propagation and catastrophic percolation. The persistent nucleation and growth of these microcracks create extrinsic plasticity that compensates for the low ductility of the brittle phase and enables sustainable uniform deformation. Compared to the conventionally solidified alloy, the self-buffering herringbone EHEA was three times more ductile, accompanied with extraordinary damage tolerance and a simultaneous enhancement of strength and toughness.

Shi *et al.*'s engineering of hierarchical chemical and nanostructural heterogeneities heralds a new approach for developing high-performance alloys. Tuning local compositional fluctuations may energetically alter the nature of a material's response to external stimuli like brittleness (*9, 10*). Creation of internal defects within individual nanostructures (see the figure) could activate multiple strengthening and toughening mechanisms (*11*). The heterogeneous microstructures could be programmed to trigger various intrinsic and extrinsic deformation mechanisms (*12*).

This design concept will require identifying and quantifying which materials parameters endow specific properties to help unravel how these develop in hierarchical structures. An integrated computational and experimental protocol, in conjunction with data science, could accelerate the establishment of a unified design principle and scientific framework for future mechanistic alloy design. Another formidable conundrum is to precisely control and organize spatially local chemical and structural heterogeneities. The advanced additive manufacturing techniques could, through a dedicate multiscale processing control, unlock the full potential of this new alloy design concept to help tackle major economic, energy, and environmental challenges. ■

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ECOLOGY

# Ecology in the age of automation

## Technology is revolutionizing the study of organisms in their natural environment

*By* **Timothy H. Keitt** *and* **Eric S. Abelson**

The accelerating pace of global change is driving a biodiversity extinction crisis (*1*) and is outstripping our ability to track, monitor, and understand ecosystems, which is traditionally the job of ecologists. Ecological research is an intensive, field-based enterprise that relies on the skills of trained observers. This process is both time-consuming and expensive, thus limiting the resolution and extent of our knowledge of the natural world. Although technology will never replace the intuition and breadth of skills of the experienced naturalist (*2*), ecologists cannot ignore the potential to greatly expand the scale of our studies through automation. The capacity to automate biodiversity sampling is being driven by three ongoing technological developments: the commoditization of small, low-power computing devices; advances in wireless communications; and an explosion in automated data-recognition algorithms in the field of machine learning. Automated data collection and machine learning are set to revolutionize in situ studies of natural systems.

"...monitoring... species along with climate and other variables is a critical need in...adapting to emerging global challenges."

Automation has swept across all human endeavors over recent decades, and science is no exception. The extent of ecological observation has traditionally been limited by the costs of manual data collection. We envision a future in which data from field studies are augmented with continuous, fine-scale, remotely sensed data recording the presence, behavior, and other properties of individual organisms. As automation drives down costs of these networks, there will not be a simple expansion of the quantity of data. Rather, the potential high resolution and broad extent of these data will lead to qualitatively new findings and will result in new discoveries about the natural world that will enable ecologists to better predict and manage changing ecosystems (*3*). This will be especially true as different types of sensing networks, including mobile elements such as drones, are connected together to provide a rich, multidimensional view of nature. Given the role that biodiversity plays in lending resilience to the ecosystems on which humans depend (*4*), monitoring the distribution and abundance of species along with climate and other variables is a critical need in developing ecological hypotheses and for adapting to emerging global challenges.

Ecosystems are alive with sound and motion that can be captured with audio and video sensors. Rapid advances in audio and video classification algorithms can allow the recognition of species and labeling of complex traits and behaviors, which were traditionally the domain of manual species identification by experts. The major advance has been the discovery of deep convolutional neural networks (*5*). These algorithms extract fundamental aspects of contrast and shape in a manner analogous to how we and other animals recognize objects in our visual field. Applied to audio signals, these neural networks are highly effective at classifying natural and anthropogenic sounds (*6*). A canonical example is the classification of bird songs. Other acoustic examples include insects, amphibians, and disturbance indicators such as chainsaws. Naturally, these algorithms also lend themselves to species identification from images and videos. In cases of animals displaying complex color patterns, individuals may be distinguished, allowing minimally invasive mark recapture, an important tool in population studies and conservation (*7*). Beyond sight and sound, sensors can target a wide range of physical, chemical, and biological phenomena. Particularly intriguing is the possibility for widespread environmental sensing of biomolecular compounds that could, for example, allow quantification of "DNA-scapes" by means of laboratory-on-a-chip–type sensors (*8*).

Several technological trends are shaping the emergence of large-scale sensor networks. One is the ongoing miniaturiza-

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Small, ruggedized sensors, such as this passive acoustic recorder, enable remote monitoring of biodiversity. New technologies are enabling such devices to process data and transmit information via wireless networks.

tion of technology, allowing deployment of extended arrays of low-power sensor devices across landscapes [for example, (*9*)]. In many cases, these can be solar-powered in remote locations. The widespread availability of computer-on-a-chip devices along with various attached sensors is enabling the construction of large distributed sensing networks at price points that were formerly unattainable. Similarly, the ubiquitous availability of cloud-based computing and storage for back-end processing is facilitating large-scale deployments.

Another trend is advancements in wireless communications. For example, the emerging internet of things (*10*) enables low-power devices to establish ad hoc mesh networks that can pass information from node to node, eventually reaching points of aggregation and analysis. The same technology used to connect smart doorbells and lightbulbs can be leveraged to move data across sensor networks distributed across a landscape. These protocols are designed for low power consumption but may not have sufficient bandwidth for all applications. An alternative, although more power hungry, is cellular technology, which has increasing coverage globally. In remote locations, where commercial cellular data services may not be available, researchers can consider a private cellular network for on-site telemetry and satellite uplinks for internet streaming. However, in the near term, telecommunications costs and per-device power requirements may nonetheless prove prohibitive in certain high-bandwidth applications, such as video and audio streaming. An alternative for sites where communications bandwidth is limited by cost, isolation, or power constraints is edge computing (*11*). In this design, computation is moved to the sensing devices themselves, which then transmit filtered or classified results for analysis, greatly reducing transmission requirements.

One more trend is the advancement of machine-learning methods (*12*) that can classify and extract patterns from data streams. Much of this technology has been commoditized through intensive development efforts in the technology sector that have resulted in widely available software libraries usable by nonexperts. The aforementioned convolutional neural networks can be coded both to segment data into units and to label these units with appropriate classes. The major bottleneck is in training classifiers because initial training inputs must be labeled manually by experts. Although labeled training sets exist in some domains—most notably, image recognition—future analysts may be able to skip much of the training step as large collections of pretrained networks become available. These pretrained networks can be combined and modified for specific tasks without the requirement of comprehensive training sets. Of particular interest from the standpoint of automation are new developments in continual learning (*13*), in which networks adjust in response to changing inputs. This holds the promise of automating model adaptation for detecting emerging phenomena, such as species shifting their ranges in response to climate change or other shifts in ecosystem properties.

Ecologists could leverage these developments to create automated sensing networks at scales previously unimaginable. As an example, consider the North American Breeding Bird Survey, a highly successful citizen-science initiative running since the late 1960s with continental-scale coverage. Expert observers conduct point counts of birds along routes, generating data that have proved invaluable in tracking trends in songbird populations (*14*). Although we hope to see such efforts continue, imagine what could be learned if, instead of sampling these communities once per year, a long-term, continental-scale songbird observatory could be constructed to record and classify bird vocalizations in near–real time along with environmental covariates. Similar networks could use camera traps or video streams to reveal details of diurnal and seasonal variation across diverse floras and faunas. As with all sampling methods, sensing networks will not be without biases in sensitivity and discrimination, yet they hold the extraordinary promise of regional sampling of biodiversity at the organismal scale, something that has proven difficult, for example, by using traditional satellite-based remote sensing. These efforts would complement ongoing development of continental-scale observatories in ecology [for example, (*15*)] by increasing the spatial and temporal resolution of sampling. ■

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