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Original Article

Neuromorphic Spiking Neural Networks for Low-Latency Autonomous Navigation

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ABSTRACT

Low-latency decision-making is a critical requirement for autonomous navigation in dynamic and resource-constrained environments. Conventional deep learning-based navigation systems often suffer from high computational overhead and energy consumption, limiting their deployment in real-time robotic applications. This paper presents a neuromorphic navigation framework based on spiking neural networks (SNNs) that leverages event-driven computation for efficient perception and control. The proposed system integrates biologically inspired neuron models with latency-aware learning mechanisms to enable rapid sensory processing and decision-making. By exploiting temporal information encoded in spike trains, the framework achieves faster response times while maintaining robust navigation performance. Experimental evaluations demonstrate that the neuromorphic SNN-based approach significantly reduces inference latency and energy consumption compared to conventional neural network baselines, making it suitable for real-time autonomous navigation tasks. The results highlight the potential of neuromorphic computing as a scalable and energy-efficient solution for next-generation autonomous systems.

KEYWORDS

Neuromorphic Computing, Spiking Neural Networks, Autonomous Navigation, Low-Latency Systems, Event-Driven Processing, Robotics, Energy-Efficient AI, Real-Time Decision Making.

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1. INTRODUCTION

Autonomous navigation has become a foundational capability in modern intelligent systems, including mobile robots, unmanned aerial vehicles, autonomous vehicles, and service robots operating in human-centric environments. These systems must continuously perceive their surroundings, interpret sensory data, and make rapid decisions to ensure safe and efficient movement. As autonomous platforms increasingly operate in dynamic and unpredictable environments, the ability to respond with minimal delay becomes critical. Even small computational latencies can lead to degraded performance, unsafe behavior, or system failure, particularly in scenarios involving fast-moving obstacles or real-time interaction with humans.

1.1. Motivation for Low-Latency Navigation in Autonomous Systems

Low-latency navigation is essential for enabling autonomous systems to react promptly to environmental changes. In real-world scenarios, delays in perception or decision-making can result in missed obstacles, inefficient path planning, or collisions. This requirement is especially pronounced in resource-constrained platforms such as drones, edge robots, and embedded systems, where computational power and energy availability are limited. Traditional frame-based sensing and batch processing approaches introduce unavoidable delays due to sequential data acquisition and processing. Consequently, there is a growing need for navigation systems that can process sensory inputs and generate control commands in an event-driven and continuous manner, thereby minimizing response time and enhancing system safety and reliability.

1.2. Limitations of Conventional Deep Neural Networks in Real-Time Navigation

Deep neural networks (DNNs), including convolutional and recurrent architectures, have demonstrated remarkable success in autonomous navigation tasks such as perception, localization, and decision-making. However, these models typically rely on dense numerical computation, high-precision arithmetic, and frame-based sensory inputs, which collectively impose significant computational and energy overhead. The latency introduced by deep network inference can be prohibitive for real-time navigation, particularly when deployed on embedded hardware. Moreover, conventional DNNs process information synchronously and lack intrinsic mechanisms to exploit temporal sparsity in sensory data, resulting in redundant computations. These limitations restrict their scalability and practicality for low-power, real-time autonomous systems.

1.3. Emergence of Neuromorphic Computing and Spiking Neural Networks

Neuromorphic computing has emerged as a promising alternative paradigm inspired by the structure and dynamics of biological neural systems. Unlike conventional von Neumann architectures, neuromorphic systems employ massively parallel, event-driven computation that closely mimics neural information processing in the brain. Spiking neural networks (SNNs) form the computational foundation of neuromorphic systems by representing information as discrete spike events over time rather than continuous-valued activations. This temporal coding mechanism enables efficient processing of dynamic sensory inputs while significantly reducing energy consumption and latency. The compatibility of SNNs with event-based sensors, such as dynamic vision sensors, further enhances their suitability for real-time navigation applications.

1.4. Research Objectives and Contributions

The primary objective of this research is to investigate the effectiveness of neuromorphic spiking neural networks in enabling low-latency autonomous navigation. This work aims to design a navigation framework that integrates spiking neural models with event-driven sensory processing to achieve rapid decision-making and energy-efficient control. The contributions of this study include the development of a latency-aware SNN architecture for navigation tasks, an evaluation of its performance against conventional deep learning approaches, and an analysis of the trade-offs between latency, accuracy, and energy consumption. Through experimental validation, this research seeks to demonstrate the practical advantages of neuromorphic computing for real-time autonomous systems.

2. BACKGROUND AND RELATED WORK

The development of low-latency autonomous navigation systems draws upon advances in neuromorphic hardware, spiking neural computation, and intelligent control algorithms. Understanding the evolution of these areas provides essential context for the proposed research and highlights the limitations of existing approaches.

2.1. Overview of Neuromorphic Computing Architectures

Neuromorphic computing architectures are designed to emulate the parallelism, adaptability, and energy efficiency of biological neural systems. These architectures typically consist of networks of artificial neurons and synapses implemented in hardware, enabling local memory storage and computation. Unlike traditional processors, neuromorphic chips operate asynchronously and process information only when events occur, which drastically reduces unnecessary computation. Notable neuromorphic platforms have demonstrated ultra-low power consumption and real-time performance, making them well-suited for embedded autonomous systems. The architectural principles of neuromorphic computing enable scalable and fault-tolerant processing, which is particularly beneficial for navigation tasks in uncertain environments.

2.2. Fundamentals of Spiking Neural Networks

Spiking neural networks represent the third generation of neural network models, incorporating biologically realistic neuron dynamics. In SNNs, neurons communicate through discrete spikes, and the timing of these spikes carries meaningful information. Neuron models such as leaky integrate-and-fire and Hodgkin–Huxley simulate membrane potential dynamics and threshold-based firing behavior. Learning in SNNs often relies on biologically inspired rules such as spike-timing-dependent plasticity, which adjusts synaptic weights based on the temporal correlation between pre- and post-synaptic spikes. These temporal processing capabilities allow SNNs to naturally encode and exploit time-dependent patterns, making them particularly effective for navigation tasks that require rapid sensory-motor integration.

2.3. Existing Navigation Approaches Using Deep Learning

Deep learning-based navigation systems commonly utilize convolutional neural networks for perception and reinforcement learning frameworks for decision-making. These approaches have achieved impressive performance in structured environments and simulation-based benchmarks. However, they often depend on high-throughput GPUs and extensive training data, which limits their applicability in real-world, energy-constrained systems. Furthermore, deep learning models typically process sensory data in fixed time intervals, leading to latency accumulation that can degrade real-time responsiveness. While optimization techniques such as model compression and hardware acceleration have been explored, fundamental architectural constraints remain.

2.4. Prior Snn-Based Navigation Systems

Recent research has explored the use of spiking neural networks for navigation tasks, including obstacle avoidance, path planning, and sensorimotor control. These studies have demonstrated that SNNs can achieve competitive navigation performance while operating at significantly lower power levels. Event-driven sensory processing and spike-based control mechanisms enable faster reaction times compared to traditional neural networks. However, many existing SNN-based navigation systems are limited to simplified environments or rely on handcrafted network designs. The lack of standardized training methodologies and benchmarking frameworks has hindered broader adoption and comparative evaluation.

2.5. Research Gaps and Challenges

Despite promising advancements, several challenges remain in applying spiking neural networks to autonomous navigation. Designing scalable SNN architectures that can handle complex, real-world environments remains an open problem. Training SNNs efficiently and effectively, particularly for end-to-end navigation tasks, is still an active area of research. Additionally, integrating neuromorphic hardware with robotic platforms presents practical challenges related to interfacing, programmability, and system reliability. Addressing these gaps is essential for realizing the full potential of neuromorphic SNNs in low-latency autonomous navigation systems.

3. NEUROMORPHIC SYSTEM ARCHITECTURE

The neuromorphic system architecture forms the foundation of the proposed low-latency autonomous navigation framework. This architecture is designed to support event-driven sensing, spike-based computation, and real-time control while minimizing latency and energy consumption. By tightly coupling neuromorphic hardware with spiking neural computation, the system enables rapid perception-to-action cycles essential for autonomous navigation in dynamic environments.

3.1. Hardware Platform

The hardware platform consists of neuromorphic processors integrated with event-based sensors to enable efficient and low-latency computation. Neuromorphic processors are specifically designed to emulate the parallel and asynchronous operation of biological neural systems, allowing neurons and synapses to compute locally without centralized control. These processors support spike-based communication, where computation occurs only when events are generated, significantly reducing redundant processing. Event-based sensors, such as dynamic vision sensors, complement this architecture by producing asynchronous output that encodes changes in the environment rather than full image frames. This tight integration between sensor and processor allows the system to respond immediately to environmental changes, making it highly suitable for autonomous navigation tasks that demand real-time performance.

3.2. System Pipeline for Perception, Decision-Making, and Control

The system pipeline follows an event-driven processing flow that connects perception, decision-making, and control in a continuous loop. Sensory events generated by event-based sensors are directly transmitted to the spiking neural network without the need for frame reconstruction or preprocessing. The SNN processes these events in real time, extracting relevant spatial and temporal features required for navigation. Based on the spiking activity patterns, decision-making neurons generate action-related spike outputs that represent navigation commands. These commands are then translated into motor control signals that drive the autonomous agent. The asynchronous nature of this pipeline ensures that perception and control operate concurrently, minimizing delay between environmental changes and system response.

3.3. Data Encoding Strategies

Efficient data encoding is critical for transforming sensory inputs into spike trains suitable for spiking neural networks. Rate coding encodes information in the frequency of spikes over a given time window, offering robustness but at the cost of increased latency. Temporal coding represents information using precise spike timing, enabling faster and more efficient information transmission. Event-driven encoding leverages the inherent sparsity of sensory data by generating spikes only when changes occur in the environment. In the proposed architecture, event-driven and temporal encoding strategies are preferred, as they align with the neuromorphic paradigm and enable rapid processing of dynamic navigation scenarios while reducing computational overhead.

4. SPIKING NEURAL NETWORK MODEL

The spiking neural network model serves as the computational core of the navigation system. It is designed to process temporally encoded sensory information and generate control decisions with minimal latency. The model emphasizes biological plausibility, computational efficiency, and adaptability to dynamic environments.

4.1. Network Topology and Neuron Models

The network topology is organized into hierarchical layers that correspond to sensory processing, feature extraction, decision-making, and motor control. Input layers receive encoded spike streams from sensors, while intermediate layers learn spatial and temporal patterns relevant to navigation. Output layers produce action-related spike signals that influence motor commands. Neurons within the network are modeled using biologically inspired formulations such as the leaky integrate-and-fire model, which captures membrane potential dynamics and threshold-based firing behavior. This neuron model balances biological realism with computational efficiency, making it suitable for real-time neuromorphic execution.

4.2. Learning Mechanisms

Learning in the spiking neural network is achieved through a combination of biologically inspired and optimization-based mechanisms. Spike-timing-dependent plasticity adjusts synaptic strengths based on the relative timing of pre- and post-synaptic spikes, enabling the network to learn temporal correlations in sensory data. Reward-modulated learning incorporates feedback from the environment, allowing the system to associate successful navigation outcomes with specific spiking patterns. Additionally, surrogate gradient methods enable gradient-based optimization by approximating non-differentiable spike functions, facilitating efficient training of deeper SNN architectures. Together, these learning mechanisms allow the network to adapt to complex navigation tasks while maintaining low latency.

4.3. Integration with Sensory Inputs for Navigation

Sensory integration is achieved by directly mapping encoded spike trains from event-based sensors to the input neurons of the SNN. This direct coupling eliminates the need for intermediate data conversion or buffering, preserving temporal precision. The network learns to associate specific spiking patterns with environmental features such as obstacles, free space, and directional cues. By processing sensory inputs continuously, the SNN maintains an up-to-date internal representation of the environment, enabling rapid and context-aware navigation decisions.

4.4. Latency-Aware Design Considerations

Latency-aware design is a central principle of the proposed SNN model. The network is optimized to minimize spike propagation delay, synaptic processing time, and decision latency. Sparse connectivity and event-driven computation reduce unnecessary neural activity, further improving responsiveness. The use of local learning rules and parallel computation ensures that latency does not scale significantly with network size. These design considerations collectively enable the system to meet the stringent timing requirements of autonomous navigation.

5. NAVIGATION FRAMEWORK

The navigation framework defines how the spiking neural network interacts with the environment to achieve goal-directed movement. It encompasses environment representation, action selection, obstacle avoidance, and real-time control, all within a neuromorphic and low-latency paradigm.

5.1. Environment Representation and State Modeling

The environment is represented implicitly through spiking activity patterns rather than explicit geometric maps. Sensory events encode environmental changes such as motion, proximity, and obstacle presence. These events are transformed into internal neural states within the SNN, which capture both spatial structure and temporal dynamics. This implicit state modeling allows the system to adapt quickly to dynamic environments without relying on computationally expensive mapping or localization procedures.

5.2. Action Selection and Motor Control Using Snns

Action selection is performed by output neurons whose spiking activity corresponds to specific navigation actions such as turning, accelerating, or stopping. Competing action neurons interact through inhibitory and excitatory connections, enabling the network to select appropriate actions based on sensory context. Motor control signals are generated directly from spike rates or spike timing patterns, allowing smooth and responsive movement. This direct spike-to-actuator mapping reduces control latency and enhances system stability.

Table 1: Action Selection and Motor Control Using Spiking Neural Networks

Component	Functional Role
Output Neurons	Encode navigation actions such as turning, acceleration, and stopping
Excitatory Connections	Promote action selection based on sensory relevance
Inhibitory Connections	Suppress competing actions to ensure stable decision-making
Control Signal Generation	Derived from spike rate or precise spike timing
Actuator Interface	Direct spike-to-motor command mapping
Response Smoothness	High due to continuous spike-based control
Control Latency	Minimal, enabling real-time operation

5.3. Obstacle Avoidance and Path Planning Strategy

Obstacle avoidance emerges from the learned association between sensory spike patterns and corrective navigation actions. When obstacle-related events are detected, the SNN rapidly produces avoidance responses without requiring explicit path replanning. For longer-term navigation goals, the network can learn preferred movement patterns through reward-modulated learning, enabling efficient path selection. This reactive yet adaptive strategy allows the system to handle both immediate hazards and goal-directed navigation.

5.4. Real-Time Inference and Decision Cycle

The real-time inference cycle operates continuously, with perception, decision-making, and control occurring in parallel. Each sensory event triggers localized computation within the network, resulting in immediate updates to the navigation state. Decisions are generated incrementally rather than in discrete steps, ensuring that the system remains responsive even under rapidly changing conditions. This continuous decision cycle is a key advantage of neuromorphic SNN-based navigation, enabling ultra-low latency operation suitable for real-world autonomous systems.

6. EXPERIMENTAL SETUP

The experimental setup is designed to rigorously evaluate the proposed neuromorphic spiking neural network–based navigation framework under controlled and reproducible conditions. Both simulation-based experiments and hardware-oriented evaluations are considered to assess the effectiveness, efficiency, and practicality of the system in real-world autonomous navigation scenarios.

6.1. Simulation and Real-World Robotic Platform

The proposed navigation system is evaluated using a combination of high-fidelity simulation environments and, where feasible, real-world robotic platforms. Simulation environments provide controlled settings that allow systematic variation of environmental complexity, obstacle density, and dynamic conditions. These simulations emulate realistic sensor noise and actuator constraints to ensure meaningful performance assessment. In parallel, real-world experiments are conducted on a mobile robotic platform equipped with event-based sensors and neuromorphic processing units. This dual evaluation strategy ensures that the system’s performance is not limited to idealized conditions and demonstrates its feasibility for practical deployment in physical environments.

6.2. Datasets and Environments Used for Evaluation

Evaluation is performed across diverse navigation environments that represent both structured and unstructured settings. Synthetic datasets generated within simulation frameworks are used to model indoor corridors, open spaces, and cluttered environments with dynamic obstacles. Additionally, event-based sensory datasets are employed to evaluate the system’s ability to process real-world asynchronous data. These datasets capture realistic motion patterns, lighting variations, and environmental changes. By testing across multiple environments, the experimental setup ensures that the proposed system generalizes well to varied navigation conditions and does not overfit to a single scenario.

6.3. Baseline Models for Comparison

To assess the effectiveness of the proposed neuromorphic SNN-based approach, performance comparisons are conducted against conventional neural network–based navigation models. These baseline models include deep learning architectures such as convolutional neural networks combined with reinforcement learning for decision-making. The baseline systems are implemented using optimized configurations to ensure fair comparison. By evaluating against well-established deep learning approaches, the experimental setup highlights the advantages and trade-offs of neuromorphic spiking computation in terms of latency, energy efficiency, and navigation performance.

6.4. Evaluation Metrics

System performance is evaluated using a comprehensive set of metrics that capture both functional and efficiency-related aspects of autonomous navigation. Latency is measured as the time elapsed between sensory event detection and action execution, reflecting real-time responsiveness. Energy efficiency is evaluated by measuring power consumption during navigation tasks, emphasizing suitability for embedded systems. Navigation accuracy is assessed based on trajectory deviation, goal-reaching performance, and collision avoidance effectiveness. Robustness is evaluated

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by testing system performance under varying environmental conditions, sensor noise, and dynamic obstacles. Together, these metrics provide a holistic assessment of the proposed framework.

7. RESULTS AND ANALYSIS

This section presents a detailed analysis of experimental results obtained from both simulation and real-world evaluations. The performance of the neuromorphic SNN-based navigation system is analyzed in comparison with conventional neural models, with particular emphasis on latency, energy efficiency, and adaptability.

7.1. Performance Comparison with Conventional Neural Models

The results demonstrate that the proposed spiking neural network achieves navigation performance comparable to, and in some cases exceeding, that of conventional deep neural network–based systems. While deep learning models perform well in static and structured environments, their performance degrades in dynamic settings due to accumulated processing delays. In contrast, the event-driven nature of the SNN allows continuous adaptation to environmental changes, resulting in smoother and more responsive navigation behavior. These findings indicate that neuromorphic SNNs offer a viable alternative to traditional deep learning approaches for real-time navigation tasks.

7.2. Latency and Power Consumption Analysis

Latency analysis reveals a significant reduction in end-to-end response time for the neuromorphic system compared to baseline models. The asynchronous processing and sparse activation of spiking neurons eliminate unnecessary computation, enabling rapid decision-making. Power consumption measurements further highlight the energy efficiency of the neuromorphic approach, with substantially lower energy usage observed during continuous navigation tasks. This reduction in power consumption is particularly advantageous for battery-operated autonomous platforms, where energy efficiency directly impacts operational longevity.

7.3. Navigation Success Rate and Adaptability

The navigation success rate is evaluated across multiple environments and task configurations. The proposed system consistently achieves high success rates in reaching target destinations while avoiding obstacles. Moreover, the system demonstrates strong adaptability to environmental changes, such as moving obstacles and altered layouts. This adaptability arises from the temporal learning capabilities of the SNN, which enable rapid adjustment of spiking patterns in response to new sensory information. The results confirm the system's robustness and suitability for real-world navigation scenarios.

7.4. Ablation Studies

Ablation studies are conducted to analyze the contribution of individual components within the proposed architecture. By selectively removing or modifying elements such as temporal encoding strategies, learning mechanisms, or network depth, the impact of each component on overall performance is assessed. These studies reveal that event-driven encoding and latency-aware network design play a critical role in achieving low-latency navigation. The ablation results validate the architectural choices and provide insights into potential optimization strategies.

8. DISCUSSION

The experimental findings underscore the potential of neuromorphic spiking neural networks as an effective solution for low-latency autonomous navigation. This section discusses the broader implications of the results, addressing system advantages, scalability, and remaining challenges.

8.1. Advantages of Neuromorphic Snns in Autonomous Navigation

Neuromorphic SNNs offer several key advantages over conventional neural network approaches. Their event-driven processing paradigm enables ultra-low latency responses, which are critical for safe and efficient navigation in dynamic environments. The inherent energy efficiency of spike-based computation makes these systems well-suited for deployment on embedded and mobile platforms. Additionally, the temporal learning capabilities of SNNs allow them to naturally process dynamic sensory information, enhancing adaptability and robustness.

8.2. Scalability and Deployment Considerations

Scalability is an important consideration for deploying neuromorphic navigation systems in complex environments. The parallel and distributed nature of neuromorphic architectures supports scaling to larger networks without a proportional increase in latency or power consumption. However, practical deployment requires careful integration with existing robotic hardware and software frameworks. Advances in neuromorphic toolchains and standardized interfaces are expected to facilitate broader adoption and deployment of SNN-based navigation systems.

8.3. Limitations and Open Challenges

Despite their advantages, neuromorphic SNN-based navigation systems face several limitations. Training spiking neural networks remains more complex than training conventional deep learning models, particularly for end-to-end navigation tasks. The lack of standardized benchmarks and evaluation protocols also complicates comparative analysis. Furthermore, neuromorphic hardware availability and programmability remain limited compared to traditional computing platforms. Addressing these challenges will be essential for advancing neuromorphic navigation systems toward widespread real-world adoption.

9. CONCLUSION AND FUTURE WORK

This paper presented a neuromorphic navigation framework based on spiking neural networks designed to achieve low-latency and energy-efficient autonomous navigation in dynamic environments. By leveraging event-driven sensing, spike-based computation, and latency-aware network design, the proposed system addresses key limitations of conventional deep learning–based navigation approaches, particularly in real-time responsiveness and power efficiency. Experimental results demonstrated that the spiking neural network architecture can achieve competitive navigation accuracy while significantly reducing inference latency and energy consumption compared to traditional neural models. The implicit environment representation through spiking activity enabled rapid adaptation to environmental changes without relying on computationally expensive mapping or localization techniques. Furthermore, the integration of biologically inspired learning mechanisms allowed the system to exhibit robust obstacle avoidance and goal-directed behavior across diverse navigation scenarios. These findings highlight the suitability of neuromorphic spiking neural networks for deployment in resource-constrained autonomous platforms such as mobile robots, drones, and embedded edge systems. The implications of this work extend beyond navigation, suggesting that neuromorphic computing can play a critical role in enabling scalable, resilient, and real-time autonomous intelligence. Despite these promising results, several challenges remain. Training methodologies for large-scale spiking neural networks require further refinement, and standardized benchmarks for evaluating neuromorphic navigation systems are still limited. Future research will focus on improving learning efficiency through hybrid training approaches, integrating more advanced neuromorphic hardware, and extending the framework to multi-agent and cooperative navigation scenarios. Additionally, incorporating higher-level cognitive functions such as semantic understanding and long-term planning into spiking neural architectures represents an important direction for future work. Overall, this study demonstrates that neuromorphic spiking neural networks provide a viable and effective pathway toward next-generation autonomous navigation systems that demand low latency, high efficiency, and robust real-world performance.

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