Universal Actuation: Using Emerging Hardware to Achieve Embodied Intelligence

by Justin Ting (last updated 1/14/21)

Motivation: The arrival of robots that assist senior citizens, coordinate disaster relief, and explore planets autonomously seems far more promising with the advent of deep learning. However, robots equipped with deep learning still have trouble adapting to their environments quickly, flexibly, and in real-time. For robots with tight energy constraints, the significant power consumption of these algorithms is also a concern [4]. Furthermore, these algorithms require copious data collection [6]. Conversely, the way humans learn, move, and adapt is very power efficient and sophisticated. **To overcome these obstacles in robotics, we must be willing to explore new algorithms and neuroscience-inspired hardware.** When brain-inspired algorithms and hardware (e.g. Spiking Neural Networks (SNN), In-Memory Compute) are introduced, two assumptions in robotics can be challenged. **First:** Dependence upon the Von Neumann architecture for computing. **Second:** Independence between perception, computation, and actuation. **Not only can the principles of neuroscience help us relinquish these assumptions, but they can also push us to develop systems that can universally actuate all robots.** In other words, instead of writing new learning algorithms for every new robot, one universal system can develop self-awareness and accurate internal perception for every robot or robot swarm. I aspire to change the way roboticists think about the evolution of our machines, not only for the sake of surpassing benchmarks, but to also gain a deeper insight into how the brain works.

Background:

a. Neuroscience: Our kinesthetic intuition, which allows us to flexibly learn and execute various movements, is dependent upon the shape of our bodies[10]. This intuition is developed because the brain develops a model of how our bodies behave through internal perception. In contrast, reinforcement learning is an algorithm focused on understanding the environment, but understanding the environment alone is not enough to develop the same level of complex motion exhibited by animals and humans. Furthermore, digital computers from the Von Neumann architecture are developed for the sole purpose of executing programs regardless of the environment or form factor of the computer. This is why, with the same Von Neumann architecture, simply scaling up the parameters of learning algorithms without changing their fundamental principles quickly becomes inefficient for robots.

In order to address how the barriers between perception, cognition, and actuation can be lifted, we can observe the signals of the nervous system. In the brain, all electric signals being passed between neurons are spikes: from sensory organs to the brain for perception, between neurons in the brain for cognition, and from the brain to the muscles for actuation [8]. Although there are certain sectors in the brain that separately process perception and actuation, it is overall a more integrated system than our current technology. The brain's model of the world is more complex than simply treating all sensors as inputs and all actions as outputs. Instead of allocating all actuation to a feedback control system, or all perception and computing to deep learning, we can re-evaluate the relationship between the three processes to find ways of creating better robots.

b. Emerging Hardware: Moving away from Von Neumann architecture to alternative hardware is already an approach being pursued by many research groups [11], including the Center of Brain-Inspired Computing (CBRIC), an organization whose projects I have been involved in [12] [7]. In these projects, I worked closely with Event-Based Vision, a new type of camera that processes video with Dynamic Vision Sensors. Not only does this technology help save plenty power, operating at around 1mW, but it can also eliminate motion blur in order to extract finer details and features. On top of these advantages over typical optical cameras, the sensors are a more accurate model of the way the human eye captures light. In addition to Event-Based Vision, emerging hardware includes technologies such as Crossbar-based architecture, In-Memory Computing [9], and Spiking Neural Network hardware [5]. These methods propose new hardware that, by imitating the brain, can speed up learning algorithms and save power. These recent innovations suggest that there is still plenty of room to explore the applications of neuromorphic hardware for robotics.

c. Algorithms: Algorithms that work for the Von Neumann architecture do not directly translate over to neuromorphic hardware. That is why new algorithms must be developed to complement it. Spiking Neural Networks

(SNN) are being explored as an alternative to Artificial Neural Networks for power-constrained scenarios in which dynamic data needs to be captured and interpreted quickly, and neuromorphic hardware can accomodate SNNs. The neurons in SNNs imitate real neuron dynamics more accurately, which is useful for merging it with new Event-based hardware. My previous work demonstrates how Event-Based Vision calls for new algorithms in order to be merged with SNNs [12], and by taking advantage of the real-time attributes of the technologies, was able to visually teach a robot to walk.

Published work on robotic control with a spiking approach demonstrates the potential of such systems [3]. Nonlinear dynamics that describe the brain's behavior can also be taken into account when writing these algorithms. A neuromorphic version of conventional algorithms, such as Simultaneous Localization and Mapping (SLAM), can also being incorporated into brain-inspired robotics[13].

d. Previous Work: The ideas related to developing a bio-inspired universal robotic actuator were accumulated from my 4 years working under Dr. Arijit Raychowdhury, who has won the 2018 IEEE/ACM "Innovator Under 40 Award" and the 2020 Qualcomm Faculty Award for his contributions in low-power SoC design. His lab is called the Integrated Circuits and Systems Research Lab (ICSRL). The first project I worked on a Deep Q-Learning chip at 1.2V and 690uW. This chip controlled and trained a robot to explore its environment and learn to avoid obstacles. I built the live demonstration for this project at ISSCC 2018 [1]. This paper established that low-power hardware approaches were useful in robotics. Moving away from Von Neumann architecture to alternative hardware is already an approach being pursued by a research group we are affiliated with called the Center for Brain-Inspired Computing (CBRIC) [9]. During our collaboration with CBRIC, I worked closely with Event-Based Vision and Spiking Neural Networks (SNNs), which are both energy-efficient bio-inspired technologies [12] [7]. In my latest conference submission at IJCNN 2020, where I gave a video presentation, I wrote a feedforward algorithm for imitation learning between two 6-legged robots by taking advantage of the real-time properties of Event-Based Vision and SNNs [12]. This combination of the algorithm and the bio-inspired hardware (Figure 1) allowed the robots to copy movements in a couple minutes with little data, as opposed to the long training times and large data workloads of typical deep learning procedures. NDSEG will enable me to investigate more ways of incorporating and designing bio-inspired technologies to explore the possibilities of embodied intelligence and universal actuation.

Research Plan: My research will incorporate the principles of brain-inspired computing to develop an electrical system that can actuate most robots, ranging between microrobots, drones, and walkers. The three phases of this research are simulation, hardware design, and field testing.

Phase 1: Simulating Brain-Inspired Algorithms: In humans, perception, processing, and actuation can all be observed as spiking electric signals, but robots that use servos or soft materials rely on completely different electrical signals. I propose that a universal learning system accounting for all perception and actuation electrical signals would require linear decomposition and recombination of the signal's Fourier components, which is very similar to how deep learning filters and rectifies its input data. Recurrent SNNs are capable of producing nonlinear signals that can be used for actuation, which suggests the potential for using neuromorphic algorithms as a foundation for universal actuation[2]. The dynamic nature of these signals raises the potential to bring in control theory to improve the algorithms. Furthermore, these continuous operations have analog circuit parallels, which opens up possibilities for using neuromorphic hardware. If the learning algorithm works as intended, the system should be able to capture the internal model of each robot to the point where the robots can understand the simple high level tasks that it can perform. BRIAN and Nengo are examples of two software tools that are used in the neuromorphic community that can help test these algorithms, and plenty of robotics simulation platforms can be used to study the virtual robot's behavior. Ideally, we can design simulations for robots of different form factors and environments and observe whether or not they are able to accomplish similar tasks. I plan to publish the results of this phase in conferences such as IJCNN or CVPR.

Phase 2: Designing Neuromorphic Hardware In addition to the Event-Based Cameras that I worked on, emerging hardware includes technologies such as Crossbar-based architecture, In-Memory Computing, and Spiking Neural Network hardware [9]. By imitating the brain, this type of hardware can speed up learning algorithms and save power. The recent innovations of this technology suggest that there is still plenty of room to explore the

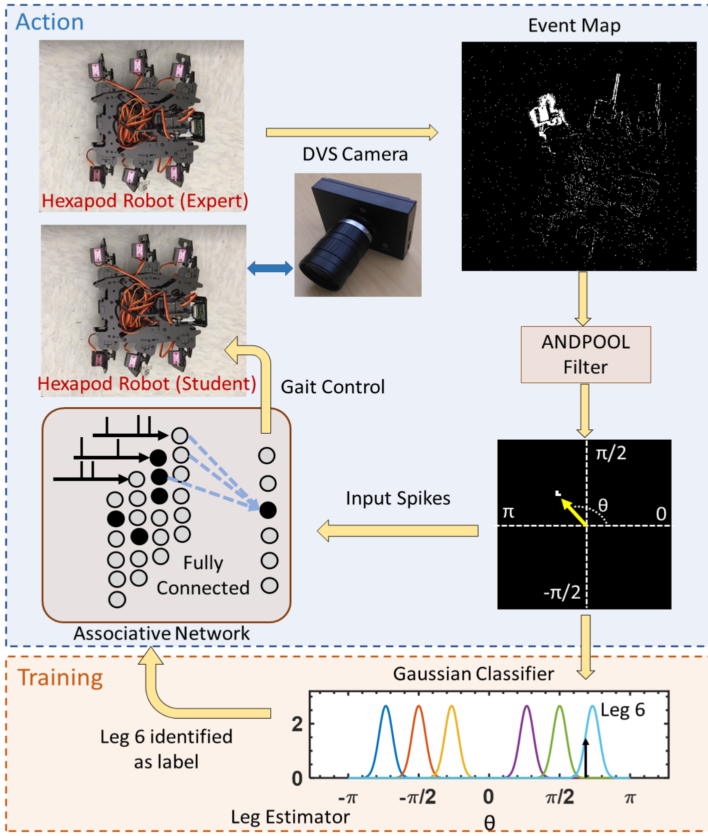

Figure 1: This figure explains the algorithm's cycle from [12]. The expert hexapod moves its legs, which the DVS camera records in order to generate the event map. The event map is filtered using an Andpool to find the region of high spike generation. The relative angle of this region (θ) is passed through the Gaussian classifier to generate a label for the leg that moved. The map is fed as the input layer to a six-neuron SNN. Using the label, the weights are adjusted to train the SNN. The neuron which spikes is the leg associated with the expert's leg and activated on the student hexapod.

applications of neuromorphic hardware on robotics. The properties of the hardware can shape the algorithm's design, so this phase can be concurrent with the previous phase. Programmable neuromorphic hardware is available for research groups. A couple options include SpiNNaker and Intel's Loihi chip. While these boards will not be directly connected to the robots, they can provide insight on how to best implement the universal algorithm. These boards can also connect to disembodied peripherals, such as Event-Based Cameras and motors, so that the signals being passed between components can be verified. These peripherals will also help me measure the energy efficiency of the system more accurately. Since the goal of this phase is to determine the best hardware architecture and specifications, the results can be submitted to a conference such as ISSCC or AICAS.

Phase 3: Field Testing with Various Robots The steps for this phase first require purchasing several different robots, such as hexapods, drones, and arms. Then, the hardware should be integrated onto a board that is small enough to accommodate all the selected robots. Finally, I will build distinct environments in the lab so I can run the same tests that will resemble the first phase's simulations. Several tasks would have to be tested in each environment. An experiment such as having robots of two different form factors perform the same tasks would clearly evaluate how successful and consistent the algorithms are. The goal of this phase is to investigate the flexibility and range of tasks that the robots can learn and execute, as well as compare which robots could perform the tasks more optimally. The results of these particular tests can be submitted to robotics conferences such as IROS.

Conclusion: The appearance of a universal robotics system can save plenty of robotics engineers time and resources so that a different system does not need to be developed for every new robot. Consequently, we can arrive at home robotics, disaster relief swarms, or autonomous vehicles more quickly. However, this research will also have a deep impact on our understanding of the brain. There are still plenty of mysteries involving how humans and animals learn through movement and touch, and patients with motor disabilities rely on these ideas from neuroscience to heal. Although our current technology will not be able to simulate all 86 billion neurons in the human brain, a functioning small-scale model that can demonstrate some quick and efficient motor skills will be substantial enough to give neuroscience a platform for understanding the brain's organization and operation.

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