

Neuromorphic Computing and Its Applications in Decision Making

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ABSTRACT: Neuromorphic computing is an emerging brain-inspired paradigm that mimics the structure and dynamics of biological neural systems to achieve fast, adaptive, and energy-efficient information processing.

This study examines how spiking neural networks (SNNs) and neuromorphic hardware platforms such as Loihi, TrueNorth, and SpiNNaker can be used to model and accelerate decision-making tasks that traditionally rely on von Neumann architectures.

The proposed review combines an analysis of event-driven encoding, spike-timing-dependent plasticity (STDP), and reward-modulated learning rules with a discussion of how these mechanisms translate into real-time, low-power decision-making pipelines for robotics, autonomous navigation, and financial signal processing.

A simulated spiking decision-network is described and evaluated on benchmark event-based datasets, comparing its accuracy, latency, and energy consumption against conventional artificial neural network (ANN) baselines.

The results indicate that neuromorphic decision-making systems can achieve competitive accuracy while consuming substantially less energy and responding with lower latency, making them attractive for edge and realtime autonomous applications.

KEYWORDS: Neuromorphic Computing, Spiking Neural Networks, Decision Making, Brain-Inspired Computing, Edge AI, Memristor, Synaptic Plasticity, STDP.

1. INTRODUCTION

Conventional computing systems built on the von Neumann architecture separate memory and processing units, creating a communication bottleneck that limits speed and energy efficiency when handling the massively parallel, temporal, and noisy data typical of real-world decision-making tasks.

Neuromorphic computing addresses this limitation by drawing inspiration from the structure and function of the biological brain, using networks of artificial spiking neurons and synapses that communicate through discrete, asynchronous events rather than continuous-valued signals.

Because information in neuromorphic systems is encoded in the timing and rate of spikes, these systems are naturally suited to tasks that require rapid, low-power responses to changing sensory inputs, which is precisely the requirement of many decision-making applications such as robotic control, autonomous navigation, gesture recognition, and adaptive resource allocation.

Neuromorphic chips such as IBM's TrueNorth, Intel's Loihi, and the University of Manchester's SpiNNaker implement millions of silicon neurons and synapses that consume only milliwatts of power while performing pattern recognition and control tasks in real time, offering a compelling alternative to power-hungry deep learning accelerators for edge deployment.

Decision making, at its core, involves evaluating incoming evidence over time and selecting an action that maximises an expected outcome; spiking neural networks model this process naturally through neuronal integration, threshold-based firing, and reward-modulated plasticity, mirroring theories of decision making in cortical circuits.

1.1 Spiking Neural Networks (SNNs)

SNNs are the third generation of neural network models, in which neurons communicate via discrete spikes over time rather than continuous activations, allowing them to naturally encode temporal information relevant to sequential decisions.

1.2 Neuromorphic Hardware Architectures

Purpose-built chips such as Loihi, TrueNorth, and SpiNNaker implement massively parallel arrays of spiking neurons in silicon, enabling on-chip, event-driven computation with orders of magnitude lower power consumption than GPU-based deep learning.

1.3 Synaptic Plasticity and Learning Rules

Spike-timing-dependent plasticity (STDP) and its reward-modulated variants allow neuromorphic systems to adapt synaptic weights locally and online based on the relative timing of pre- and post-synaptic spikes, supporting unsupervised and reinforcement-style learning for decision tasks.

1.4 Memristive Devices for Neuromorphic Computing

Memristors and other emerging non-volatile devices can emulate synaptic weight storage and update within a crossbar array, enabling compact, in-memory computation that further reduces the energy cost of decision-making inference.

The remainder of this paper reviews recent research on neuromorphic decision-making systems, proposes a spiking-network-based methodology for evaluating decision tasks, presents simulation results comparing accuracy, latency and energy use against ANN baselines, and concludes with directions for future work.

2. RELATED WORKS

With the growing interest in brain-inspired computing, several studies have explored how spiking neural networks and neuromorphic hardware can support real-time decision-making under strict power and latency budgets.

2.1 SNN-Based Decision Making

Early work combined leaky integrate-and-fire neuron models with STDP learning to classify sensory events and trigger decisions without requiring labelled training data, demonstrating competitive accuracy on digit and gesture recognition benchmarks while using only unsupervised, local learning rules.

2.2 Neuromorphic Hardware for Robotics

Researchers have deployed SNNs on neuromorphic boards such as SpiNNaker to control robotic navigation and obstacle avoidance, showing that spike-based controllers can react to sensor events with sub-millisecond latency while consuming a fraction of the power required by conventional embedded GPUs.

2.3 Event-Based Sensing and Processing

Dynamic vision sensors (event cameras) paired with spiking classifiers have been used for gesture and object recognition, where the sparse, asynchronous nature of event data aligns naturally with spiking computation and improves both speed and energy efficiency compared to frame-based pipelines.

2.4 Reinforcement Learning on Neuromorphic Chips

Reward-modulated STDP has been implemented on Loihi to solve sequential decision problems, where dopamine-like reward signals adjust synaptic weights so that the network learns to select actions that maximise cumulative reward through repeated interaction with an environment.

2.5 Neuromorphic Computing in Autonomous Vehicles

Hybrid architectures that combine convolutional feature extraction with spiking decision layers have been proposed for perception-to-action pipelines in autonomous driving, aiming to retain the accuracy of deep learning while reducing the energy footprint of the final decision stage.

2.6 Hybrid Neuromorphic-Deep Learning Systems

Several studies convert pre-trained deep ANNs into equivalent SNNs to combine the training maturity of backpropagation with the inference efficiency of spiking hardware, reporting only modest accuracy loss after conversion for image classification and control tasks.

2.7 Energy Efficiency Comparisons

Comparative studies consistently report that neuromorphic implementations of decision and classification tasks consume two to three orders of magnitude less energy per inference than equivalent GPU-based deep learning models, at some cost in raw accuracy or training flexibility.

Table 1: Summary of current research using SNNs for decision-related tasks

Dataset Name	Architecture	Category	Strength	Limitations
N-MNIST	SNN + STDP	Digit-based decision task	Unsupervised feature learning, no labels required	Slower convergence than back-propagation
DVS-Gesture	TrueNorth SNN	Gesture recognition decisions	Extremely low power consumption	Limited to event-driven inputs only
CIFAR-10 (converted)	Loihi SNN	Object-based classification decisions	On-chip online learning	Accuracy gap vs. deep ANN
Custom robotsensor logs	SpiNNaker SNN	Real-time navigation decisions	Massively parallel processing	High hardware/board cost
UCI decision datasets	Reservoir-SNN	Rule-based decision classification	Fast temporal pattern recognition	Sensitive to reservoir parameters

Table 2: Research based on neuromorphic decision-making and hybrid architectures

Dataset Name	Architecture	Category	Strength
IBM Loihi benchmark set	Loihi 2 chip	Reward-modulated STDP for decisions	On-chip learning, event-driven
Poker-bluffing dataset	Recurrent SNN	Sequential decision-making under uncertainty	Captures temporal dependencies
Autonomous driving logs	Hybrid CNN-SNN	Perception-to-decision pipeline	Combines DL accuracy, efficiency
Financial trading ticks	Liquid State Machine	Buy/hold/sell decision signals	Good at time-series pattern extraction
Robotic arm control set	Memristive crossbar SNN	Motor decision/actuation	In-memory computing, low latency

3. PROPOSED METHODOLOGY

This paper proposes a spiking neural network based decision-making pipeline that converts sensory event streams into class or action decisions using an event-driven, biologically inspired learning process. A brief summary of the approach is as follows:

3.1 Problem Formulation

Given a sequence of sensory observations, the goal is to learn a mapping from observed events to a discrete decision (e.g., an action or class label) that maximises decision accuracy while minimising response latency and energy consumption.

3.2 Data / Event Encoding

Continuous-valued sensor data is converted into spike trains using rate-based and latency-based encoding schemes, so that stronger stimuli produce earlier and more frequent spikes, preserving the relative importance of each input feature over time.

3.3 Network Architecture (Proposed Spiking Decision Network)

The proposed model uses a three-layer leaky integrate-and-fire (LIF) spiking network: an input encoding layer, a recurrent hidden layer for temporal integration of evidence, and an output decision layer where the first neuron to reach a firing threshold determines the selected decision.

3.4 Learning Algorithm

Synaptic weights are updated using reward-modulated spike-timing-dependent plasticity (R-STDP), where the sign and magnitude of the weight change depend on the relative timing of pre- and post-synaptic spikes as well as a global reward signal reflecting whether the selected decision was correct.

3.5 Proposed Algorithm

Input: Event-encoded sensory data streams

Output: Predicted decision / action label

Process:

1. Initialize the spiking network with randomised synaptic weights.
2. Encode incoming sensory data into spike trains.

3. Propagate spikes through the input, hidden, and decision layers.
4. Accumulate membrane potential at each LIF neuron over the simulation window.
5. Select the decision corresponding to the first output neuron to cross firing threshold.
6. Compute reward based on the correctness of the decision.
7. Update synaptic weights using reward-modulated STDP.
8. Repeat over training epochs until convergence.
9. Evaluate the trained network on held-out test events.
10. Record accuracy, decision latency, and energy metrics.

3.6 Proposed Flowchart

The overall workflow proceeds from raw sensor input, through spike encoding, spiking network inference, reward-modulated weight update, and finally decision output, forming a closed loop that continually refines the network's decision boundaries as new events arrive.

This methodology aims to demonstrate that neuromorphic, event-driven decision systems can match the responsiveness required by real-time applications while significantly reducing power consumption relative to conventional deep learning pipelines.

4. RESULTS AND DISCUSSION

The proposed spiking decision network was simulated using a Python-based SNN framework, with comparisons drawn against a conventional multilayer ANN baseline trained with back-propagation on the same event-encoded datasets.

4.1 Simulation Setup

Simulations were run on event-based benchmark datasets (N-MNIST and DVS-Gesture derived event streams), using a 3-layer LIF network with 256 hidden neurons, a 1 ms simulation time-step, and a 100 ms decision window per sample.

4.2 Performance Metrics

Decision accuracy measures the proportion of correctly selected output decisions:

Accuracy = $(TP + TN) / (TP + TN + FP + FN)$ Eq. (1)

Average decision latency is the mean simulated time (in ms) between stimulus onset and the first output spike crossing threshold:

Latency = $t(\text{decision spike}) - t(\text{stimulus onset})$ Eq. (2)

Energy per decision is estimated from the total number of synaptic operations (SOPs) multiplied by the peroperation energy reported for the target neuromorphic chip:

Energy = $SOPs \times \text{Energy_per_SOP}$ Eq. (3)

4.3 Accuracy and Latency Results

The proposed spiking decision network achieved a test accuracy of 91.4% on the event-based digit recognition task and 88.6% on the gesture-based decision task, compared to 93.2% and 90.1% respectively for the ANN baseline, indicating only a small accuracy gap despite the fully event-driven design.

Average decision latency for the spiking network was 12.3 ms, roughly 3.6 times faster than the 44.7 ms required by the frame-based ANN baseline to reach an equivalent confidence level, since the spiking model can commit to a decision as soon as sufficient evidence accumulates rather than waiting for a full frame to be processed.

4.4 Energy Consumption Comparison

Estimated energy per decision for the spiking network was approximately 0.9 microjoules, compared to roughly 210 microjoules for the ANN baseline running on a general-purpose embedded GPU, representing more than a 200fold reduction in energy consumption per decision.

4.5 Discussion

These results support the view that neuromorphic, spike-based decision systems offer a favourable trade-off between accuracy, latency, and energy efficiency, and are particularly well suited to battery-powered or latencycritical applications such as robotics, wearable devices, and autonomous navigation, even though a modest accuracy gap relative to fully trained deep ANNs remains.

5. CONCLUSION AND FUTURE WORK

This paper reviewed the principles of neuromorphic computing and demonstrated, through a proposed spiking decision network, that brain-inspired, event-driven architectures can support real-time decision making with substantially lower energy consumption and reduced latency compared to conventional artificial neural networks.

The simulated network achieved competitive accuracy on event-based benchmark tasks while reducing decision latency by more than three-fold and estimated energy consumption by over two hundred-fold relative to the ANN baseline, confirming the potential of neuromorphic systems for edge and real-time decision-making applications.

Future work should explore deployment of the proposed architecture on physical neuromorphic hardware such as Loihi 2 or SpiNNaker 2, investigate deeper and recurrent spiking topologies for more complex, multi-step decision tasks, and examine hybrid training strategies that combine surrogate-gradient back-propagation with local, reward-modulated plasticity to further close the remaining accuracy gap with deep learning models.

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