On Neuromorphic Architectures for Efficient, Robust and Adaptable Autonomy in Life Detection and Other Deep Space Missions

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Motivation

Deep space missions share *stringent constraints* on mass, power, volume, and often require tolerance to extreme temperatures or radiation, long lifespans, and, most critically, *autonomy* to carry out mission activities. Future life detection missions will require to navigate through challenging environments, acquire and analyze samples, and to select and summarize data.

Neuromorphic architectures, i.e. the implementations of biologically inspired algorithms and hardware (processors and sensors) that are powering drones, autonomous cars and other nascent industries on Earth, can address these challenges. Future planetary science missions should leverage these massive investments and develop implementations offering the efficiency and robustness required for deep space missions.

The 2011 Planetary Science Decadal Survey describes technological needs, including "increased spacecraft autonomy", "new and improved sensors", and highlights prospects for life beyond Earth. We recognize that neuromorphic architectures are a cross-cutting technology with applicability to all deep space missions.

Sequencing based life detection: Approaches for *in situ* detection and sequencing of informational polymers (IPs) are possible through *strand sequencing*, a technology that detects translocations of IP bases through an array of nanopores by monitoring the ionic current blockage variations throughout the pores, which informs the assignment of sequence data (e.g., A,C,G,T bases for DNA). The simplicity and versatility of pore sequencing is *not limited to DNA* and can be used to detect RNA, modified or non-standard bases, and, potentially, other IPs.

The Search for Extra-Terrestrial Genomes (SETG) is an example of life detection instrument for space applications that utilizes protein nanopores based strand sequencing coupled to recurrent neural network (RNN) base-calling, deployed on a traditional (von Neumann) architecture.
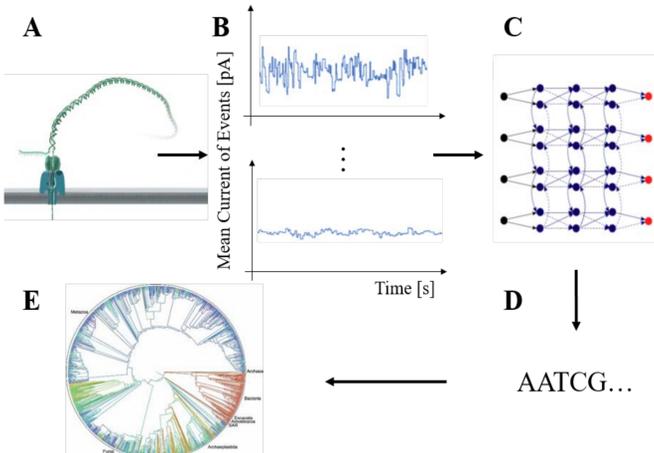

Fig. 1 Typical pipeline for single molecule nanopore-based sequencing. Translocation of IPs through a nanopore array (A) generates a large quantity of ionic current measurements (B), that are processed through a RNN to detect the polymer type and (C) to generate an estimated base sequence (D), which, for DNA or RNA, is mapped to the known tree of life (E) to detect ancestral relationships or identify contaminants.

Challenges

Major mission challenges for life detection include access to habitable zones, sample acquisition, *in situ* data processing, and, when the data are too extensive to transmit back to Earth, selection of data or analyses to return to Earth.

In situ life detection and other deep space missions highlight a need for increased efficiency, adaptability and robustness of control architectures.

Interesting sampling sites on *Mars* include cave systems and other subsurface environments, or recurring slope lineae, locations sheltered from space radiation and where liquid water brines may exist, respectively, that are typically unreachable with a rover.

Plumes from Enceladus may host high molecular weight organic materials. An orbital plume sampling mission to *Enceladus* would require fine orbit and attitude control to compensate for the instability of the polar orbit, if low relative velocities are required in order to preserve biomarkers of interest.

Europa is a candidate ocean world but presents an extreme *radiation environment*, in addition to *limited bandwidth* to Earth. Payload operations will have to push the balance between performance, power efficiency, and robustness, e.g., to radiation induced memory errors. Future missions may extend into Europa's icy shell or explore its ocean, requiring extreme autonomy to permit operation without Earth contact for extended periods.

Fig. 2 Artistic impressions of a Mars drone and Europa underwater explorer. Both missions rely on autonomy to perform their tasks. Credit to NASA.

Neuromorphic Architectures

While neuromorphic computing has been pursued since the '50s, concrete implementations of neuromorphic sensors (e.g., Dynamic Vision Sensor) or processors (e.g., IBM's *TrueNorth*) are more recent.

Results Found	2158
Sum of the Times Cited	21837
Citing Articles	10599
Average Citations per Item	10.12
H-index	65

Fig. 3 Trends for the use of the word "*neuromorphic*" in recent scientific literature (data from Web of Science and Scopus) and a synthetic timeline of milestone achievements in neuromorphic engineering (based on Soman et al., 2016).

Neuromorphic architectures (NA) use a *distributed* representation, in which independent units cooperate to perform a computation and communications are encoded via *events* (inspired by spikes).

In NAs, computation and memory are co-localized and distributed through massive parallelism, while these functions are separated through dedicated hardware in typical computational architectures.

Efficiency: Neuromorphic systems are *asynchronous* and *event-driven*, instead of periodically sampled, which allows for treatment of *salient data exclusively*, easing the extraction of useful information from the measured data. Moreover, implementations of neuromorphic processing has shown significant power savings.

Adaptability: Biomarkers such as IPs could include DNA or involve non-standard bases or polymers, requiring *adaptability* of the processing algorithms, i.e. a formal way to *expect the unexpected*. Neuromorphic algorithms offer this potential through *training*, leading to adjust their input/output behavior to process peculiar findings.

Robustness: Just as a brain can heal, NAs can likely be made resilient to radiation noise. While in a conventional processor a bit flip can provoke catastrophic failure, in distributed neural coding an error or permanent fault of one unit does not propagate catastrophically. It is *a model of computation* that can *tolerate* noise. Thus*, bounded interference* or *damage* on the network, e.g., caused by radiation-induced memory errors, will produce *bounded degeneration* of the output. This would allow the performance of the instrument to *degrade gracefully* with time.
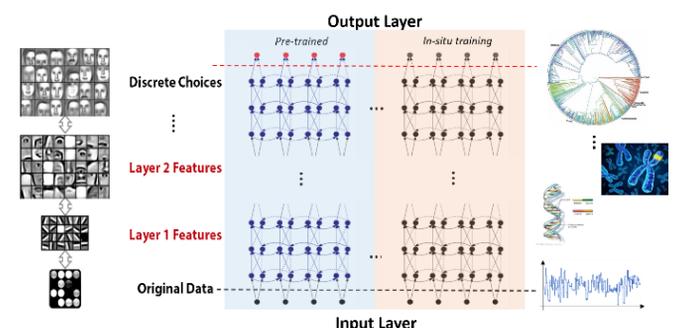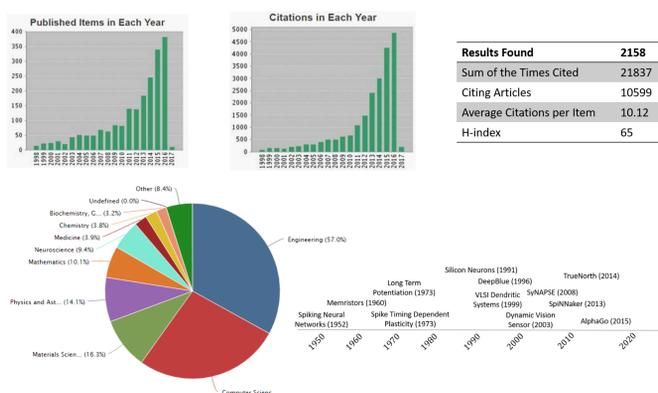

Fig. 3 Neuromorphic algorithms in computer vision and speech recognition learn hierarchies of relevant features within noisy data for pattern recognition applications. A similar process applies to *in situ* detection of IPs. Augmenting pre-trained networks with *in situ* training supports adaptation.

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