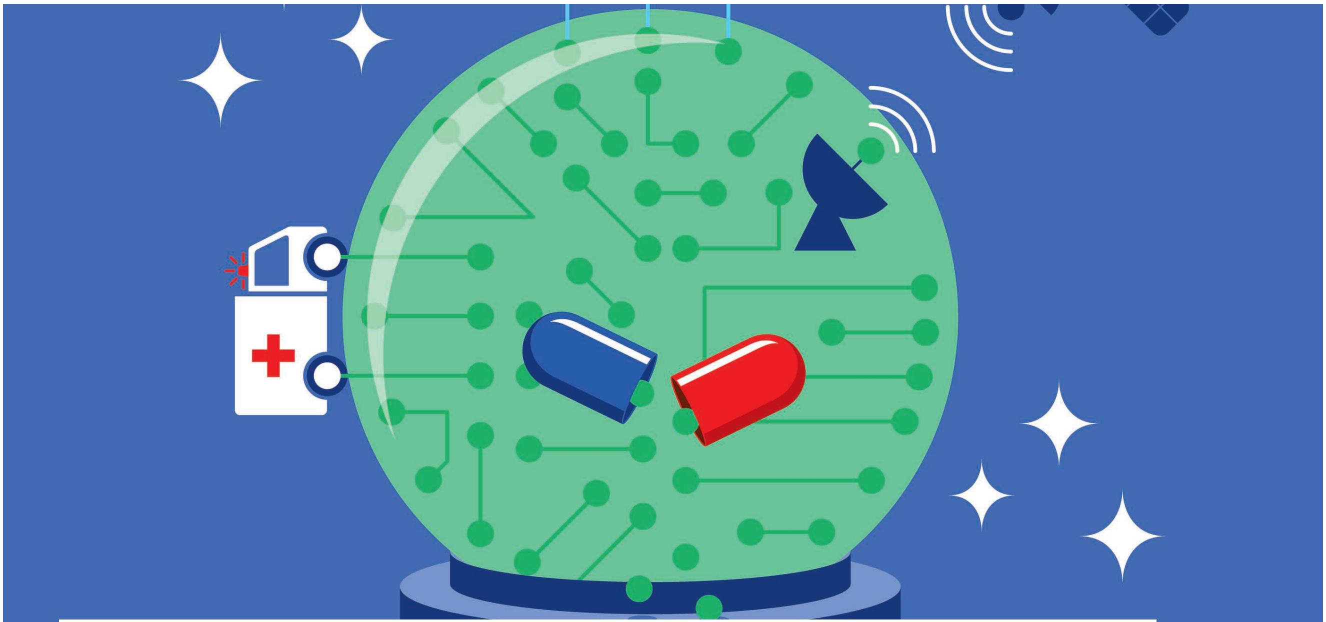

Cognizant and Socially Aware Robotics

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Based on current developments in soft electronics, artificial intelligence, energy storage and harvesting strategies, and manufacturing technologies, this article presents how advances in several fields can unite to create an intelligent robotic system and predicts how close we are to the cognizant, socially aware robot.

The sci-fi film *Blade Runner*, made almost 50 years ago, depicts a futuristic yet evocative scene that would hypothetically happen, according to the director's prediction at that time: in the year 2019, bioengineered humanoids, humanlike robots called replicants, can be massively produced using the latest science and technology combining biotechnology, genetic engineering, cybernetics, and artificial intelligence. Able to think like a human and behave like a human, possessing human feelings, emotions, and memories of the past, they have been massively deployed and integrated into human society, performing social duties and forming relationships with others just as a normal human would. The lines between humans and replicants become so blurred that distinguishing between the two becomes a specialty

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that requires specialized training; without it, it is even impossible for the replicants themselves to tell one from another or to recognize themselves as replicants or not.

What was in the director's mind is possibly the all-time dream of many in the robotics community. No doubt there have been significant and transformative advances in robotics, but looking at the current state of the art, it is obvious that the director has been way too optimistic. In 2025, we have robots that look like humans and other animals, but we are still far from achieving humanoids that can perfectly "replicate" the human. Even creating a robot that can perform certain tasks safely and autonomously in a dynamic and unstructured environment without humans' intervention is a big challenge, not to mention the development of humanlike intelligence, self-awareness and awareness of the world, rationalities, irrationalities, and emotions, some of which are believed to be uniquely possessed by living beings. Nevertheless, from where we stand today, it is thought-provoking to look back at the state of the art in the relevant disciplines and the trajectory of robotics advances and to predict the near-term and midterm future landscape toward the realization of a qualified "cognizant humanoid" that can mimic human perception, intelligence, and even emotion at a decent level.

SENSORS AND ACTUATORS

Sensors

People in the past believed that humans have five basic senses: sight, touch, hearing, smell, and taste. Over time, research has started to explore some more. For humanoid robots today, we primarily rely on visual; auditory[1,2]; and, particularly in recent years, tactile sensing.[3] Indeed, there have been robotics related studies on smell and taste sensors,[4] but they are not as mature as the other three modalities. To give a few exemplary advancements, research on tactile sensors has evolved from being distributed in certain critical regions to the whole-body scale. The large-area distribution of tactile sensors, also termed electronic skin, has been applied in several humanoid platforms such as iCub and ASIMO,[5] providing crucial information for human–machine interaction.[6] Vision-based sensors, including RGB and depth cameras, have been widely used in robotic systems to obtain visual input data. Recent advances in flexible electronics have also enabled the development of an electronic nose responding to various odors with classification capabilities. However, these demonstrations are comparatively limited, especially in the humanoid robot context.

That said, even for the popularly studied sensing modalities we are integrating in humanoids, their sensor density remains far below that of the human body. For example, we humans have ~100,000 to 400,000 mechanoreceptors located at different depths in the skin, responding to tactile inputs of different frequencies, adapting to the environment with different time constants. Additionally, there are thermoreceptors and nociceptors that allow us to sense temperature and pain, respectively. These receptors specify in different aspects of touch, each with different receptive fields. Collectively, they help capture the rich tactile information and contribute to forming a holistic, dynamic perception of the environment. Today, even the most advanced humanoid robots are unable to integrate such a large number of tactile sensors on the robot's outer surface, which is only the first step toward replicating the human skin. This is due not only to the technical challenges of sensor fabrication but also to how they can be assembled or integrated to work together with ultralow power consumption and data transmission latency (Figure 1). This is likely to be one of the focuses of sensor studies in the future.

The integration of sensors of different modalities has created the need for sensor fusion. Currently, the robotics community addresses this aspect

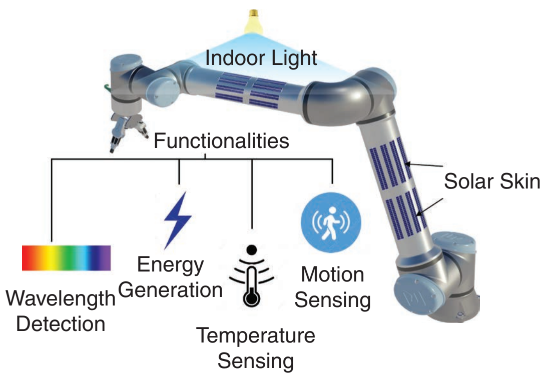

FIGURE 1. Multimodal solar skin performs sensing and energy generating functionalities. (Source: Chirila et al.,[7] used with permission.)

using model-based approaches such as Kalman filters, as well as machine learning-based, data-driven techniques. While these methods have proven to be effective, they introduce a certain amount of latency that may not be desirable in many time-critical applications such as telerobotic surgery. In this respect, a combination of centralized and decentralized fusion, based on both hardware and software approaches, may be promising in the future, as will be discussed later.

Actuators

Animals have muscles covering the body, whose contraction or expansion produces movements. The touch-related receptors are integrated seamlessly with the muscles to provide feedback related to movements and the sense of space. Similarly, robots also need actuators that are tightly coupled with touch sensors. In many robotic systems, their locomotion is achieved using actuators such as miniaturized rotary or linear motors. Unlike natural muscles, these motors are usually stiff and rigid and show compromises between resolution and range. Recent studies on soft materials and shape memory alloys have fostered the development in artificial muscles.[8] They are soft and flexible and can even be programmed to be more adaptive than the muscles of the organism. Advances in this direction have led to progress in soft robotics, exoskeletons, rehabilitation devices, etc. While these explorations continue, what is missing is how to control the actuators in an efficient manner, using ultralow power consumption, and if the need arises, to respond in an ultrafast manner. In nature, there are many examples showing synergistic integration of sensing, actuating, and computing in living beings, which has inspired biomimetic robotics studies.[9]

COMPUTING HARDWARE

Computing capability is critical for robots. It has been predicted by Moravec[40] a computing capacity of 20 thousand million instructions per second (MIPS, an old way to measure a computer's speed) could allow a robot to perform simple tasks, 100 thousand MIPS for reinforcement learning from the environment, 5 million MIPS for mental rehearsal, and 100 million MIPS for abstraction and generalization. While the total amount of computational resources is important, how those resources are allocated and used is also important as they need to be coordinated with the sensors and actuators to allow efficient interaction with the environment.

Algorithms and learning rules

Until now, computing in robotics has mainly relied on software methods that use a general-purpose computing platform to run various algorithms to process the sensory data to form perceptions. For example, convolutional neural networks have been widely used to process the visual data for tasks such as image recognition, simultaneous localization and mapping has been used to create an internal map of the environment, and spiking neural networks have also been used to process tactile and sometimes visual data. Usually, these algorithms are run on a general computing platform (for example, a microcontroller or microprocessor), and they induce significant data latency, which can easily accumulate to minutes. Compared with human reaction time, they are far too slow. This highlights the need for a new computing paradigm in both the hardware architecture and the computing algorithm.

A more fundamental question is how we can achieve perception and develop intelligence in machines like we humans do. To this end, the development of neuroscience studies has greatly inspired the development of neurorobotics. For humans and other organisms, the most well-known learning rule discovered in the biological nervous system is the spiking-time-dependent plasticity. This allows the formation of correlation between external stimuli and internal representations. Studies have been carried out that leverage such a learning rule to perform several tasks, including arm controlling,[10] navigation,[11] categorization, and decision making.[12]

Being one of the most well-known learning rules in neuroscience, it is a local rule that largely relies on coincidence. On top of this, there is also a mechanism that modulates the synaptic plasticity based on environmental feedback: the three-factor learning. Indeed, there are also many other learning rules discovered from living beings, and it is a still-developing research area. In fact, such biologically observed learning rules have already been implemented in robotics as may be noted from previous reports.[11,13]

Although emulating these cellular-level biological learning rules in robotics is important, it is somewhat still distant from realizing an embodied system that generates perception like humans. Historically, perception has been viewed as an active interpretation of sensory input, a view championed by Hermann von Helmholtz, who proposed that the brain infers the causes of sensory data through probabilistic reasoning. The close linkage of sensation and perception is now well accepted, but some neuroscientists argue that the formation of perception is more of a top-down generative process[14]: the brain generates the understanding of the world and constantly updates it by using the external sensory inputs, for example, the predictive coding. In this context, the cellular level of biological learning has more concrete meanings. For example, the three-factor learning mentioned above has been suggested to govern the precision level of the environment and adjust the "learning rate" of the internal world.[15] Such an understanding has been implemented by roboticists to develop cognitive robots.[16] Distributed adaptive control theory has also been developed, which aims to establish connection between brain and body (that is, embodied intelligence) by answering four fundamental questions: why, what, where, and when, the H4W problem.[17] This hierarchical control framework leverages the Hebbian-like learning rule with the prediction term, which provides the system-level control to the famous local biological learning rule. Preliminary exploration on emotion-involved neural networks (for example, affective computing, emotion modeling, and emotion-influenced AI) has also been carried out in the past decades, which has served as the basis to create artificial emotion circuits.[18]

Compared with the neuroscience-based model, another direction worthy of mention is symbolic AI and the cognitive and social models based on this. A famous example is the Kismet from MIT, whose synthetic nervous system functionally mimics infants' cognition and emotion.[19] Other models worthy of mentioning include adaptive control of thought—rational,[20] distributed integrated affect reflection and cognition,[21] and more. These classic cognitive architectures have notably contributed to the development of social robots. Furthermore, combining symbolic and neuroscience-based approaches can effectively reduce the amount of computing resources required.

Hardware implementation

Implementation of various algorithms in hardware is attractive as this drastically decreases the data and computing latency (usually down to microseconds or even lower). In robotics, there have been many such research works, where the very large-scale hardware neural network or other algorithms act as the brain equivalent for robots.[22] While such a solution has clear advantages over the software-based approaches, in the current form of implementation it is still more suitable for centralized computing, as for vision sensing, and is not suitable for large-area distribution, as needed for electronic skin or tactile sensing. In the latter case, the computing resources need to be integrated with sensors and actuators. Considering the large number of tactile sensors and actuators distributed over the body, this unavoidably upscales the size of input and output data, thus quickly overloading the data transmission channels (having limited bandwidth) among the sensing, actuating, and computing hardware. As a result, considerable delay can be experienced between sensing and actuation if traditional computing hardware is to be used. This is where decentralized computing becomes attractive.

In fact, decentralized computing has been widely observed in biology. For instance, distributed computing has been found to be one key strategy for handling large amounts of tactile data. The perception of the edge orientation of an object in contact takes place at the skin itself, owing to the location-specific tactile sensing characteristics inside the receptive field of sensory neuron and the soft nature of the skin, which deforms during contact.[23] This inspires the development of distributed hardware that can process and scale down the large touch sensing data collected from the whole body, by using the near-sensors computing (or edge computing), before the data are transmitted to the higher perceptual level.

The decentralized strategy has also been widely observed in biology to form localized sensorimotor correlations. Simple insects like locusts have shown localized correlations critical for various biological phenomena such as grooming; gap crossing; and danger escape, which requires a fast response.[24] Human bodies exhibit the patellar reflex, which is controlled by a low level of spinal cord and not influenced by higher levels of the nervous system (that is, the brain).[25] The fast responsive knee reflex is critical in posture and balance maintaining. These examples show how organisms reduce computation latency and power consumption and obtain a fast-responding system by offloading computation to the periphery.

Novel neuromorphic devices

Although it is still at a very early stage, realizing decentralized computing using suitable hardware has drawn increasing attention over the past decade. To this end, one direction worthy of mention is the development of novel neuromorphic devices, such as memristors and synaptic transistors.[26,27] These devices exploit the rich electronic behavior arising from new materials and nanoscale interfaces, thereby enabling the emulation of the functionality of neurons and synapses using either a single device or a highly concise circuit. They can also be developed on a flexible substrate, as well as large areas. This serves as the basis for the realization of decentralized computing as the distribution of computing near the sensor end in humanoid robots, where the mechanical conformability on the curved surface is required.

While these novel devices represent novel analog computing paradigms and are far less mature for technology uptake, we could also actively explore other material-based transistors, such as organic semiconductors, metal oxides,[28] carbon nanotubes, 2D transition metal dichalcogenides, etc.[26,29] To this end, a critical aspect is the simplicity of the design so that the targeted circuits and systems can be implemented using these emerging technologies of a lower technological readiness level.

Weightless neural networks

One direction worthy of mention is the weightless neural network (WNN). The WNN is a special class of neural model,[30] which is inspired by the dendritic trees of biological neurons. WNNs do not use weights to determine their responses. Instead, they concatenate inputs to form an address and perform a lookup table to determine the response. With only one or a few layers, WNNs are inherently low power and significantly solve the inference latency problem. They have been implemented in hardware using field programmable gate arrays (FPGAs)[30] or application specific integrated circuits.[31] They can also be implemented with logic gates in combinational form[31] or with flip-flops or lookup tables (Figure 2).[30] Deep neural networks have been very successful employing training based on gradients, adjusting the coefficients (weights) in the model based on the error between the predicted and actual outputs. Binary values and lookup tables are not differentiable, but important advances have happened in recent years on approximate differentiations of binary and lookup tables.[30,32] WNNs have not received much attention in the past due to their low accuracy. However, recent results provide interesting solutions. For example, FPGA prototypes of WNNs with counting bloom filters, arithmetic-free hashing, and bleaching consume 85%–99% fewer cycles and 80%–95% less energy compared with convolutional neural networks and multilayer perceptrons of the same accuracy.[30] These WNNs yielded 10 times inferences/Joule on a keyword spotting dataset with 105,829 utterances from 2,618 speakers, compared with industry-grade binarized neural network models of iso-accuracy created using AMD/Xilinx FINN.[33] The hardware implementation of WNNs requires a much lower number of transistors, which means fabrication complexity is much lower and can be attempted using non-CMOS Si-based technology on flexible substrates. This may be a possible venue for localized computing using tiny intelligent circuits that are possible because of these emerging shallow neural networks.

Reviewing the development in centralized and decentralized computing, we would like to argue that they largely complement each other, and the future humanoid system may require both to coordinate the sensory input and motor output, just as observed with the central nervous system and the peripheral nervous system in our human body. Decentralized computing mainly deals with simple tasks but requires a fast response time. Several reflex-based sensorimotor correlations listed above can be vivid examples. On the other hand, centralized computing is more powerful but induces more data transmission and processing, thus inducing a longer latency time. They can be responsible for high-level planning such as decision making, reasoning, task management, and more. There are also several

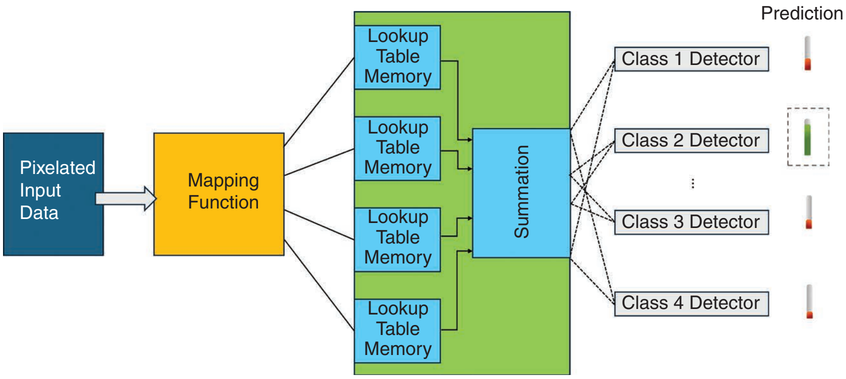

FIGURE 2. A diagram showing the flow of the WNN.

aspects that should be handled using both manners. For example, social behaviors and humanlike emotions involve not only high-level cognitive processes but also the real-time generation of facial expressions and body language. The former is more relevant for centralized computing, while the latter is more relevant for decentralized computing. With respect to employing emerging devices to emulate emotion generation and decision-making processes, some preliminary attempts have been made,[18] although further studies in neuroscience and robotics are very much needed.

ENERGY

Given the evolution of electric vehicles, it is possible that the main energy source for humanoids and other mobile robots in the future will also be based on batteries, thanks to their large energy density and mature manufacturing technology. However, it is also very possible that this will be complemented by many other types of energy sources, such as solar, wind, wireless transfer of power, etc. Energy harvesting may also be applied in robotic systems such as triboelectric, thermal electric, etc. These novel and lightweight energy sources will be particularly important for prolonged outdoor operations and for those soft robots.

It is interesting to predict the power consumption of cognizant and socially aware robots. The power consumption of conventional robots largely depends on their size and applications. It can vary between tens of watts and kilowatts. For example, a 3D-printed hand that can perform sensing and actuating functions shows a power consumption of ~10 W, mostly contributed by the actuators.[34] In a social robot, more distributed sensors and actuators are needed, along with the neural circuit that is responsible for cognition and social interaction. In this regard, the power requirement will be considerably higher. However, if we only consider the power consumption of the neural circuits responsible for primitive cognition and social interaction, it may not result in a significant increase in power consumption. Memristor-based systems have been demonstrated, consuming possibly only a few watts of power. Further optimization could reduce power consumption even more.

MANUFACTURING

Thus far, the main workhorses of computing and communications are Si chips based on CMOS technology. They are mature, reliable, and deeply embedded in almost every aspect of society. Robots such as humanoids also require many soft components, such as the above-mentioned tactile sensors, artificial muscles, distributed computing hardware with flexible and stretchable form factors, and so on.

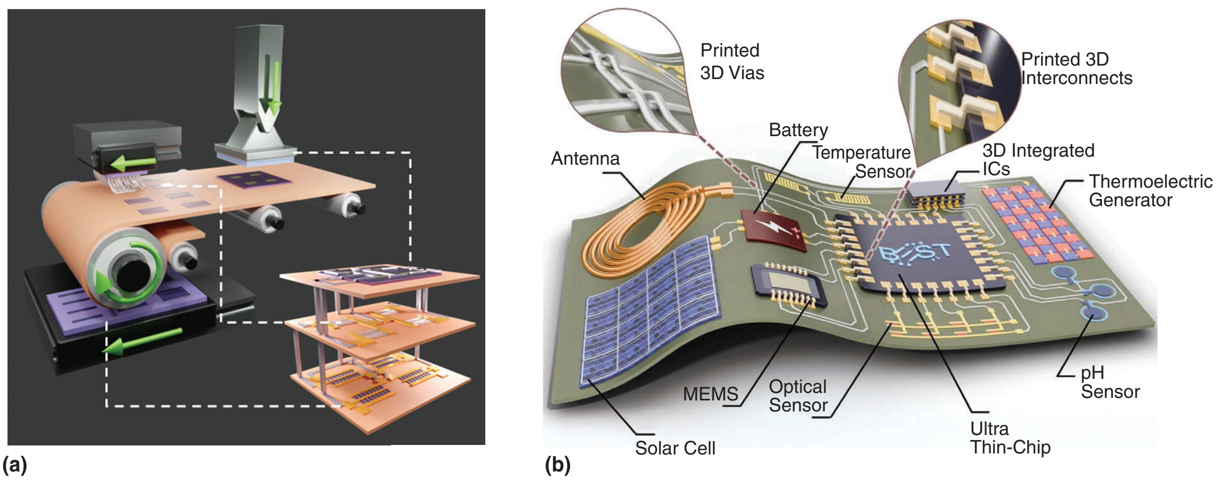

FIGURE 3. Manufacturing a flexible hybrid system using printing techniques. (a) The roll-to-roll manufacturing of a flexible, 3D hybrid system using printing. (Source: Liu et al.,[29] used with permission.) (b) A prototype showing a heterogeneously integrated flexible electronic skin. (Source: Dahiya et al.,[36] used with permission.)

Such features require nonstandard manufacturing routes as Si chips are rigid and stiff. The ecological footprint of the traditional lithography-based route for the fabrication of Si chips is another challenge. For this, printed electronics is a promising alternative as desired components can be developed in a drop-on-demand manner (Figure 3). It is also compatible with various polymeric substrates because of the possibility of printing sensitive layers at room temperatures. In contrast to lithography-based processes, printing is a purely additive process with significantly lower energy, water, and chemical solvent consumption. In this sense, printed electronics has great potential for environmentally friendly and resource-efficient production.[29]

Although various case studies of printed sensors, actuators, and transistors have been reported, they have limitations compared with those manufactured using conventional technologies. The limitations are in terms of minimum feature size, density, performance, etc. For example, even with the most advanced printing technologies, transistors still have dimensions no smaller than the submicrometer scale. This is close to the process node in Si CMOS three to four decades ago. Looking to the future, it is optimistic to predict that the size and performance of printed devices, particularly printed transistors, will follow the trajectory of traditional electronics but perhaps at a much slower pace.

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Today we talk about Industry 5.0, where robots will work closely with humans, autonomously and intelligently performing various duplicative tasks. Like the rapid development and deployment of personal computers in almost every household in the past few decades, it is predicted that robots may follow a similar trajectory in the next decade or two. For those robots with intelligence and social awareness, they may become human companions rather than electronic devices. Several studies on human–robot interaction have suggested that social robots can engage more closely with humans and accomplish intended tasks far more effectively.[37,38]

On the other hand, notable advances have been achieved in social robots: a good example is Sophia, the humanoid robot produced by Hanson Robotics, which emulates human expressions and emotions by integrating dozens of actuators underneath the facial skin (Frubber) of the robot. While such facial expression would not be possible without rubbery skin-like materials, the current version still lacks the critical tactile sensory feedback, which limits the perceptual capability and the level of social interaction. Another recent example is the anthropomorphic facial robot, Emo, which is capable of anticipatory expression by capturing the visual cues.[39] Here, too, tactile feedback could be introduced to allow for a richer sensation and perception.

The advances highlighted in this article could potentially lead to a distributed cognition system having tightly coupled sensors and motors. Such a system could improve understanding of the environment and react accordingly, reduce the processing and response time, and promote social engagement, eventually leading to a scenario where humans and robots collaborate more frequently and extensively as with human coworkers.

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REFERENCES

1. P. Dudek et al., “Sensor-level computer vision with pixel processor arrays for agile robots,” *Sci. Robot.*, vol. 7, no. 67, 2022, Art. no. eabl7755, doi: 10.1126/scirobotics.abl7755.
2. B. J. Zhang and N. T. Fitter, “Nonverbal sound in human-robot interaction: A systematic review,” *ACM Trans. Hum.-Robot Interact.*, vol. 12, no. 4, pp. 1–46, 2023, doi: 10.1145/3583743.
3. A. S. Dahiya et al., “Printing semiconductor-based devices and circuits for flexible electronic skin,” *Appl. Phys. Rev.*, vol. 11, no. 4, 2024, Art. no. 041334, doi: 10.1063/5.0217297.
4. H. T. Nagle and S. S. Schiffman, “Electronic taste and smell: The case for performance standards [Point of View],” *Proc. IEEE*, vol. 106, no. 9, pp. 1471–1478, Sep. 2018, doi: 10.1109/JPROC.2018.2859678.
5. L. Natale, C. Bartolozzi, D. Pucci, A. Wykowska, and G. Metta, “iCub: The not-yet-finished story of building a robot child,” *Sci. Robot.*, vol. 2, no. 13, 2017, Art. no. eaaq1026, doi: 10.1126/scirobotics.aaq1026.
6. G. Cheng, E. Dean-Leon, F. Bergner, J. R. G. Olvera, Q. Leboutet, and P. Mittendorfer, “A comprehensive realization of robot skin: Sensors, sensing, control, and applications,” *Proc. IEEE*, vol. 107, no. 10, pp. 2034–2051, Oct. 2019, doi: 10.1109/JPROC.2019.2933348.
7. R. Chirila, A. S. Dahiya, P. Schyns, and R. Dahiya, “Self-powered multimodal sensing using energy-generating solar skin for robotics and smart wearables,” *Adv. Intell. Syst.*, vol. 6, no. 7, 2024, Art. no. 2300824.
8. M. Pan et al., “Soft actuators and robotic devices for rehabilitation and assistance,” *Adv. Intell. Syst.*, vol. 4, no. 4, 2022, Art. no. 2100140, doi: 10.1002/aisy.202100140.
9. T. Yue et al., “Embodying soft robots with octopus-inspired hierarchical suction intelligence,” *Sci. Robot.*, vol. 10, no. 102, 2025, Art. no. eadr4264, doi: 10.1126/scirobotics.adr4264.
10. A. Bouganis and M. Shanahan, “Training a spiking neural network to control a 4-dof robotic arm based on spike timing-dependent plasticity,” in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Piscataway, NJ, USA: IEEE Press, 2010, pp. 1–8, doi: 10.1109/IJCNN.2010.5596525.
11. A. Safa et al., “Fusing event-based camera and radar for SLAM using spiking neural networks with continual STDP learning,” in *Proc. IEEE Int. Conf. Robot. Automat. (ICRA)*, Piscataway, NJ, USA: IEEE Press, 2023, pp. 2782–2788, doi: 10.1109/ICRA48891.2023.10160681.
12. M. Beyeler, N. D. Dutt, and J. L. Krichmar, “Categorization and decision-making in a neurobiologically plausible spiking network using a STDP-like learning rule,” *Neural Netw.*, vol. 48, pp. 109–124, Dec. 2013, doi: 10.1016/j.neunet.2013.07.012.
13. S. A. Lobov, A. N. Mikhaylov, M. Shamshin, V. A. Makarov, and V. B. Kazantsev, “Spatial properties of STDP in a self-learning spiking neural network enable controlling a mobile robot,” *Front. Neurosci.*, vol. 14, p. 88, Feb. 2020, doi: 10.3389/fnins.2020.00088.
14. C. L. Buckley, C. S. Kim, S. McGregor, and A. K. Seth, “The free energy principle for action and perception: A mathematical review,” *J. Math. Psychol.*, vol. 81, pp. 55–79, Dec. 2017, doi: 10.1016/j.jmp.2017.09.004.
15. H. Bottemanne, “Bayesian brain theory: Computational neuroscience of belief,” *Neuroscience*, vol. 566, pp. 198–204, Feb. 2025.
16. A. Ciria, G. Schillaci, G. Pezzulo, V. V. Hafner, and B. Lara, “Predictive processing in cognitive robotics: A review,” *Neural Comput.*, vol. 33, no. 5, pp. 1402–1432, Apr. 2021, doi: 10.1162/neco_a_01383.
17. P. F. Verschure, “Distributed adaptive control: A theory of the mind,

brain, body nexus," *Biologically Inspired Cogn. Archit.*, vol. 1, pp. 55–72, Jul. 2012, doi: 10.1016/j.bica.2012.04.005.
18. Z. Wang, X. Wang, and Z. Zeng, "Memristive circuit design of brain-like emotional learning and generation," *IEEE Trans. Cybern.*, vol. 53, no. 1, pp. 222–235, Jan. 2023, doi: 10.1109/TCYB.2021.3090811.
19. C. L. Breazeal, "Sociable machines: Expressive social exchange between humans and robots," Massachusetts Inst. Technol., Cambridge, MA, USA, 2000. [Online]. Available: https://groups.csail.mit.edu/lbr/hrg/2000/phd.pdf
20. F. E. Ritter, F. Tehranchi, and J. D. Oury, "ACT-R: A cognitive architecture for modeling cognition," *Wiley Interdisciplinary Rev., Cogn. Sci.*, vol. 10, no. 3, 2019, Art. no. e1488, doi: 10.1002/wcs.1488.
21. M. Scheutz, T. Williams, E. Krause, B. Oosterveld, V. Sarathy, and T. Frasca, "An overview of the distributed integrated cognition affect and reflection DIARC architecture," in *Cognitive Architectures*, M. Aldinhas Ferreira, J. Silva Sequeira, and R. Ventura, Eds. Cham, Switzerland: Springer-Verlag, 2019, pp. 165–193.
22. Y. Sandamirskaya, M. Kaboli, J. Conradt, and T. Celikel, "Neuromorphic computing hardware and neural architectures for robotics," *Sci. Robot.*, vol. 7, no. 67, 2022, pp. eabl8419, doi: 10.1126/scirobotics.abl8419.
23. F. Liu, S. Deswal, A. Christou, Y. Sandamirskaya, M. Kaboli, and R. Dahiya, "Neuro-inspired electronic skin for robots," *Sci. Robot.*, vol. 7, no. 67, 2022, Art. no. eabl7344, doi: 10.1126/scirobotics.abl7344.
24. S. J. Huston and V. Jayaraman, "Studying sensorimotor integration in insects," *Curr. Opin. Neurobiol.*, vol. 21, no. 4, pp. 527–534, 2011, doi: 10.1016/j.conb.2011.05.030.
25. D. Denny-Brown, "On the nature of postural reflexes," *Proc. Roy. Soc. B, Biol. Sci.*, vol. 104, no. 730, pp. 252–301, 1929.
26. F. Liu et al., "Printed synaptic transistor–based electronic skin for robots to feel and learn," *Sci. Robot.*, vol. 7, no. 67, 2022, Art. no. eabl7286, doi: 10.1126/scirobotics.abl7286.
27. S. Wang et al., "Memristor-based adaptive neuromorphic perception in unstructured environments," *Nature Commun.*, vol. 15, no. 1, 2024, Art. no. 4671, doi: 10.1038/s41467-024-48908-8.
28. F. Liu, A. Christou, R. Chirila, L. De Pamphilis, and R. Dahiya, "Stochastic nature of large-scale contact printed ZnO nanowires based transistors," *Adv. Funct. Mater.*, vol. 35, no. 2, 2025, Art. no. 2412299, doi: 10.1002/adfm.202412299.
29. F. Liu, A. Christou, A. S. Dahiya, and R. Dahiya, "From printed devices to vertically stacked, 3D flexible hybrid systems," *Adv. Mater.*, vol. 37, no. 10, 2025, Art. no. 2411151, doi: 10.1002/adma.202411151.
30. Z. Susskind et al., "Weightless neural networks for efficient edge inference," in *Proc. Int. Conf. Parallel Archit. Compilation Techn.*, 2023, pp. 279–290, doi: 10.1145/3559009.3569680.
31. V. Pillai et al., "arrWNN: Arrhythmia-detecting weightless neural network FlexIC," in *Proc. IEEE Int. Flexible Electron. Technol. Conf. (IFETC)*, Piscataway, NJ, USA: IEEE Press, 2024, pp. 1–4, doi: 10.1109/IFETC61155.2024.10771885.
32. A. T. L. Bacellar et al., "Differentiable weightless neural networks," in *Proc. 41st Int. Conf. Mach. Learn. (ICML)*, 2024, pp. 2277–2295.
33. Z. Susskind et al., "ULEEN: A novel architecture for ultra-low-energy edge neural networks," *ACM Trans. Archit. Code Optim.*, vol. 20, no. 4, pp. 1–24, 2023, doi: 10.1145/3629522.
34. M. Ntagios, H. Nassar, A. Pullanchiyodan, W. T. Navaraj, and R. Dahiya, "Robotic hands with intrinsic tactile sensing via 3D printed soft pressure sensors," *Adv. Intell. Syst.*, vol. 2, no. 6, 2020, Art. no. 1900080, doi: 10.1002/aisy.201900080.
35. J. Sun, J. Han, Y. Wang, and P. Liu, "Memristor-based neural network circuit of emotion congruent memory with mental fatigue and emotion inhibition," *IEEE Trans. Biomed. Circuits Syst.*, vol. 15, no. 3, pp. 606–616, Jun. 2021, doi: 10.1109/TBCAS.2021.3090786.
36. A. S. Dahiya, A. Christou, S. Ma, and R. Dahiya, "Printed interconnects for heterogeneous systems integration on flexible substrates," *Adv. Mater. Technol.*, vol. 10, no. 6, 2025, Art. no. 2401213.
37. V. Vasco et al., "Train with me: A study comparing a socially assistive robot and a virtual agent for a rehabilitation task," in *Proc. 11th Int. Conf. Social Robotics (ICSR)*, Madrid, Spain, Cham, Switzerland: Springer-Verlag, 2019, pp. 453–463.
38. K. Kompatsiari, F. Ciardo, V. Tikhanoff, G. Metta, and A. Wykowska, "It's in the eyes: The engaging role of eye contact in HRI," *Int. J. Social Robot.*, vol. 13, no. 3, pp. 525–535, 2021, doi: 10.1007/s12369-019-00565-4.
39. Y. Hu et al., "Human-robot facial coexpression," *Sci. Robot.*, vol. 9, no. 88, 2024, Art. no. eadi4724, doi: 10.1126/scirobotics.adi4724.
40. H. Moravec, "Rise of the robots-the future of artificial intelligence," *Sci. Amer.*, vol. 23, 2009.