Robotics in Remote and Hostile Environments

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REVIEW

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James G. Bellingham* and Kanna Rajan

In our continuing quest for knowledge, robots are powerful tools for accessing environments too dangerous or too remote for human exploration. Early systems functioned under close human supervision, effectively limited to executing preprogrammed tasks. However, as exploration moves to regions where communication is ineffective or unviable, robots will need to carry out complex tasks without human supervision. To enable such capabilities, robots are being enhanced by advances ranging from new sensor development to automated mission planning software, distributed robotic control, and more efficient power systems. As robotics technology becomes simultaneously more capable and economically viable, individual robots operated at large expense by teams of experts are increasingly supplemented by teams of robots used cooperatively under minimal human supervision.

The drive to explore is a human quality that has changed our understanding of the world and the universe we inhabit. Today the frontiers of exploration have moved to distant and hostile environments, to which we can travel only at great expense. Visiting the abyssal sea floor requires a sophisticated submersible launched from a ship staffed with highly trained specialists. Venturing as far as Earth orbit requires the resources of a nation. The technical challenges and costs of keeping humans alive in harsh and distant environments have led to an increasing use of robots as proxies. In space, scientific results obtained by unmanned robotic spacecraft are already impressive. Their many discoveries include providing the best evidence that water once ran on the martian surface (*1*), discovering the existence of methane lakes on Titan (*2*), and verifying the runaway greenhouse effect on Venus (*3*). In contrast to deep space, the ocean has been accessible to humans, although only at substantial cost. What robots promise for the ocean sciences is a great reduction in the threshold for access, allowing a much more pervasive presence in the ocean. Already mobile robots are in use in almost every domain in the ocean, from the previously unsurveyed cavities under floating ice shelves (*4*) to the volcanically active mid-ocean ridge system where new sea floor is being formed (*5*).

Deep space and the ocean's interior are often associated with difficulty in communications; consequently, an important measure of a robot's effectiveness there is its ability to function with little or no human supervision. Unless an underwater vehicle is operating within acoustic communication range of an appropriately equipped ship (typically on the order of a few kilometers), the only communication option is to surface and communicate via satellite. Typically, satellite communications options for small vehicles provide bandwidths up to only 10 kilobits per second at sea. This contrasts with communication rates over 10 times higher available to the Mars Exploration Rover (MER) vehicles on the surface of Mars (Fig. 1). However, the round-trip communication time to Mars can be as long at 40 min. For many tasks, introducing such a lag in the control loop is either fatal or debilitating to productivity. Thus the marine environment and the space environment provide a common motivation to endow robotic platforms with greater onboard autonomy.

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Autonomous mobile robots used in exploration activities are highly dependent on their ability to sense and respond to their environment. In contrast to a robot in structured settings, such as a factory floor, an exploration robot must accomplish its goals in a previously unmapped environment with unpredictable disturbances and threats. At one time, building a robot that reliably carried out a set of preprogrammed tasks was a technical accomplishment. Today, exploration robots are expected to sense their surroundings and act to avoid problems or improve performance. For example, operational underwater robots are expected to avoid bottom collisions in most circumstances. The more sophisticated their perception of their surroundings, the greater their ability to respond constructively. Consequently, attention is now turning to fielding practical robots capable of replanning their mission in response to changing circumstances while deliberating on how best to satisfy the goals and expectations given to them by human operators.

The technological evolution of exploration robotics is shaped by our understanding of emerging scientific needs. Although space and ocean robotics present many of the same problems, the importance of the ocean to climate prediction on Earth creates additional imperatives for marine robots. The ocean is a large thermal reservoir, and its circulation, determined by winds, Earth's rotation, and variations in temperature and salinity, moves heat from low to high latitudes. Beyond its physical properties, the ocean comprises the largest ecosystem on the planet; although the function of the vast majority of marine organisms is yet to be determined, one known function is to produce approximately half of the oxygen we breathe (*6*). Yet at the same time, the ocean is one of the least-well-observed portions of the planet. Remote sensing techniques examine the sea surface while leaving the bulk of the ocean unobserved. What is emerging is a need for observation systems that are capable of making coordinated measurements in many places at the same time.

Scientific challenges, such as understanding global climate change, are addressed in a highly interdisciplinary environment. A particular robot, or collection of robots, will need to respond to a wide array of scientific goals, which may be intertwined by operational necessities evolving on a short time frame. For example, ocean observing systems composed of large numbers of coordinated observation assets (described later in this paper) serve many investigators, each with their own research agenda. Thus, an emerging model is the use of the Internet to support collaborative frameworks, allowing participants to engage each other in the simultaneous development of scientific understanding and operational plans.

Interplanetary Exploration

Early failures of robotic and launch platforms for space missions in the 1960s helped focus technology development toward making spacecraft hardware robust. Software to run these vehicles for interplanetary exploration has been created with comparably simple command-and-control software both onboard and on Earth. To this day, spacecraft are predominantly controlled with predefined commands that are generated a priori by human controllers and communicated to the vehicle. The control sequence is then executed onboard with limited contextual awareness. In the void of interplanetary space, such lack of situational awareness has a limited impact on the operation of the spacecraft. However, inevitable contact with the environment on planetary surfaces, coupled with round-trip light time delays, have to date implied large numbers of human operators on Earth who are carefully crafting commands to ensure the health and safety of the robot. This has often led to less-than-optimal use of these robotic proxies, if not affecting their economic efficiency. For instance, during the nominal mission, the twin MER vehicles were supported around the clock, by upwards of 200 engineers colocated at the Jet Propulsion Laboratory (JPL).

In 1999, NASA's Deep Space 1 spacecraft (DS1) demonstrated a truly autonomous robotic mission capability with the deployment of the Remote Agent artificial intelligence (AI) (*7*, *8*) system. Sixty-five million miles from Earth, it was able to deliberate onboard and demonstrate failure diagnosis and recovery from injected faults. Also onboard was an autonomous navigation (*9*) capability that used pattern recognition to compare images of stars with a known star catalog to triangulate the spacecraft's position during its interplanetary cruise. This coalesced a long-espoused view by researchers in the fields of robotics and AI: the sense-plan-act (SPA) model, in which the robot senses its environment, decides whether an a priori (or newly) generated course of action is appropriate, and based on that determination, actuates its sensors to observe, sample, or move in its environment. More recently, in laboratory tests, science-based autonomous operations have demonstrated detection and tracking of pre-specified events of scientific interest (*10*), coupling pattern recognition with onboard deliberation on wheeled robots. This points to an interesting and necessary convergence between the fields of autonomy, machine learning, and robotics to tackle real-world problems of scientific interest in detecting and tracking episodic events, such as dust devils on the martian surface.

On DS1, the onboard autonomy requirements necessitated the coordinated use of pattern matching with deliberation and command execution. In performing a trajectory correction, the Remote Agent would throttle down the engine, request the attitude control system to execute the turn while keeping the solar panels aligned to the Sun, take pictures of an appropriate star to validate its course correction using the AutoNav system and onboard star catalogs, and then throttle up to resume its cruise. It would do so by averaging out image jitters while damping the turn, ensuring that Sun-angle constraints and the uncertainty of turn times, as well as mitigation for camera component failures, were taken into consideration during command execution. During the course of the experiment, failures were injected to demonstrate the system could gracefully recover and continue without undue human intervention, demonstrating the impact such techniques have in mission operations as well as in dealing with events of scientific opportunity. This was an early and dramatic demonstration to prove that AI techniques are finally maturing while dealing with real-world complexity. They have done so after decades of fundamental research in knowledge representation, automated reasoning, and computational search [see (*11*) for a comprehensive view of fundamental AI techniques], which are central to deliberation and AI as a whole.

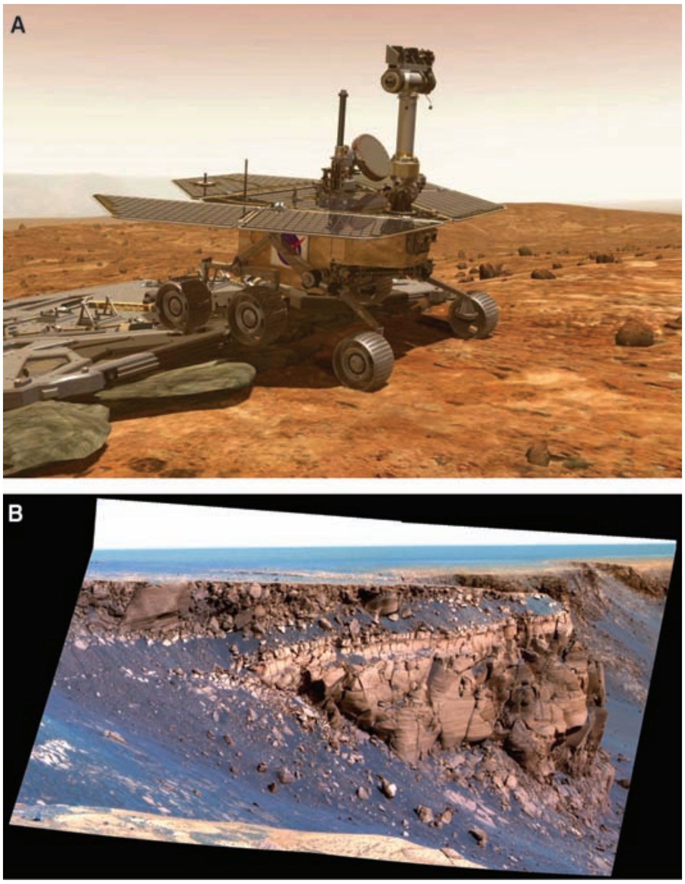

Fig. 1. Robots now roam the surface of a distant planet, exercising increasing levels of autonomy. (**A**) A MER vehicle leaving the lander platform to begin its exploration of Mars. [Credit courtesy NASA/JPL-Caltech] (**B**) False-color image of a promontory jutting out from the walls of Victoria Crater, Mars, which is being explored by NASA's MER Opportunity rover. This image was taken by Opportunity's panoramic camera on sol 1167 (6 May 2007). It is presented in false color to accentuate differences in surface materials. [Image credit: NASA/JPL/Cornell]

However, because of the perception of risk, the adoption of onboard deliberation techniques by the operations and science communities has proceeded slowly. One variation of the SPA paradigm that is increasingly popular is that of mixed-initiative systems (*12*), in which humans are aided by and in turn guide the formulation of plans by a computer. Such mixed-mode interaction uses the substantial cognitive capabilities of humans together with the intrinsic capability of computers to deal with numerical computation when aiding robots in decision-making. The command and control of the MER vehicles, for instance, uses techniques originally used for onboard deliberation but now used on the ground at JPL in the Mixed-Initiative Activity Plan GENerator (MAPGEN) (*13*) for planning science and engineering activities. Although this system does not close real-time sensing loops, it allows scientists on Earth to decide what science activities to plan by specifying constraints on their observations while abstracting out and dealing with the engineering details of the rover hardware situated remotely on Mars. Early proving tests at JPL showed a 20% increase in the quantity of science data returned while sustaining the quality when using such mixed-initiative techniques over a purely manual approach. This led to confidence in deploying the MAPGEN tool set, which to date is the longest-running AI program in a mission-critical role in the space domain. Such modalities hold promise for engineered systems where the complexity of the environment, if not of the platform itself, currently necessitates human/computer interaction, another key area of research in AI and robotics.

Software engineering techniques have progressed substantially to exploit hardware breakthroughs in computation and sensing. Lower-level functionalities are no longer where AI and robotics researchers are spending the bulk of their efforts in attempting to make robots more effective; rather, higher-level decision-making capabilities stemming from better understanding of robotic control, coupled with progress in AI search and automated reasoning techniques, are pushing the boundary of how robots deal with the real world.

Observing Earth's Ocean

In contrast to space robotics, which is shaped by the high costs of launch and the complete absence of opportunity for human intervention should problems be encountered, robotics in the ocean sciences has been a grassroots affair. Most efforts start with comparatively small budgets and only gradually develop into larger programs. Developers of undersea robots often accompanied their systems to sea, sometimes working in rough weather or in the middle of icebound oceans. The development of autonomous marine robots for science started in the 1960s with the Self-Propelled Underwater Research Vehicle (SPURV) (*14*). SPURV was the first autonomous underwater vehicle, or AUV, and was used to measure horizontal variability in the ocean, a property that is hard to characterize from a ship. By the early 1990s, over 56 different AUVs were described in the published literature, although almost all were demonstration vehicles rather than operational platforms, and many had never been successfully operated (*15*). In the past half-decade, AUVs have seen adoption by not just the science community but also the military and the oil and gas industy. The result is a growing number of commercial companies that make AUVs and their specialized subsystems. As a consequence, the state of AUV technology and AUV capabilities is evolving rapidly (Fig. 2).

Early applications of AUV's started in some of the most remote environments, such as the deep ocean and the Arctic; as the platforms have matured, they're increasingly used even in easily accessible locations and in a variety of roles. The efficiency and stability of AUVs as both sonar and imaging platforms have encouraged a growing use of AUVs for producing high-resolution maps of the deep sea floor (*16*, *17*) as well as photomosaics (*18*) to support a wide range of science interests (Fig. 3). The Autonomous Benthic Explorer (ABE) uses progressive search strategies to find hydrothermal vents, in which the vehicle starts with a wide area search for a neutrally buoyant hydrothermal vent plume and then progresses to finding the more localized buoyant plume and sea floor structure of hydrothermal vents (*19*). At high latitudes, AUVs have been used to make measurements under ice, measuring heat flux (*20*, *21*) and distributions of biological populations (*22*), both key observations for understanding the current rapid rate of change of Arctic climate and ecosystems. AUVs are also being used for more routine operations, such as in shallow coastal environments (*23*).

Limitations on energy storage are a fundamental driver in AUV design, and different applications motivate quite different types of vehicles. To achieve long endurances or ranges, designers have two options: to make the vehicle very large and thus capable of carrying large quantities of batteries, or to make the vehicle very slow and low-powered. In many cases, factors such as the size and power consumption of the scientific sensors force the vehicle to be large. Vehicles such as Autosub (*24*), ABE (*25*), Hugin (*26*), and Dorado (*27*) are all examples of larger systems used to carry more sophisticated ocean science payloads such as mapping sonar or diverse collections of sensors for characterizing physical, chemical, optical, and biological properties of seawater. Gliders (*28*–*30*) are an example of small underwater platforms with long endurance. They are a cousin to the profiling floats already present in large numbers in the ocean (*31*). Gliders move by changing their buoyancy and using lifting surfaces, such as wings, to translate vertical into horizontal motion, instead of the propellers used by most other AUVs.

The success of autonomous platforms has encouraged the development of sensors that capitalize on and complement the availability of lower-cost methods of observing the ocean. Although sensors to measure physical properties such as temperature, salinity, and current have been available for many years, many research laboratories are creating sensors for the chemistry (*32*) and biology of the ocean. For example, the introduction of instrumentation for determining nitrate concentrations (*33*) allows AUVs to characterize nutrient availability in situ, where it previously could be determined only by laboratory analysis of samples taken from ships. A range of techniques for identifying small organisms is being developed as well, including systems that optically image organisms and use computer recognition to classify them (*34*).

The need to observe and understand the internal weather of the ocean and the changing composition of ocean ecosystems at ever-higher spatial and temporal resolutions has motivated the creation of observing systems using fleets of AUVs. Such observations provide a density of ocean observation that has not been possible before, useful for a range of purposes, including the improvement of understanding and parameterization of ocean processes important to climate models. The Autonomous Ocean Sampling Network (AOSN) (*35*, *36*) uses fleets of small, highly capable mobile systems as a coordinated sampling network, linked to predictive assimilative ocean models to observe and predict ocean processes. AOSN is both enabled by, and has motivated, small, long-endurance underwater platforms but also relies on larger vehicles carrying chemical and biological sensors. By combining vehicles optimized around different observational objectives, a more complete observing system can be created. Integral to AOSN is the coupling of observations to real-time physics-based oceanographic models, which both synthesize disparate measurements into a realization of the environment and provide a predictive tool. The need to opti-

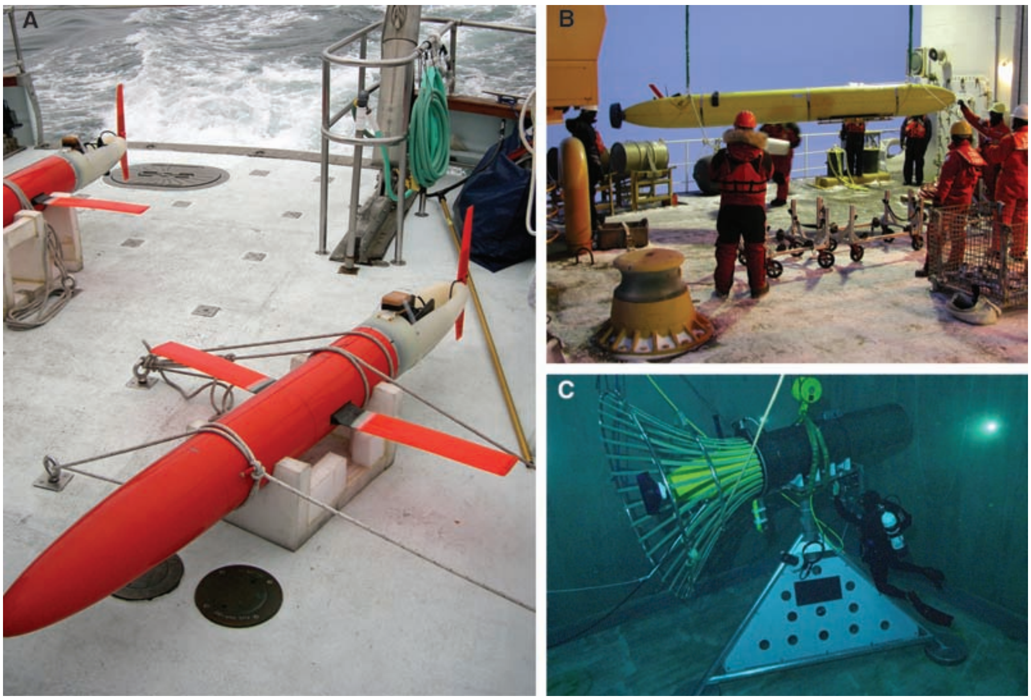

Fig. 2. (**A**) An underwater glider on the deck of a boat, ready for deployment. Gliders can make simple measurements of ocean properties such as temperature and salinity for months at a time, traveling at a speed of about 25 cm/s. (**B**) A Dorado AUV, capable of carrying complex payloads such as mapping sonar and comprehensive suites for analyzing the physical, chemical, and biological properties of seawater at speeds of 1.5 m/s. This image shows the AUV after recovery by the U.S. Coast Guard cutter *Healy*, in the icepack north of Svalbard. (**C**) A docking station with a Dorado vehicle captured in the docking cone, shown in testing before deployment. This device was connected to a cabled observatory, allowing Internet connectivity with the vehicle and the charging of vehicle batteries (*46*).

mize the performance of such complex collections of observation elements and models motivates study of survey optimization and adaptive sampling (*37–39*). Thus, the success of AUV technology is leading to the creation of ocean observing systems composed of diverse assemblies of underwater robots.

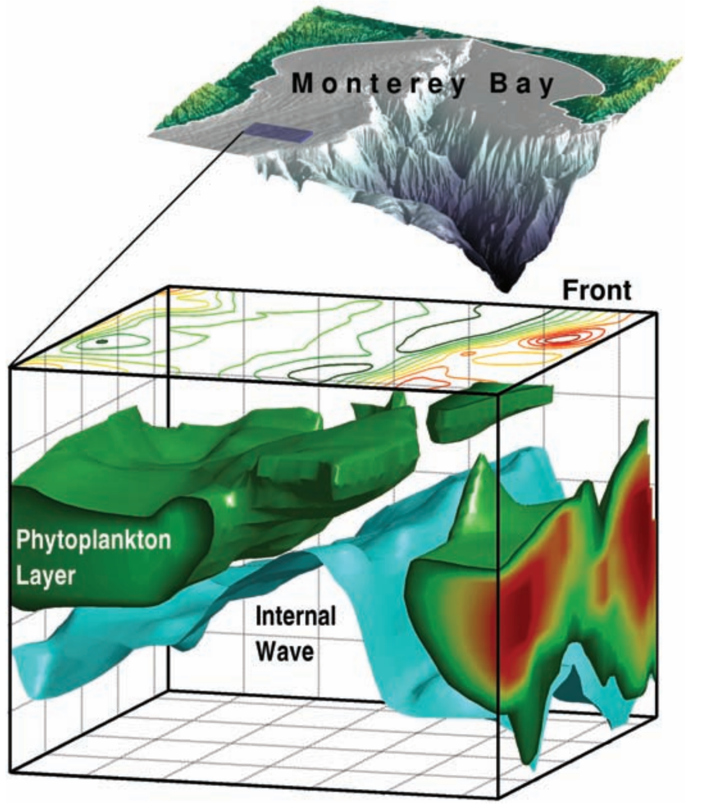

Fig. 3. A three-dimensional image of the interaction of physical and biological processes, as mapped by an Odyssey AUV off the coast of California (*52*). The green volumes show a phytoplankton layer, detected by its chlorophyll fluorescence. The underlying cyan surface shows deflection of the constant-density surface by an internal wave, interrupting the phytoplankton layer. To accomplish this survey, the AUV moved in a sawtooth pattern across the survey area while profiling vertically. The volume shown is 6.5 by 2.5 km in horizontal extent and 23 m in depth.

Trends for the Future

Exploration robotics is transforming from an activity in which individual robots are deployed for fixed periods and operated by teams of specialists to a pervasive activity operating continuously by distributed multidisciplinary teams. This will be driven by technological advances in four key areas: sensing, autonomy, development of supporting infrastructure, and collaborative software systems. In the oceans, the energy limitations of existing systems will be surmounted by new strategies for extracting power from the environment and using scientific power and communications infrastructure being installed in the ocean.

A robot's capability is a strong function of the sophistication of its capability to sense its environment. For example, a sensing system that processes camera imagery to identify and locate rocks makes rock sampling an easier task for onboard control software. However, a scientist will want the robot to be selective in choosing rocks. Thus a more sophisticated system might classify rocks, allowing their prioritization for sampling. In essence, the decision-making process is made much simpler if sensing systems can provide the right information. Autonomous robots are already able to build perception-based semantic networks (*40–42*) that allow them to label and localize objects in structured surroundings; the models that leverage such capabilities will migrate from meticulously handcrafted entities to ones increasingly learned by the robot during exploration. Thus the rapid advances of the sensor community will be augmented by advances from the artificial intelligence community to provide information to decision-making software in a much more relevant form.

Advances in autonomy will not only be driven by better sensing, but it in turn will drive and increasingly be driven by online learning, novel methods for representing and reasoning about uncertainty, and software engineering capabilities for verification and validation. Machine-learning techniques are already learning the evolution of simple natural phenomena (*43*); the next logical step will be to build models of the environmental changes, allowing robots to make more informed (and potentially optimal) decisions while executing mission plans, thus making them more adaptive. Robots will then be able to deal with unstructured environments and hostile conditions on planetary surfaces while simultaneously deliberating about their mission goals and real and potential failure conditions. Those in the ocean will be able to "sniff" out and follow gradients toward their sources, whether they be freshwater plumes, harmful algal blooms, or effluents from mid-ocean hydrothermal vents, characterizing and sampling their environment and generating high-resolution bathymetric data while determining their own location and ensuring their health and safety, all without any human supervision. Yet none of these advances in robotic autonomy is likely without increased trust in how implemented software is working or is expected to work. Validation (is this the right system for the job) and verification (is the system built right) techniques before long will certify the viability of the software for the tasks for which it was designed and deployed.

Mobile robots are particularly restricted by their ability to generate or store energy. Over the past several decades, batteries have become safer, and secondary batteries can be recharged more often, but only incremental changes in energy density have been realized. Space robots have mitigated battery limitations by using solar panels to greatly increase the lifetimes of space missions. Efforts are under way to build solar-powered AUVs (*44*) and AUVs that draw their energy from thermal gradients in the ocean (*30*). Efforts targeting the creation of untethered buoys that can hold their position against prevailing currents and winds are attempting to extract energy from wind and waves. Tapping the chemical energy stored in sediments on the sea floor is the goal of yet other efforts, which are creating microbial fuel cells (*45*) producing useful power levels. Complementing these are development programs that have created docking systems that allow an AUV to connect to an underwater structure to establish power and communication links (*46*, *47*). Using a docking station, an AUV's deployment would no longer be limited by the energy storage capacity of the vehicle.

As the productivity of fielded systems improves, operational demands on science teams increase dramatically, motivating the development of software to facilitate interacting with robotic exploration systems. Typically, researchers from geographically diverse institutions move to a common location. However, this is viable only when missions are short and science teams are small. In the case of MER, the planned 90–martian solar day (sol) duration of the surface exploration mission brought upwards of 400 scientists and engineers from the United States and Europe to JPL. With the extension of MER, now in its fourth year of operation, the mission is operated by 50 personnel at JPL, supported by a distributed science team (*48*). Thus the success of robotic exploration creates the need for collaborative portals that allow distributed research teams to efficiently interpret data and collaborate on the development of new operational plans. An early example of such a collaborative infrastructure was the Collaborative Ocean Observatory Portal (COOP), designed for the Monterey Bay 2006 field program (*49*). COOP leveraged data from a diverse array of observational assets and models to create synoptic views of oceanographic fields and fluxes over an area of approximately 1000 km^2, provided forums for the discussion of results, provided direct access to data and models, and included a highly successful framework for building consensus on planning remote asset deployments. In operation, the system relayed information from platforms and sensors to shore in near real time, where it could be assimilated into three independent ocean models. The collaborative tools now emerging are lowering the barriers to participation in scientific exploration and will be key to the success of future observatories.

Finally, as robots become more pervasive, emerging trends include the creation of supporting infrastructure and the increasing specialization of individual robots. The benefits of this evolution are visible in both deep space and the ocean. The MER vehicles now relay their information to Earth via a series of Mars orbiters, which allows the MER platforms to transmit more data while simultaneously preserving energy for science activities (*50*). The net result is the creation of a valuable infrastructure for communication, increasing the scientific utility of the MER mission. In the ocean, the benefits of using specialized platforms with complementary capabilities are integral to the development of a distributed observing system such as AOSN. One of the largest initiatives under way in the ocean sciences is the creation of an infrastructure to distribute power and communications to the sea floor (*51*). These sea-floor observatories will use combinations of moorings and sea-floor cables to distribute power to nodes in the deep ocean. Although the diverse approaches to ocean observing have roots in different research communities and have developed different technologies, their complementary capabilities are likely to coalesce to enable a more comprehensive robotic presence in the ocean. In space and beneath the waves, we see a trend toward more specialized robots, with more effective sensing capabilities resulting in more autonomy, accessible via collaborative portals through which researchers can engage with each other, the data, and their robot surrogates.

Conclusions

Robots are gaining acceptance in both space and ocean exploration. In the oceans, the need to more comprehensively understand Earth's climate and the great difficulty of making observations in the ocean's interior have created the need for persistent large-scale observing systems composed of heterogeneous mixes of robots. In space, the closely choreographed operation of robots by a large number of operators on Earth is slowly giving way to a model in which humans supervise increasingly capable robots. In both domains, the need to carry out complex tasks at distances, with either delayed or absent communications, precludes human control of every action. Full autonomy is becoming a necessity. Vehicles that seem like science fiction, capable of simple self-repair and dealing with the complexities of the hazardous environment around them, may well provide a more permanent and pervasive presence in the distant reaches of our planet's oceans as well as in the solar system in the coming decades.

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