy, including homes, schools, and hospitals. Questions that must be addressed in the near future include: Can a robot adapt to the unique demands of complex and dynamic human-centered environments so that it maintains the capability to make appropriate decisions without needing to have perfect perceptual understanding of its environment? Can a robot autonomously determine appropriate motivational and behavioral strategies to maintain a productive working relationship as the novelty of the interaction fades? How can a robot continue to adapt to and autonomously guide its user through successive milestones in order to achieve desired learning or behavior change outcomes over longitudinal time scales?

Assistive interactions are unique among social engagements as they must both support the needs of the engagement itself (by maintaining interest, novelty, and the conventions of social behavior) and guide the interaction toward the long-term behavioral or educational goals of the system. These two aspects can often be in conflict; at times a good teacher (or coach, or socially assistive robot) must sacrifice some of the enjoyment of the interaction, or bend a social rule, in order to promote an educational goal. Huang and Mutlu [2013] recently found some evidence that a robot could make some of these trade-offs by changing its nonverbal behavior, focusing either on improving task performance (recall in a storytelling task) or on improving social engagement by varying the type of gesture behavior used by the robot. Because the socially assistive robot must take an active part in shaping this interaction toward particular goals, the nature of the task and goal representations and the way in which this influence can be applied to shape the dynamics of the assistive interaction represents a core research question for SAR. Researchers address questions such as: What social behaviors and attributes are needed to establish and sustain trust, rapport, and comfort with the user over time to build a successful relationship that continues to provide value? Can we construct representations of interactions that capture not just moment-to-moment activity, but rather allow us to define long-term trends and preferences while maintaining sufficient detail to support rich, complex interactions?

Finally, as SAR systems use social pressure to encourage behavior change, these systems naturally raise safety and ethical considerations [Feil-Seifer, 2011]. Because these robots avoid physical manipulation and direct contact, the safety considerations differ from those in traditional robotics. Specific physical safety considerations need to be applied when dealing with children and other special needs populations, for example, to protect pinch points and secure small components. Care must also be taken in shaping the relationship between user and robot to ensure that appropriate consideration is paid to the emotional state of the user and the consequences of the robot's actions. Some more pragmatic ethical considerations take into account the inevitable progress of technology, which will render any particular system obsolete well within a user's lifetime, therefore undermining the user's attachment and likely making long-term system operation impossible. As one example of ethics applied to SAR in particular, Feil-Seifer and Matarić [2011] outline the ethical issues of SAR around the core principles of ethics applied to all human subjects research, namely beneficence, non-maleficence, autonomy, and justice. The first two principles, beneficence and non-maleficence, encompass the SAR issues of relationships, authority and attachment, perception and personifications of the robot, and replacement of human care/changes to human-human interaction. The third principle, autonomy, spans the issues of privacy, choice, and intentional user deception. Finally, justice spans the complex issues of cost/benefit analysis, and locus of responsibility in the case of failure or harm.

3 Domestic Service Robots

With the advent of robots available as consumer electronic devices for purchase at reasonable prices by the public, domestic service robots have become a popular research area that has the potential for wide-scale economic impact. Domestic service robots are used as productivity tools for household tasks. They must perform their tasks well with minimal intervention and without any expectation of maintenance by a robot technician. The primary challenge for domestic service robots is the real world itself – the home environment does not resemble a well controlled lab environment. Houses differ with respect to size, layout, and furnishings, and rooms can be cluttered and messy. The complexity of a home is a reflection of the collective needs and desires of each of its residents [Baillie and Benyon, 2008]. Both consumer electronics market trends and academic analyses of end-user needs (see [Auger, 2014; Beer et al., 2012; Ju and Takayama, 2011; Scopelliti et al., 2004; Takayama et al., 2008]) point toward two emerging use cases: (1) a general purpose, dexterous, humanoid robot that is capable of many household tasks (akin to *The Jetsons*' Rosie, the robot maid), and (2) appliance robots – capable of only specific low-level tasks.

Current commercially available domestic service robots are largely appliance robots. Floor cleaning robots have been the most successfully adopted home-use robot with 37 current and 80 discontinued models of robot vacuums, dry floor sweepers, and wet mops [Antalóczy, 2015d]. iRobot leads the consumer electronics robot market and in 2002 introduced the Roomba robot vacuum cleaner (Fig. 1(b)), a low-profile circular robot with a rotating side brush to sweep dirt into its path and infrared sensing to prevent the robot from falling down stairs and avoid user-specified restricted areas [iRobot Corp., 2015]. Over 6 million Roombas have been sold worldwide as of early 2013 [Christensen, 2013, p. 63]. Many Roomba owners and their families treat their robots as more than just appliances; 2 out of 3 Roomba owners named their robot, and 1 out of 3 have brought their Roomba to a friend's house [Forlizzi and DiSalvo, 2006; Sung et al., 2010]. Researchers have shown that people treat their Roombas as social agents by ascribing gender and personality to it and by verbally greeting and praising it [Sung et al., 2008].

There are a growing number of appliance robots designed to autonomously clean or groom other household surfaces. Lawnmowers robots are the next in consumer popularity; there are 36 current and 12 discontinued models of robotic lawnmowers, including Husqvarna's Automower, Friendly Robotics' Robomow, John Deere's Tango, and Bosch's Indego [Antalóczy, 2015b]. There are several companies producing pool cleaning robots, including iRobot, Polaris, and Solar Pool Technologies [Antalóczy, 2015c]. Robots for window cleaning (e.g., Ecovacs Winbot, PIRO Windoro, Hobot 168) and air purification (e.g., Diya One, Ecovacs Atmobot and Famlibot) are recent entries to the consumer electronics market [Antalóczy, 2015a,c; Hornyak, 2013; Partnering Robotics, 2014]. There are three robots without competitors. The Grillbot and Auto Mee S electronics screen cleaner [Antalóczy, 2013; Fingas, 2013] are novelty items, as opposed to the iRobot Looje gutter cleaner which has four models [Antalóczy, 2015c].

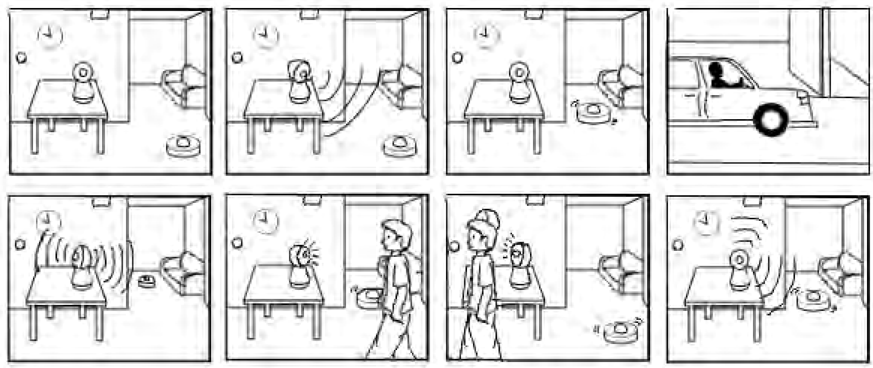
While appliance robots have had some commercial success, consumer demand and research interests have more naturally gravitated toward the fictional all-in-one, humanoid personal assistants. Researchers and companies alike see the domestic humanoid as a technology-based method for addressing the growing percentage of the population above the age of retirement; a personal assistant robot is placed in the home of an elderly family member, thereby allowing the senior to remain in his/her home and maintain his/her independence and quality of life with the help of the robot (See Beer et al. [2012] and Yamazaki et al. [2012]). The research community has made steps toward this inclusive vision by designing dexterous mobile robots to autonomously perform elect portions of household tasks under specific conditions (see Smith et al. [2012] for a summary). For example, IRT's Home-Assistant Robot can load clothes into a washer machine [Yamazaki et al., 2012], and the Willow Garage PR2 can fold the laundry [Miller et al., 2012]. The PR2 can also prepare food, such as baking cookies and making pancakes [Beetz et al., 2011; Bollini et al., 2013], and CMU's Home Exploring Robot Butler, or simply HERB, can load and unload the dishwasher [Washington Post, 2014]. This vision has also been the focus of competitions in which research robots must master typical household tasks. Over 100 RoboCup@Home teams have demonstrated their domestic service robot entries in a series of tests set in a realistic home environment or real-world setting (i.e., restaurant, grocery store) [Holz et al., 2013, 2014; van der Zant and Iocchi, 2011; Wisspeintner et al., 2009]. The challenges comprehensively and holistically evaluate a robot's functional abilities, which have included mapping an unknown environment, navigating within it and avoiding dynamic obstacles, recognizing and manipulating an object recognizing a human and tracking him/her, recognizing and understanding a human's speech and/or gestures, and high-level reasoning abilities. However, the challenges of addressing multiple tasks on the same robot in generalized environments still remains largely unaddressed.

While consumers wait for the arrival of an affordable version of Rosie the robot maid, an intermediate trend is emerging – the confluence of smart devices and domestic robots. (See Gomez and Paradells [2010], Brush et al. [2011], and

Wilson et al. [2014] for surveys on smart homes and home automation.) In this hybrid approach, homes will have several different appliance robots in order to perform a heterogeneous collection of household tasks. New task-specific robots will enter the consumer electronics market, perhaps potentially to locate lost or misplaced objects or retrieve fallen objects from the floor (e.g., Dusty [Healthcare Robotics, 2015; King et al., 2012]), for example. This next generation of domestic robots will be able to communicate with each other and other smart home devices [Turcu et al., 2012]. Researchers have already begun developing laboratory-based smart homes staffed with robot assistants (e.g., [Badii et al., 2009; Baeg et al., 2007; Heuvel et al., 2012; Huijnen et al., 2011; Johnson et al., 2014; Lu et al., 2012; Petridis et al., 2010; Torta et al., 2012]), and the 2015 RoboCup@Home competition will test the integration of domestic service robots with smart home devices [van Beek et al., 2015]. An embodied social companion-type robot is a likely liaison between the residents and the smart devices and the appliance-based domestic robots; see Fig. 2. Note that one adoption barrier of commercial smart homes has been the coordinated control over the assortment of home automation and smart environment devices [Wilson et al., 2014]. It will be imperative for the residents to feel in control over their households and that the domestic service robots understand their preferences, as forewarned by Yamazaki [2006]; Cha et al. [2015] corroborated this for a domestic robot assistant helping to organize the kitchen. Initially, it may be preferable for the residents to interact with the robot liaison in order to manually start a robot on its task, or similarly, to explicitly program the robot cleaning schedule. The robot liaison can report back to the residents about successful task executions or outstanding issues that occurred. As residents acclimate to their robotics-enhanced smart home over time, their routines and preferences can be observed; the robot liaison can accordingly suggest changes when the residents are present and/or automatically reschedule their tasks.

4 Cooperative Manufacturing

Whereas traditional industrial automation focused on speed and precision of repetitive tasks that replaced the need for human workers, a shifting focus to flexibility in the manufacturing process and a revival of the small-scale manufacturer has resulted in an emphasis on constructing robots that enhance manufacturing capabilities by working side-by-side with human workers. Cooperative manufacturing takes the approach that humans should do the tasks that humans are good at (including cognitive planning and fine dexterous manipulation) while relying on robots to do the tasks that robots show superior capabilities (including matching tool ends to parts, handling heavy or dangerous materials, or stabilizing parts). The expectation of cooperation and collaboration between the human and robot teammates may be implicit or explicit in cooperative manufacturing and depends upon the complexity of the task, the capabilities of the robot, and the communication modality be-



Imagine a scenario in which a robot liaison oversees a network of smart home devices and domestic robots in a condo shared by two roommates. Today, the liaison needs to task the robot vacuum to clean the family room and kitchen. It has learned that the residents are away during working hours, and it is now 10am. The liaison confirms that no one is currently home by checking the smart devices in the family room and schedules the robot vacuum for immediate operation. Minutes later, the garage door opening event is detected. The liaison turns up the temperature and recalls the robot vacuum; vacuuming will have to wait until later. As one of the residents passes quickly through the kitchen, the liaison turns its head to follow the resident's movement, trying to announce that there is a new alert. The roommate walks past and leaves the house again. The robot vacuum is redeployed and the alert is reset.

Fig. 2 Example of a companion robot coordinating control over appliance robots and smart home devices

tween the human worker and the robot. Within this research area, two main applications have been attracting the most attention: (1) automated package handling, and (2) humans and robots sharing workcells.

While much enthusiasm has been shown recently towards using drones, or unmanned aerial vehicles (UAVs), for automated package delivery [Amazon.com; Koebler, 2013], the reality is that automated guided vehicles (AGVs) – such as carriers, tow units, and forklifts – have been used in warehouses and factories for decades [Ullrich, 2015]. Large platform AGVs have been used since the 1950s in limited capacities, such as transporting heavyweight payloads such as engine blocks [Wurman et al., 2008]. In these traditional roles, human workers and robotic AGVs are separated to ensure safety; if a human worker is present in an area, then the robot must not enter that area.

A more modern cooperative approach can be seen in order fulfillment systems in warehouses. Order fulfillment traditionally has involved human workers who are assigned to zones within a warehouse to batch "pick" items in their zones for several customer orders and convey these items to a centralized packaging station [Wurman et al., 2008]. Today, distribution centers utilize fleets of robots to bring racks of merchandise to central packing centers where human workers verify orders and place objects into shipping boxes (Fig. 1(c)). One human worker packing items at a station may be supported by 5 to 10 robots, which retrieve pods in parallel and move at human walking speeds (up to 5km/h) [D'Andrea, 2012; Kiva Systems, 2010]. Controlled by a centralized scheduling and planning system, these fleets of robots have been shown in practice to double the productivity of the human workers [Wurman et al., 2008].

Existing manufacturing facilities are beginning to adopt the practice of humans and robots sharing workcells on assembly lines. According to Powley [2014], a small percentage of 179,000 industrial robots sold each year are designated for human-robot collaboration; Universal Robots leads this market, having sold 2,500 UR collaborative robot arms from 2008 to 2014 [Powley, 2014]. At a Volkswagen automotive factory in Germany, a robot inserts glow plugs into drill holes within the engine's cylinder heads, which are difficult for human workers to reach; the human worker then follows with insulating the cylinder heads [Powley, 2014; Tobe, 2013]. Similarly, BMW uses a collaborative robot to assist human workers during the final car door assembly in which the doors are insulated from sound and water [Knight, 2013]. The two real-world deployments by Volkswagen and BMW demonstrate tasks in which the human worker and the robot are physically collocated in a shared workcell. However, these tasks are simplistic and discretized such that the robot first completes its subtask and then the human worker finishes the task. It is implied that they are working together as teammates, albeit asynchronously taking turns. The human worker can accommodate the robot, waiting until it is finished inserting the glow plugs or applying the sealant; thus, it is not necessary to model the task and subtasks.

Modelling and recognition of tasks (and subtasks) allow for increased scheduling flexibility, teamwork fluency between the robot and the human worker, and efficiency with respect to throughput (e.g., decreased idle time, decreased task completion time). For example, a robot can act as an assistant by predicting the human worker's subsequent task and providing the necessary tool(s) and/or component(s) [Hayes and Scassellati, 2014]. Task models can be explicitly programmed as with traditional industrial robot arms or acquired through demonstration [Muxfeldt et al., 2014]. The ability to acquire new tasks and skills has opened the possibility of utilizing collaborative robots in smaller manufacturing enterprises, as one robot investment can be re-tasked by human workers to a variety of tasks without extensive training or experience [Anandan, 2014]. Once the robots are trained, they usually operate alone until completing their task or retraining is needed to accommodate a new part or a change in the process. The wide-scale deployment of these collaborative robots has the potential to radically alter the manufacturing world, as the creation of customized products or the manufacturing of products in areas where labor is more expensive becomes possible.

Currently, there are no real-world examples of human workers and robot manipulators physically working together on the same task, at the same time, in the same place. Traditional robotics approaches are insufficient for realizing this level of cooperative manufacturing. The immediate and low-level challenge is for the robot to robustly detect the presence of a human worker, as opposed to an object or environmental constraint (e.g., table). Subsequently, the robot must be able to detect and track the body pose of the human worker; additionally, it must always be aware of its own pose and trajectory, estimate the human worker's trajectory, monitor for collisions, and stop or adjust its trajectory if necessary. Another low-level challenge is for the robot to recognize the human worker's current action. It must also detect any unexpected behavior by the human worker, determine if its current action should stop, and do so if necessary. Based on the human worker's current action, one mid-level challenge is for the robot to determine the current task or subtask, if more than one exists. Finally, high-level challenges the robot include monitoring task progress, predicting the subsequent actions for itself and the human worker, determining how its current action effects the overall task, and changing if necessary.

Before there can be true side-by-side collaboration between human-robot pairs, many technical challenges need to be overcome. Object recognition, grasp planning, motion planning, and compliant manipulation are all deep and open problems that must contribute solutions to a viable collaborative system. (Frey and Osborne [2013] note that object perception and manipulation is one of three factors preventing the computerization of certain types of human worker jobs.) Beyond improved object perception and manipulation skills, robot manipulators must also be aware of human's physicality, cognitive state, and preferences and factor this into their motion planning. There is hope though that progress can be made with mixed-autonomy systems that rely not on a completely self-sufficient robot but rather leverage the strengths of the human partner to overcome some of the shortcomings of the robotic partner.

5 Summary and the Future

This chapter has demonstrated the significantly altered trajectory of robotics research from its roots in industrial automation to the dominant domains today that feature robots working in human environments, in concert with human activity, and in order to impact the quality of life of human users. This evolution has been enabled by the convergence of research in human-centered sciences including sociology, healthcare, psychology, and cognitive science. This convergence can be seen in many sub-areas of robotics, including ones in which robots are evolving to coexist with humans, functioning as coaches, assistants, and teammates, albeit for now in limited settings.

In order to function in complex, unconstrained, and dynamic human environments and interact with humans, robots will need cognitive, linguistic, social, perceptual, and motor competencies beyond the current skill level, and this suite of competences must function in concert. The computational and algorithmic demands on these systems are unlike those that led to successful factory automation, and new research methods that utilize methods from converging areas will be needed to create and test these systems. Among the many examples of these transformative applications, techniques that enable robots to easily acquire new skills as they encounter novel situations by generalizing from their prior experiences and applying their existing competences will certainly be essential. Modeling the complexities of human environments, engaging in collaborative and personalized interactions, and developing mechanisms for engaging, useful, and viable long-term interactions are also certain to be critical.

The most significant impact of this transformation in robotics is the range of application domains that could potentially undergo dramatic change. From providing personalized health coaches to educational tutors that supplement the instruction that teachers and therapists can provide, from robots that help seniors to stay independent in their own homes for longer to domestic aids that help manage the interconnected services in the home of the future, and from efforts to bring manufacturing back to small and medium sized enterprises to robots that lend a hand assembling furniture, the potential impact of this new generation of co-robots may instigate wide-reaching changes.

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