Chapter 33

Communication

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From a traditional engineering perspective, communication is about effecting control over a distance, and its primary concern is the reliability of transmission. As with much in biomimetics, we find that such traditional problems and practices are not entirely separable from the situation in nature, but that a natural perspective better informs the true requirements of even engineered autonomous systems. In particular, nature allows for collaborative control with minimal signals, generating robust, distributed systems. Human communication also employs the exceptional capacity of language, but robot–human interaction requires an understanding of implicit mechanisms of human communication as well.

Here we review communication in nature, describing the evolution of communication from the perspective of the selfish gene. We explore whether communication arose from collaboration or manipulation, and the reasons why communication in nature is ubiquitous and generally honest, given the apparent evolutionary benefits of free-riding. We consider the content necessary for communication, and show that context and relevance allow a message to be effectively communicated with very little information transfer. Humans possess the unique ability to communicate with language, and we explore how this differs from the non-verbal communication we share with other animals, and the challenges that robots face when using language for communication.

We then review communication in contemporary biomimetic systems. From the perspective of communication, these fall into several categories, depending on whether the communication is between robots, or between robot and human, and also whether the robotic system is fully autonomous (has its own goals), or is in some sense collaborating with a human to achieve a goal. Swarm robotics, inspired by social insects such as bees and ants, requires non-centralized, distributed communication mechanisms and we consider some of the work in this area to date (see Nolfi, Chapter 43, this volume). Designing autonomous human–robot interaction predicates an understanding of human social interaction, and we review relevant background psychology. We also review work to date in the generation of synthetic emotion and the ability of robots to sense and classify human emotion. Finally, we provide some pointers for future directions and further reading.

Biological principles

Collaboration or manipulation?

When thinking of the fundamentals of natural communication—in fact, all communication—we need to define what communication essentially entails. First, there must be some kind of signal. Second, there must be a receiver that has beliefs or behavior which are modified by reception of the signal. The degree to which receipt of a signal benefits either sender or receiver necessarily depends on what the receiver would have chosen to do without the signal. For intentional communication, the sender must knowingly want the signal to achieve the definite purpose of modifying the beliefs or behavior of another. But the term *communication* is used widely in the natural sciences, including to describe behavior in plants and microbia that are not ordinarily considered to have intentions. Even linguistic communication in humans can include unintended, unconscious signaling, sometimes even counter to the known goals of the sender. For example, a speaker's tone may reveal an emotional state the speaker wishes to keep hidden.

Intuitively, one might think of communication as facilitating cooperation, both in animals and humans. We might imagine that the capacity to communicate arose from a desire by natural agents to interact with each other to achieve shared objectives. Communication may indeed appear cooperative when it facilitates the achievement of a shared goals, such as reproduction, food collection in colonies, and so on. Even antagonistic communication can be seen as cooperative if it facilitates finding lower-cost resolution to conflicting goals, as in competition over a particular mate or access to another scarce resource. We might therefore suppose that, historically, organisms that cooperated via communication were better able to achieve their goals, and so prospered from an evolutionary perspective. Unfortunately this kind of common sense thinking arises from what Oxford ethologist David McFarland called the "incurable disease" of anthropomorphism (McFarland and Bösser 1993, p. 1). That is, we might apply human characteristics (or *assumed* human characteristics) to non-human entities and thus infer human thought patterns where none exist.

In stark contrast, Dawkins (1976) forwards the perspective of Darwinian evolution. All living organisms are driven by a set of "selfish genes" that succeed only through replicating themselves. However, genes do not fight the necessary battles for survival and reliable replication on their own. Rather, they collaborate, fighting inside "survival machines" or "Vehicles" composed also of other genes—the organisms we observe in nature. These organisms are themselves driven to compete in order to advance the reproductive goals of their genes, and any communication that evolves between organisms will only evolve if it benefits the organism sending the signal (or at least the gene triggering it to do so) relative to others. Thus Dawkins (1982) frames communication as arising as coercion, not cooperation. Dawkins argues that all such inter-organism communication, whether between individuals (e.g. sexes) of the same species, or between differing species can be viewed as one organism manipulating another with the ultimate goal of replicating its genes. Further, Scott-Phillips et al. (2012a) show that a state of non-interaction is an evolutionarily stable strategy, and so communication will not necessarily emerge even when it is in both parties' interest.

However, these observations do not mean that cooperative, mutually beneficial, or even altruistic communication cannot evolve. Because genes are shared within and even across species, they can also motivate behavior that is costly to an individual Vehicle, so long as that behavior is beneficial to securing copies of those genes existing in the future (Hamilton 1964; Gardner and West 2014). Nevertheless, it is worthwhile for a robotics developer to remember that biologists always think of communication in terms of its costs, risks, and benefits for all individuals involved, and that coercion may be a more useful metaphor, particularly for systems that are self-learning, or involve components owned by multiple parties, each with their own goals and constraints.

Origins and stability of communication

Communication incurs measurable cost arising both from the energy expended and time used in order to generate signal, and from the risk that the signal may transmit information to competitors rather than collaborators, for example a predator drawn by bird song. Additionally, the presence of a signaling mechanism may otherwise affect the performance of an animal, for example the weight of the peacock's tail. Biology now views this cost as part of the signal's mechanism—the cost itself communicates the value(s) of the signaler, for example the quality of the individual that can support such a handicap (Zahavi and Zahavi 1997). The essential argument of the handicap principle is that observable handicaps serve as necessarily honest signals—signals that can be trusted by the recipient—because of the increased cost to the signaler incurred by the handicap. Honest signals are important for recipients given the evolutionary pressure for coercion, for example a peahen prefers to find the best mate to inseminate her eggs. Honesty may also be assured via two mechanisms: Indices and Deterrents (Scott-Phillips 2011). Indices are mechanisms where the signal form is tied to signal meaning. For example, the frequency of an animal's roar being directly tied to its size. Deterrents are mechanisms that punish dishonest signals with excessive cost, such as weight, visibility, or duration (e.g. Tibbetts and Izzo 2010).

Viewing communication through this evolutionary lens raises two questions: Firstly, how does communication come to emerge at all, and secondly, why is it an evolutionarily stable strategy (ESS), when there are selfish individual benefits to both non-participation and dishonesty?

The first question raises the chicken and egg problem of communication: how did communication first arise, since there is always a cost (opportunity, risk, or metabolic) to creating a signal, and may be some similar cost to having the apparatus to receive the signal (Smith and Harper 1995). Who would bear this cost first? There is no benefit to creating a signal if there is no capable receiver. Similarly, why would there be an adaptation to receive signals, when then are no signals to receive? This question is neatly addressed by Hauser (1996) and Scott-Phillips et al. (2012a), who show how communication evolves from precursor interactions that do not fully meet our definition of *communication*. These interactions can be categorized as either ritualization or sensory manipulation. For example, an animal may use urine or faeces to mark territory. How does this arise? Initially the animal may experience fear when at the boundary of its territory, and so may relieve itself there, without communicative intent. The presence of this material may act as a cue for others and thus become associated with territorial boundaries. Through ritualization of this behavior a communication channel is established. Hauser makes the useful distinction between *cues* and *signs* as precursors to communicative intent: cues vary over time, whereas signs are temporally invariant.

Sensory manipulation involves one individual stimulating the senses of another in order to affect the receiver's behavior to the benefit of the signaler, but without intending to communicate that intention to the receiver. The example often given here is of a male insect wishing to mate with a female. He brings the female food, coercing her to stay and eat the food, allowing mating. Since this behavior is beneficial to the species (or more precisely, beneficial to the replication of genes shared by two individuals capable of breeding), females also evolve to recognize the bringing of food as a precursor to mating, and hence communication arises. Only if recognizing the signal is generally of benefit to the receiver will the receiver evolve to do so. However, sometimes evolution may exploit a normally useful signal in a way that does not benefit the receiver, as in the case of mimicry (Wickler 1968; Johnstone 2002). If recognizing the signal is not of more general benefit than cost, then receivers will evolve to ignore the signal, and the signaler will incur its costs without benefit. This begins to show us why animal communication is generally "honest" rather than "deceptive;" for further discussion see Hauser (1996). Scott-Phillips et al. (2012a) postulate that ritualization is the more common route to communication, since the prerequisites are less restrictive, and also the initial cues are implicitly honest.

Content necessary for communication

Much research in artificial multi-agent systems has focused on the expressive power of communicative languages (Wooldridge 2009). In contrast, natural communication systems tend to exploit relatively simple and minimal signals, the meaning of which essentially derives from extensive models. In other words, evolution, or a shared phylogenetic history, provides adequate priors such that minimal data is required to communicate context. For example, mating calls primarily discriminate which species is calling, and secondarily the quality and possibly other attributes of the caller. Calls between offspring and mothers signal identity and emotional state, and must be hard for a predator to imitate coercively (de Oliveira Calleia et al. 2009; in robotics, identity and associated forgery concerns are ordinarily handled with encryption.) The pronking of gazelles not only signals to herdmates the presence of a predator, but also to the predator that that the individual at least is fit enough to have detected them and as such is probably a bad target for an attempted kill (Caro 1994).

Tinbergen (1952) offers four useful perspectives through which natural communication can be understood:

- Mechanistic: the physical communication mechanisms—neural, physiological, psychological.
- Ontogenetic: the genetic and environmental factors that guide development of communication.
- Functional: the effect of communication on survival and reproduction.
- Phylogenetic: the historic origins of the species and its communicative traits, which determine available mechanisms.

Tinbergen's fascinating research with gulls set the precedent for demonstrating that only very basic signaling is required for effective communication to facilitate the entire lifecycle (Tinbergen and Falkus 1970). The power of this sort of communication is still present in human communicative systems, and may still often implicitly determine our behavior. Humans are communication machines, having not only language, but an extrordinary array of pheremones for an ape (Stoddart 1990). Even in language, we are influenced by implicit information such as affect and dialect. Newborn babies are more likely to attend to (and therefore learn from) people sharing their mother's dialect (Fitch 2004). Of course, human language also contains explicit content, discussed further below.

Shannon and Weaver (1971) provide us with a quantitative methodology for the evaluation of the information content involved in any communication. They start from the assumption that we can measure information transmission by investigating the reduction in uncertainty that follows from the successful transmission of a message. The general architecture employed in the analysis is

$$source \rightarrow message \rightarrow signal \rightarrow +noise \rightarrow receiver \rightarrow destination \tag{1}$$

The theory shows that information content is proportional to the logarithm of the number of choices in the message.

$$H(X) = -\sum_i P(x_i)\log_n P(x_i) \tag{2}$$

where X is a sequence of symbols forming the message, i is the number of symbols in the message, and n is the number of choices for each symbol in the message (for a message consisting of binary 1's and 0's then $n = 2$).

If there are few choices (i.e. the received signal is from a small set of possible choices) then this implies little actual information transfer. If we then add to this context the interpretation of the signal by the receiver, i.e. given the internal state of the receiver, what valid subset of messages it is expecting to receive, we see that often the actual information required to transfer a message is very low. The addition of *noise* during signal transmission reduces the rate at which a communication channel of given capacity can accurately transmit the desired message.

$$C = W \log_2 \frac{P+N}{N} \tag{3}$$

Where C is the capacity of the channel given the noise, W is the bandwidth of the channel, P is the power of the signal, and N is the power of the noise. We can see that the higher the noise level, the lower the rate of information transmission, determined by the relative power of the noise, compared with the power of the signal. Shannon's theory can be very usefully applied to natural, human, and artificial communication (see further Allen and Hauser 1993).

Language as an exception

Humans have long assumed that other animals have languages we just haven't learned, yet despite extensive research there is in fact no evidence that any other extant species shares a communication system with anything like the power for expression and innovation displayed in all human languages. Given its core importance not only for communication but for cognition, explanations for this unique trait are a holy grail for much of biological anthropology and cognitive science. Possible answers range from the theological to the technical, the latter including an also-mysteriously-unique capacity for representations supporting indefinite recursion (Hauser et al. 2002) or at least being able to reason about minds (Stiller and Dunbar 2007; Moll and Tomasello 2007). A simpler explanation is that hominids share with other apes adaptations such as long lives and big brains that facilitate exploiting *culture*—the communicating of novel behavior between local conspecifics—but are unique among simians in the otherwise rather common adaptation for vocal imitation (Bryson 2009). However, since there is no consensus on explaining human language in particular or uniqueness more generally, we leave this question to the section on further reading.

One radical theory related to language origins that is becoming increasingly accepted (though not in its details) is the idea of *memetics*, again first postulated by Dawkins (1976). This is the theory that humans have a dual replicator system, that is, that we are subject to two orthogonal strands of evolution (Richerson and Boyd 2005). The first is genetic evolution, common to the rest of biology, but the second is the evolution of concepts and ideas—memetic material. Although no one has identified exactly what a meme might be, the same is true of genes. Although DNA, the genetic material and substrate by which biological information is transmitted, has now been identified (long after it was first hypothesized), the discrete units thought to be genes are still not well understood (Dennett 1995). Language is currently the main substrate by which human ideas are transmitted and innovated, but it is by no means the only one: we also learn from gestures, models, and other artifacts. In addition, language itself is generally presumed to be a result of memetic cultural evolution.

What is critical to understand for a roboticist is that language evolves continuously. Contrary to much schooling, there is no "correct" way to speak English or any other language, only ways that signal particular educational or social backgrounds, or ways that are more or less effective for communicating in a particular community. Also, the words in languages represent a set of concepts found historically to be of value for communication and thinking. Just because a concept has its own word in one language does not guarantee that there is a single-word translation for that concept in any other language, or indeed that that concept will make sense in another culture. As our concepts and communities constantly change, so do our languages. Nevertheless, people have historically managed to transact complex commercial and individual negotiations with people with whom they do not share a language. This is again partly because we can assume a set of likely desires and capacities for any other human, so can guess the meaning of some essential phrases and gestures with only a limited amount of context. We also tend to create simplified languages, called *pigeons*, when two language groups come together. These concepts may be useful for communicating with robots.

When human language is involved, there is little apparent cost to employing deception to gain advantage that would be evolutionarily advantageous. The problem of creating an evolutionarily stable strategy (ESS) for human language is therefore more complex. Scott-Phillips (2011) has proposed a mechanism by which human communication could become evolutionarily stable, and this relies heavily on the idea of reputation as a social governor of honesty. Uniquely in nature, human communication also involves epistemic vigilance; the ability to evaluate reliably received communications as to whether they are true or false before acting on them. Human language is also famously symbolic, with one term able to reference multiple real-world objects, but as implied by our earlier discussion of information theory, this capacity for generalization may be a fairly common attribute of communicative systems.

Biomimetic systems

Typically in robotics we broaden the idea of *communication* to include all types of social interaction between actors. Robot social interaction can thus be divided into two broad categories: robot–robot interaction, and human–robot interaction (HRI). For biomimetic robots, the major current field of study for multiple autonomous interacting robots is termed "swarm robotics." HRI can be further subdivided into human-directed collaboration with robots versus interaction with autonomous robots. In the former, the robot and human work collaboratively to achieve a given task. The robot, whilst intelligent, does not have sufficient cognitive capacity, or more simply the motivational agency, to choose high-level goals or perform tasks alone. Human collaborators may be required to assist with planning, expert knowledge, dexterous manipulation, or other aspects of the task. More autonomous HRI provides the greatest challenge, and here various techniques have been adopted to enable the robot to communicate effectively with humans.

Swarm robotics

Parker (2008) describes three commonly used paradigms for building distributed intelligent systems:

- bio-inspired, emergent swarms paradigm;
- organizational and social paradigms; and
- knowledge-based, ontological, and semantic paradigms.

Swarm robotics takes its inspiration from social insects, and involves the distributed self-coordination of significant numbers of relatively simple robots. Robot swarms may be homogeneous, where all robots have the same physical morphology and AI capabilities, or heterogeneous, where robots within the swarm may be specialized for different tasks, or have differing capabilities. Rather than some centralized or remote controlling system, swarm robotics predicates local sensing and communication abilities (Şahin 2005). The advantages of such a decentralized approach are that it provides both scalability (number of robots) and robustness (resilience to failure; Winfield 2000; Rubenstein et al. 2014).

One of the notable characteristics of swarm robotics research is the (relatively) complex behaviors that can be coordinated with very simple signaling. Parker (1998) developed the ALLIANCE heterogeneous swarm control architecture, where all communication was broadcast, rather than directed to individuals within the swarm. Each robot broadcast its location and current behavior, avoiding the need for others to gather this information via sensors. The robot's location and activity were broadcast at a known frequency (rate). If others did not receive this information after a pre-determined timeout, then they assumed the robot was no longer active.

Howard et al. (2006) demonstrate a large heterogeneous mobile robot team, with the shared task of mapping an unknown territory. Each robot is identified with a unique fiducial marker rather like a "bar code," simply and effectively communicating its identity. RFID tags may also be used for this task. Each robot measures the identity, range, and heading of adjacent robots. The estimated position and pose data of each robot is combined using UDP (broadcast) messaging over a wireless network to create a shared global map. Interesting communication features here include:

- The use of "mapper/leader" robots that have better sensors, leading "sensor" robots with much cheaper and less functional sensor capabilities.
- The use of broadcast messaging to achieve scalable information transfer, and the ability of the overall system to tolerate lossy communications.

Fredslund and Mataric (2002) examine the problem of achieving and maintaining robot formations. In keeping with the norms of artificial swarm research more generally (Reynolds 1987), robot formations were found that could be maintained by a simple shared algorithm that focuses solely on a neighbor in the formation. Minimal communication is needed to establish the desired formation and the role of each robot within the formation, e.g. who is the leader. Werfel et al. (2014) have extended such work, presenting an algorithm that, taking a three-dimensional shape as input, produces distributed instructions such that a robot swarm can construct that shape. Rubenstein et al. (2014) demonstrate a similar algorithm that works in two dimensions for a swarm of 1000 robots. The lesson here is that once again, very minimal broadcast communication is needed, in addition to sensor input, to achieve sophisticated and coordinated behavior, although how to generate the individual heuristics or "plans" for the robots is an ongoing and promising area of research.

Swarm robotics can be sufficiently biomimetic that they may be used for scientific studies in the the evolution of communication. Floreano et al. (2007) investigated whether altruistic communication could evolve in robot swarms. Robots were able to emit and perceive a blue light, and also a red light that was colocated with a food source (charging station). Each robot was equipped with an omnidirectional, color-sensitive camera. In this experiment the learning was not individual (ontogenetic), but evolutionary (phylogenetic), using genetic algorithms over a neural controller. A physics-based robot simulation environment was used for many of the generations, but at regular intervals generations occurred on real robots. As predicted by the theory of inclusive fitness described above, Floreano et al. (2007) found that communication readily evolves when colonies consist of genetically similar individuals and when selection acts at the colony level. Further, Mitri et al. (2011) found that when associated with unrelated individuals, the robots evolved "deceptive" signals, leading to worldwide headlines that scientists had evolved lying robots.

More often though, science demands the simplest model necessary for parsimony, validation, and analytic tractability. There is a recent trend in using biomimetic "robots" to provide controlled input for examining animal social cognition. However, in many cases the robots are only biomimetic in shape or other appearance, with no appreciable cognitive skills (Faria et al. 2010).

Human–robot collaboration

Robots may be thought of as tools, facilitating the achievement of goals for humans (Bryson 2010). Some tasks are currently too complex, or involve too much risk, to allow a fully autonomous robot to attempt them unaided. Human–robot collaboration (HRC) provides a methodology enabling humans and robots to work as partners to accomplish these tasks. Fong et al. (2002) explore human–robot dialogue to facilitate mutual assistance for the achievement of common goals. Interestingly, in this study the human functions as a resource for the robot, providing information and processing like other system modules. Using a very structured textual communication system, the robot can ask questions of the human as it works. This approach provides the robot with more freedom in execution and is more likely to find good solutions to its problems. Effective collaboration requires information sharing between parties, so collaborative control considers both user (human) and robot needs (Sheridan 1997). The need to make robots comprehensible to human partners is in fact sometimes used as a justification for bio-inspired approaches to robotics (Brooks and Stein 1994; Sengers 1998; Novikova and Watts 2015).

One effective means to share information with human collaborators is via Augmented Reality (AR), the overlaying of computer-generated graphics onto the real worldview. Green et al. (2008) introduce AR techniques by first discussing the communication necessary for human–human collaborative activity. In order to achieve useful work together, a common ground of shared understanding about the world must be achieved. Within a human–robot collaboration scenario, this grounding of symbols and their meanings is similarly vitally important (Steels 2008). Green et al. (2008) review work carried out at NASA and elsewhere to implement AR. Within an AR environment, in addition to speech, humans can communicate using a wide variety of nonverbal cues such as gaze, nodding, and other deictic gestures, with AR providing the grounding context.

More recent work takes a probabilistic approach to collaborative decision making (Kaupp et al. 2010). Human "operators" can be regarded as remotely located, valuable information sources which need to be managed carefully. Robots then decide when to query operators using Value-Of-Information theory, i.e. humans are only queried if the expected benefit of their observation exceeds the cost of obtaining it. In this study a navigation task is executed jointly by robot and human. The robot navigates a maze with local sensory input (a laser scanner), but transmits its visual camera signal to the remote human operator for interpretation. When the robot needs high-level visual information in order to make a decision, it simply queries the human, rather than having to interpret the raw visual information from the camera. This sort of "human in the loop" approach is also often proposed for actions that may have ethical consequences, such as assaults by military robots (Vallor 2014; Hellström 2013).

Autonomous human robot interaction

In order to use a biomimetic approach for autonomous HRI, we first need to consider human–human social interaction. When we communicate, we claim the attention of one or more others. This implies that the information communicated is relevant to the receiver. Therefore relevance may be seen as the key to human communication and cognition (Sperber and Wilson 1986). In order to communicate in a relevant manner, we may need to understand the mental state of others. Understanding this mental state is known as Theory of Mind (ToM). There is strong empirical evidence for ToM in adult humans, including fMRI studies of contexts where ToM is exploited (Saxe et al. 2006). However, Gallagher (2006) proposes a more direct understanding of the mental state and intent of others from directly observable phenomena. For example, one can read emotion and infer intention directly from the faces of others, without having to conduct any "mind reading." This background psychology is important for understanding and designing effective human–robot communications, not least because all human–robot interactions inevitably involve some anthropomorphization on the part of the human.

Kanda et al. (2002) describe studies using a humanoid robot able to generate many human-like communication behaviors, and equipped with sensors enabling human non-verbal and verbal communication to be sensed. This work develops the idea of communicative relationships between human and robot, based on relevance theory. For example, humans more easily understand a robot's verbal utterances once they have built a prior relationship with the robot. This idea of communication requiring perceived relevance in order to be successful is reinforced by Kuchenbrandt et al. (2014), who found that the efficacy of human–robot interaction is significantly affected by the perceived gender of the robot, the gender of the human, and the stereotypic gender association of the task.

One of the major breakthroughs in autonomous robotics has been the design and development of robotic imitation learning. This enables robots to be taught new tasks by human demonstration (supervised learning), and then to perfect these tasks through practice (unsupervised learning). This essentially biomimetic—and memetic—approach of social learning through communication (Meltzoff and Moore 1995; Schaal 1999) continues to deliver increasingly outstanding results, and is a major success in human–robot (primarily) nonverbal communication. The work of Billard and Hayes (1997), Klingspor et al. (1997), and Breazeal and Scassellati (2002) foresaw that this approach would produce machines that are useful, flexible, and easy to use. Movement primitives can be learned from demonstration and then combined generatively by the robot to produce novel behaviors for new tasks as they arise. Grasping and manipulation are good examples of such behaviors. Recently this work has developed using advanced probabilistic techniques to allow previously unseen objects to be effectively grasped and manipulated by interpolating known behaviors (Huang et al. 2013; Kopicki et al. 2014).

Non-verbal communication by robots can be used to great effect to significantly improve the productivity of human–robot teams, both in terms of speed of communication, and robustness to errors in communication (Breazeal et al. 2005). Humans maintain a mental model of the robot and non-verbal communication has been found to help with inference of the internal "mental" state of the robot. The design principles for non-verbal communication can again be taken from psychology, e.g. feedback, affordances, causality, and natural mappings (Sengers 1998; Breazeal et al. 2005). Humans typically display emotions non-verbally as part of normal communication, and whilst this may be synthesized readily in humanoid robots (Zecca et al. 2009), body expressions alone have also been successfully used to indicate emotional responses in non-humanoid robots (Novikova and Watts 2014). It should not be forgotten that only a small percentage of human communication involves words. Non-verbal, and particularly synthetic emotional, communication can significantly enhance the persuasive power of an autonomous robot (André et al. 2011).

Future directions

There is clear market pressure for further biomemetic communication in domestic robotics. Users find natural communication intuitive and often attractive. This approach is not without hazards or at least critics, however. The imitation of life may cause humans to over-respond to robots or misattribute value or fragility, leading consumers to waste time or money on attending to robots (Ashrafian et al. 2015). However, such concerns only apply to transmission *by* the robot, and may be ameliorated by sufficiently transparent signals (Bryson and Kime 2011; Boden et al. 2011). As mentioned in our review of nature, *reception* and comprehension of signals will generally take precedence in any communication system involving learning or evolving actors, as recognizing and categorizing stimuli and associating these with appropriate beliefs or actions are fundamental to cognitive capacity.

Substantial advances are currently being made not only in vision and speech recognition, but also in sensing human emotion. By fusing Bayesian classification of speech audio, facial expression, and gesture, higher recognition rates have been achieved than by analysing speech alone. Kessous et al. (2009) already report high recognition rates for anger, irritation, joy, pride, and sadness. Even deception can be detected (Schuller et al. 2008). However, there is still much work to do in this area. Schuller (2012) lists “confidence, deception, frustration, interest, intimacy, pain, politeness, pride, sarcasm, shame, stress, and uncertainty,” as reasonable targets for comprehension, and the same may be needed for production.

Returning to consider nature, we are only just beginning to understand the importance of altruistic communication—the sharing of knowledge—and information networks as an adaptive strategy for animals. At the same time, we are eliminating most of the non-human biomass on our planet (Barnosky 2008) creating gaps in critical ecosystem webs, including information networks. Williams (2013) suggests that biomemetic robots might serve not only to replace animals, but to guide or instruct those animals that remain. However, the tractability and economic feasibility of large-scale application of technologies of this type have yet to be demonstrated. In contrast, the use of robotics in experimental biology and psychology is a promising trend likely to accelerate (Krause et al. 2011). Such applications produce immediate value in scientific research, and may also serve as testbeds for more ambitious ecological projects.

Finally, the widespread use of robotics promises a growing need for the improved capacity for distributed autonomous robot control and communication. From robot mining (Bonchis et al. 2014; hopefully a means to return to the less ecologically damaging but more individually hazardous strategy of pit mining) to urban disaster intervention (Sahingoz, 2013; dos Santos and Bazzan, 2011) to bridge and sewer maintenance, the deployment of self-organizing, self-healing robot-only or human-and-robot systems holds promise for a better future with more robust and responsive infrastructure (Abelson et al. 2000). Realizing that future in a way that benefits everyone involved requires—among many other advances—excellent communication.

Learning more

For further reading we suggest the following. For those wishing to get to grips with Darwinian evolution and evolutionarily stable strategies, Dawkins (1982) is still the obvious starting point. The emergence of communication is neatly covered by Scott-Phillips et al. (2012b). Those with a further interest in animal communication should read Bradbury and Vehrencamp (2011) or Hauser (1996). For further details on ecological and evolutionary constraints that affect the design of signals, see Davies et al. (2012). Hauser and Konishi (1999) supplement this with additional detail on the design of animal communication. McFarland (1986) is an excellent book covering animal behavior from the perspective of psychobiology, ethology, and evolution. Finally, Scott-Phillips (2014) provides a recent book-length introduction to human language from a comparative biological perspective.

McFarland and Bösser (1993) is an early but seminal book, concerned with the application of animal behavior (including communication) to robots. Parker (2008) provides a useful overview of the field of distributed intelligence and its application in multi-robot systems. Breazeal et al. (2005) provide a useful introduction to nonverbal human–robot interaction. Pobil et al. (2014) is an example of the wide range of communication-related topics included within the study of autonomous agents, and these proceedings contain several papers covering topics such as perceptual prediction and collective and social behavior achieved using swarm robotics techniques. Nourbakhsh (2013) predicts how we might interact with robots in the near and far future.

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