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Forum

Edge computing in wildlife behavior and ecology

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Modern sensor technologies increasingly enrich studies in wildlife behavior and ecology. However, constraints on weight, connectivity, energy and memory availability limit their implementation. With the advent of edge computing, there is increasing potential to mitigate these constraints, and drive major advancements in wildlife studies.

What is the problem?

Wildlife research rapidly evolves because of ongoing development in **automated sensing** (see Glossary), where both animal-borne **biologging** devices (biologgers) and **monitoring devices** produce data at ever increasing spatial and temporal resolutions [1,2]. Furthermore, automated-sensing devices become more multifunctional with increased incorporation of complementary sensors (e.g., physiological sensors, environmental sensors, and cameras). These developments open new avenues to assess novel and more detailed information on animal behavior, biomechanics, energetics, physiology, and the animal's environment.

However, the increasing sensory capabilities of automated-sensing devices also create new challenges. First, because of memory capacity limitations, storing substantial amounts of raw data on a device may become impractical. This could be partially addressed by adding a wireless data transmission module to the device, but data transmission might lead to elevated power consumption and may suffer from **bandwidth** limitations, as high bandwidth comes at the cost of decreased transmission distance. For devices without data transmission, retrieval of devices and their data may become impractical due to time, labor and financial limitations. Moreover, the latency between sensor-data recording and data extraction may be long, thus slowing down research progress and limiting real-time interventions.

Edge computing (EC) can serve as a solution for the above-mentioned constraints. EC is the deployment of computing resources close to the data source [3]. In recent years, the development of the **Internet of Things (IoT)** has boosted the popularity of EC. Here, we highlight the key advantages of EC in wildlife behavior and ecology applications, encompassing both bio-loggers and monitoring devices (Figure 1). Crucially, EC enables raw sensor data to be pre-processed directly on the device or close to it. We identify five key advantages of EC-enabled devices. (i) EC can increase storage efficiency of logging devices. Using EC-based real-time filtering and compressing, the volume of data to be stored on the device can be greatly reduced. (ii) If data require transmission to a storage hub or user, EC-based data compression can increase energy efficiency of the device. (iii) EC-based data compression can release bandwidth constraints for data transmission. (iv) EC-enabled devices have enhanced context awareness and automation capabilities, as they can adjust their operations based on sensory input (prevailing conditions, researcher input). (v) EC allows for reducing latency in data processing.

Glossary

Automated sensing: the applications using biologging and monitoring devices (see below) for biology related sensing.
Autonomous underwater vehicle: a robot that travels underwater without requiring continuous input from an operator.
Bandwidth: the maximum temporal rate of data transfer.
Biologging: the use of animal-borne/implanted/ingestible sensory devices for logging and/or relaying data about the movements, behavior, physiology, and/or environment of animals. In the main text, biologging devices are named biologgers.
Edge computing (EC): the deployment of computing and data storage close to the data source. The edge here denotes the edge of a network. Broadly speaking, edge computing includes all computing external to what happens on a central computer or in the cloud. The communication between the edge and the cloud can be direct (i.e., via fixed links or wireless transmission) or indirect (e.g., in case of logging devices without transmission capabilities).
Internet of things (IoT): a things-connecting data network, where things are wirelessly connected via smart sensors, which can operate without human intervention.
LoRa: a wireless radio communication technology.
Monitoring device: non-animal-borne biology related sensing devices such as audio recorder and camera trap.
Tiny machine learning (TinyML): machine learning optimized for use on microcontrollers with limited computation resources and low power capacity.

Since EC data is processed near the source, interpretable sensory data is readily available, providing increasing possibilities for (near) real-time observations and interventions. As highlighted in the following section, these five advantages of EC particularly benefit the data recording, data transmission, data processing, and results interpretation procedures associated with automated sensing in wildlife research.

Data recording

Miniaturized bio-loggers with limited storage can benefit from EC-enabled data reduction. For example, Liechti *et al.* [4] summarized accelerometer data on 1.5-g loggers through EC into representative values for body posture and activity level, providing evidence that Alpine swifts *Tachymarptis melba* engage in nonstop flights for >200 days. Animal-borne

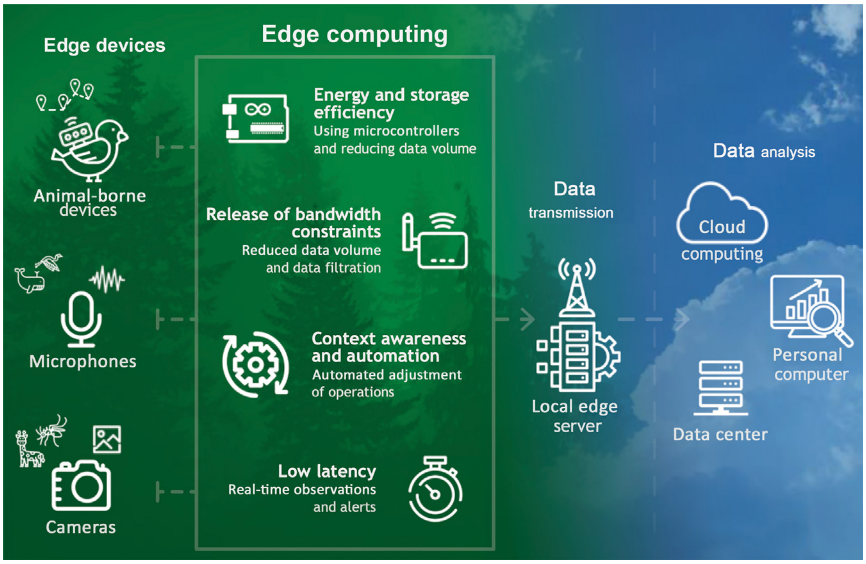

Figure 1. Crucial avenues through which edge computing (EC) facilitates biologging in wildlife ecological research. EC can be applied to the edge devices (wearable biologgers, microphones/hydrophones, and camera systems), such that only filtered or compressed data needs to be transmitted to the cloud, data center or user for further analysis. EC increases energy and storage efficiency, reduces bandwidth constraints, increases context awareness and automization, and reduces latency.

bioacoustics, notably in small flying animals, is another area where data volume may constrain research. EC could revolutionize studies of animal vocalizations on the move by using real-time call or song detection. Admittedly, an important limitation of EC in data recording is the loss of raw sensor data for *post hoc* processing. However, this problem could be limited by designing EC systems that collect and store raw sensor data when the confidence score of EC-generated results is low.

EC allows for coordination among onboard sensors, thereby increasing energy and storage efficiency, and enabling automation. Korpela *et al.* [5] applied EC to detect hunting events through accelerometer data on biologgers on gulls. When a prey capture event was identified, an onboard camera was activated to film the prey. Aside from such automation in EC-based data processing contributing to studies in animal foraging behavior, this approach can also be used to actively manipulate the observed animals or their surroundings. For example, Stanton *et al*. [6] used such an EC-based approach to study cognitive abilities in wild raccoons *Procyon lotor*.

Data transmission

Monitoring aquatic wildlife poses specific challenges because of the difficulties with underwater radio communication. Under such conditions, **autonomous underwater vehicles** equipped with acoustic monitors can record data during gliding dives, perform initial analysis, pre-selection and prioritization through EC, and transmit the extracted information wirelessly during intermittent surfacing intervals. This EC-based approach mitigates both data storage and bandwidth limitations. Such platforms were used to detect whales based on real-time identification of vocalizations, which can also reveal migration strategies [7]. Exploring other avenues, interdevice communications between EC-enabled devices can greatly advance terrestrial wildlife tracking. For example, larger-bodied animals may be equipped with EC-enabled receivers and serve as roaming receiving stations to survey areas with sparse communication coverage.

Data processing

In wildlife disease ecology and conservation biology, the low latency of EC-based wildlife-activity monitoring may facilitate prompt human intervention [8]. Hua *et al.* [9] developed and tested a prototype of an EC-enabled drone system for animal and human video detection, which was tested in Namibia. The real-time species recognition could provide sub-minute timely warnings through local networks for wildlife conservation.

Interpretation of results

Since EC can alleviate the constraints on device storage, EC also contributes to high-throughput data yields [10]. In addition, because of the contribution of EC to energy efficiency, the longevity of devices and research projects can be increased. This allows for sampling that potentially encompasses multiple life-history events, which in turn yields insights for behavioral responses to the environment. Another avenue where EC plays an important role is automated monitoring of ecological communities (e.g., Figure 2). When data collection and processing can be integrated into a pipeline through EC, such a system will allow automated monitoring of individual behaviors and traits, and species abundance and distributions [11], which can advance biodiversity monitoring for ecological research and conservation policy making, and even potentially be used in predictive frameworks for early warning of population collapse.

Outlooks

The booming IoT industry has facilitated the deployment of new data transmission technologies such as **LoRa** or advanced automated radio-tracking systems [12],

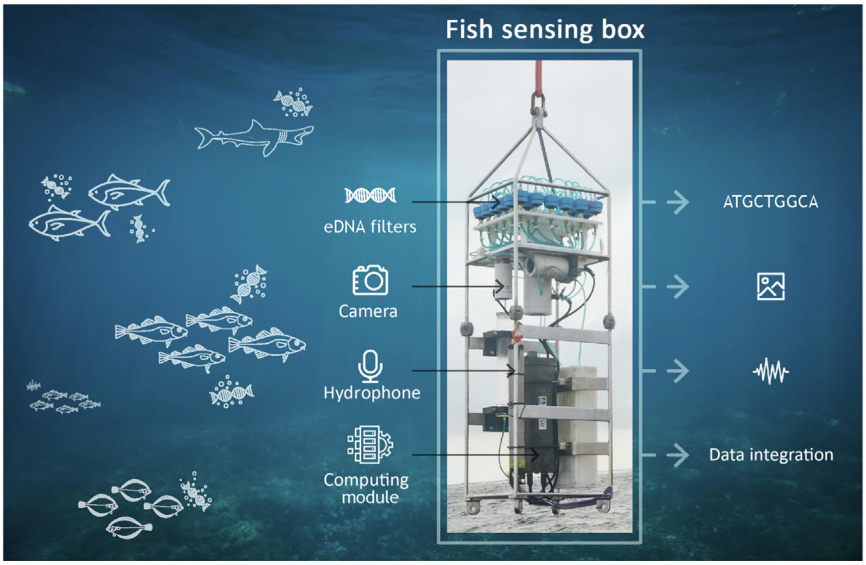

Figure 2. The biodiversity sensing box is an EC-based device for quantifying wildlife biodiversity in the marine environment. It is a fully autonomous, integrated, multisensory system equipped with an eDNA sampling module, videography and hydrophone systems, and an on-board computing module for real-time processing of auditory and videography data. For example, using EC, it can sample eDNA based on auditory or videography input, and store only relevant event-triggered derived data.

which also benefit EC applications in wildlife research. Open source, low power, multi-sensor platforms increasingly facilitate innovative developments incorporating EC by researchers such as acoustical AudioMoth [13], and various Raspberry Pi–based applications [14]. These devices provide great opportunities for user customization with EC functions. Also, the development of supportive software for EC is evolving rapidly, including the advance of **tiny machine learning models (TinyML) (**https://rb.gy/hdohay). In addition, the recent Internet of Animals concept [15] that links live data, databases and automated analytics require EC as a crucial technology.

Concluding remarks

Given the rapid pace at which data sensing, recording, processing, transmitting and other EC-relevant technologies develop, we expect that the increase in interdisciplinary collaborations between ecologists, computer scientists and engineers will spark many novel EC applications. The creative implementation of EC in multisensory systems has enormous potential to open new research frontiers for answering fundamental and applied questions in wildlife behavior and ecology.

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Declaration of interests

No interests are declared.

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